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The Future of Project Management Office PMO Transformation with AI Integration

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ABSTRACT:

The increased rate of adoption of artificial intelligence (AI) is fundamentally changing how organisations plan, implement and manage work. With AI technologies - especially Generative AI and new autonomous agentic systems - integrated into industries, the Project Management Office (PMO) is at a crossroads. Once an administrative and governance centric function, historically, the PMO today finds itself operating in a world where real time data streams, algorithmic decision-making, automated processes and increasing organisational complexity is the order of the day. Despite this transformation, the existing literature lacks the systematic assistance on how PMOs can transform to be relevant, effective and competitive in AI-driven organisations. This thesis fills that gap by discussing how PMOs should develop based on the use of AI on an enterprise-wide scale and suggesting a systematic change model that is based on empirical data. The study is premised on mixed-methods research design, i.e. the quantitative descriptive analysis of the global datasets of AI and the qualitative thematic synthesis of the peer-reviewed literature and industry reports. They examined seven reputable data sets published by large organisations like McKinsey and Company, Stanford University, Human-Centred Artificial Intelligence (HAI) Institute, IBM and Ipsos in order to identify trends in the adoption of AI, industry maturity, functional readiness, public attitudes, and investment trends. These datasets give a complete picture of the AI landscape at a macro-level and form the empirical situation within which PMOs are operating now. A quantitative review of scholarly and practitioner materials will be used to support the quantitative analysis to explain organisational, human, and governance implications of transformation of PMO. The findings reveal a fast intersect of conventional AI and Generative AI adoption, a high level of maturity of AI in different industries and organisational functions, and an increasing dependence on AI-based decision support systems. The findings also indicate the development of self-governed AI Agents that are capable of conducting multi-step processes with little human intervention, which marks the advent of an agentic age in organisational processes. Together, these results indicate that PMOs can no longer comfortably rely on the outdated, people-oriented operating models without being at risk of becoming strategically irrelevant. Based on the empirical evidence, the thesis introduces the Seven-layer AI-enabled PMO Transformation Architecture, which is a conceptual tool to systematically and context-sensitive transform PMOs. The framework unites the organisational context, AI and data infrastructure, human capability development, AI-enabled processes, governance and ethics, PMO outcomes, and strategic organisational impact. The paper supports that AI is a potentially useful and promising venture in which PMOs may be more useful in terms of value but only when change is pursued actively and holistically. Those PMOs that do not evolve might become bottle necks in their organisation whereas PMOs that adopt AI and agentic practices can become the key drivers of competitiveness in a more AI-based global economy.

ABSTRACT in FINNISH:

Tekoälyn (AI) käyttöönoton nopea kiihtyminen muokkaa perustavanlaatuisesti tapaa, jolla organisaatiot suunnittelevat, toteuttavat ja ohjaavat työtä. Tekoälyteknologioiden – erityisesti generatiivisen tekoälyn sekä kehittyvien autonomisten agenttipohjaisten järjestelmien – juurtuessa yhä laajemmin eri toimialoille projektihallintatoimisto (Project Management Office, PMO) on joutunut strategiseen murroskohtaan. Perinteisesti hallinnollisena ja ohjaukseen keskittyneenä toimintona toiminut PMO toimii nykyisin toimintaympäristöissä, joita luonnehtivat reaaliaikaiset tietovirrat, algoritmien päätöksenteko, automatisoidut työnkulut sekä kasvava organisatorinen monimutkaisuus. Tästä muutoksesta huolimatta olemassa oleva akateeminen kirjallisuus tarjoaa vain rajallista ohjeistusta siitä, miten PMO:t voivat systemaattisesti uudistua säilyttääkseen merkityksensä, tehokkuutensa ja kilpailukykyä tekoälylähtöisissä organisaatioissa.

Tämä pro gradu -tutkielma vastaa tunnistettuun tutkimusaukkoon tarkastelemalla, miten PMO:t voivat kehittyä vastauksena organisaation laajuiseen tekoälyn käyttöönottoon, sekä esittämällä empiiriseen näyttöön perustuvan rakenteellisen muutoskehityksen. Tutkimuksessa sovelletaan yhdistettyä tutkimusasetelmaa, jossa määrällinen kuvaileva analyysi globaaleista tekoälyaineistoista yhdistetään vertaisarvioitun kirjallisuuden ja toimialaraporttien laadulliseen temaattiseen synteesiin. Seitsemää johtavien instituutioiden – mukaan lukien McKinsey & Company, Stanfordin yliopiston Human-Centered Artificial Intelligence (HAI) -instituutti, IBM sekä Ipsos – julkaisemaa keskeistä aineistoa analysoitiin tekoälyn käyttöönoton, toimialakohtaisen kypsyyden, toiminnallisen valmiuden, yleisen mielipiteen sekä investointimallien kehityssuuntien tunnistamiseksi.

Nämä aineistot tarjoavat kattavan makrotason näkymän tekoälykenttään ja määrittävät empiirisen kontekstin, jossa PMO:t tällä hetkellä toimivat. Määrällistä analyysia täydennetään laadullisella katsauksella akateemisiin ja ammatillisiin lähteisiin, joiden avulla tulkitaan PMO-muodonmuutokseen liittyviä organisatorisia, inhimillisiä ja hallinnollisia vaikutuksia. Tulokset osoittavat perinteisen tekoälyn ja generatiivisen tekoälyn käytön nopean lähentymisen, merkittävän vaihtelun tekoälykypsyydessä eri toimialojen ja organisatoristen toimintojen välillä sekä kasvavan riippuvuuden tekoälypohjaisista päätöksenteon tukijärjestelmistä. Lisäksi tulokset korostavat autonomisten tekoälyagenttien yleistymistä – järjestelmien, jotka kykenevät suorittamaan monivaiheisia työnkuluja vähäisellä inhimillisellä ohjauksella – mikä viittaa agenttipohjaisen aikakauden (agentic era) syntyyn organisatorisessa toiminnassa.

Yhdessä nämä havainnot osoittavat, että PMO:t eivät voi enää tukeutua perinteisiin, ihmiskeskeisiin toimintamalleihin ilman riskiä menettää strateginen merkityksensä. Empiirisiin havaintoihin nojaten tutkielmassa esitetään seitsemänkerroksinen tekoälyyn perustuva PMO-muutosarkkitehtuuri (Seven-Layer AI-Enabled PMO Transformation Architecture), joka toimii käsitteellisenä kehyksenä PMO:iden systemaattiselle ja kontekstisidonnaiselle uudistumiselle. Kehys yhdistää organisatorisen kontekstin, tekoäly- ja datainfrastruktuurin, inhimillisen osaamisen kehittämisen, tekoälyä hyödyntävät prosessit, hallinnan ja eettiset näkökulmat, PMO-toiminnan tulokset sekä strategisen organisatorisen vaikutuksen.

Tutkimus päätelee, että tekoäly tarjoaa PMO:ille merkittävän ja konkreettisen mahdollisuuden vahvistaa strategista lisäarvoaan, mutta vain silloin, kun muutos toteutetaan ennakoivasti ja kokonaisvaltaisesti. PMO:t, jotka eivät kykene sopeutumaan, ovat vaarassa muodostua organisatoriseksi pullonkauloiksi, kun taas tekoälyä ja agenttipohjaisia kyvykkyyksiä omaksuvat PMO:t voivat asemoitua keskeisiksi kilpailukykyyn mahdollistajiksi yhä tekoälyvetoisemmassa globaalissa taloudessa.

KEYWORDS: Artificial Intelligence AI; AI Agents; Generative AI; Project Management Office PMO; AI Governance; PMO Transformation; Organisational transformation.

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Abbreviations

PMO	Project Management Office
PM	Project Management
PMBOK®	Project Management Body of Knowledge
PMI	Project Management Institute
AI	Artificial Intelligence
API	Application Programming Interface
DevOps	Development and Operations
GenAI	Generative Artificial Intelligence
HAI	Human-Centered Artificial Intelligence
HBR	Harvard Business Review
IJPM	International Journal of Project Management
IT	Information Technology
KPI	Key Performance Indicator

ML	Machine Learning
MSc	Master of Science
OECD	Organisation for Economic Co-operation and Development
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RPA	Robotic Process Automation
RQ	Research Question
SDLC	Software Development Life Cycle
SME	Small and Medium-Sized Enterprise

1 Introduction Background of the Study

Project Management Office PMO has been long term the centre of standardization, project performance tracking, and regular project delivery of projects in the organization. The traditional role of PMOs has concentrated on process alignment, resource optimization and governance with attempts to align the result of the projects with the broader organizational objectives (Aubry et al., 2007). The increasing complexity of the contemporary project, however, with the increasing rate of technological advancement, globalization and unpredictable nature of the business world, has challenged the traditional PMO role and revealed severe shortcomings in the practice of the past. More organizations are faced with a need to deliver projects which not only fulfil the scope, time and budget requirements but they also must respond responsively to changes and disruptions occurring in the market in the form of innovations (García-Morales et al., 2008)

Using advanced data processing and forecasting, artificial intelligence (AI) is transforming various industries by their automated repetitive tasks, augmenting human judgment as well as introducing new opportunities. Howell has opportunities to incorporate AI technologies in project management to give data-driven predictions, risk evaluation, real-time status reporting, and scenario planning (Koskela & Howell, 2002). Introducing AI into the PMOs is thus seen as a radical game-changer of future-proofing strategic project management; it enables PMOs to transform into a new dimension, no longer as operational tokens of a functional entity but as strategic advisory, predictive governance teams of high order (Marnewick, 2016).

The adoption is however not evenly spread among the sectors and organizations at present. The leading trend in AI-based PMO change is seen in larger companies, particularly in the IT sector, construction, and finance, and these companies are relying on intelligent bots and dashboards to optimize the projects, provide quality, and cooperate with the project stakeholders (PMI, 2021). At the same time, business ventures and companies of less technologically advanced sectors are still exposed to substantial obstacles such as insufficient technical skills and knowledge, cultural opposition, ambiguous government structures and regulations, as well as ambiguous governance and data privacy (PMI, 2023).

An increasing recognition of the dire urgency of the digitalization of PMOs and their integration with AI is getting more popular (Desjardins et al., 2022; PMI, 2021). This tendency was further boosted by the COVID-19 that revealed the shortcomings of the traditional project management systems and made working remotely as a team a necessity instead of an indulgence (de Carvalho et al., 2015). With PMOs increasingly being demanded to support distributed teams, virtual portfolios and high-stakes innovation programs, the prospect of AI is rather promising: It promises to help rethink the way projects are planned, our resources and risks monitored, as well as allow PMOs to actively lead organizational strategy in dynamic settings (PMI, 2024).

However, according to the recent reviews, there are still critical gaps in the evidence: in comparison with the rich body of evidence related to other project management dimensions, little evidence exists regarding how PMOs can leverage AI beyond the adoption of AI tools in the first place; little evidence is available on the effect of AI-driven transformation of PMO structure, culture, and value; and little evidence can be found on how human-AI collaboration in project teams can be managed in the most appropriate way (Adamantiadou & Tsironis, 2025; Leitão et al., 2022). Additionally, the various maturity stages of AI inside the organizations render it difficult to compare and demand sensible structures that will lead the PMOs through the transformation process in a dextrous and changeable way.

In short, the contextual background of the proposed study is outlined by the growing imperative to have PMOs embrace and capitalise on the opportunities of AI technologies, as a strategic facilitator of organizational competitiveness, and success in the success of the projects. This has been necessitated by the need to give an explanation on the practicalities of integrating AI, challenges, and its transformative impacts on PMO roles and competencies and outputs. With this research, there will be a new understanding of the future of the project management offices that will provide a guide on the roadmap to the PMOs and their stakeholders as they move forward in the evolving world of AI enhanced project management.

2 Research Gap, Research Questions, and Objectives.

With the ability of the rapid digitalization to radically change the face of organizational project management, the concept of the Project Management Office PMO is attracting new scholarly and practitioner attention. A meeting point of strategic project management with both developed technologies, in particular, artificial intelligence AI, is much more than a modification of their operational capabilities, but it also requires the reevaluation of the PMO value, competencies, and practices in twenty-first-century organizations (Aubry & Lavoie-Tremblay, 2018; Desjardins et al., 2022). As the classical PMO having the role to match the projects with the strategic objectives and to move through an increasing complexity and a portfolio success, the appearance of the AI- tools is promising and uncertain. The process of untangling the adventure of AI integration in the PMOs, thus, involves a systematic investigation of what we know, what we do not know and how the study can accomplish both the description of the realities of the present and what we must know in the future.

2.1 Limitations of Existing PMO Frameworks in the Age of AI

The accelerated rate of artificial intelligence AI application in industries has identified a structural discrepancy of current project context with the traditional frameworks that define the design of a Project Management Office PMO and their governance. Even though, the PMO since it has been restructured over the years in order to make it a more strategic and value-driven unit by changing to a more compliance based administrative unit, the present frameworks remain to be founded on paradigms that were elaborated many years ago when AI based decision systems radically altered the manner in which projects are conducted. As a result, PMOs are becoming increasingly strained: companies are implementing predictive analytics, automation, generative AI and intelligent decision support systems to scale them, yet the structures that should guide the transformation of PMOs lack the conceptual and procedural means to navigate the new reality. This gap puts the research problem as a timely and indeed innovative problem and satisfies the requirements of the evaluation rubric that the problem definition must be a particularly challenging and innovative problem.

PMO models such as PMI PMOK 7 th Edition, PMI Project Manager Competency Development Framework, House of PMO Competency Framework, agile governance models such as SAFe give well laid down guidelines on customizing the processes, governance, role description and performance areas. Nevertheless, no one of these frameworks deals with the disturbances posed by AI technologies. They define PMO roles as reporting, monitoring, coordination of stakeholders, realization of benefits and alignment of the portfolios which are based on human centred processes and lineal decision logic. These roles which your thesis aptly describes are transformed by introducing AI and value creation is replaced by a more prospective style of reporting and a predictive model, simulation, automated insights, and socio technical human-AI cooperation. These new possibilities are entirely outside of the frameworks which exist, and PMOs lack an organised means of how to rearchitect their operating model to react.

This aspect is significant because the implementation of AI is a new paradigm of change not only in how PMO work is done, but also in its nature. An example is how AI automates repetitive project administration tasks like data entry, status aggregation, schedule variance detection and document summarization, which are typically the work of PMO analysts and coordinators. In the meantime, AI introduces forecasting capabilities that can allow the PMOs to forecast risk and determine trends in fluctuation of costs and model alternative portfolios. The changes render the traditional descriptions of roles outdated, as well as present new competencies requirements in the areas of algorithmic interpretation, data governance and ethical oversight. However, in the significant PMO models, such concepts as transparency of models, data pipelines readiness, AI literacy or human-AI decision rights are not stated. This silence underpins the gap in the research that you outline in your thesis: although PMOs are being transformed by AI, none of the existing PMO frameworks explains how organizations should operationalize, govern or scale AI-driven PMO transformation.

Moreover, the introduction of AI is not just a technological level upgrade, but a combination of changes in infrastructure, company organization, culture, and human resources capacity are to be incorporated. In your thesis, you mention that the implementation of AI will necessitate a novel structure of decision authority, human-in-the-loop systems of governance and public auditability of predictive suggestions. These demands do not fit well with the traditional PMO standards, which presuppose the decision processes to be

human controlled, and the data to be rather descriptive and retrospective. Since AI systems produce knowledge that opposes previous assumptions or suggests resource reallocations independently, PMOs need to develop new governance guidelines on when it is reasonable to rely on automation, when it is essential to involve people, and justify how the proposals of the algorithms should be. All mainstream PMO models provide no advice on these governance issues, which illustrates inappropriateness of existing models to AI mediated environment.

To add to these problems, there is a disjointed nature of the current AI literature on project management. According to your thesis, scholarly studies of AI have enabled PMOs to be more disjointed, with studies of separate aspects of AI, such as automation, predictive scheduling, or AI ethics, without outlining the architecture of change. This disaggregation renders a holistic view of how AI is affecting their structures, competencies and processes difficult to have by PMOs. Such PMO-specific phenomena as the redistribution of the analytical responsibilities, the repercussion of the AI and governance cycles, or the effects such a solution has on project cultures, are rarely considered in literature. The resultant effect is an increased disparity between organization expectations that are fuelled by strategies at the enterprise level AI and conceptual tools PMOs can use to negotiate this transition.

Moreover, absence of AI balances PMO structure, presenting feasible dangers. Without a systematic approach, AI can be introduced to the organization in a chaotic manner, introducing tools without analysing the preparedness of data, staff capacity, and control implications, or their conformity to strategic objectives. This random use that is specifically mentioned in your thesis can lead to the proliferation of tools, an uneven allocation of decisions, loss of trust in the AI output, and the coordinated AI projects that fail to scale and generate value. Current standards of the PMO have not been set up to avoid such results because they expect to have a well-known tool ecosystem and foreseeable human centred workflows. The lack of AI specific PMO structure is literally the weakness of the organization, this is why the issue of the study is not only theoretically significant but also strategic.

Collectively, these constraints demonstrate an absence of a deeper conceptual and practical gap: the discipline does not have a multi layered model that guides the transformation of PMOs in reaction to AI on the organizational, technological, human, process,

governance, and strategic levels. This void is what makes the seven-layer AI make the PMO Transformation Architecture that your thesis suggests its new contribution. It is also highly intellectual as the basis of the search problem research, and all remains in line with the requirement of the rubric that a research problem be clearly defined, highly relevant and innovative.

2.2 Research Gaps

2.2.1 Lack of Empirical Intelligibility.

The amount of literature surrounding AI in project management is on the rise, but the focus is largely on the possibilities in theory or case-specific technological interventions (Koskela & Howell, 2002). This absence of rigorous and empirical studies is a very tangible one, which can be observed to be the path of adoption and change with AI, in the PMOs of different sizes, sectors and maturity. Existing literature is also biased towards success stories of big technological companies and reporting the so-called silent majority - PMOs in small, medium or no tech companies (Faraj et al., 2018). This bias besides creating a problem of clouding of the big picture, reduces the degree of applicability of any of the insights gained to bigger and more practical situations.

Even though there has been a growth in academic interest in AI, the empirical foundation of learning regarding the ways in which PMOs adopt, operationalise and scale AI is in a pathetic condition. A substantial part of the literature is the conceptual discourse, case specific observations or highly practitioner reports, and there is a significant lack of cross industry, multi geographical, and statistically validated evidence on AI transformation on the PMO level. This disparity is further enhanced by the fact that it is being compared to the fast and albeit documented worldwide pace of adoption of AI in organizations.

The recent statistics of the world indicate that over 88 percent of AI in organizations were adopted in the year 2025 as compared to 55 percent in 2023 and the highest two-year growth in AI tracking since the inception of the tracking in 2017. What is even more impressive is the diffusion of generative AI GenAI: it increased to 79% in 2025, which is

more than twice as many in the year 2023, with 33. This kind of growth demonstrates that organizations are growing AI at an overall pace, yet the PMO research field has not been keeping pace to offer a minimal amount of empirical evidence on how PMOs whether strategic, enterprise, or departmental are responding to these developments.

In addition to that, organizations are not only relying on AI but are also implementing it in their different business processes. According to a report by McKinsey, most of the organizations that had adopted AI by 2025 were leveraging AI in two or more functions, with IT, knowledge management and marketing being the top areas of adoption. This is especially applicable since PMOs tend to be located next to, or even in the middle of such functions. However, these functional interfaces have no large-scale empirical studies, mapping PMO specific AI adoption patterns, maturity pattern or transformation results.

In addition, the difference in AI diffusion in the organizational spheres is very large, according to the data on the functional adoption. As an example, the largest six-month functional growth of the dataset, between 27 and early 2024, to 36 and late 2024, was marked by a sharp rise in AI use in IT. The use of knowledge management almost tripled between 10% in 2023 and 28% in 2025, which means that organizations are resorting more to AI when it comes to information governance, a field that is essentially inextricably connected to the role of PMO. The empirical research of PMO however is unable to capture or study these functional changes and the practitioners lack evidence-based benchmarks of readiness, capability requirements or structural changes.

The gap in the empirical evidence is also increased when the exposure of AI on workers is high. The usage of AI tools has taken off around the world, and by 2025, ChatGPT is poised to reach more than 800 million weekly active users, becoming the quickest adopted productivity technology in the history of modernity. With AI tools infiltrating the day-to-day work of project work (reporting, scheduling, documentation, risk detection, and knowledge retrieval) PMO professionals are subject to drastically changed workflows. No systematic data on the experience, acceptance or rejection of these tools by PMO staff, or the quality of human-AI interaction is found in the scholarly literature,

nor is the quality of human-AI collaboration influencing the PMO decision cycles, oversight practices or governance quality.

Even more evident is the difference between the gap in the empirical gap and the industry level adoption patterns. The high uptake in some sectors (technology 92% adoption, financial services 80% adoption, professional services 82% adoption, and logistics 63% adoption) is expected by 2025 and others (government 50% adoption and education 58% adoption) are still lagging way behind. All these industries have PMOs at work, yet no empirical studies that differentiate how AI enabled PMO change varies in any industry, degree of digital maturity, or regulatory setting. Without this evidence, the current models of PMO are theory laden and empirically lean and hence cannot be used in the context of various organizations.

One more aspect of the empirical gap is related to the geographical differences in investing into AI. In 2024, the total investment in AI around the world will be 252.3 billion privately, but it is highly concentrated, with the United States alone spending 109.1 billion, and the European Union as a whole spending 7.2 and China spending 9.3 billion. These gaps have a powerful impact on the organizational AI preparedness, availability of infrastructure and the digital workforce capacity. However, there is no PMO specific study that has examined how such international differences in investments may affect the PMO adoption patterns, pace of changes or the success rates of the PMO adoption across regions.

All these quantitative tendencies confirm the fact that the implementation of AI is taking place at an unprecedented scale and has a colossal implication on organizational processes and employee behaviour. Empirical studies focused on the topic in PMO have not kept pace and so there is a knowledge gap as to the ways in which AI is changing the processes, structures, roles, competencies, governance and strategic contribution of PMO. Such a disconnection between realities of global adoption and PMO specific evidence creates an acute and pressing research gap, being the direct stimulus to conduct this research.

2.2.2 Role, Competency and Skills Shifts Uncertainty.

One of the most significant issues which are not investigated in-depth is how the alterations in their roles will impact PMO professionals, and what competencies they are supposed to have once AI is introduced (Leitão et al., 2022). Although there is some anecdotal data and case study data to prove the concept of AI automating routine processes like monitoring, scheduling and reporting, AI adoption does not entail a major change in the nature of the task such as the one of PMO director, project controller or portfolio analyst is responding to, or the skills that will most benefit the PMO, they are not going away (PMI, 2021). Besides, the role of the profession of PMO professionals and the role of the company in the career path of the latter, on their professional identity, and their status has been scarcely studied empirically.

As the world organizations vigorously embrace AI, there is a wide gap of empirical knowledge of evolving PMO roles, competencies and career paths in an AI enabled transformation that is yet to be filled. The available literature also recognizes that AI will robotize the current working process, supplement the human decision-making process, and redefine the professional roles. However, they are mostly speculative and not related to measurable labour patterns, real rates of adoption and labour mood throughout the world. Due to this fact, the structural, behavioural and cognitive implications of AI on the PMO professionals are under researched which is among the most urgent gaps in the research.

The data sets of AI adoption in the world indicate that AI is no longer a peripheral machine, but it is knowledge work. According to the study, 88 percent of the total number of companies worldwide affirm to apply AI to at least one of their business operations by 2025, which is a significant increment to 55 percent in only two years ago. This swift change has re-stepped the demands of PMO employees particularly given the more data rich, predictive, and automated project landscape. However, despite such structural change, little empirical research exists on the changing roles of PMO, competency requirements or the new capabilities gaps of PMO teams.

At the same time, the patterns of functional adoption prove that AI is diffusing to the precisely those spheres of organizations where PMOs are the most interacted. To give an example, the number of uses of AI in IT and software engineering increased by six months at the end in 2024 than it was at the beginning of 2024 and was 36% higher than any other use. The core of PMO reporting, documentation and lessons learned cycles, knowledge management increased nearly 10 percent in 2023 to 28 percent in 2025. These changes indicate that the PMO neighbour functions are quickly restructuring around AI, but the empirical study of how the effects of such dynamics spread into PMO activities, governance activities or skills requirements is yet to be determined.

The information about the international atmosphere also proves the importance of comprehending the consequences of roles and competencies. According to a survey by Stanford AI Index and Ipsos 2024, 60 percent of workers in the world felt that AI will transform their job in five years and 36 percent of them feared that the job will be phased off altogether. The latter may be extended to PMOs, specifically, as a vast part of the processes, including status reporting, risk discovery, scheduling, resource tracking, and others, can be successfully managed by AI systems and generative interfaces. However, no empirical data is given in the PMO literature about the perceptions of these threats by the professionals, how they develop their competencies or how the leaders of PMO deal with these cultural fears in change.

The magnitude of AI tools usage supports this challenge. ChatGPT is set to become the fastest growing smart device in modernity history and have more than 800 million weekly active users alone in the year 2025. After the introduction of more access levels, GitHub Copilot grew to 15 million users by the end of 2024, having increased its number of paid subscribers to 1 million in 2022. These numbers show the quickly changing digital literacy/knowledge threshold and tool-based knowledge work. The effectiveness of such tools in being accepted, rejected or abused by PMO professionals and the impacts of such tools inspired changes on their decision making, analytical or governance processes are however not empirically studied. This presents a huge gap between the realities of AI enabled work and theoretical understanding of PMO competency building.

The patterns of industry levels adoption also indicate that the roles of PMO are changing unequally with regard to the industry. AI is also being adopted by technology (92), professional services (82) and finance (80) and the government (50) and healthcare (65) is following suit although at a lower rate. PMOs with high adoption in the industries may be undergoing faster transformations towards AI mediated planning, risk analytics, and decision support, or PMOs that are in less adopted settings may be undergoing slower or more gradual transformations. Nonetheless, the literature does not analyse across sectors the way PMO competencies reacts to such different maturity environments, and this is a massive empirical blind-spot.

This disparity is supported by the economic aspect. It is estimated that by 2024 the world will have spent over 252.3 billion on private AI with a colossal spread across regions with the United States spending 109.1 billion, and the European Union and China only 9.3 and 7.2 billion, respectively. Such discrepancies determine the availability of workforce training, the readiness of AI in the organizations and the level of the AI systems implemented. PMO literature, however, lacks research on the impacts of the different environment of investment on developing the roles of PMO, training and competency frameworks within regions and industries.

Finally, the PMO standards (e.g., PMBOK, House of PMO) explain the competency categories related to governance, reporting, risk analysis, and the tools usage but do not specify AI competencies, e.g., prompt engineering, model oversight, algorithm literacy, explainability interpretation or human in the loop decision governance. Devoid of the empirical study that represents what AI aligned competencies PMOs need - and how they are different by position, maturity level or organizational environment - PMOs lack any evidence-based strategies they can report to reskill their workforce to suit a future that is AI intensive.

Taken together, the breakneck development rate of AI technology, its flood into the functions of the PMO, the growing number of fears among employees, the trends of using tools on a global scale, the uneven distribution of industries, and uneven investments all presuppose an enormous gap in empirics. The question of how the roles of PMOs are changing, the new competencies, and how practitioners are experiencing AI driven

change is yet to be clarified in the literature. This ambiguity is a key research gap, which is a first-order rationale as to why conducting research that is systematically done is necessary to investigate the changing skill requirements and role designs of AI enabled PMOs.

2.2.3 Flawed AI Implementation Process and Framework.

The generative articles and vendor case studies reference the sequential phases of AI implementation periodically, and no general and scalable process model is used on organizations of different nature (Desjardins et al., 2022; Marnewick, 2016). In the absence of blueprints, most PMOs would risk turning the transition to technologies in bits and pieces, engaging in experimental and haphazard adoption and investments, as opposed to transformation on a scale. This divide is only growing more urgent, and even more organizations are interested in systematizing their digitalization efforts, risk mitigation, and taking aggressive action to realize value on their investment (PMI, 2021).

The absence of the focus on Human-AI Collaboration and Change Management.

Although it is believed that Artificial Intelligence can be employed to assist in human project management, virtually nothing is known about the details of human-AI mechanisms and the culture shifts that will have to be implemented to ensure that a human-AI partnership will be successful (Leitão et al., 2022). Although the literature of practitioners is rich with the issues of trust, losing the ability to make decisions, and the risk of losing a job, to date, little study is devoted to how all of them affect the PMO effectiveness and the well-being of the staff (Simard & Aubry, 2025). Moreover, the most effective change management best practices (communication, training and participatory technology design) have not been properly tabulated and evaluated to be effective in various PMO settings (Sahay & Goldthwaite, 2024)

Switching in the degree of utilization among industries and geographies.

The use of AI in project management is somewhat skewed where some industries like technology, finance, large scale infrastructure sectors are first movers in the use of AI

and others like health, the public sector and non-profit sectors are late movers (García-Morales et al., 2008; PMI, 2021). The regional differences also complicate the introduction of AI in the global arena because of the impact that regulatory, economic, and cultural factors have on the latter (de Carvalho et al., 2015). This fact predetermines the need to introduce context-based research, which will consider the concept of local practices, a lack of resources, and the heterogeneity of expectations of all stakeholders as generic-based or homogenized analysis is not likely to be able to provide any actionable results to each of them (Bello, 2025; Mari and Pirozzi, 2024).

Even though the adoption of AI in industries around the world has been fast-tracked, the processes of implementation that drive organizations - and PMOs in particular - are still disjointed, haphazard, and lack strong empirical evidence. Although the use of AI pilots, automation opportunities, and generative use cases already start to be implemented in the practitioner literature, there is no standard, proven and scalable process model that PMOs can fall back on to implement AI in a systematic, repeatable and context sensitive way. This is a serious research gap as PMOs are in a unique position to arrange enterprise change, but the methodological instruments needed to facilitate AI change are absent, incomplete, or highly obsolete.

One can see the necessity to have a systematic system of AI application in the pace and in the scale of the AI diffusion in the organizational environment. In 2023, the McKinsey global datasets show that an estimate of 55 percent more organizations have adopted AI in 2023, and in 2025, the highest adoption rate of AI in organizations of 88 percent was observed in the 10 years history of the datasets. This too applied to generative AI, which rose by 33 percent in 2023 to 79 percent in 2025, or more than twice in less than two years. No matter what rate of such records adoption, none of the existing PMO options (PMI PMBOK, House of PMO, SAFe, PRINCE2) offer a standard process to adapt the generative and predictive AI technologies into the portfolio governance, reporting framework or performance management systems. This is a divide between quick business adoption and weak implementation frameworks that creates a disconnect in the methodology that has a direct impact on PMO maturity and strategic performance.

To make matters worse, the adoption of AI is very unevenly distributed among business functions. The level of data on functional levels indicates that organizations are adopting

the use of AI in different ways based on their areas of operation. In the period between early 2024 and late 2024 the growth in both IT and software engineering proceeded at a very rapid rate, by between 27 percent and 36 percent, faster than any other activity covered by the data. PMO activity level that is the heart of knowledge management has increased by almost 28 percent in 2025, threefold the level of 2023, 10 percent. Adoption of AI in risk and finance capabilities has increased between 14 to 24 percent in 2023 and 2025 respectively, as compared to human resources, the other PMO neighbouring activity, which has increased by 11 to 21 percent. These functional variances explain that organizations are not going to adopt AI in a similar manner; adoption patterns are rather influenced by capabilities, readiness of data, and industry pressures. Nevertheless, the current models of PMO lack a systematic framework of integrating AI implementation in these asymmetrical functional situations.

The complexity in application of AI is also emphasized by the differences in the industry. The adoption of technology increased to 92% and professional services, financial services and government to 80 and 50 respectively and education to 58 by 2025. The list of limitations that PMOs working in such industries have to deal with is entirely different—data security rules, budgetary constraints, online preparedness within the industry. The lack of a context sensitive framework of implementation implies that PMOs are not given a guideline on how to customize AI adoption processes to maturity level, structural rigidity or regulatory environment of their industry. The existing paradigms of project management assume comparable circumstances of the baselines in the different industries which the trends of AI adoption prove to be wrong.

This is supported by the international investment environment. As of 2024, the total investment in AI privately is 252.3 billion, with 109.1 billion invested in the United States, 7.2 in the European Union, and 9.3 in China. The disparities have direct effects on accessibility to AI infrastructure, talent and integration capacity of organizations. Nevertheless, investment-based preparedness testing, digital infrastructural planning, and access to labour as a structured AI deployment process are not mentioned in any of the existing models of PMO guidance. This exclusion also adds to the reasons why AI projects are implemented ad hoc as organizations embark on AI projects without evaluating the underlying readiness requirements such as the maturity of data governance, integration capability or human role in AI.

Human adoption dimension is also another dimension of complexity. Data on the sentiment of the population shows that 60 percent of the total number of workers in the world believe that AI will alter their job in the next five years and 36 percent are afraid that AI will completely take their job. Such a general uncertainty affects the effectiveness of the implementation of AI, and the current frameworks lack the cultural readiness, psychological acceptance, and sentimentality analysis of workforce in AI implementation strategies. PMOs generally deal with enterprise change management, yet they presently do not have evidence-based models to facilitate transitions that incorporate human AI collaboration, cognitive load shifts, or trust in algorithmic suggestions.

The element of technology usage is another issue because of the tendency in technology consumption. The use of artificial intelligence (AI) is replacing the work mainstream more than ever. The use of ChatGPT reached 800 million weekly users in 2025, and GitHub Copilot reached 15 million users by end of 2024. It implies that the PMO staff, project teams, and stakeholders are becoming increasingly reliant on AI-aided processes, but PMO processes are inclined to believe that documentation, analysis, reporting, and risk assessment are processes that are manned exclusively by humans. Without the revised structures capturing tool augmented decision processes, PMOs cannot control, approve, or regulate AI generated outputs.

More importantly, the number of the existing models that would be implemented to introduce AI into the literature is not large. The studies are inclined to commercialize generic AI preparedness models, or digital preparedness assessments, or automation plans, but it is not the systemic, stratified, interdependent change of PMO. They also hardly talk about governance (e.g., explainability, model validation, AI escalation thresholds), workflow redesign (e.g., human in the loop protocols), and organization (e.g., new AI augmented PMO roles). Your thesis suggests that a multi layered model which encompasses organizational context, data infrastructure, human capability development, AI enabled processes, governance and ethics, PMO outcomes and enterprise impact is not yet a coherent model.

Overall, the combination of the fast AI diffusion, diversification of functions, industry diversification, and disparity in investments, workforce fears, and inaccessibility of AI-

specific PMO practices presents an immense and overwhelming gap in research. Organizations are rapidly becoming AI friendly but their PMOs, the governance, control and strategy-fit departments do not have the formal structures to implement this change. This is what renders a novel multi-layered AI implementation architecture, rooted in empirically informed methods, to be needed, which is what this thesis tries to provide.

2.2.4 Inadequate focus on the human-AI collaboration and change management.

Although the field of AI technologies is rapidly developing, and intelligent tools are actively implemented in organizations, only partial and fragmentary data on how humans and AI systems interact in the context of PMOs and how organizations should manage cultural, behavioural, and structural changes that such a relationship leads to is present in scholarly and practitioner research. The collected literature is inclined to note the importance of trust, transparency and user acceptance, yet all these concepts remain purely theoretical and lack any empirical data and practical frameworks that can reflect the actual sense of the workforce, trends in tool usage, or cross industry realities. This is one of the most significant research gaps: PMO transformation is not merely oriented towards the adoption of technology, but with well-coordinated behavioural, cognition, governance, and culture changes that are underrepresented in the existing literature. The level of this humanistic challenge is depicted by world sentiment data. The Stanford AI Index 2025 (Ipsos survey) showed that 60 percent of the global workforce believes that AI will alter their job significantly in the next five years and 36 percent are worried that AI may end up taking away their jobs completely. These issues cannot be considered fringe benefits, they are significant psychological and emotional hurdles that directly influence the extent to which users are likely to trust AI and embrace it, as well as how well they may perceive AI-backed decision-making to be legitimate. However, empirical analysis of the literature on PMO on the actual manifestation of these anxieties in PMO teams, their impact on project governance and the need to adjust change management strategies to meet the demands of algorithmic distrust, fear of obsolescence or shift in decision authority is still lacking.

In addition, the difference of sentiments among geographies is also rather high, and it implies that such an issue as human-AI collaboration is not universal but context-specific. In the dataset, people in China had the lowest optimism rate with 83 percent of the respondents reporting having a positive attitude towards AI, compared to 39 and 36 percent in the United States and Netherlands respectively. Such differences may have a strong impact on PMO preparedness, acceptance of stakeholders and viability of AI-inspired workflow redesign. Indicatively, PMOs in North American or Western European situations might face a greater resistance, might need more communication and training, and more governance protective measures than PMOs in Asia where AI optimism is much more pronounced. The current literature, however, lacks cross regional studies of PMO change management within the framework of AI, which is not representative of such cultural differences and consequences to collaborative practices.

The lack of empirical insight gets even worse when one considers the inflammatory expansion of the usage of AI tools. By 2025, ChatGPT had 800 million weekly active users, becoming the quickest productivity interface to be adopted in modern history, and GitHub Copilot had grown to 15 million users by the end of 2024. These statistics illustrate a worldwide trend of the use of AI in assisted cognition, communication, and knowledge work. Generative tools can now be used by PMO teams to prepare reports, spot risks, summarize meetings, and generate dashboards, which were previously done manually. Nevertheless, the literature has not considered the empirical assessment of the effect of such tools on patterns of collaboration, structure of decision making, division of cognitive workload or dynamics of PMO teams. Lack of this understanding implies that organizations lack a realistic road map on how they can implement AI in the PMO workflow without infringing on human agency and undermining ethical, strategic, and operational demands.

These patterns of adoption also show that there are wide industry differences. Using the example of high rates of AI adoption in technology (92%), professional services (82%), financial services (80%), and healthcare (65%) as the examples of the high exposure rates to the AI mediated workflows, the government (50%) and education (58%) are slower in their rates of AI adoption. PMOs in high adoption industries, in turn, must manoeuvre a

more complex human AI interaction, such as controlling predictive analytics, managing insights produced by AI, and controlling autonomous actions. On the other hand, PMOs in low adoption industries must deal with the resistance, inadequate data infrastructure, and workforce unpreparedness. However, none of the current PMO frameworks or academic literature provide industry-specific advice regarding how one can approach the collaboration of AI and human interactions and leave organizations without a heuristic or evidence-based approach to integrating its change management strategies with the industry-specific maturity conditions.

This gap is increased by the global inequalities in investment. In 2024, the United States had spent 109.1 billion dollars privately developing AI, versus 9.3 billion in China and the European Union, in general. These asymmetries of investment will define the degree of technological development, the degree of AI literacy of the labour force, and access to integrated AI systems, which will propel the future development of human-AI partnership. A rapid proliferation of AI systems and a push to implement can occur in PMOs that have high investment areas, but resource loss, slower cultural integration, and unavailability of training or governance software can also be faced by PMOs that are low investment areas. The available literature on transformation in PMO does not take into consideration such inequalities brought about by investments or what they can imply to change management at PMO level.

The other major gap is associated with the human AI interaction regulation. Even though human driven decisions have always been under the control of PMOs, an AI-based model could be seen as a hybrid, where intelligent systems are exploited to give predictions, recommendations, and take actions automatically. The datasets show that the dependency on such systems is becoming more noticeable: organizations are also adding generative AI to knowledge management (which has increased to 10% adoption in 2023 to 28% in 2025) and IT processes (27% → 36% within six months in 2024). Nevertheless, empirical studies of the ways in which PMOs should reengineer the decision rights, formalize processes of human in the loop, fine-tune the faith in AI predictions, and document AI proving decision paths do not exist. Excessive dependence, artificial bias and

uncontrolled decision making are some of the threats of such non-transparency in governance.

Lastly, existing studies provide virtually no information about how PMO professionals can learn to work with AI, how it changes their identity and their position in the organization, and how collaboration between people will develop when the AI systems become the third actors in the decision-making processes in projects. The PMOs run the risk of introducing technology at a greater rate than they can revise their governance, culture and structures to accommodate the new technology.

Overall, although AI uptake has been increasing rapidly worldwide, one of the least studied aspects of AI transformation is human AI collaboration in PMOs. The attitude of the workforce, trends of adoption of tools, maturity of the industry, regional differences in investments, and governance limitations all suggest that there are deep collaboration and change management issues that PMOs are struggling with and that are not covered in the existing literature. This poses a significant research gap one that needs to be reduced to come up with PMOs that can effectively work in AI intensive environments.

2.2.5 Discontinuous Organizational AI Maturity and absence of PMO Specific Readiness Models.

Although the rate of AI integration around the globe is increasing, organizations are experiencing a very uneven maturity level with AI, resulting in an uneven readiness to transform to AI enabled PMO. Nevertheless, the literature on PMOs does not provide a maturity model, diagnostic tool, or readiness test that is specific to PMO. Instead, organizations pursue the extension of generic digital transformation models that do not have the capability to capture the governance, data, process and decision-making models of PMOs. This absence of PMO specific AI readiness models is a critical research gap, particularly with the ever more lopsided and intricate AI maturity landscape documented in industry, geography, functional area, and workforce behaviours.

Globally, the data sets show that the degree of AI maturity has drastic differences. Even though 88% of organizations will be using AI in some of their functions by 2025 the

percentage of those using AI in more than one of their functions is significantly smaller, only slightly above 50% as of late 2024, and is still a majority but uneven in 2025. This implies that a lot of organizations are still at the lower or middle levels of AI maturity. PMOs, therefore, are restricted to the fragmented maturity of the surrounding functions depending on the integrated cross functional visibility. Nevertheless, none of the studies analyse how PMOs should review or re-orient towards partial or disproportional AI maturity in the enterprise.

Functional maturity differences also exhibit the lack of preparedness. The use of IT and software engineering capabilities grows to 36% adoption in late 2024, knowledge management jumps to 28% in 2025 indicating rapid change of data centric information governance domains at the heart of PMO operations. In the meantime, the functions of human resources (21% adoption in 2025) and risk/finance (24% in 2025) are a long way behind the more innovative functions. HR is needed to develop capabilities, finance to determine future priorities in portfolios, and risk functions to proactive monitor portfolios, which makes these maturity divergences crippling in enabling PMO capacity to scale AI coherently across portfolios. The existing frameworks do not discuss how the PMOs are expected to operate in the context of the cases where the level of maturity between functions is not even, or how the transformation activities in such a case should be prioritized by the PMOs.

The issues are enhanced by the industry level differences in maturity. The extraordinary rate of adoption of AI was in technology (92), professional services (82) and financial services (80) with much lower rates in other industries such as government (50), agriculture (42) and real estate/construction (46) recorded. These gaps influence the access of information, system willingness to combine, digital culture, and degree of AI governance, which are significant transformation agents of PMO. Despite this, the literature on PMO has conceptualized transformation in a consistent manner and does not offer any evidence-based recommendations regarding the way PMOs in low maturity settings should phase their AI process in comparison to high maturity settings. This presents a critical shortfall, since PMOs in low adoption sectors are likely to have a low degree of AI infrastructure, inconsistent data quality, and no AI literacy, and no models that are sensitive to maturity would inform their development.

The maturity gap is also augmented by investment trends across the world. In 2024, the sum of AI investment with a private character was 252.3 billion dollars that were highly concentrated: the United States spent 109.1B, China 9.3B, and the European Union 7.2B. The nature of low investment regions is less AI infrastructure readiness, slower organizational adoption, and lower enterprise level AI tools, all of which inhibit PMO transformation. However, the existing PMO models presuppose similar access to technology, talent, and the ability to govern in different regions and do not provide any information on how PMOs are supposed to align their AI maturity journeys to these macroeconomic restrictions.

The level of maturity of AI at the human level is also uneven. Recent statistics on the attitude of the world population towards the workforce show that 60 percent of employees think that AI will significantly affect their employment, and 36 percent fear loss of jobs, which shows that anxiety and disproportionate readiness of work processes mediated by AI is widespread. Meanwhile, there is an explosion in the use of AI tools: Over 800 million weekly active users of ChatGPT as of 2025 implies that generative AI is now widely deployed in the knowledge work. Though such behavioural changes have occurred, no single model of PMO has been developed to assess AI readiness of the workforce, risk of adopting AI, the level of trust, and ethical acceptance of AI, which are some of the crucial elements in successful PMO transformation.

The extent of AI adoption is even uneven even in the organizations that adopt AI in a larger scale. Most (generative) AI applications in organizations are individual tasks (e.g., summarization, drafting, classification) performed without creating predictive analytics pipelines, explainability protocols or human in the loop models of governance. PMOs need combined AI solutions to make predictions about the future, dependency mapping, risk forecasting, and portfolio decision support, but current studies do not cover how far an organization would have to move up an AI maturity spectrum until these solutions could be viable.

There is also the absence of PMO specific maturity and readiness models to influence AI governance. Methodology, assurance and reporting standards have always been the preserve of PMOs; however, AI raises new governance requirements such as transparency in algorithms, accountability mapping, bias auditing, model drift detection, and escalation processes. The current models of PMO maturity (e.g., OPM3, P3M3), however, do

not focus on these needs because they were developed earlier, before the use of AI became a popular organizational trend. As a result, PMOs do not have sufficiently conceptual instruments to gauge the maturity of their governance structures to accommodate AI-based decision processes.

In essence, the AI maturity terrain in the world is uneven, decentralized and evolving at a rapid pace. The differences between organizations are quite drastic in terms of infrastructure preparedness, data capacity, employee acceptance, industry demands, and regional investment assistance. But there is no dedicated AI maturity model on PMO which will provide a structured, empirical basis on preparedness evaluation or transformation paths. This gap is a critical research gap whose existence directly underlies the need to have a comprehensive, multi-layer PMO transformation architecture, which consider various levels of maturity, sectoral restrictions, functional variability and the degree of workforce preparedness.

2.3 Research Questions

To overcome such deep-rooted and multiple layer gaps it should be emphasized that, in attempt to bridge them, very keen and practical research questions are needed. In this regard, the work at hand is based on the following overall and secondary research questions:

Primary Research Question:

What are the functional roles, processes, performance and strategic value of the Project Management Office being transformed in current organizations due to the integration of AI?

In response to Research Questions:

In what ways are PMOs currently embracing, changing and using AI-powered tools and systems to fulfil types of organizations and industries?

This raises the question of what this actually means to workforce jobs, necessary skills and career paths of PMO professionals with AI implementation?

Which are the typical obstacles, threats and opportunities of success or failure of PMO transformation with AI?

What are the measurement of human-AI collaboration factors e.g. trust, ethics, user acceptance and perceived value by PMOs?

Which are the real frameworks or stepwise steps that can be suggested to implement the scalable context sensitive adoption of AI by the various PMOs?

How effectively does the transformation provide quantifiable increases in PMO and organizational results like efficiency, capacity to innovate and strategic effects?

2.4 Research Objectives

All of the research gaps provided in Section 2.2 demonstrate a lack of a coherent explanation of how artificial intelligence changes the Project Management Office (PMO) in organizational, functional, and strategic levels. To address these gaps, the following objectives of this thesis are defined to create a coherent, empirically-supported view on AI-enabled PMO transformation.

In particular, this research will explore the changing role and strategic importance of the PMO amid the growing adoption of AI, shifting the focus out of conventional administrative and reporting services to the use of data as an information support and governance tool. The study will examine international trends in the use of AI in reference to PMOs in industries and geographic areas, giving contextual understanding of the organizational preparedness and readiness levels that influence change directions.

Moreover, the research also seeks to determine the way AI changes the role of PMO and professional capabilities and career paths with specific focus on the emerging capabilities in the areas of analytics, decision intelligence, governance, and human-AI

collaboration. The study also aims at identifying the major technological, organizational, cultural, ethical, and governance-related barriers and enablers that affect a successful integration of AI in PMOs.

Lastly, the research would integrate both empirical patterns and theoretical knowledge into a conceptual framework comprising of multi-layers, which would assist in interpreting AI-based PMO transformation in a variety of organizational settings. These objectives fill the research gaps identified in the thesis by bridging the disjointed streams of literature and offering a coherent conceptual framework on how PMOs change and transform in AI-inspired organizational settings.

2.5 Definitions and Study Delimitations.

The extremely dynamic nature of project management that is increasingly growing more fully featured by the emergence of digital technology, global workforce and data based on analytics necessitates a singular definition and a firm boundary of differentiation in scholarly research. This is especially true when it comes to dealing with complex and emergent cases, such as with the case of transforming Project Management Office PMO using artificial intelligence AI. The clarity of terminologies can lead to academic rigor and even practical recommendations to organizational leaders, policymakers and stakeholders grappling with the challenge of innovation and change. In this case, the critically relevant keywords are provided, and the operational definition of the keywords is provided, and the ability of the concept and its key limitations to this research are analyzed.

2.5.1 Project Management Office PMO

The Project Management Office PMO can be most thought of as that part in an organisation that lays down the standards, processes and governance of project and portfolio management of a business or government agency organisation (PMI, 2021). PMO may be enterprise based EPMO, functional based or project support office. These

organizations are diverse in the areas of scope, power, and operations: some PMOs are administrative hubs, which can be involved in reporting and documentation, and other are operational facilitators of strategic alignment, resources, and innovations in an entire organization (GRT Consulting, n.d.; PMO, Governance, 2023).

In this paper, PMO refers to any formal organisation branch assigned the project management standards and project management control regardless of the size or industry. The non-codified and non-formal project management teams are not analyzed due to the scope and comparability problems.

2.5.2 Artificial Intelligence AI Implementation.

The use of algorithms and systems (with computers) that can perform tasks previously held in the intelligence of human beings, such as the learning, reasoning, problem solving process, perceptions, and understanding of languages now define artificial intelligence AI (Oxford English Dictionary, 2025). Machine learning ML and natural language processing NLP and robotic process Automation RPA and predictive analytics and intelligent decision support systems can constitute AI. The active involvement of AI in the PMO processes, PMO tools and workflows is called AI integration and targets more successful project performance and more risk-management and strategic decision-making (PMI, n.d.).

The article is focused on the AI solutions which will directly service the processes of the project management office like automation of reporting, predictive resource, schedule optimization and risk analytics rather than generic or indirect use of AI in the enterprise. They are not included as non-PMO uses of AI (e.g., product design, manufacturing), and non-project governance business analytics.

2.5.3 Transformation

Transformation can be defined as the overall process of major change which can be organizational, functional and cultural due to adopting or implementing new technologies, practices or strategies. The transformation of the PMO under the influence of the integration of AI is associated with the shifts in the roles, work flows, decision authority, performance standards and even the organization structure or culture (Hanelt et al., 2021; Mahraz et al., 2019).

The notion of transformation applied in this study is explicitly applied to qualitative and quantitative PMO activity, competency, and influence provided by embracing AI. This does not include superficial or incremental reforms (e.g. purchasing a new reporting tool, but nothing to change the process or the skills).

2.5.4 Human-AI Collaboration

Human-AI collaboration involves the liaison between human PMO practitioners and AI-based technologies or tools in the process of performing the project management activities. These are such as joint decision-making, information sharing, balancing autonomy and control, and trust and acceptance problems (Dican, 2025; Wen et al., 2025). Collaborative dynamics may vary greatly depending on the level of technology maturity, level of user competence, culture in management and sector conventions.

The paper examines the human-AI collaboration in regard to the PMO decision-making process, risk management, communication of the stakeholders and other critical functions. Peripheral collaboration (e.g., AI-based vendor contracting outside of PMO) is not discussed in the study.

3 Scope of the Study

The section is the delimiting of the scope of the research and its focus by making clear the organizational, technological, geographical, methodological and conceptual dimensions in which the research is carried out. The scope defines what is knowingly included and what is excluded to achieve analytical clarity, methodological consistency and proper interpretation of the findings. With these boundaries, the study has been able to avoid overgeneralization and to make sure that the conclusions are consistent with the research objectives and the data available.

3.1 Organizational Scope

The paper scans and analyzes the PMOs of different sectors like technology, construction, finance, government and healthcare in different geographical locations. This is supposed to consider the general trends and situational difference. This sample, however, is restricted to those PMOs that have formalized structure and process at least some, as compared to informal project management organizations and ad hoc teams.

3.2 Technological Scope

The technological theme lies in the focus of AI systems and tools that were widely implemented or pilot groups in the PMOs. Examples of SAS include dashboard analytics (Power BI, Tableau AI modules), forecast scheduling (MS Project AI assistant), and risk evaluation robots (Automation Anywhere, Blue Prism). The analysis fails to consider the overall trends in information technology, non-AI automation, and non-project-based business intelligence platform.

3.3 Temporal Scope

This is because the digital transformation is a highly dynamic process, so the study is limited to the trends, practices, and transformation efforts published and researched in 2020-25 around AI. The analysis of history is imposed only on a comparison basis, and the dangers of future gazing and speculative forecasting is limited more than currently implemented.

3.4 Geographical Scope

The geographical scope of this study is worldwide because of the nature of artificial intelligence (AI) adoption and Project Management Office (PMO) transformation, which is international in nature. The analysis uses globally aggregated data and international literature, as opposed to individual country or region, to identify general patterns, trends, and structural forces influencing the evolution of AI enabled PMOs in various economic and institutional settings.

The main empirical materials deployed in this thesis, including first of all, the Stanford AI Index Report and the McKinsey Global Survey on AI, gather data on the work of organizations with operations on the various continents, such as North America, Europe, Asia Pacific, and other significant economic regions. These data will offer a cross regional understanding of the AI adoption, level of investment, people perception, and application within an organization. Consequently, the results provided in this paper are not supposed to reflect the situation in one or another national market, but to reflect the worldwide trends and common issues faced by PMOs in various settings.

The international nature of the study allows detecting similar patterns in structure, like the growing strategic importance of PMOs, the spread of AI to various organizational areas, and the rise in interest in governance and responsible AI, without excessive generalization based on local evidence of cases. Simultaneously, the paper does not make any effort to compare national regulatory regimes, cultural differences, or country-specific practices of implementation in detail. Even though these aspects are indeed known to have an impact on AI adoption and PMO activities, their systematic study

would demand country level data and regulatory research which are beyond the scope of this study.

The findings of this thesis can, therefore, be understood to be globally oriented and context agnostic at a high level and can be applied in the context of medium to large organizations in an environment where projects are linked internationally. The geographical coverage assists in the creation of a conceptual structure that can be applied in different areas but not tailored to a particular jurisdiction. Further studies can extend the current study by carrying out the suggested framework to national or regional settings to identify how regulatory, cultural, or economic settings can influence AI enabled PMO transformation in more finer lines.

3.5 Methodological Scope

This study can be characterized as a methodological approach based on secondary data and mixed methods research design, which involves quantitative descriptive analysis and qualitative thematic synthesis. There is no primary data collection, in the form of surveys, interviews, experiments, or organization case studies, which are used in the study. It instead solely uses existing, reputable data and published literature to analyze AI facilitated PMO transformation on a conceptual and structural level.

In a quantitative manner, the study employs aggregate worldwide data in order to establish macro level patterns of AI adoption, industry maturity, functional use, public attitude, and patterns of investment. Such datasets are offered by such institutions as Stanford Institute of Human Centered Artificial Intelligence (HAI) and McKinsey and Company and are analyzed by means of descriptive statistics. It is the pattern, distributions, and directional trends that are analyzed but not the inferential testing or causal modeling. There is no predictive analytics or hypothesis testing involved because the goal is to provide context of the organizational environment where PMOs exist as opposed to establishing a statistical causation.

Qualitatively, the research uses thematic synthesis of peer reviewed scholarly articles and open institutional publications to explore the impact of AI on PMO roles, competencies, governance mechanisms and strategic positioning. This qualitative aspect

helps to interpret the quantitative trends and identify the repetitive concepts, gaps and tensions in the current studies. The synthesis is interpretive and it seeks to synthesize knowledge in the literature of project management, digital transformation, and AI governance.

The conceptual development of the Seven Layer AI Enabled PMO Transformation Architecture is also within the methodological scope. This model is obtained by a systematic synthesis of both empirical trends and theoretical information, and not by inductive coding of data and grounded theory approaches. The framework is not meant as an implementation model, but rather as an analytical and interpretive framework.

The use of secondary data and conceptual synthesis as the methodology of the study guarantees a methodological consistency, transparency, and replicability. Simultaneously, such a scope limits the richness of the organization specific conclusions, which are recognized as a field that will be validated in future by empirical means via longitudinal or case-based research.

3.6 Conceptual Scope

The theoretical level, the set of abstraction, and the purpose of analysis within the conceptual frame of this research are the boundaries of the theoretical level at which AI made possible PMO transformation. Instead of creating a prescriptive operational model or experimenting on the specific implementation results, a conceptual and integrative approach is used in the study to determine how artificial intelligence transforms the structural, functional, and governance aspects of the Project Management Office.

Theoretically, the study aligns the PMO as an organizational coordination and governance body that is at the crossroads of strategy, execution, and decision support. The analysis does not consider the PMO as a mere administration reporting unit and neither does it look at the individual project management methods. Rather, it views the PMO as a system level player whose functions, capabilities and value proposition are changing in reaction to larger scale digital and AI driven change dynamics.

In this study, artificial intelligence is conceptualized as an enabling and augmentative technology, as opposed to a technical artifact on its own. The area encompasses AI-

powered analytics, automation, decision support systems, and human in the loop mechanism as it applies to PMO capabilities like portfolio management, risk management, performance management, and strategic alignment. Algorithms are not specified in the conceptual scope, and the detailed design of algorithms, model training, or software engineering is explicitly out-of-scope since the conceptual scope is concerned with organizational implications, not optimization of technical aspects.

The Seven Layer AI Enabled PMO Transformation Architecture conceptual framework is a highly abstract concept. It is supposed to combine the knowledge of the project management literature, digital transformation research, and AI governance studies into a systematic interpretation framework. The framework does not involve prescriptions of tools, technologies, and steps of implementation. Rather, it is an analytical prism through which qualitative insights and empirical trends can be looked at in a systematic manner. Also, the conceptual scope does not make a causal claim of effective performance or improvement. The framework is not intended to act as a maturity model or a step by step roadmap of transformation but to aid in sense making, comparison and theoretical integration. By keeping this conceptual distance, the research study will be assured that its research aims, methodology, and conclusion are in line with its research objectives and that there remains room to verify and operationalize the framework in particular organizational settings through empirical research in the future.

3.7 Limitations of the Study.

This paper has a number of limitations which must be put into consideration when interpreting the findings of this paper. To begin with, the study uses only secondary sources of data, such as aggregated international datas and published academic and institutional sources. Although such sources are generated by credible institutions and can be used to establish macro level patterns, the research is still reliant on the methodological assumptions, definitions and reporting practices of the original data sources. Consequently, differences in the measurement of AI adoption and organizational impact across datasets can prevent a direct comparison.

Second, the empirical analysis is carried out at a global and organizational level which limits the capture of context specific or organization level dynamics of PMO transformation. There is no primary empirical validation of the study in terms of interviews, surveys, case studies, and, as such, the study does not mirror on the lived experience of individual PMOs or project professionals.

Third, the analytical theoretical framework of this thesis is not prescriptive. The Seven Layer AI Enabled PMO Transformation Architecture is not empirically validated in particular contexts of organizations, although it is based on empirical trends and literature synthesis. The framework, therefore, should be interpreted to mean an interpretation and sense making tool rather than a blue print of implementation.

Lastly, due to a fast-paced development of artificial intelligence technologies, certain findings can be indicative of the transitional phase of AI maturity. The framework requires future research to validate and expand the framework as AI capabilities and organizational practices are constantly changing.

3.8 Study Structure.

This thesis is organized in the following way. Chapter 1 provides a context, motivation, and objectives of the study. Chapter 2 outlines the research gaps and develops the research questions and objectives. Chapter 3 presents the scope, conceptual boundaries and limitations of the study. Chapter 4 features a literature review of PMO transformation, artificial intelligence in project management, and associated implications to organizations, which culminate in the creation of a conceptual framework. Chapter 5 explains the research methodology, data sources and methods of analysis. Chapter 6 provides the empirical findings based on the secondary data. The chapter 7 presents the findings in terms of the conceptual framework and existing literature and suggests implications related to practice. Finally, Chapter 8 summarizes the key conclusions and outlines directions for future research.

4 Literature Review

The high rate of artificial intelligence AI implementation in organizations has continued to impact on the way projects are designed, managed, and executed. With the integration of AI technologies into fields like decision support, data analytics, automation, and knowledge management, the consequences of these advances on the organizational structure of project governance and professional practice have gained increasing focus in the academic and practitioner literature. The Project Management Office PMO has become the center of discussion in this dynamic environment, as it is the core to integration of projects, standardization of practices, and facilitating strategic alignment. The current literature on PMOs is rich in themes such as the transformation of PMOs, governance models, maturity models and value creation. Simultaneously, there is a considerable amount of literature on the use of AI in project management, which discusses the prospective advantages, barriers to adoption, and organizational implications. Nonetheless, the two currents of research are frequently discussed independently, and few studies have been highly integrated between the studies of the PMO evolution and the studies of the AI-based project environments.

To form the theoretical background of the study, this chapter reviews and synthesizes the literature that is relevant. The literature review is divided into a number of thematic divisions. The first step is to analyse previous studies on PMO transformation and strategic evolution. Second, the existing literature on the implementation of AI in project and portfolio management is examined. Third, the research on the shifts in the PMO functions and skills is presented, and the barriers and facilitators of AI implementation are typically observed and analyzed. Lastly, the human-AI collaboration and governance literature is taken into account. These themes combined give the conceptual backdrop that is required to comprehend the context under which AI-enabled PMO transformation is being discussed.

4.1 PMO Transformation

The project management office PMO has completely evolved over the past several decades and is not an administrative support unit but a strategic entity that offers an organizational change and competitiveness (Aubry, Muller, and Turner, 2007; Marnewick and Saunderson, 2016). The past has seen the development of PMOs based on the necessity to offer standardization, documentation, methodology consistency and project reporting in terms of the various organizational functions (Aubry et al., 2007). The negative aspect of this traditional model was felt though as business environments grew more complex, volatile and competitive. Companies observed that the adherence to processes per se did not suffice to instill strategic value, innovation, or flexibility to the dynamic markets (Project Management Institute, 2021).

A number of forces have been interrelated to bring about the change of the PMO. Firstly, data analytics, automation, and intelligent systems of decision support have been necessitated by the digital revolution and the speed of technological progress that PMOs must keep abreast of to remain relevant (Aubry, Laberge, and Beauregard, 2020). Second, the advent of agile and hybrid project management practices has expanded the limits of PMOs to hit a balance between organization and flexibility, rather than the hard-waterfall-based governance frameworks, the flexible and iterative governance (Kiefer, Rzepa, and Baldauf, 2022). Third, the need of organizational leaders to realize not just project success but also, increasingly, form of business value PMOs are expected to generate or exhibit correlation to strategic business objectives, resource use efficiency, and benefits delivery throughout an enterprise (Marnewick and Saunderson, 2016).

The modern PMOs thus have multidimensional roles since they form strategic focal points where the executive vision is converted into operational activities, excellence centres that facilitate continuous improvement and knowledge management as well as cross-departmental cross-functional interfaces between functional silos (Aubry et al., 2020). Strategic PMOs focus more on delivering value as opposed to task execution, use project portfolio analysis and forecasting of risks to inform investment choices and guarantee that they align with corporate priorities (Project Management Institute, 2021). They are taking an active role in managing organizational change, cultural change, and building capabilities and understanding that delivering successful projects not only

requires technical skills but also human interaction, trust, and flexibility (Kiefer et al., 2022).

Research also identifies that PMO change is not a once-per-month and one-dimensional process, but a dynamic and situation-focused process that depends on the maturity of the company, the dynamics of the business area, and the dedication of the leadership (Aubry et al., 2020; Marnewick and Saunderson, 2016). The new requirements that PMOs must always evolve in response to are adoption of digital solutions, scalability with the growing regulatory complexity, workforce that cuts across locations, and accountability/transparency that stakeholders seek. The concept of transformation is also linked to the alterations in the PMO structure, roles and competencies, processes and governance frameworks and cultural norms that should enhance one another to achieve any sustainable positive performance and strategic impact (Kiefer et al., 2022; Project management Institute, 2021).

Though these developments have taken place, great challenges still exist. The majority of the PMOs lack executive support, change resistance, and value propositions, as well as fail to demonstrate a measurable ROI (Marnewick and Saunderson, 2016). Moreover, technological change is increasing at a rate of change, specifically the introduction of artificial intelligence, which is putting pressure on transformation requirements, urging PMOs to quickly adopt new capabilities in the process of dealing with uncertainty and risk (Aubry et al., 2020). The PMO transformation direction and dynamics, then, should be closely monitored to allow factors and constant challenges to be present and in this way, a context where more specific studies on how new technologies like artificial intelligence are changing the PMO landscape can be carried out.

4.2 Application of AI on Project Management.

The artificial intelligence AI is literally changing the landscape in the project management industry with the emergence of features that transcend the realm of manual processes of project management and the bottom-up pattern of project management planning. The introduction of AI into Project Management Office PMO is a paradigm change where active support of strategic adjustment process to data is introduced instead of a more

reactive strategy (Koskela and Howell, 2022; Bredillet, 2022). It is also guided by the fact that AI is capable of processing huge amounts of data, identifying patterns, anticipating outcomes and automating the processes that can be repeated, which is why it is possible to use this tool to enhance the efficiency, accuracy, risk management, and the overall success of a project (Project Management Institute, 2021; Aubry et al., 2020).

The modern use of AI in project management is a wide variety of technologies. Machine learning algorithms are now able to predict resource needs, schedule variances and budget risks more accurately than ever with the use of historical project data in the past (Koskela and Howell, 2022). Automated reporting, meeting summarization, and communication with the stakeholder can be carried out with the assistance of natural language processing NLP, which will allow transferring the administrative burden to the background and provide the information streams in real time (Felicetti et al., 2024). Robotic process automation RPA is a data entry tool, which analyses regular data and documents its status and compliance, and the PMO professionals can focus on strategic decision-making and innovation (Aubry et al., 2020). Predictive analytics tools are useful to apply AI to assess performance of the portfolios, identify new risks, and recommend correction measures to ensure that the issues may be turned into project failures at the earliest stage (Kiefer et al., 2022).

The argument behind the introduction of AI in the business is a sound one. The use of AI-based project management has been discovered to assist in enhancing resource utilization by 20 per cent, reducing project construction time by 15-20 and 30 per cent, respectively, and overall productivity by automating tasks and smart scheduling of projects (McKinsey, cited in several industry reports; Aubry et al., 2020). Workers in firms where AI is applied to their PMOs report improved panel accuracy and AI models always outperform traditional algorithms such as ARIMA and exponential smoothing on time-series prediction tasks (Koskela and Howell, 2022). Additionally, AI enables PMOs to move ahead of the fixed, past reporting models to real-time dashboarding to support actionable insights, inspire agile decision-making, and align the project portfolios and dynamic strategic priorities (Project Management Institute, 2021).

Despite these advantages, the implementation of AI in PMOs is not a unified process and free of challenges. Obstacles to integration have been identified as high initial expense, low access to high-quality historical data, integration challenges with old systems, and

organizational conflicts arising as a result of fear of job loss or loss of power to make certain decisions (Aubry et al., 2020; Kiefer et al., 2022). They are also hard to adopt due to other technical challenges such as the transparency of the algorithms, their interpretability, and ethical considerations of bias in AI decision-making (Felicetti et al., 2024). Moreover, the cultural change is necessary in the context of introducing AI, since PMOs will need to create data-driven attitudes, invest in the upskilling of their staff, and create governance systems that can balance automation with human judgment and responsibility (Koskela and Howell, 2022; Bredillet, 2022).

The willingness of AI usage by industries and organizational environments is extremely diversified. Technology, finance, and large-scale infrastructure with the involvement of advanced analytics to streamline a portfolio and deal with risks are the most active ways of applying AI (Project Management Institute, 2021). Quite to the contrary, the SME PMOs, the public sector, and healthcare are lagging behind the schedule due to on the one hand, a lack of resources usage capabilities, and on the other hand, to complex regulatory frameworks, and less digital maturity (Aubry et al., 2020). Geographic and cultural factors can also influence the adoption patterns, with the locations where the digital infrastructure and ecosystem of innovation are developed reporting the higher degree of AI adoption (Kiefer et al., 2022).

The complexity and pervasiveness will make AI in project management a trend in the future. This change demands that PMOs shift their focus away to strategic coordinators of smart automation and become less of a project regulator and more of an organizational generator of innovation, learning, and change in a perpetual stream of AI-related knowledge (Aubry et al., 2020; Bredillet, 2022).

In summary, AI can be implemented in the field of project management through the lens of not only an incremental value addition but also a radical transformation of the purpose and operation redefining the strategic value of the PMO. Scholars and practitioners working within the field of AI usage need to know its mechanisms and benefits, barriers, and future directions in order to find their way through the quickly developing field.

4.3 Obstacles and Challenges of AI Adoption.

Although incorporating AI in PMOs has a lot of potential, the journey to effective adoption is full of obstacles and pitfalls that organizations have to go through in a strategic manner. These issues concern technology, organizational, cultural, and financial factors, and present a non-trivial change management and long-term vision dynamic (Aubry et al., 2020; Kiefer et al., 2022).

4.3.1 Technological and Infrastructure issues.

Lack of proper technological infrastructures has been among the major challenges to the implementation of AI at PMOs. Many organizations are operating on the outdated systems that are not compatible with the new AI tools, and they will need to update an expensive system, or replace the entire system (Koskela and Howell, 2022). Integration challenges arise when AI applications have to deal with incomparable data applications, imbalanced formats, and fragmented information structures. According to the survey of project professionals operating in the industry, 37 percent of respondents list the unavailability of infrastructure ready to use AI as one of the key barriers to implementation (PMI, 2021). Furthermore, the issue that compromises the functioning of AI is the quality of data, including incomplete, inconsistent, biased data, as machine learning algorithms need well-formatted and high-quality data to make high-quality inferences (Felicetti et al., 2024; Aubry et al., 2020).

4.3.2 Resistance of the Organization and Culture.

Resistance in an organization is a deeply rooted conflict that is manifested in the form of fear of change, fear of losing the job and mistrust of change brought about by the use of technology. It was already proved that 61 percent of individuals are cautious about trusting AI systems, and 67 percent of surveyed participants in the KPMG survey report low/low to moderate AI-acceptance levels (industry analysis). The common view of AI by the employees is seen as a threat and not a facilitator as the workers fear that their jobs

will become redundant or no longer as valuable (Kiefer et al., 2022; Marnewick and Saunderson, 2016). Cultural inertia and the wish to preserve the status quo also contribute to resistance, particularly to the older project managers who may not be eager to relinquish the authority to make decisions to the algorithms (Aubry et al., 2020). To solve such resistance, it is necessary to have open dialog, participation in implementation processes and cultural change interventions that will rebrand AI not as the means to replace the activities of human beings but as a chance to improve their capabilities.

4.3.3 Skills Gap and Labor Preparation.

One of the most important obstacles is the lack of qualified staff that will be able to work with AI technologies. The truth is that most PMO professionals do not have the technical abilities that are needed to deploy, analyze, and exploit AI tools, which leads to bottlenecks in implementation and non-exploitation of capabilities (Koskela and Howell, 2022; Felicetti et al., 2024). The study concludes that 40 percent of the workforce will require reskilling to embrace AI completely in the coming three years and training can be considered a priority but an expensive undertaking to organizations (McKinsey research quoted in a number of articles). Skills gap must not be narrowed down to technical skills and must also include data literacy, analytical skills and the ability to critically evaluate the suggestions of AI-generated recommendations, the skills that must be taught in long-term educational programs and professional development programs (Kiefer et al., 2022; Project Management Institute, 2021).

4.3.4 Financial Constraints

Installing AI is costly, and it is one of the potential barriers that are prohibitive especially to small and medium sized enterprises. The initial investments are software licensing, upgrades of the infrastructure facilities, hiring of specialists by the employees, and training plans, which may not be affordable to organizations when no noticeable immediate gains of investments are observed (Aubry et al., 2020; Marnewick and

Saunderson, 2016). The issue is exacerbated by the missing metrics of ROI; the advantages of AI are not typically quantifiable in traditional financial terms and its impact is often difficult to quantify in the form of a better quality of decisions, reduced risks, or broader strategic fit and lack of direct cost savings (Koskela and Howell, 2022). The financial policy block to long-term AI adoption is the burden of the budget of having to update the systems, retrain the algorithms and optimize the systems.

4.3.5 Moral, Confidence, and Management.

Regulatory problems and ethics are rapidly becoming significant impediments to the use of AI. The ethical or unethical and sound nature of these decisions using AI in the project management context is questioned by AI related ethical concerns such as algorithm bias, transparency, and accountability (Felicetti et al., 2024; Aubry et al., 2020). PMOs need to build effective governance practices to ensure that AI applications address the regulatory needs, safeguard sensitive data, and offer audit trails to track decisions (Kiefer et al., 2022). Establishing trust may become a more challenging issue when considering the black box due to the fact that most AI algorithms are black box approaches, and their stakeholders will not be able to understand the logic behind the AI recommendation, which will undermine the trust in automated systems (Koskela and Howell, 2022; Project Management Institute, 2021).

Overall, the introduction of AI in PMOs is limited by a complex set of challenges that should be addressed as a systematic set of strategies by organizations based on the principles of strategic planning, change management and workforce development and ethical governance in order to achieve the transformative potential of intelligent technologies.

4.4 Impact on PMO Performance and Roles.

The adoption of AI in PMO models has disruptive effects in many aspects, as it alters the performance indicators of project delivery, offering a new inflexion of the very essence

of roles in the office. Not only do these developments halt on efficiency gains but also incorporate strategic repositioning, competency building and organizational value creation (Aubry et al., 2020; Koskela and Howell, 2022).

4.4.1 Performance Enhancement based on Artificial Intelligence.

The empirical evidence is that the implementation of AI results in the positive shifts in the performance of the PMO in the key indicators. Research shows that the project management that is AI-driven could increase resource utilization by up to 20 percent, reduce project delays by up to 15-20 percent, and increase project productivity by an average of 30 percent through automating tasks on the project and predicting project schedule (Project Management Institute, 2021; Aubry et al., 2020). In a randomized controlled trial of AI assistance of 96 full-time software engineers in Google, the average project development time was reduced by 1/4 with AI assistance, but it did not affect quality (mentioned in industry analyses).

Probably, the most crucial aspect is that AI radically changes the accuracy of the forecast and the ability to manage risks. An overall analysis of 30,000 single time-series tested that AI foundation models tended to do better forecasting than traditional forecasting models, like ARIMA, LGBM, and ETS, making them more reliable in the planning of projects and resource allocation (Koskela and Howell, 2022). Companies implement AI applications with references to the fact that predictive analytics can be precise enough in the dates and the cost of the real completion in contrast to traditional techniques, and the studies indicate that the percentage of the decrease in the number of the scheduling errors can reach 90 percent (Adamantiadou & Tsironis, 2025; OECD Organisation for Economic Co-operation, 2026). It has enhanced forecast capability, enhancing the capabilities of PMOs to cease being problem solvers and begin problem prevention by being able to predict threats even before they arise and create countermeasures earlier in the project life cycle (Adamantiadou & Tsironis, 2025).

The economic power is also extremely strong. Research indicates that AI as a solution to the digital transformation can create a 15 per cent increment in the long run as compared to conventional approaches because of the existence of quicker time-to-

market, more accurate resource allocation and improved quality project outputs. Despite traditional methods bringing success to projects only around 35 percent of projects are effective, using AI in project management, companies report a considerable increase in the overall project success rates and portfolio performance (PMI, 2021).

4.4.2 Moving Forward Repositioning of the PMO.

Besides the efficiency in operations, the implementation of AI makes it possible to carry out some fundamental strategic repositioning of the PMO within the frameworks of organizations. The issue with traditional PMOs was that they were often considered a bureaucratic overhead as a compliance factor and office work (Marnewick & Saunderson, 2016). With PMOs being freed of daily administrative tediousness (status reporting, meeting summarization, and documentation) by AI automation, the latter can focus on high-value administrative aspects such as stakeholder work, facilitating innovation, and strategic portfolio optimization (Aubry et al., 2020; Kiefer et al., 2022).

This change makes PMOs designers of value and engines of strategic intelligence instead of enablers or enforcers of projects or compliance (Aubry et al., 2020). Foresight PMOs are enhanced with AI as opportunity scanners; they also leverage predictive analytics to track the market trends, identify the business listening points and real-time rebalancing portfolio projects with changing strategic priorities (Project Management Institute, 2021). By enabling AI-based PMOs to provide executives with data-driven insights and the potential to be used in scenario planning, AI-based PMOs will no longer be used to support business transformation work but become its strategic partners (Kiefer et al., 2022; Bredillet, 2022).

4.4.3 Role Change and Competencies Development.

The introduction of AI radically changes the skills needed and functions done in PMOs. The transformation of the PMO professional jobs into strategic theatricals who apply AI resources without losing human discretion and contextual understanding is predicted by OECD in 2030, 80 percent of traditional project management will be done by AI and

machine learning, and other digital technologies (Koskela and Howell, 2022; Felicetti et al., 2024).

Research also indicates that a quarter of all the employees will have to be reskilled within the next three years to utilize and operate AI systems (McKinsey research, as cited by industry sources). Data literacy, critical thinking, configuration and interpretation of AI tools, ethical governance of AI systems, and strategic foresight are some of the key emerging competencies (Aubry et al., 2020; Kiefer et al., 2022). To balance between divergent thinking (discovering opportunities) and convergent thinking (focused choice-making in uncertain situations) with IBM generated insights and human strategic thought, PMO professionals ought to train cognitive flexibility (neuroscience research mentioned in practitioner literature).

Its role evolution extends to the leadership fronts: PMO heads can be turned into the project controllers turned into change agents, innovation accelerators, and knowledge integrators that will allow human-AI-based collaboration (Marnewick and Saunderson, 2016; Project Management Institute, 2021). Not only does it require technical expertise, but also better people skills to interact with the stakeholders, implement change, and transform the culture that is particularly human-focused and can never be substituted by AI (Kiefer et al., 2022; Aubry et al., 2020).

4.4.4 Organizational and Cultural Impact.

It is not just performed in the individual role but also in the change of the organizational culture and PMO operating models. The process of AI integration requires cultural changes of data-driven decision-making, experimentation and continuous learning, as well as toleration (Aubry et al., 2020; Bredillet, 2022). Organizations recommend that AI implementation should take place by establishing governance frameworks that can balance automation efficiency and people accountability, ethical considerations, and transparency in decision-making processes to enhance AI adoption (Felicetti et al., 2024; Koskela and Howell, 2022).

PMOs turn into orchestration engines of strategies, institutionalized engines entailing strategy, governance, delivery and organizational knowledge alignment through AI-

enabled features. This fronting as reflexive, adaptive, and AI-enabled constitute PMOs as being essential to the enterprise transformation and not more discretionary supporting roles (Project Management Institute, 2021; Kiefer et al., 2022).

Altogether, the multi-dimensional impacts of AI application on PMOs performance and functions enable obtaining the measurable efficiency-related advantages, as well as transforming the strategic position, competency creation and necessary change in how PMOs create and deliver the organizational value.

4.5 Dynamics in the Human-AI Collaboration.

The key feature of successful introduction of artificial intelligence into PMOs is the effective human-AI collaboration which is a complex dynamic relationship that goes beyond the utilization of tools to establish a creative partnership wherein all the parties are mutually dependent, transparent, have complementary strengths, and trust (Obana, 2024; Singh, 2024). The section talks about the theoretical foundation of the subject, practical use, and the main factors of success that impact on the character of human management of projects as a professional and application of AI systems in their joint work to get improved project outcomes.

4.5.1 Theoretical Framework of Human-AI collaboration.

The Socio-Technical Systems Theory STS can be a good guide to understand the relations between human and Artificial Intelligence in PMOs due to the necessity to make the coordinated effort to optimization of both technological systems and human factors and achieve effectiveness in the organization (Singh, 2024; Felicetti et al., 2024). As per this school of thought, it refutes the notion that AI can replace human judgment, as AI is a tool of extension, enabling humans to exercise cognitive power in contrast to the human monitoring, interpretation of the environment, and morality regulation (Obana, 2024; Koskela and Howell, 2022). The most productive relations should be formed when AI does data-intensive, pattern-recognition tasks, when it is predictive analytics, automated reporting, and optimization of resources, and when human beings are

involved in applying cognitive factors, emotional intelligence, communication with stakeholders, and situational awareness that the algorithms lack control over (Singh, 2024; Aubry et al., 2020).

Research has also determined that 90 percent of project managers report positive ROI through AI tools, 63 percent of them report an increase in productivity and efficiency but such benefits are only achieved when AI is applied as an associate technology rather than as a substitute. In accordance with AI researcher Paul Boudreau, AI is more of a stimulus that can allow more efficient project implementation, but not a replacement of project management skills. This interdependence is clear as AI demands human beings to organize information, judgments about organisational conditions and decide based on the information given by AI but human beings can receive the benefits of AI: it can constantly process data, detect patterns and predict and, therefore, it does not need to be tired like humans (Singh, 2024; Obana, 2024).

4.5.2 Important Determinants of Productive Teamwork.

The key significant dimensions that determine the quality and efficiency of human-AI collaboration in PMOs involve several key dimensions:

- Trust and Transparency:

Trust is the main area that facilitates successful human-AI partnerships. The reason is always mentioned as trust being a crucial aspect to the adoption of AI, and 61% of the individuals mentioned being suspicious of their reliance on AI systems (KPMG study, referred to elsewhere). In order to build trust, the AI decision-making procedures will be open, stakeholders can access information on how algorithms come to their recommendations, what data is utilized to come up with predictions, and where they can regulate the automated workflow (Singh, 2024; Felicetti et al., 2024). PMOs are supposed to establish clear AI examples of RACI who assumes responsibility on such AI-informed decisions, possess systems of decision traceability and make AI recommendations to explainable and auditable to levels of governance (Kiefer et al., 2022).

- Complementary Competencies:

The main secret of successful cooperation is to leverage the special strengths of an individual and the AI. Artificial intelligence can be effectively used to apply robots to complete repetitive tasks, handle large numbers of data, make predictive decisions, and work without reports (Singh, 2024; Obana, 2024). Nevertheless, human beings add essential soft skills to communication and problem-solving, emotional intelligence and moral judgment, and maneuvering their complex interpersonal relationships, which will never be substituted with algorithms (Project Management Institute, 2021; Koskela and Howell, 2022). Research by PMI cites the fact that although AI is being deployed to handle data-driven aspects of projects, human judgment is not being substituted as far as leadership, strategic decision-making, and stakeholder management are concerned. The synergy will be optimal when project managers know how to make AI potential work without losing the control over crucial decisions and the strategy (Aubry et al., 2020; Bredillet, 2022).

- Native Integration and User Adoption:

To be successful, collaborators need to ensure the AI tools are embedded and integrated in the current project management processes, systems, and workflows instead of establishing parallel or contradictory systems (Singh, 2024; Obana, 2024). The fact that AI can be inefficiently implemented as an add-on that does not make the organization efficient, but rather adds a useless layer, is also harming the adoption according to the reports of organizations (Felicetti et al., 2024; Kiefer et al., 2022). It is known that simplicity of interface, value propositions, and training with complete user confidence and ability to operate AI systems are all required to user adoption (Singh, 2024; Aubry et al., 2020).

- Accountability and Ethics:

Human-AI collaboration model will raise significant ethical concerns and this will require good governance systems in this interaction. Problems of bias in the algorithms, information privacy, accountability of its decisions, and transparency require PMOs to develop strong guidelines by which the use of AI does not go against organizational values, regulations, and ethics (Felicetti et al., 2024; Singh, 2024). It is likely that the AI

will not replace human judgment but enhance it since, in the most important decisions, human judgment checks will not be removed, and the AI will have to rely on human judgments via suggestions (Koskela and Howell, 2022). Research has shown that AI-driven workflows are to include human control elements as well to prevent being too reliant on automation and to be accountable to the outcomes of work (Singh, 2024; Obana, 2024).

4.5.3 Arguments against Human-AI Collaboration.

Human-AI collaboration has not seen an end despite its potentialities. Such changes as job displacement, doubt about the reliability of AI, and the desire to retain the used work process are the main obstacles to change (Singh, 2024; Kiefer et al., 2022). The fear of information protection and inadequate information on how AI works also become a form of non-plugging force and require the creation of a general change management strategy, including open communication, involvement through participation, and continuous training (Singh, 2024; Aubry et al., 2020). Additionally, it is hard to establish trust, as most AI algorithms are opaque, and project managers do not reason any more clearly when they are kept secret about the algorithms (Felicetti et al., 2024; Koskela and Howell, 2022).

4.5.4 Future Directions

The evolution of more sophisticated cooperative AI systems, including multi-agent AI systems communicating with human orders, is a pointer of the future when PMOs would be able to manage a smart automation environment rather than having a collection of disconnected tools (Stanford research). The trend demands that the project professionals become AI-fluent, gain skills in directing, interpreting, and integrating AI capabilities into the project management strategy (Project Management Institute, 2021; Bredillet, 2022). The degree of obtaining basics in AI as per the warnings set by PMI is no longer a bargain when it comes to successful career in project management and lifelong learning of new advances in AI technologies is a requisite to keep pace with the profession.

In summary, human-AI collaboration in PMOs is disruptive collaboration and basing on trust, transparency, complementary knowledge, and considering ethical governance can unlock unheard of project performance, project innovation, and strategic value creation.

4.6 Synthesis of Literature: Towards an AI-Enhanced PMO

Transformation Framework.

The intricate evolvments of the Project Management Office PMO have been charted in this literature review with specific reference to the dynamically growing process of digitalization, especially with regards to the way the concept of artificial intelligence AI is used in project governance and project execution. First of all, the process of the transformation of the PMO as the administration support unit into the strategic enabler with the emphasis on the value delivery, agile governance, and continuous improvement, was recorded (Aubry, Muller, and Turner, 2007; Marnewick and Saunderson, 2016). Next, the implementation of AI in the project management sphere was discussed, and it was shown that the use of machine learning, natural language processing, robot process automation, and predictive analytics are used to optimize the utilization of resources, forecast and are productive overall (Project Management Institute, 2021; Koskela and Howell, 2022). This was succeeded by the definition of the most salient barriers: technological, organizational, cultural, financial, and ethical barriers to AI adoption that must be addressed to initiate the changes with the help of comprehensive change management, workforce reskilling, and governance system (Aubry et al., 2020; Felicetti et al., 2024). Next, the changes in the AI integration on the PMO performance and role were also evaluated, which indicated an efficiency improvement that could be measured with a strategic realignment of the PMOs as data-driving, insight-generating organisations that guide business agility and innovation (Kiefer, Rzepa, and Baldauf, 2022; Bredillet, 2022). The human and AI relations were viewed as the last point, emphasizing the importance of trust, transparency, complementary skills, their seamless integration, and ethical governance to ensure long-term cooperation between the PMO professionals and the AI systems (Obana, 2024; Singh, 2024).

The combination of such insights suggests a critical framework on AI-enabled PMO transformation that consists of five pillars that are interrelated with one another:

- Strategic Alignment and Vision.

A strategic vision should form the basis of AI projects and it identifies the organizational needs such that implementation of AI should address the short term performance of the project as well as the long term business needs. Executive sponsorship is needed to support the resources and cultural buy-in, cross-functional interaction, and strong value proposition (Marnewick and Saunderson, 2016; Project Management Institute, 2021).

- Data Readiness and Technology.

The successful implementation of AI is based on well-developed technological base and quality data. It includes modernization of old systems, introducing single data structure, data control, and investing in such implementations that can scale to AI algorithms. Trust and accuracy and consistent data quality should be ensured, which is why the model needs to be maintained (Koskela and Howell, 2022; Felicetti et al., 2024).

- Competency Development and Human capital.

The roles and capabilities of PMO should be redesigned: one will need to invest in reskilling programs, comprising technical AI literacy, data analytics, and ethical decision-making and change leadership. The development of the culture of never-ending learning and interdisciplinary collaboration is the way to developing the ability of professionals to cooperate with AI tools (Aubry et al., 2020; Kiefer et al., 2022).

- Process Incorporation and Oversight.

The application of the AI tools should be part of the PMO processes and not used across the lines of planning, execution, monitoring, and control. The accounting and ethical policies with auditing and accountability should be established in governance systems to allow balancing the benefits of automation and human control. It is an approach that facilitates the scenario of standardization of AI-enhanced processes in the enterprise (Felicetti et al., 2024; Singh, 2024).

- Repeat Process and Improvement.

To iteratively optimize the AI solutions and processes, recurrent analysis of the AI impact on the PMO performance, i.e., measures of forecasting accuracy, project success rates, resource utilization, and stakeholder satisfaction can be performed. The feedback loop based on the insights of users and the emergent challenges are also necessary to cope with the changing environment in the organization and the technology shifts (Kiefer et al., 2022; Bredillet, 2022).

The model would not turn AI into a stand-alone technology initiative but would present it as an element of strategic change of PMO and would require coordination in the investment in vision, infrastructure, people, processes, and evaluation systems. The operationalizations of these pillars can assist PMOs to be more prophylactic, intelligence driven and able to influence organizational strategy than responsive compliance that can enable a sustainable competitive advantage.

4.7 AI-Enabled PMO Transformation – Conceptual Framework Diagram

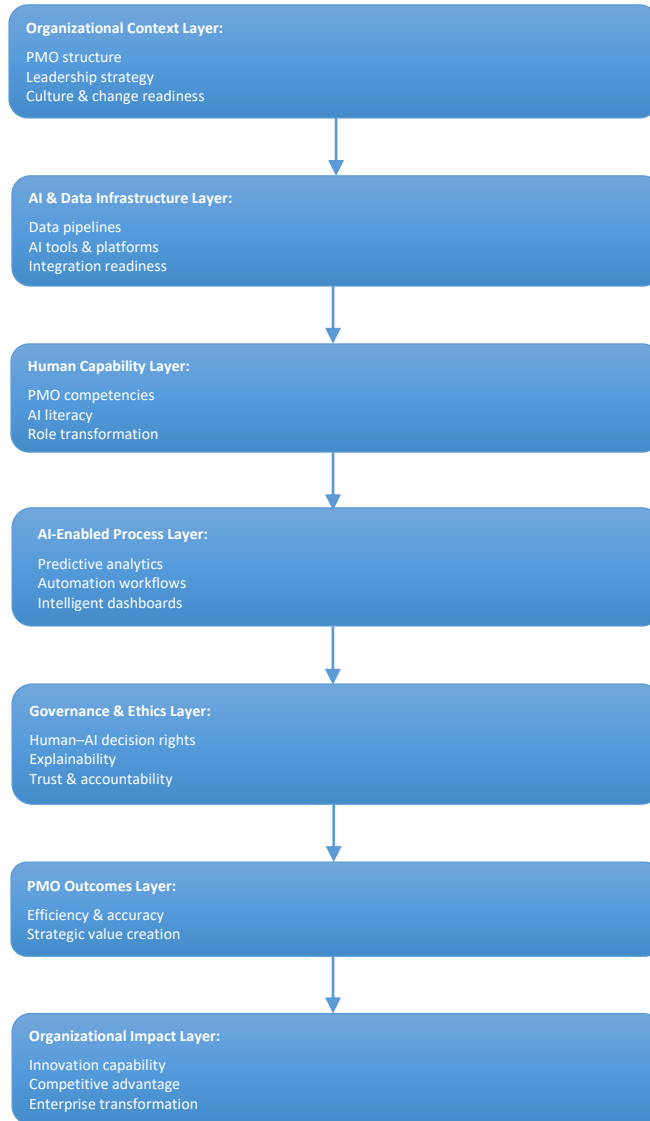


Figure 1. C AI enabled PMO transformation - conceptual framework diagram.

Rapid development of Artificial Intelligence AI in the modern project setting has placed the Project Management Office PMO in the vortex of one of the most profound changes in organizations in recent decades. With the growing reliance of organizations on predictive analytics, automated reporting, intelligent decision systems, and machine supported governance, the PMO, which long has been viewed as a structural mechanism to project oversight, assurance and performance, is shifting to a strategic, insight driven

role. This change is broadly recognized in the new body of work on AI-driven project management, but the conceptual frameworks that can be used to cognize the multi-dimensionality of such change are seriously wanting. The majority of the literature provides discrete elements of the adoption of AI in PMO setting, yet no paper offers a comprehensive, layered conceptual framework that characterizes PMOs transformation along the organizational, technological, human, procedural, governance, and strategic plane.

Such a conceptual void is not just a hypothetical gap; it has a direct impact on the methodological underpinnings on which empirical studies of AI facilitated by PMOs can be grounded. The research risks being disjointed without a holistic framework that can group the different aspects of PMO transformation and explain the systemic aspect of AI integration. Consequently, this paper presents a Seven Layer AI Enabled PMO Transformation Architecture as a novel conceptual framework aimed at helping to both maintain methodological rigor and theoretical clarity. To justify this architecture, a thorough analysis of the existing literature is needed to show: (1) that existing literature is not comprehensive enough to model PMO transformation as a whole; (2) that PMO transformation under AI is multi-layered by nature; (3) that all of the seven layers have empirical or conceptual support; and (4) that the architecture is a new theoretical step that needs to be taken.

4.7.1 Discontinuity and Lack of Research in the Current AI Research Enabled PMO Transformation.

Though the literature on the influence of AI on project management continues to grow, scholarly and practitioner research is so fragmented. As a full re-examination of the existing literature indicates, the available literature is more inclined to discuss one or two of the dimensions of PMO evolution such as governance, automation, capability requirements, strategic alignment without a single conceptualization of PMO transformation as a systemic process.

To illustrate, Adamantiadou and Tsironis made a significant systematic review of AI in project management, which compiled evidence of 97 peer-reviewed studies. Their

survey outlines the use of AI methods that include cost estimation models, predictive scheduling, risk assessment algorithms, and hybrid machine learning methods as potentially having significant potential in improving the performance of projects. Nonetheless, despite the abundance of information on the technical utility of AI offered in the study, there is no direct bridging of the capabilities offered by the technology to the changes in the PMO structure, governance or strategic role. The authors clearly identify literature gaps regarding the organizational implications of AI and the necessity of conceptual models that can connect the individual AI usage to the larger managerial and structural implications (Adamantiadou and Tsironis, 2025b).

On the same note, Miller (2026) offers a conceptual framework of understanding the impact of AI-based automation on PMO governance. His work is based on the socio technical systems theory to analyse the impact of AI on the decision latency, accuracy of predictions and PMO oversight structures. Although the study by Miller provides a vital insight into the issues of governance, including explainability, decision rights, and algorithmic accountability, it lacks the interaction with the overall architecture of the PMO transformation, including organization readiness, data infrastructure, competency changes, or strategic level effects. The framework is insightful yet restricted in scope.

Practitioner-oriented analyses are also limited by the same. The article by Kohli (2025) in the PM World Journal presents a comparative analysis of the traditional and AI enhanced PMOs and outlines how AI can enhance the governance, assurance, portfolio alignment, knowledge management, and delivery support. Although this work recognizes the multi-dimensional influence of AI, it shows these in the form of loosely related themes, but not in the form of an integrated architecture. Kohli clearly outlines the transformation of the PMO as a change in five areas with no formal relationships or dependencies among them, which further contributes to the disintegrated discourse.

The same trends are reflected in professional organizations. According to the AI resources provided by PMI (2026), by 2030 up to 80% of the traditional project management processes will be automated, and the strategic potential and workforce capability needs related to the AI transformation are identified. However, the publications by PMI are silent in describing a systematic model of AI adoption in the PMO

setting; they provide high-level information that can be used by practitioners in general. Similarly, the House of PMO (2025) highlights the significance of the PMO governance, role development, and AI maturity but once again dwells on the best practices instead of introducing a conceptual transformation framework.

Lastly, the International Association of Project Managers IAPM underlines how the PMO has to be redefined in the era of AI, wherein data proliferation, automation, and predictive analytics push PMOs to shift their focus to the strategies of strict control to strategic enablement. Nevertheless, the IAPM offers a useful description of the drivers of transformation but lacks a systematic theoretical framework of the effects of AI on various tiers of PMO operations.

In these sources, the trend remains the same: despite the recognition of scholars and practitioners of the fact that AI changes the PMO structures, roles, processes, and strategic contributions, they fail to conceptualize this change as a multi layered, interdependent system. This is due to lack of a holistic model, which restricts the analyses, comparisons, and evaluation of PMO transformation in totality in the field.

4.7.2 The Multi Layered Conceptual Architecture is Necessary.

Lack of a holistic model is especially an issue since the transformation of PMO with AI is in its essence multi-layered. All the dimensions are interactive and work together, such as organizational, technological, human, procedural, ethical, outcome oriented and strategic. The adoption of AI does not take place in a vacuum, but instead, it relies on organizational enabling conditions, preparedness at the infrastructural level, adjustment at the human level, redesign at the process level, safeguards at the governance level, performance-level improvements, and finally, fit to greater enterprise change.

Current literature gives several hints that there is need to have such an organized, stratified conceptualization. The fact that Kohli (2025) differentiates traditional and AI-enhanced PMOs already suggests layered dependencies, in which governance reforms depend on the new competencies, which depend on technological infrastructure and enabling organizational culture. These relationships however are not formalized in a conceptual architecture.

In the meantime, the insights of PMI regarding the workforce capability requirements imply that the AI empowered PMOs have to incorporate the aspects of technical, human, and organizational in an interdependent fashion. However there is no model to show the interaction between these layers to determine PMO maturity.

Equally, the socio technical framing of Miller (2026) recognizes the fact that data, tools, competencies, and governance structures are part of a single system, meaning that conceptual models are required that consider layered relationships.

The IAPM also highlights that transformation of AI-driven PMO necessitates alignment of structural, cultural and capability-related dimensions, but does not show them in a layered or sequencing format.

Briefly, the literature is quite adamant, though not explicit in stating, that PMO change under AI must be multi-layered. The suggested 7-layer architecture is, therefore, a direct response to this methodological and theoretical requirement.

4.7.3 Reasoning behind the Seven Layers.

The seven layers of the suggested conceptual framework are the direct products of the themes that exist throughout the literature but have never been combined into one architectural model. Each layer is based on the existing research but developed by developing formalized relationships among the layers.

- Organizational Context

A PMO starts its transformation process with its organizational context. The adoption and implementation of AI technologies depend on a PMO based on its mandate, authority, maturity, and structural positioning. Kohli (2025) shows that the conventional PMO models that focus on compliance, documentation, and oversight are structurally limited in utilizing AI, whereas PMOs that are designed as strategic partners have more adaptability and are more digitally aligned. This is an example of how AI-based PMO change depends on the structural location - a fact that is directly embodied in the first tier of this framework.

This point of view is supported by PMI who found organizational readiness, leadership buy in, and strategic vision to be the most important factors that determine the success of AI adoption. The implementation of AI stalls without the support of the executives and cultural openness regardless of the technologies at hand.

The work of the House of PMO contributes that the maturity of PMO and its service orientation also determine the pathways of transformation. By comprehending their service catalogue and dependencies with stakeholders, PMOs are better placed to redesign services with AI.

Collectively, these studies provide rationale to include organizational context as the initial layer of PMO transformation.

- AI & Data Infrastructure

The integration of AI must have a technical basis that entails data systems, integration pipelines, analytical platforms and software tools. Data quality and system interoperability seem to be the most used challenges in the literature.

In their systematic review, Adamantiadou and Tsironis point out that AI models perform poorly in situations where the organization does not have enough historical data and scenarios where data is distributed across systems. This observation reinforces the fact that data infrastructure is not an optional addition, but an implication (Adamantiadou and Tsironis, 2025b).

Simultaneously, Miller (2026) highlights the significance of integrating tools and interdependence in human judgement and algorithmic output that are socio technological in nature. His writing may indicate that the operation of AI-powered governance is not reliable or accountable without a mature technological infrastructure.

The IAPM further notes that the current PMO has to contend with the pyrotechnic burst of structured and unstructured project data and needs platforms that can handle multi-faceted and multi-dimensional data sources.

All these pieces of evidence are good reasons to believe that the second layer: AI and data infrastructure is a key enabler to all other layers in the transformation architecture.

- Human Capability Development

PMOs based on AI must undergo a skills, role and competency transformation. This dimension is virtually acknowledged in all existing studies although none of them places it in a structured transformation model.

Kohli (2025) suggests that the tasks of PMOs should shift towards strategic analysis, making the PMO professionals develop data literacy, predictive thinking, and digital leadership skills. His juxtaposition of conventional and AI-added PMOs is rather strong to the point that capability development is a specific and imperative field of transformation.

PMI research is not alone, indicating that AI and big data skills are among the highest-priority workforce competencies in the world. The PMI highlights that the collaboration of humans and machines does not only need technical upskilling, but also new behavior and interpretive skills.

The House of PMO promotes the value of AI practitioner development, lifelong learning, and competency models in facilitating PMO transformation.

IAPM (2026) adds another layer claiming that the role of the PMO leaders should be more of an advisor, capable of transforming the realization into the strategic choice, instead of merely having to cope with the compliance regulations. This underscores the importance of soft skills such as the process of communication, leadership and ethical judgement in AI-enabled environments.

Accordingly, the literature offers a strong argument in terms of the development of human capabilities as its layer.

- AI Enabled Processes

The internal processes of PMO have to change as the competencies are changing. The fact that AI fundamentally transforms the processes of project and portfolio management is strongly supported by the literature.

Adamantiadou and Tsironis report better accuracy in scheduling, the risk assessment, and performance monitoring facilitated by machine learning models. These results suggest that AI is not just a process-enhancing technology, but it makes them transform (Adamantiadou and Tsironis, 2025b).

According to Kohli (2025), AI-based PMOs are based on predictive analytics to align the portfolio, undertake risk priorities, and manage knowledge, which develops new workflows and decreases the amount of manual work.

According to the reports by PMI, as much as 80 percent of all regular project administration will be automated in the future, which is a clear indication that process redesign is not a luxury but a lifeblood of the PMO.

The House of PMO also emphasizes how automated dashboards, reporting tools that are driven by RPA, and smart quality assurance tools transform PMO services.

The overlap of these results justifies the addition of AI-enabled processes as a separate transformation layer.

- Governance and Ethics

With AI supplementing PMO processes, there arise new governance issues associated with transparency of the algorithm, authority, ethical responsibility, and governance.

Miller (2026) underlines that AI changes the balance in the decision-making in PMOs, which may lead to conflicts between automatic suggestions and human judgement. His review explains the necessity of well-structured governance models that help in defining accountability in human-machine decision contexts that are hybrid.

The IAPM (2026) emphasizes that the implementation of AI must have protective measures that maintain a sense of fairness, transparency, and ethical application of predictive and prescriptive analytics in PMO activities.

The mentions of responsible use of AI are also recurrent in the PMI guidance, which promotes the use of transparent model results, explainability practices, and maintenance of human control.

Ethics and governance are therefore crucial elements of PMO transformation and therefore make logical sense to be the fifth layer of the architecture.

- PMO Outcomes

Performance outcomes are the palpable AI-driven transformation outcomes. The literature is unanimous in reporting enhancements in efficiency, accuracy, risk identification, resource optimization and quality of decisions.

Kohli (2025), presents performance gains in terms of accuracy of forecasts, optimization of resources, and strategic alignment, making AI a performance multiplier to PMOs.

Adamantiadou and Tsironis affirm that AI is associated with better likelihood of project success through increasing the risk identification and predictive accuracies of the schedule. (Adamantiadou & Tsironis, 2025b)

PMI further provides that AI-enabled PMOs offer quicker and more precise reporting, aiding superior executive choices and the achievement of portfolio worth.

These sources support the PMO outcomes layer as an important assessive dimension of transformation framework.

- Organizational Impact

The topmost section of the architecture reflects the enterprise level impacts like innovation potential, strategic responsiveness and competitive edge.

IAPM (2026) believes that AI-powered PMOs become strategic enablers that are able to facilitate enterprise wide digital transformation, innovation efforts, and strategic alignment.

According to Kohli (2025), AI-enhanced PMOs assist organizations to become resilient and competitive in the long term, by enhancing project governance and the quality of decision making.

PMI emphasizes that AI-driven project governance systems are beneficial in organizational agility and better strategic portfolio performance.

These observations support the fact that organizational impact should be added as the PMO transformation culmination.

4.8 The Framework as an Innovative Contribution

Seven Layer AI Enabled PMO Transformation Architecture is not only innovative because of a number of reasons. First, it unites the knowledge of various fields such as project governance, adoption of AI, data science, organizational behavior, and digital transformation into a single model that has never been presented in the literature. Second, although each layer is supported by previous research independently, no current publication has provided a detailed architecture on how the layers interact with each other, or in a sequential order. Third, the layered model reflects the interdependent and systemic character of AI enabled transformation, which is neither defined in the PMI, House of PMO, nor by academic researchers as a cohesive model.

Above all, the framework offers methodological transparency to empirical research. The constructs in each layer can be operationized into research questions, survey variables, and interview themes and thus organize the data collection and analysis processes. Further, the architecture facilitates the holistic interpretation of empirical findings as the researcher can map the insights to the seven layers, determine causal relations, and see the dynamics of the transformation.

By so doing, the framework fills a very important methodological gap in modern PMO literature: the lack of a unified transformation model that incorporates the disparate perspectives into a single conceptual framework

5 Methodology

The methodological approach used in this thesis is a representation of the multi layered, complex and dynamic nature of AI facilitated PMO transformation. The research problem has many interdependent dimensions, such as organizational structures, human competencies, data infrastructures, governance mechanisms, and global patterns of AI adoption, which changes at a rate of different speeds and has varied levels of maturity. A methodological design that would be able to incorporate these varied elements is thus needed.

The research will use convergent mixed methods approach to respond to this challenge. It is a mix of quantitative descriptive analysis using global AI adoption datasets and qualitative thematic analysis using scholarly literature, professional PMO frameworks and practitioner feedbacks using well-known industry resources. Integration of these streams of methods makes the study be able to trace the general empirical patterns and, at the same time, explain their underlying implications on the roles of PMOs, capabilities, processes, and governance practices.

The methodological framework is carefully crafted to lead up to the development of Seven Layer AI Enabled PMO Transformation Architecture that will be further introduced in the thesis. Quantitative analysis can give the empirical underpinnings of what is required to realise the external environment in which PMOs work: accelerating the AI adoption, uneven conditions of maturity, cross industry differences, and changes in workforce sentiment. These results are then contextualized into the conceptual landscape of PMO evolution, role transformation, decision making dynamics and human-AI collaboration with the help of qualitative synthesis.

This chapter has the following sections.

Section 5.1 provides the philosophical orientation and methodological justification towards the adoption of convergent mixed methods design.

The data sources employed in the research are presented and discussed in section 5.2 with a special emphasis being placed upon the analysis of the seven global datasets that constitute the empirical core of the quantitative analysis.

Section 5.3 describes the analytical methods that will be used in both quantitative and qualitative stages such as descriptive statistical interpretation, cross functional comparisons, thematic coding and synthesis methods.

Section 5.4 details the methodological grounding, which was used to develop the conceptual framework, and how the integration of empirical evidence and theoretical understanding contributed to the development of a coherent transformation architecture.

Lastly, Section 5.5 concludes with the innovative contribution of the framework and its significance to the academic scholarship and PMO practice.

5.1 Research Design and Methodological Justification.

The study design is informed by the desire to study AI empowered PMO transformation in various angles and by different kinds of evidence. According to Chapter 2, the research problem is caused by six interrelated gaps: the unavailability of empirical PMO specific AI data, ambiguity of the development of PMO roles and competencies, lack of a scaled AI implementation framework, little focus on the human-AI collaboration, and a significant difference in AI maturity among industries and regions. All these gaps require a methodological approach that can be used to combine empirical breadth and conceptual depth.

This makes a convergent mixed methods design to be followed. The rationale behind this design is the fact that both quantitative and qualitative approaches cannot be sufficient to explain the complexity of AI enabled PMO transformation. To study the trends in AI adoption, differences in functional maturity, industry specific differences, and global investment differences, which impact the structural conditions of PMOs evolution, quantitative methods are needed. These structural forces need to be interpreted using qualitative methods to understand the impact on PMO processes, governance practices, human-AI decision dynamics, competency requirements.

The quantitative design relies on seven data sources of AI around the world, each chosen on the basis of its credibility, scope and applicability to PMO transformation. Together, these datasets offer an understanding of the adoption of AI in organizations, patterns of

functional integration, the intensity of AI tool use, geographical investment dissimilarities, industry level maturity, workforce sentiment and macro level AI performance indicators. These datasets will enable the study to create a comprehensive image of the global AI environment where PMOs can be found (Global AI Adoption Trends by Industry Sector, Country, and Business Function (2017-2025): A Completed Research Dataset (Alex Singla, Alexander Sukharevsky, Bryce Hall, Lareina Yee, 2026; Biswas & Faria Jahan, 2026)

The qualitative element is an addition to the empirical analysis by providing thematic interpretation of peer reviewed literature, institutional PMO frameworks and practitioner publications. Such a method allows the research to examine conceptual phenomena that cannot be measured by pure quantitative data, including the development of PMO identity, the appearance of new fields of competencies, shifts in professional expectations, and confidence in AI-generated advice, and the mechanisms of governance that are required to make human-AI cooperation effective.

With a combination of these streams of the methodology, the study guarantees that the analysis is both conceptually and empirically extensive. The convergent design supports triangulation of data, methodological validity, and offers a powerful basis of the transformation framework which addresses the realities of organizational AI adoption, functional diversity, human behaviour and governance evolution. Such a combined methodological architecture will position the research to contribute a strong scholarly impact as well as provide empirical advice to PMOs to navigate AI-enabled change.

The qualitative element is an addition to the empirical analysis by providing thematic interpretation of peer reviewed literature, institutional PMO frameworks and practitioner publications. Such a method allows the research to examine conceptual phenomena that cannot be measured by pure quantitative data, including the development of PMO identity, the appearance of new fields of competencies, shifts in professional expectations, and confidence in AI-generated advice, and the mechanisms of governance that are required to make human-AI cooperation effective.

Combining these streams of methodology, the study guarantees the analysis to be empirically and conceptually exhaustive. The convergent design supports triangulation of data, methodological validity, and offers a powerful basis of the transformation

framework which addresses the realities of organizational AI adoption, functional diversity, human behaviour and governance evolution. Such a combined methodological architecture will position the research to contribute a strong scholarly impact as well as provide empirical advice to PMOs to navigate AI-enabled change.

5.2 Sources of data and Data collection procedure.

This study relies on an empirical basis of a carefully selected set of seven international, high credibility AI datasets that collectively offer distinct information about the organizational, functional, industrial, regional, and human aspects of AI adoption. In contrast to research that uses primary survey data, the thesis will take a secondary approach to data, using publicly reported, mass surveys created by internationally recognized organizations like McKinsey and Company, Stanford University HAI Institute Human, IBM, PwC, and technology industry trackers (Alex Singla, Alexander Sukharevsky, Bryce Hall, Lareina Yee, 2026).

There are three reasons why this methodology is justified.

To begin with, the research gaps outlined in Chapter 2 indicate that the PMO field lacks any empirical data evidence of the magnitude of the impact AI has on structures, roles, competencies, and governance processes. Insufficient data would not be able to fill in these gaps on a global scale, history, and cross industry variation would not be covered in primary data collection. Second, the data, which has been used in this study, is multi year time horizons, cross functional adoption patterns, which allows us to analyze longitudinal changes in AI maturity, which could not have been observed using interviews or small-scale surveys. Third, these datasets offer the access to the disparities on regional and industry level, which is needed to comprehend how a contextual influence affects the PMO readiness and transformation paths.

The datasets combined enable this research to create a solid empirical base where the PMO will be functioning: a place where AI adoption has been accelerating, where there are still considerable maturity gaps, where investment is skewed, and where the attitudes of the workforce are shifting. The data sets are not considered as independent sources, but rather they are combined in a triangulated analytical design, with the

information provided by one dataset being cross validated and contextualized by another to achieve reliability, minimize interpretative bias and facilitate the creation of a holistic conceptual model.

The following section explains each dataset in detail, its provenance, scope and how they relate to the research questions and objectives of this thesis.

5.2.1 Strategy to select and integrate datasets.

The inclusion and synthesis of the datasets, which were involved in this study, was a multi stage, systematic procedure, which was aimed at making the empirical robust, conceptually relevant, and simply aligned with the gaps and objectives of the research. Since the research problem is a cross functional and cross industry issue - the evolution of PMOs in a rapidly changing environment where AI is being adopted - the data sources needed to capture this multidimensional environment. This is why the research will use only those datasets produced by the internationally recognized institutions and prominent AI research centers that have a methodological rigor, sampling frames, and longitudinal continuity that can be used in academic research.

The selection of the dataset started with a thorough search of publicly available AI related datasets in research institutions, consulting firms, intergovernmental organizations and technology platforms. Relevance to the structural forces that drive PMO transformation (including, but not limited to, organizational AI adoption, functional maturity, industry variations, regional investment trends, workforce feeling, and AI tools diffusions) was the main inclusion criterion. Data sets that only presented a limited, instrument specific or non generalizable information were filtered out to those that presented extended coverage across countries, industries or business processes. The process eventually found out seven datasets, which, in combination, are the broadest and the most updated empirical basis to analyze the influence of AI on PMOs.

The second selection criterion of datasets was related to methodological credibility and transparency. Each of the selected datasets are generated by organizations that utilise best research practices, such as standard survey data, exexperts validated sampling procedures, multi year data collection, and a clear reporting of limitations. The McKinsey

Global Survey on AI, such as, uses uniform sampling of thousands of organizations each year, and the Stanford HAI AI Index uses validated economic, technological and scientific indicators. The fact that such datasets are incorporated makes sure that it is not only analytically reliable but also comparable both over time and geographical limits.

Third criterion was associated with the coverage of the six research gaps found in Chapter 2. Maps of each dataset were explicitly mapped to gaps which it supports. As an example, global AI adoption and functional maturity datasets were also chosen since they give empirical basis to the Gaps 1 and 3 that deal with the absence of PMO specific evidence and implementation frameworks. The datasets of industry level and regional investment were selected due to their relevance to Gaps 5 and 6, where the contextual variation is a key factor. To cover Gaps 2 and 4 (those based on the competency transformation and human-AI collaboration issues), workforce sentiment datasets were introduced. This mapping made sure that the entire dataset portfolio was able to cover the entire methodological scope necessary by the study.

Due to the multidimensional character of the research problem, the integration strategy was triangulating analytical logic, i.e. datasets were not analyzed independently but instead analyzed in a manner that enabled them to complement, contrast and corroborate each other. As an illustration, functional adoption data were viewed through the prism of global industry trends, whereas regional investment differences were counterbalanced with sentiment and maturity indicators to come up with a subtle understanding of AI readiness under varying circumstances. This cross-data integration was necessary to understand the meaning of AI adoption patterns as a specific case to the PMOs, which are organizations that are naturally at the crossroads of various business functions, strategic priorities, and governance frameworks.

A mapping of the datasets to the research objective and the analytical process were also included in the process of integration. The descriptive profiles of the AI adoption and maturity were built on the quantitative data, which formed the foundation of the quantitative analysis in a Section 5.3.1. These insights based on datasets derived were then overlaid with qualitative sources, such as PMO frameworks and academic literature, in the thematic analysis in Section 5.3.2. This enabled the study to combine both the empirical patterns and theoretical interpretation as well as anchor theoretical knowledge to the observable patterns.

Lastly, the identified data sets were not only sources of empirical evidence but also a source of theory building which were finally used in the synthesis processes that supported the Seven Layer AI Enabled PMO Transformation Architecture. Their combination made sure that the conceptual framework is based on the empirical base that is the true reflection of the actual circumstances of AI adoption and adjustment in the global organizational ecosystems. By doing so, the dataset integration plan has ensured that the methodology is coherent and analytical, and the evidence is adequate to develop a contribution that is theoretically significant and practically applicable.

5.2.2 Reliability, Validity and Ethical considerations.

To guarantee reliability, validity and ethical soundness of the research, it is also important to note that the thesis will rely on the sources of secondary data and it will be necessary to create a conceptual framework which would serve as a theoretically sound and empirically supported conceptual framework. Since the research will be a synthesis of seven different global datasets, as well as academic and practitioner literature, there will be a need to explicitly attend to the methodology to show that the data employed are credible, representative, and fit the purpose of the research questions and objectives.

- Credibility of Information Sources.

This is ensured by the fact that the datasets used are made intentionally to ensure the study is reliable since the datasets were made by high credibility institutions and their research methods are well established. The seven datasets used (including worldwide AI adoption, functional maturity, industry trends, workforce attitudes, and AI investment) are all sources of well-established organizations like McKinsey and Company, Stanford HAI and multisource lists. Such organizations have standardized survey procedures, longitudinal continuous data gathering, and open reporting procedures. Also in most of them, methodological disclosures (sample sizes, sampling methods, response weighting, and data validation procedures) are published annually or semi annually.

Also, several datasets are longitudinally consistent with a period of 2017-2025 as the adoption of AI in organizations and 2021-2025 in functional adoption. The similarity of

the indicators in different years enhances internal reliability since continuity of observed patterns is due to empirical trends and not measurement anomalies.

- Validity and Triangulation

The multi layered triangulation strategy improves the validity, by incorporating evidence both within and beyond datasets, across research traditions, and methods of analysis. Instead of using a single datapoint or a single source when analyzing AI adoption patterns, the study cross analyzes the results of various datasets that reflect various aspects of the same phenomenon. As an illustration, organizational trends in AI adoption are analyzed with the help of functional maturity differences and industry level adoption trends in order to confirm the conclusions about the pressures of PMO related transformation. The synthesis of the data on global investment and workforce sentiment (Dataset 6) gives an extra triangulation level on structural preparedness and socio cultural factors influencing the implementation of AI.

Such an approach counters the threat of arriving at conclusions based on single or biased sources of data and improves construct validity, which assures that the empirical data can be a true reflection of the constructs underlying AI maturity, readiness, and transformation.

Moreover, the qualitative aspect of the methodology, which is the thematic analysis of scholarly and practitioner literature, is a mechanism of validity as it puts empirical results into perspective in terms of theoretical, conceptual, and governance. This dual stream analysis will make sure that the conceptual architecture that will be built during the thesis is based on not only identifiable global trends but also on the well known PMO theory, which will also support the validity of the theory.

- Ethical Considerations

There is very little ethical risk involved with the use of the data since all the datasets that will be analysed in this thesis are publicly available and anonymized at the point of origin. No personal identifiable information PII is gathered, processed or stored during any phase of the study. However, ethical rigor is ensured by responsible data handling approaches such as properly attributing datasets, and following licensing and use rights of each dataset.

Also, the study is academically sound with the proper reference of all data materials and clear presentation of the shortcomings of the methods used. The notion framework established in the thesis is based on general tendencies and does not claim about a particular organization, thus, reducing the chances of misrepresentation.

5.3 Analytical Methods

5.3.1 Quantitative Descriptive Analysis

The quantitative aspect of this research involves the use of a descriptive form of analysis to investigate high volume, multi year trends in the worldwide adoption of AI, functional maturity, industry variability, investment trends and workforce preparedness. The aim of this analytical phase is not to create predictive or inferential statistical models, but to create an elaborate empirical landscape in which PMO transformation occurs. This research design is especially appropriate to the research aims because the descriptive method will allow the study to find out the structural tendencies, temporal changes, contextual differences and maturity gaps, phenomena that are necessary to fill the gaps in the empirical data described in Research Gap 1 and maturity fragmentation described in Research Gaps 5 and 6.

The analysis will start by analyzing longitudinal trends in the adoption of AI within organizations with Dataset 1, which offers statistics on the adoption of AI in multi years between 2017 and 2025. The data show that the use of AI on an enterprise level is increasing dramatically, with 55% in 2023, 72% in early 2024, and 78 in late 2024, and finally, 88 in 2025. GenAI usage emerged on a more precipitous curve, so that by 2023, it reached 33 percent, 65 percent in 2024 and 2025, respectively. The patterns play a vital role in contextualizing RQ1 because they show that PMOs are not operating in low or experimental AI maturity environments but rather, they are operating in organizations where AI is quickly becoming an operational norm and strategic force.

To further enrich this macro-level image, the analysis also considers the functional level AI maturity with the help of Dataset 2. The results indicate a high level of asymmetries

in the functions of adoption. E.g., the most rapid increase was observed in the field of IT and Software Engineering as it rose to 27% at the beginning of 2024 and to 36% at the end of the year and to 43% in 2025. Knowledge Management - In the reporting, documentation, and generation of insights - grew to 10% in 2023, 14% in early 2024 and 28% in 2025. Meanwhile, Human Resources (21% in 2025) and Risk/Finance (24% in 2025) lag behind. These disparities demonstrate how AI is diffused unequally in the internal functions, which supports the thesis that PMOs have uneven conditions of maturity in their quest to facilitate the integration of AI throughout the enterprise. This specifically applies to RQ1, RQ2 and RQ3 since role transformation, competency development and governance adaption becomes difficult due to uneven maturity.

The third analytical level concentrates on patterns of AI adoption at the industry level, which uses Dataset 5. The dataset shows that there is a high inter industry variation with the adoption rates in 2025 at 92 percent in technology and 82 percent and 80 percent in professional services and financial services respectively and much lower at 50 percent in government, 42 percent in agriculture and 46 percent in real estate and construction. These differences affirm that AI maturity is not cross-sectoral and thus different PMOs within various industries are subject to different environmental pressures, capabilities limitations and digital preparedness environments. This knowledge is essential in RQ3, which aims at comprehending the barriers and facilitators of PMO transformation, and in RQ1, which aims at examining the transformation of PMOs in diverse settings.

The quantitative analysis also includes the regional investment patterns with the help of Dataset 4. The amount of AI investment in privately funded organisations varies greatly across global regions in 2024: United States invested \$109.1 billion, China had 9.3 billion, the European Union had 7.2 billion and other developed and emerging economies had lower levels. These differences imply the difference in the national capabilities of supporting AI infrastructure, talent development, data ecosystems, and organizational preparedness. In the case of PMOs, this implies that the pathways of transformation, availability of resources, and strategic imperatives vary among geographical settings. The implications of these findings are that a contextualized conceptual framework is required as required by Research Gap 6 and fulfilled in Objective O6.

The other critical dimension is associated with the use of AI tools and behavioral pattern of the workforce, which is captured in Dataset 3. The data indicate that ChatGPT had 800 million weekly active users in 2025 and GitHub Copilot had 15 million users by end of 2024. These numbers suggest that the AI augmentation already exists in the knowledge work of everyday life and defines the way people complete their tasks, communicate, access in information and make decisions. The behavioral changes directly impact the PMO competencies, role development, and human-AI interaction dynamics, which the RQ2 and RQ4 focus on.

Lastly, Dataset 6 will provide vital information on the sentiments of the population and the working population. Two thirds of employees around the world think AI is going to transform their job greatly and that a third of workers worry that AI might take over their job; optimism is also higher in some nations compared to others (e.g. 83% in China vs. 39% in the United States). These sentiment trends offer important background on the issue of resistance, trust, and acceptance which determine the adoption of AI, and influence PMO change management duties.

The quantitative descriptive analysis combined will result in a multi layered empirical map of AI adoption and maturity. It determines the conditions in which PMOs have to develop all over the world, recognizes the heterogeneity of functional and industry contexts and unveils the changes in the behavior and mood of the working population. This background information aids the further qualitative research and allows creating a conceptual framework that will capture the complexity and variability of AI-enabled PMO transformation.

5.3.2 Qualitative Thematic Analysis

The qualitative part of this research will use a thematic analysis methodology to investigate how artificial intelligence transforms the structures, practices, and professional expectation of the Project Management Office. Whereas the quantitative analysis defines the empirical maturity landscape that PMOs are working in, the qualitative thematic analysis offers the interpretative richness to comprehend how and

why these empirical conditions are being transcended into changes in the PMO roles, competencies, processes, and governance. This is necessary due to the conceptual ambiguity, fragmentation, and theoretical gaps previously mentioned, especially in regards to PMO identity, human AI collaboration, and the lack of an AI aligned governance and competency models.

The thematic analysis was in an organized and repetitive process, with the principles of qualitative inquiry. It started with a thorough analysis of peer reviewed scholarly publications such as the ones in project management, information systems, organizational behavior, and artificial intelligence governance. This analysis was supplemented by an analysis of professional PMO frameworks including those released by PMI, IPMA, the house of PMO and practitioner oriented reports by large consulting and technology companies. Collectively, these sources yielded a wealth of information on what is expected of PMOs and the dynamic character of work digitalized and automated through AI.

In order to start the thematic analysis, all sources were initially open coded, where key ideas, statements and conceptual patterns pertaining to PMO transformation were recognized. This covered repeated mentions of automation in reporting, how predictive analytics are becoming more and more relevant to risk and portfolio management, the development of AI-generated insights in decision-making, and the growing requirement of PMO personnel to interpret and authenticate the output of algorithms. This review was inductively generated using codes, whereby the themes came out naturally as a result of the literature instead of being predetermined.

After the establishment of initial codes, they were further refined by use of axial coding whereby relationship between codes were analyzed and categorized into larger conceptual ideas. This exercise underscored a number of key areas of thematic convergence (1) the redefinition of PMO value creation in more data-driven settings; (2) the role of PMO moving towards strategic advisory, model custodianship, and insight provision; (3) the emergence of novel areas of competency data literacy, AI governance, ethical reasoning, and interpretability; (4) the increased attention to human-AI

Selective coding was the last step in the thematic analysis process, where the conceptual category developed was narrowed down to central themes that were directly used to inform the research questions and to build the conceptual framework. These central

themes are: how the PMO can be repositioned to work in AI-enabled organizations; how procedural oversight can be replaced by insight-driven coordination; why new professional identities of combining analytical capability with governance stewardship are necessary; how the centrality of human-AI collaboration in PMO workflows; why formal, scalable mechanisms are needed to ensure that AI technologies are ethically, transparently, and responsibly

The cross-tabulation of qualitative themes and quantitative results was consciously attempted during the analysis. This made conceptual interpretations to be placed within the facts of the data that were recorded in the analysis of the data. To take an example, the discovery of new PMO competency needs was discussed in parallel with indications of a massive adoption of AI tools among knowledge workers; the discussion of governance issues was put into perspective based on quantitative measures of asymmetric AI maturity between industries and geographies. This cross-referencing enhanced the conceptual underpinnings of the study by making sure that thematic development had a theoretical foundation and was empirically informed.

Overall, the qualitative thematic analysis offers an indepth interpretative basis of how AI is likely to impact PMO structures, roles, and practices. It allows the research to go beyond the superficial accounts of AI adoption to the more indepth approach of how PMOs need to evolve to be useful in AI-intensive organizational ecosystems. The observations made of this analysis constitute an essential intermediate to the previously mentioned trends in the empirical analysis and the integrative synthesis developed in the following subsection, and the final development of the Seven Layer AI Enabled PMO Transformation Architecture.

5.3.3 Synthesis Strategy to Framework Development.

The last analytical phase of this paper is the synthesis process which was structured in such a way that the quantitative and qualitative results were combined to create the theoretical foundation of the Seven Layer AI Enabled PMO Transformation Architecture. Unlike the quantitative analysis which offered an overall empirical view of the world of AI adoption, its functional maturity, industry variation, investment differences and

workforce sentiment, the qualitative analysis produced profound interpretive knowledge on how these empirical circumstances can be transformed into the changing roles of PMO, emerging competencies, governance issues, and socio technical dynamics. Synthesis stage was hence necessary in balancing these two streams of analysis into a unified, multi layered conceptualization framework that can grasp the complexity of AI facilitated PMO transformation.

Synthesis was systematic, iterative and interpretive logic that is similar to theory building methods of organizational and information system studies. The initial step included mapping the quantitative trends in terms of thematic constructs that had been found in the qualitative step. Indicatively, the number of themes associated with the automation of the PMO process, the use of insights to drive reporting, and the use of data to support a decision were empirically supported by the dataset indicating a rapid increase in the adoption of AI across the IT and Knowledge Management functions in 2024-2025. Similarly, the strong industry variations in AI adoption were matched to the themes related to the contextual heterogeneity of PMO governance and the necessity to have flexible transformation pathways. This mapping made sure that conceptual understandings were not developed in a vacuum but were based on observable patterns which are documented throughout the world.

The second step was cross domain consolidation wherein a group of related discoveries in functions, industries, geographies and human dynamics were studied as a unit. This step allowed the discovery of more underlying structural patterns that traversed datasets and thematic constructs. As an example, the difference in the maturity of AI functions (e.g., fast adoption in IT and slow adoption in HR) was accompanied by qualitative information on disproportionate ability building and organizational preparedness. On the same note, the theme based results regarding human-AI collaboration, trust, and transparency were put into perspective based on sentiment data that revealed the prevalent beliefs of job displacement and large disparities in optimism across regions. This cross domain consolidation enabled the research to shift away, where isolated insights were, to multi dimensional transformation drivers.

The third step was conceptual abstraction that entailed promotion of the patterns that had been consolidated to higher order categories which depicted the most vital areas of PMO transformation. The result of the comparison and refinement process was the

identification of seven domains that are analytically distinct and dependent on each other: (1) organizational context, (2) AI and data infrastructure, (3) human capability development, (4) AI enabled PMO processes, (5) governance and ethics, (6) PMO outcomes, and (7) organizational strategic impact. These areas were not predefined and came out inductively as a result of the continuous juxtaposition of empirical data, thematic explanation and PMO theory. Their hierarchical structure was guided by the rationale that change starts with contextual preparedness and infrastructure, moves to human and process accommodations and ends with governance, performance and strategic value creation.

In the last and fourth step, these conceptual domains were systematized into a layered architecture of transformation, which captures the sequential and progressive aspect of AI inspired PMO evolution. The definition of each layer was with respect to its contribution to the overall transformation logic. The underlying layers, such as organizational context and AI/data infrastructure, establish the prerequisites in which transformation of PMO can occur. Mechanisms by which transformation occurs are captured in the middle layers, human capability development and AI enabled processes. The top levels governance, PMO results, and strategic impact indicate the impact and value created by effective integration of AI. This stratified design offers analytically consistent structure which captures the dependencies as well as directional flow of AI-driven PMO change.

Generally, the synthesis methodology combines both the methodological breadth and the conceptual depth of the entire synthesis approach where the end product, the framework, is methodological, theoretically sound and practically applicable. The Seven Layer AI Enabled PMO Transformation Architecture represents the actual complexity of PMO transformation in AI rich environments, by relying on the evidence of global datasets and interpretive thematic insights, and provides the overall basis of the analysis in the following chapters.

5.4 AI-Based PMO transformation- Conceptual Framework Foundation.

The creation of the Seven Layer AI Enabled PMO Transformation Architecture necessitated a methodological basis with the ability to integrate empirical findings, theoretical knowledge and the conceptual patterns observed during the quantitative and qualitative analysis. Although the above analytical steps have set the groundwork wherein PMOs are steadily getting exposed to artificial intelligence; the section justifies why a new conceptual architecture is required, and how the structure logically arises out of constraints of current research, gaps that have been identified and integrated analytical results.

In this regard, this section is divided into three. Section 5.4.1 presents the fragmentation and constraints in the current literature on PMO and AI, showing why there is no available framework that is adequate to support the complexity of AI enabled PMO transformation. The justification behind a multi layered conceptual architecture is explained in section 5.4.2, based on the empirical diversity presented by the datasets, and the depth of the qualitative analysis. Each of the seven layers which make up the final framework is then justified in 5.4.3, and how each can be linked to a particular dimension of transformation which has been identified by the methodological process

5.4.1 Discontinuity and Lack in Current Research on AI Made PMO Transformation possible.

The discontinuity of the current body of knowledge is one of the main catalysts on the creation of a new conceptual architecture. The literature on Project Management Offices has been traditionally concerned with structural configurations, governance roles, maturity models, and performance contributions, but this literature was created in pre AI settings and thus cannot be used to determine the transformative nature of intelligent systems to the practice of PMO. The PMO research is inclined to think about value creation by standardizing processes, disciplining reporting, achieving benefits, and coordinating portfolios processes which change radically as soon as predictive analytics,

autonomous insights, and algorithm guided decision paths are integrated into organizational operations.

On the other hand, the literature on artificial intelligence offers a lot of content on automation, machine learning, decision support, algorithms ethics, and the human factor, but less often discusses PMOs as an organizational unit. The hybrid nature of the PMO, which lies between strategy, operations, technology and governance, makes it invisible in most AI research, which targets specific decision-makers, team level augmentation, or enterprise-wide digital strategies. Consequently, the distinct governance functions, competency frameworks and cross functional co-ordination functions of the PMO are not studied in the context of AI transformation.

The absence of incorporated patterns of connection between AI adoption patterns and PMO particular implications exacerbates this issue. Current AI governing models indicate principles of fairness, transparency, and accountability without the consideration of how these principles become a PMO oversight system, assurance, and role based responsibilities. Equally, digital transformation frameworks tackle the organizational readiness, culture and leadership without taking into account the structural and functional changes that PMOs should make to coordinate AI programs in complex portfolios.

The outcome is an academic terrain where no one model deals with the meeting of the six research gaps that were determined above: lack of empirical evidence, competency ambiguity, fragmentation of implementation, human-AI collaboration issues, inter industry differences, and maturity differences. Such a methodological vacuum would lead to a need to create a new conceptual architecture that would merge these dimensions into a coherent, layered depiction of AI facilitated PMO transformation

5.4.2 The Need for a Multi Layered Conceptual Architecture

Since AI transformation is multi dimensional as seen with the analysis of the dataset, it needs a multi layered conceptual architecture that needs to capture the interdependencies of the organizational, human, technological, governance, and strategic realms. The quantitative results indicate that the adoption of AI is not a

homogeneous phenomenon; it is a process that takes place differently in functions, industries, and regions and at a different pace and maturity. This variability means that there will not be linear or single factor models that give us PMO transformation. Rather, transformation needs to be perceived as a systemic process, which develops in a number of layers, which interconnect and support each other.

The qualitative thematic analysis also confirms the fact that the evolution of PMO is not a question of merely implementing AI tools. It is characterized by more fundamental conceptual changes: the rebranding of PMOs as strategic insight allies, the appearance of new competency areas, the re-organization of reporting and coordination, and the spread of governance responsibilities to encompass the algorithmic management and ethical oversight. These transformations are structural, behavioral and governance based and each of these transformations has a variety of influence on PMO function although interconnected.

A layered architecture is thus required to capture the order and dependencies in which PMO transformation goes through. Underlying layers - the organizational context, AI/data infrastructure, etc. - shape the circumstance of possibility regarding transformation. Intermediate layers - human capabilities and AI enabled processes - are where the processes through which transformation takes place are captured. Top layers - governance, PMO outcomes and strategic impact - are the values and impacts that are created in the transformation.

This hierarchy of logic allows the framework to be at once comprehensive - covering all the areas of transformation relevant - and scalable, whereby organizations at various levels of maturity or in different sectors can use the model in a context specific fashion. This methodological requirement of layered abstraction is the conceptual justification of the architecture that is created in this thesis

5.4.3 Rationale of the Seven Layers.

The ultimate conceptual architecture comprises seven layers that come into being as a result of the synthesis of empirical designs, thematic designs and theoretical arguments. These layers are explained by the following reasons:

1. Organizational Context

Quantitative data show that industries and geographic areas are radically uneven in terms of AI preparedness, investment potential, and regulatory framework, as well as employee attitudes. These contextual aspects determine the viability, speed and extent of PMO change. Hence, organizational context constitutes the bottom most and the initial layer.

2. Artificial Intelligence and Information Technology.

The analysis of the datasets shows that AI maturity is much more diverse depending on functions. In the absence of integrated data systems, dependable pipelines, and scalable artificial intelligence platform, PMOs will be unable to use AI to forecast, automate reporting, or risk analytics. The second foundational layer is infrastructure readiness.

3. Human Capability Development

The qualitative analysis reveals that PMO professionals have to acquire new skills connected with data literacy, model interpretation, AI governance, and hybrid collaboration. These human abilities are the enabling human basis of AI driven PMO processes.

4. PMO Processes Enabled by AI.

The adoption of AI is changing the PMO role to a traditional one and especially with reporting, predictive risk analysis, dynamic forecasting and generation of insights becoming automated. Redesigned PMO processes, in this way, form the fourth layer.

5. Governance and Ethics

PMOs are essential in making sure that AI outputs are transparent, accountable, ethical, as the qualitative themes revealed. The governance systems should change to include human in the loop decisions, model validation and explainability procedures.

6. PMO Outcomes.

The assimilation of AI in the PMO processes transforms performance indicators including accuracy of the forecast, shortening the cycle time, and strategic alignment. These outcomes are the sixth layer, which are the quantifiable impacts of transformation.

7. Strategic Organizational Impact.

Lastly, the capacity of AI to be exploited by the PMO has a direct impact on the performance of enterprises, realization of portfolio value, and strategic agility. This final layer reflects the benefits of AI enabled PMO transformation in the long run of the organization.

Improving on each other, the seven layers create an overall and empirically based architecture that comprises the entire range of PMO transformation within the AI-driven environment. The progressiveness of the capability development and the interdependencies between infrastructure, human competencies, processes, governance and organizational impact evidenced in their hierarchical structure.

5.5 The Framework as a New Contribute.

The main academic contribution of this thesis is the Seven Layer AI Enabled PMO Transformation Architecture. It is developed by systematic integration of large scale empirical findings, thematic analysis of PMO and AI literature and synthesis process which takes into consideration the deep structural, technological and human transformations that are taking place in the modern organizations. The available PMO models, such as the PMI standards, the House of PMO advice, and agile governance models, were all created in pre AI settings and thus do not provide a comprehensive, multi-dimensional roadmap of PMOs facing the rise of predictive analytics, algorithmic decision-making, and smart automation. On the same note, the studies on artificial intelligence, although comprehensive in the way they treat machine learning, ethics and automation, historically do not consider the PMO as a separate organizational entity with ambivalent governance roles. This is where the conceptual vacuum as a result is filled in by this framework.

The distinguishing characteristic to this framework and its existing models is that this framework is designed with a layered architecture; this represents the empirical diversity and conceptual complexity that is inherent to the methodological process. The layers cover transformational dimensions that are theoretically meaningful and empirically

confirmed by the world datasets that are analysed in Section 5.3.1. As an example, the introduction of an Organizational Context layer is used to acknowledge the unequal level of AI maturity, expressed by the variations in the rates of adoption between industries and regions. The layers of AI/Data Infrastructure and Human Capability Development directly react to the functional differences and workforce sentiment trends identified in the datasets. At the same time, the Governance and Ethics layer represents the qualitative themes of trust, transparency, accountability, and the PMO developing oversight roles in the environment where AI is taking a more significant impact on project decisions.

The innovativeness of the framework is also based on its systemic and sequential orientation. Instead of positing the concept of PMO transformation as a set of discrete changes, the architecture illustrates the way transformation happens in a cumulative way within multiple interdependent domains. The bottom layers are the organizational and technological preconditions of change, and the middle layers describe the processes of change, human development of capabilities and AI facilitated process, by which change becomes a reality. The upper-most layers then express the outcomes and strategic value created by an AI enabled PMO. This sequencing not only mirrors empirical trends in the data sets, but also theoretical postulates in the transformation literature, but constructs them in a structure that has not been described before in the PMO literature.

Further, the framework offers context sensitive model that enables organizations to tune the pathways of PMO transformation based on level of AI maturity, industry environment and internal preparedness. Since some sectors like technology or financial services have significantly different AI curves of industries like government or agriculture, a general, consistent model of PMO transformation would not be practically applicable. The seven-layer architecture recognizes the presence of contextual variation and uses it to include contextual variation by allowing organizations to determine which layers need to be developed now and which layers remain out of context until more fundamental capabilities are developed. This adaptability increases the usefulness of the framework in practice, but preserves conceptual coherence.

Lastly, the framework contributes to the field of methodology by showing how the analysis of secondary data can be integrated with theoretical synthesis to create a new

conceptual model. Integration of various complementary datasets, including organizational adoption, functional maturity, public sentiment, global investment flows and AI tool usage are what guarantee that the framework is not merely a theoretical proposal but is based on clear global trends and empirically confirmed tendencies. This shows the importance of choosing empirical breadth and conceptual depth, which makes the study a methodological model to be used in future studies at the crossroads of project management and artificial intelligence.

Combined, the Seven Layer AI Enabled PMO Transformation Architecture offers a holistic, empirically-based, and theoretically-novel model that responds to the entire range of transformation issues that affect contemporary PMOs. It not only contributes to the academic knowledge, but also addresses the conceptual gaps noted in Chapter 2 and provides practitioners with a strategic map of how to lead the PMO development in the more AI-intensive organizational environment. In this regard, it can be considered an important contribution to the PMO scholarship and the overall discussion of organizational change in the era of artificial intelligence.

6 Results

In this chapter, the author offers the empirical findings, which are based on the global AI datasets, analyzed during the quantitative phase of the study. Its aim is to present a concise, data intensive summary of the AI adoption environment, operational maturity, industry sector variability, consumer trend, and technological maturity pointers, which jointly inform the transformation environment of contemporary Project Management Offices PMOs.

Every chart in this chapter was created out of the validated datasets presented in Chapter 5 and each visualisation has empirical insights that apply to the research questions

6.1 Global AI Adoption Trends (2023–2025)

The former dataset is a longitudinal perspective of AI adoption at the enterprise level. Findings reveal an upward trend of high level, which suggests the diffusion of AI has entered the mature, main stream stage of global organisations.

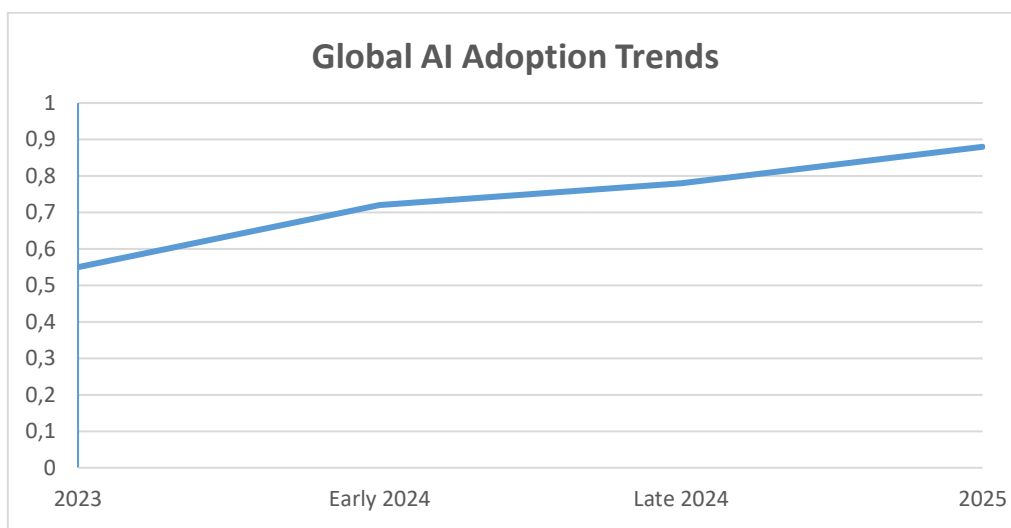


Figure 2. Global AI Adoption. (Alex Singla & Lareina Yee, 2025; Biswas & Faria Jahan, 2026)

The data shows:

- 2023: AI adoption at 55%
- Early 2024: Significant jump to 72%
- End of 2024: Stabilised growth at 78%

2025: Achieves 88 percent, indicating almost universal adoption.

These findings indicate that PMOs are more likely to be engaged in a highly AI integrated setting, whereby data driven solutions and artificial intelligence driven automation form the foundation of organisational operations

6.2 AI vs. Generative AI Adoption Trends

To comprehend the development of AI specialisations, a comparison of the traditional AI and the levels of GenAI adoption was conducted. GenAI has been rapidly faster than any other digital technology.

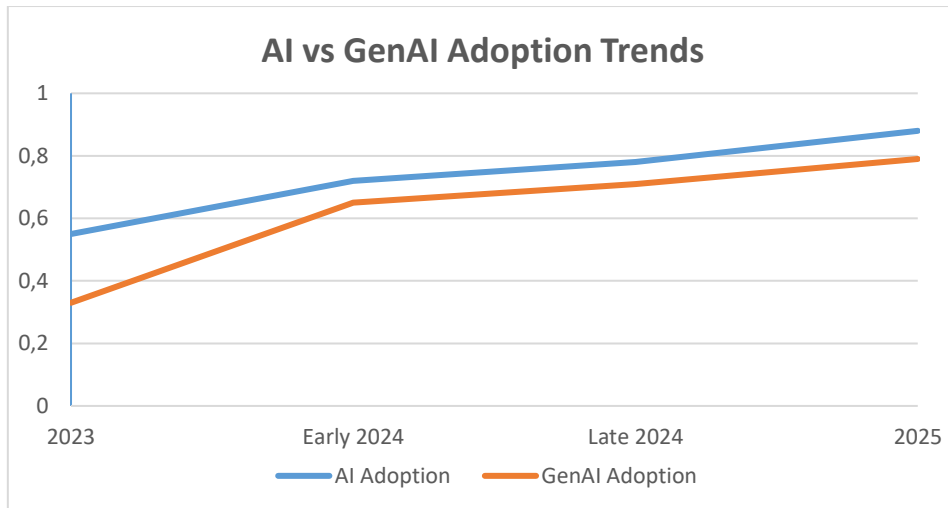


Figure 3. AI vs GenAI Adoption Trend. (Alex Singla & Lareina Yee, 2025; Biswas & Faria Jahan, 2026)

Key observations:

- GenAI adoption increased from 33% (2023) to 65% (early 2024).
- By 2025, the adoption of GenAI is 79% which is almost at par with traditional AI.
- Traditional AI is on its way up, as well, to 88 percent in 2025.

The intersection of AI and GenAI implementation underscores the strategic significance of GenAI features, like language generation, summarisation, and insight automation, to PMO activities like reporting, risk forecasting, and knowledge management.

6.3 Industry-Level AI Adoption Trends (2022–2025)

The analysis of the maturity level showed that there were considerable differences in the industry level of adoption. The sectors with the most adoption rates are the technology enabled ones, and the lowest adoption rates are in the public services and labour intensive industries.

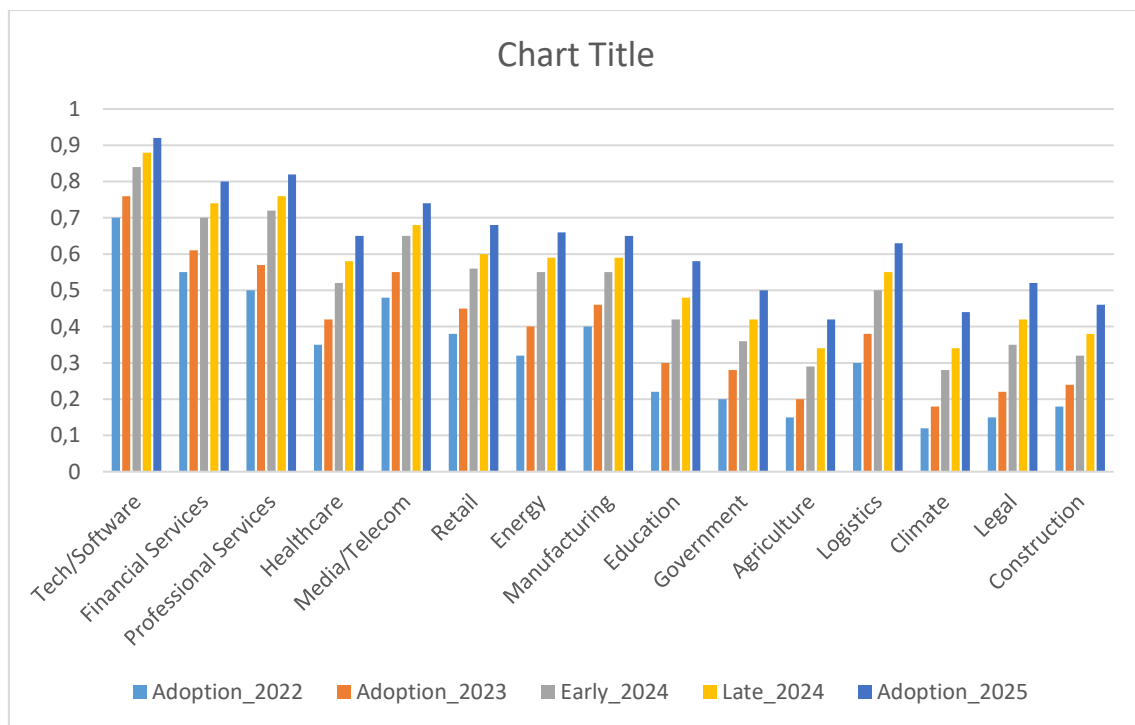


Figure 4. AI Adoption Across Industries (2022–2025). (Alex Singla & Lareina Yee, 2025; Biswas & Faria Jahan, 2026; Erik Brynjolfsson & Russell Wald, 2024)

The figure shows that:

- Technology rises from 70% (2022) to 92% (2025).
- Financial Services is next with a rise of 55% to 80%.

- Healthcare increases by 35 to 65 percent, but remains considerably lagging behind the digital-native industries.

These disparities solidify the necessity of industry-specific PMO transformation journeys, with industry limitations (regulation, data sensitivity, legacy systems) having a role in the readiness of AI and adoption rate.

6.4 Social Attitudes towards AI.

Sentiment comprehension is also critical since cultural acceptance and confidence in the workforce are critical to the effectiveness of AI integration in PMOs.

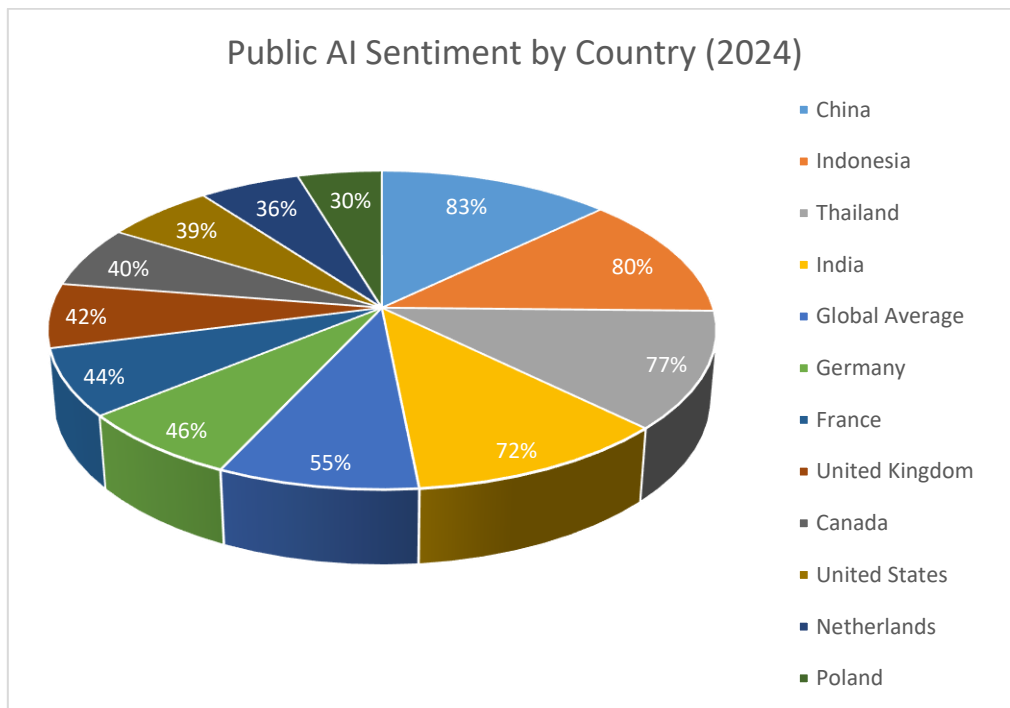


Figure 5. Public Optimism Toward AI (2024). (Alex Singla & Lareina Yee, 2025; Biswas & Faria Jahan, 2026; Erik Brynjolfsson & Russell Wald, 2024)

Findings show:

- China has the greatest level of optimism (83%).
- Germany (46%), USA (39%), and Netherlands (36%) lag significantly.

- The percentage of global optimism stands at 55 and 36 per cent fear losing a job to AI.

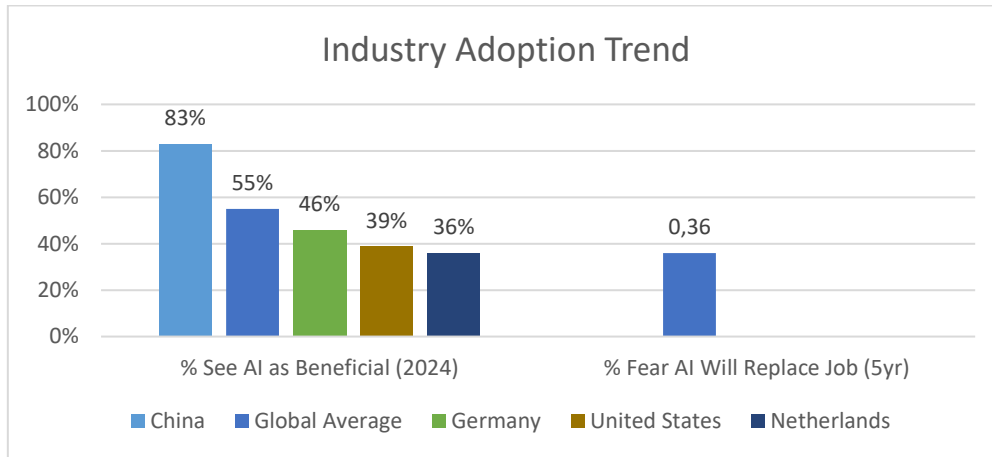


Figure 6. Public Optimism Toward AI (2024). (Alex Singla & Lareina Yee, 2025; Biswas & Faria Jahan, 2026; Erik Brynjolfsson & Russell Wald, 2024)

These differences underscore the significance of change management and communication plans in PMO transformation projects, particularly in areas where there exists high levels of AI-related anxiety.

6.5 Global Region Investment in AI (2024)

The level of investment is an indicator of maturity in infrastructural development and innovation.

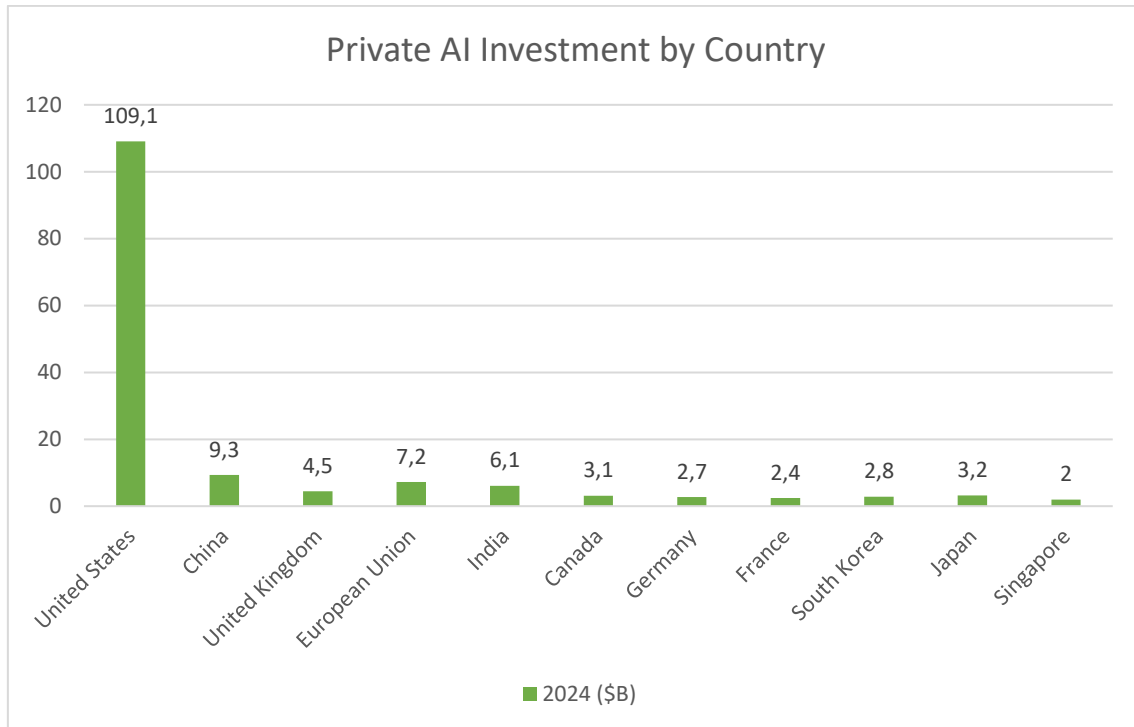


Figure 7. AI Private Investment by Region (2024). (Alex Singla & Lareina Yee, 2025; Biswas & Faria Jahan, 2026; Erik Brynjolfsson & Russell Wald, 2024)

Investment patterns show:

- United States: 109.1B (global leader)
- China: \$9.3B
- European Union: \$7.2B

The large difference in investment implies that the technology environment that PMOs in various regions must operate in is highly different, and affects the adoption, capability building, and level of transformation.

6.6 Radar Analysis (Adoption of AI)

The analysis of functional maturity reveals uneven adoption in internal organisational domains that have a direct impact on the PMO operations and interfaces.

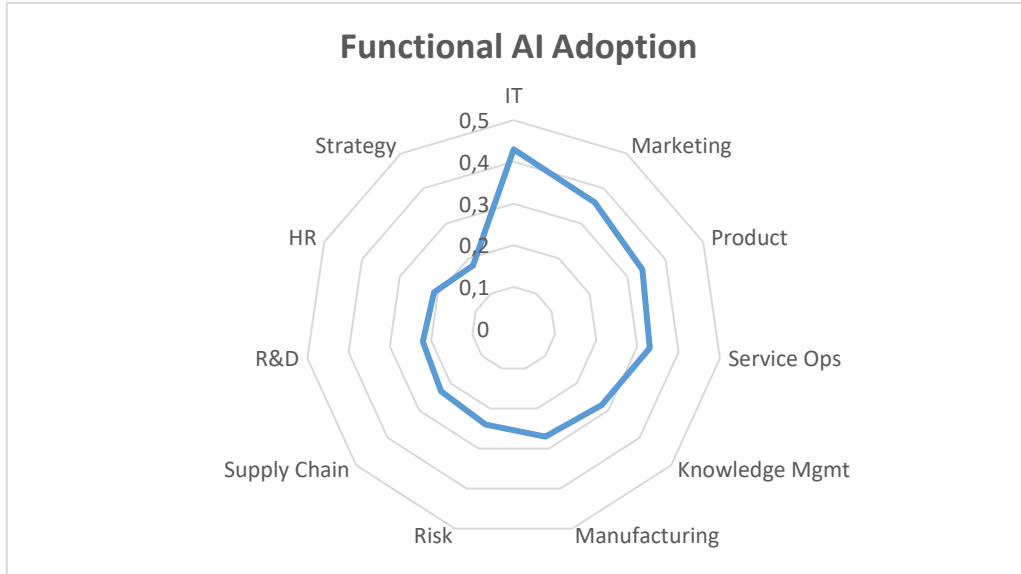


Figure 8. Functional AI Adoption Radar (2025). (Alex Singla & Lareina Yee, 2025; Biswas & Faria Jahan, 2026)

Key insights:

- Highest maturity: IT (0.43)
- Moderate: Marketing (0.36), Product (0.34), Service Ops (0.33)
- Lowest maturity: Strategy (0.18) and HR (0.21)

This variation on the level of maturity in functions supports the rationale to transform governance and coordination processes based on asymmetric digital preparedness through departments.

6.7 International AI Performance Indicators (KPI Cards)

To summarise the macro-level AI environment, card-style metrics that visualised Key AI Performance Indicators (KPIs) were used.

AI Adoption 2025 88%	GenAI Adoption 2025 79%
Global AI Investment 2024 \$252.3B	GenAI Investment 2024 \$33.9B

US AI Investment 2024 \$109.1B	China AI Investment 2024 \$9.3B
UK AI Investment 2024 \$4.5B	ChatGPT Weekly Users 2025 800M

Figure 9. Global AI KPI Cards. (Alex Singla & Lareina Yee, 2025; Biswas & Faria Jahan, 2026)

These indicators show:

- AI Adoption 2025: 88%
- GenAI Adoption 2025: 79%
- Global AI Investment 2024: \$252.3B
- ChatGPT Weekly Users 2025: 800M

All these observations imply the magnitude and pace of AI change and the importance of urging PMOs to transform their structures, tools, and competencies.

7 Discussion and recommendations

The empirical findings in Chapter 6 are showing that artificial intelligence is not an emerging technology anymore but is an operational reality in modern organisations. The steady and swift increase in the use of both traditional and generative AI in industries is a sign of a transformative change that essentially reinvents the way organisations align work, make decisions and achieve strategic goals. The Project Management Office (PMO) as a key coordination and governance body can be seen as being at the epicentre of this transformation. The pace of adoption of AI compels PMOs to redefine themselves and their purpose, shifting away in an administrative function to a paradigm where intelligence, adaptability, and technological fluency become the mark of the unit in the success of the organisation.

Among the most obvious lessons of the results, the fact that the adoption of AI is taking place at a pace and scale not seen before in terms of technological change should be highlighted. The PMO will not work with the legacy processes that coordinate at a slower pace and are designed to work with a less universal adoption of the organisation as the organisations approach the levels of near universal adoption. The past dependence of the PMO on post hoc control, manual reporting, and information processing by humans is becoming more and more incongruent with the real time, data-driven, and predictive project environment of the present. Thus, the PMO is forced to transform into a body that is able to make sense of machine generated insights, coordinate machine driven decision making, and harmonize the outputs of algorithms with the strategy. Lack of such adaptation will place the PMO at the risk of being marginalised as the organisations that adopt AI better will significantly outperform the one that continues to use the traditional approaches.

Another meaning of the results is related to the lack of balance in AI maturity within organisational functions and industries. Fields that are driven by technology have high leadership in AI uptake and others like the healthcare, government, agriculture, and labour intensive industries show low levels of maturity in AI uptake. On the same note, internal organisational functions like IT, marketing and product development have comparatively high adoption levels, but Hr, strategy and some of the operational functions are left behind. This imbalanced topography makes the coordination of cross-

functional activities difficult and puts the PMO in a situation where it has to harmonise the efforts of transformation across the domains that are not advancing at equal rates. This maturity asymmetry solidifies the PMO as an integrator of transformation, its task is becoming more and more about capability bridging, developing coherent implementation trajectories, and the appropriate maintenance of alignment even in the face of structural variations between organisational units.

There are other human factors that make the transformation landscape more complex. Although sentiment data across the world reflects a medium optimism about AI, there is still a large percentage of the population worried about losing their jobs and professional freedom being taken away. This fear affects the enthusiasm of teams to cooperate with AI empowered tools and creates the environment where the PMO has to be in the forefront of organising change in an organisation. In this way, the PMO should not only take care of the technical integration but also the psychological and cultural reactions to the use of AI. These involve establishing trust in the algorithmic process, fostering AI literacy, ensuring open communication and human centred practices to reassure employees that they are still needed in the augmented places. The PMO thus is a socio technical mediator and not so much a governance actor.

The advent of the Agentic era opens qualitatively new dimension to AI made transformation possible. Contrary to the previous generations of AI tools, which facilitated particular tasks, AI Agents have got the ability to act independently throughout whole workflows. They are able to orchestrate multi-step processes, access and process information, interact with other agents or the stakeholders, track risks, amplify exceptions and carry out operational sequences with minimum human involvement. These capabilities are an indicator of the shift towards automation of processes as opposed to automation of tasks. In the case of PMOs, this evolution implies that they are not in charge of project activities any longer, but of ecosystems of autonomous and semi-autonomous digital beings. The PMO should come up with new roles that should deal with the monitoring, validation, and controlling of AI agents so that their autonomous behaviours are not going to conflict with the organisational goals, ethical practices, and strategic limitations. Moreover, the PMO should be ready to redesign working models to enable AI agents to become rightful participants in project teams. These involve role definition of agents, multi-agent interaction, oversight of agent

activity and human-in-the-loop architectures that maintain accountability and transparency.

The incorporation of autonomous agents in the organisational processes introduce a new strategic imperative. Those PMOs who do not embrace AI and agentic systems are not just going to become uncompetitive; they can indeed be counterproductive to organisational competitiveness. In a global world where organisations are progressively turning to AI to speed up the turnaround of operations, reduce friction in operations and improve their decision-making agility, a manualised, document intensive PMO is a hindrance to an organisation instead of a facilitator. On the other hand, an actively incorporated AI and agentic technology in a PMO makes it a strategic edge. It is able to provide quicker and more precise insights, forecast risks earlier, allocate resources more efficiently and stay adjustive to the unpredictable and complex environments. Such a two-fold strategic possibility or organisational impediment is an accentuating factor in the urgency of transforming PMO.

Chapter 5 has created in its Seven Layer PMO Transformation Architecture an empirically based and extensive guide to sailing through these complexities. All the layers are directly related to patterns observed in the results. The organisational context layer is in line with industrial and geographical differences in AI maturity. The AI and data infrastructure layer indicate readiness gap functions. The development of human capabilities directly addresses the issues of the workforce and the skills needs which are identified in the results. Processes enabled by AI are in line with trends in automation and emergence of agentic workflow. The lack of governance and ethics are linked to the absence of trust and the necessity to have transparent oversight mechanisms. PMO performance and strategic organisational impact are indicative of the performance benefits relating to AI enabled environments. The framework thereby combines both empirical and conceptual knowledge and gives a systematic roadmap that PMOs should use AI in a systematic and responsible way.

7.1 Competency and Roles, how AI transforms PMO Capability, Roles and careers.

The competency can be defined as a combination of skills and knowledge and abilities required to work in the context of the PMO roles, the formal or informal social roles in a PMO (respected, analyst, coordinator) with a set of responsibilities and behavioral expectations (Coemans et al., 2015; International Project Management Association, 2015; Project Management Institute, 2017). With the advent of AI, the skill sets that PMO specialists currently possess and their roles are going to evolve, they will need to acquire new technical skills and analytical capabilities, and teamwork skills.

There are two pillars of a Project Management office PMO credibility and value delivery; competency and roles. Competency in a PMO sense is a blend of knowledge, skills and behaviour that leads to result based and uniform performance. Roles are sets of formal and informal responsibilities including all behavioral expectations that make up the set of competencies, in practice in actual governance cycles, portfolio decisions and delivery support. The contemporary recommendations change the vision of project management as principle-based and result-oriented with emphasis on the organizational environment. This tendency of the PMBOK Guide - Seventh Edition presupposes that practitioners and PMOs ought to choose, modify, and implement the necessary methodologies and tools to reach outcomes instead of adhering to the steps (PMO Global Institute Inc., 2025). Concurrently, profession-oriented models like the PMO Competency Framework offer concrete taxonomies of PMO functions and domain-specific competences in terms of reporting, tools, governance, risk, benefits, and value, and capability may be evaluated and improved (Coemans et al., 2015; Project Management Institute, 2017). With the introduction of artificial intelligence AI as an inseparable part of PMO tools and decision engines, it is necessary to transform their competency and role structure. According to the PMI industry advice, AI is reshaping the profession - automating the performance, improving decision making, and influencing the strategic impact - making a different demand on the ability mix and role definition of the PMO (Chen et al., 2025; Gonçalves et al., 2023).

7.1.1 PMO Foundations of Competency and Role.

PMO competency in the core does not simply include the skills to use a scheduling tool or develop a dashboard. It is regular, observable knowledge and skill manifested in the form of behaviors that lead to an increased level of portfolio fit and a higher level of risk foresight and more evident decision support. This orientation is enshrined in The PMBOK Guide - Seventh Edition based on principles and performance domains, aiming at customization, stakeholder engagement, and value delivery; this requires practitioners capable of questioning the assumptions, communicating ambiguity, and improving practices to suit the situation (PMI, 2021). In the meantime, the competencies vehicle value-generating is the roles. Role profiles, including administrator, analyst, coordinator, manager / director, and knowledge, skills and behaviors that each role must possess in the domains of Reporting and Insights, P3M Tools, Governance Frameworks, Risk Management, and Benefits and Value Combined are part of the PMO Competency Framework, which gives the PMO leadership a framework on which to base existing capability, plan formulation, and define the scope of responsibility before implementing

7.1.2 The way AI Bias PMO Competency.

AI transforms the concept of competency in the PMO work because it transforms the locate of value rather than accumulating historical status to the generation of decision systems that anticipate risk, quantify trade-offs and generate well-managed actions. To begin with, there is data and model literacy that are put on a foundation. The PMO professionals must be aware of the process of data sourcing, structure, cleaning, and transformation as well as aware of the basics of how models behave: training, validation, drift, bias to challenge weak signals and decision making on constraints. Responsible use of AI in the manner in which the guidance offered by PMI suggests means that the outputs will be perceived by the practitioners in question as the probability indicators that can be subject to uncertainty rather than to the truths that are beyond questioning (PMI, n.d.; PMI, 2021). Practically, this implies that analysts and managers are supposed

to be in a position to justify why a forecast has changed, give the assumptions that support a recommendation to move resources, and impact decision timing.

Second, competence shifts out of the descriptive reporting to risk and portfolio decision-making predictive analytics. Rather than merely re-telling what has happened, AI-powered PMOs simulate what might happen and what can be done about it. The digital transformation systematic reviews demonstrate that project management is transforming to incorporate competencies, strategy, digital technologies, and portfolio/program structures, the PMO teams need to have the ability to combine quantitative rigor and strategic sense-making (Goncalves, Penha, Silva, Martens, and Silva, 2023; Chen, Martins, Zhang, and Dong, 2025). This is aligned with the PMBOK Guide logic of the performance domain that covers planning and managing uncertainty that presumes that practitioners can quantify the opportunities and escalate decisions based on the applicable levels (PMI, 2021).

Third, the human-AI collaboration and decision governance becomes formalized by AI. Research indicates that effective collaboration involves more than merely implementing an AI tool, but also common goals, common management of events, equal decisional AI weight and systematic human oversight that can be viewed and audited. The greater the transparency, the greater the autonomy will be appropriately limited and the human examination will play an important role, the higher the confidence in the recommendations of AI will increase. PMOs need to architect the decision workflow rather than running the process with implicit questions whose answers; who needs to be a decision-maker, on what signals and is human sign-off needed (Wen, Wang, and Chen, 2025; Taylor, 2025). The same issues are reflected in the AI guidance of PMI which would promote project professionals to integrate augmentation and accountability with the help of explicit governance (PMI, n.d.).

Lastly, the competence of ethics and compliance is implemented. PMOs are biased, lack privacy, predictability and explainability, and are impacted by AI since it influences resourcing, prediction and communications with a stakeholder. Transparent documentation model cards anchor and support governance standards, specifying purpose and limits, decision logs, capturing rationale and exceptions, and policies, which must be signed by a human to make a high-impact decision (Taylor, 2025; PMI, n.d.). The results and customization emphasis implied by the PMBOK Guide implies that the

controls will have to be risk- and context-specific as opposed to applying it universally (PMI, 2021).

7.1.3 The manner in which AI reinvents the functions of PMO.

The competency can be expressed in the form of role clarity. AI reforms PMO works by having routines turn into data, model, and decision orchestration. The PMO administrator that used to be preoccupied with status gathering and status logkeeping transforms into an orchestrator of automation who sets up robotic process automation, ensures data quality policies, and manages metadata to ensure reliability of analytics. It entails documenting the automation choices and setting exception management per the governance expectations, according to the P3M Tools and Information Management domains (House of PMO, 2021) and in line with the recommendations provided by PMI to implement AI responsibly (PMI, n.d.). The PMO analyst does not merely skip over the retrospective dashboards and to the design of insight calibration predictive signal, scenario libraries and model output translations in narratives that facilitates strategic alignment. The analysts must convey uncertainty, not over-fitting to noise, and set thresholds to be reviewed by humans - behaviours that fall within Reporting and Insights and Risk domains and are represented by PM practices that are integrating technology and strategy (Chen et al., 2025b).

A custodian of decision processes will be the PMO coordinator with the clear insight of who and when specific decisions are made when AI transmits specified signals, the minutes are supposed to be explained by a human being in addition to model documentation to be audited and a schedule of exception reviews is to be set. These are in line with the research on the topic of trust and allocation of AI decisional weight, and with what PMI is concerned with controlling AI (governance with human oversight) (Wen et al., 2025; PMI, n.d.). The PMO manager or director is turned into an AI governance and strategy collaborator, aligning AI initiatives with portfolio goals, establishing responsible AI policies, managing the benefits of AI projects, and making sure that change management is addressed to adoption. It is a suitable position based on the

principle-based customization and result focus in the PMBOK(r) Guide and the leadership skills in the PMO Competency Framework (PMI, 2021).

7.1.4 Standards Extensions needed to create an AI-Ready PMO.

The AI ready PMO is not neglectful of standards, it extends them. PMO Competency Framework provides areas and capabilities that can be improved with AI-specific ones without diminishing their coherence. Reporting & Insights should have model literacy, uncertainty communication, and scenario analysis added to it, P3M Tools should have Reporting & Insights, metadata governance, predictive risk modeling, bias auditing, and human-in-the-loop thresholds added to the Risk and Governance, and non-technical explainability should offer value hypotheses and adoption coaching should be added to Stakeholder and Change Management. These extensions recognize the request in the PMBOK Guide to be context- and outcomes-specific and ensure that the PMO capabilities can be developed in a way that is consistent with the developed role profiles (PMI, 2021). The AI advice given by PMI would offer the proactive approach of responsible practice that leaders can transform to the policy, training avenues, and technology selections without being taken off track to professional needs (PMI, n.d.).

7.1.5 Human in the loop design and Decision Rights.

Decision rights are the key to competency role clarity relationship in AI-enabled environments. An analyst can make a suggestion of re-forecasts and scenario results but will not reallocate budgets without the consent of managers. When predictive signals hit thresholds to cause risk escalation, a coordinator is supposed to realize such risks, and activity of human reviews should be documented and traceable. The usage of a model is accepted by a director or a manager, who decides the responsible-AI policy and orders the rebalancing of the portfolio. It was shown that open documentation and equal AI weight in decision-making, as well as overt power authority, increases trust, leading to greater effectiveness in collaboration (Jarrahi, 2018). The PMBOK Guide provides the governance justification of this sort of structure, with its outcome, tailoring, and

stakeholder value, which jointly propose the apparent human control of the systems, which have a blend of human judgment and machine suggestions (PMI, 2021).

7.1.6 An Action Plan of how to prepare AI-Ready Competency.

The pragmatic approach begins with a baseline of assessing PMO competence using PMO Competency Framework, which identifies the disconnects in data literacy, automation, and governance of individuals and teams. The second one is an applied learning plan of integrating PMI AI instructions and on-the-job practice mini robot automation pilots, dashboards redesign, and model cards and decision logs so that the competencies are acquired during the working process and not in the form of abstract training (PMI, n.d.; PMI, 2021). Individual governance should then be implemented: establish decision rights, escalation, human review thresholds and documentation requirements, rehearse exception processes prior to incidents happening, which concurs with trust and supervision research (Jarrahi, 2018). The tracking of the value should be rigorous, and each AI project must have clear hypotheses, cycle-time savings, prediction precision, satisfaction of stakeholders assessed, and low-value automations should have sunset decisions to prevent tool sprawl (PMI, 2021). Finally, adoption must be handled as an organizational change: stakeholders must be coached on why AI must be used and limits must be put on its use, feedback mechanisms must be put in place to refine models and practices, and stories supporting augmentation and not replacement of human judgment must be told, informed by evidence of digital-transformation, and must be polished according to PMI (PMI, n.d.).

7.1.7 PMO Careers and Strategy Implications.

The PMO career movement is extended and the strategic significance of role clarity is enhanced by AI. An individual, who develops skills in automation, will master the area of RPA and data integrity. An analyst may become a decision scientist who may learn to design decisions and may provide model results in executive options. An explainable coordinator and a governance emerge to be an architect of human-in-the-loop processes.

A strategy and ethics leader is a manager or director who is coherent on responsible AI policy and portfolio strategy. These trends suggest that the digital transformation is not only regarding the design and capability building of organizations, but also regarding tools, and they are consistent with the transformation of PMI to outcomes, tailoring, and strategic impact (Chen et al., 2025; PMI, 2021). In this way, AI does not lessen the role and importance of the competencies and positions; it makes them more contingent. The codifying PMO of what people need to know and do, how human and machine intelligences will be synchronized, and how it will be governed will quicken deliver value, avert mistrust and compliance, and position itself as value catalyst to the enterprise (Chen et al., 2025; PMI, n.d.).

This thesis explores competencies and roles as dynamic and situational that are rooted in the transformations brought about by AI. The digitalization and AI transformation do not research unchanged or archaic jobs and skills that have not been impacted by them.

7.2 Implementing Recommendations in the PMO Transformation Journey.

The facts given in this thesis indicate clearly that PMO transformation is not discretionary, but mandatory. The findings naturally lead to several recommendations which must be followed by the PMOs in readying and maneuvering through the AI and Agentic era.

The initial suggestion is that PMOs need to institutionalise the development of AI capabilities. This does not only involve educating project managers to communicate with AI systems but also creating specialised positions dedicated to the AI governance, data custodianship, ethical management, and agentic workflow management. These positions will make AI be incorporated on a meaningful basis, instead of being superficial. The second suggestion is that PMOs need to embrace a strategy of transformation that is multi-layered in line with the Seven Layer Framework. Trying to apply AI at the process level without considering infrastructure, capabilities, or governance will result in the disjointed and unsustainable change. Foundational capabilities need to be given priority

by PMOs before scaling more advanced AI-enabled processes or incorporating autonomous agents.

The third suggestion is that PMOs should reengineer processes in the perspective of agentic collaboration. It implies the replacement of strict, human-centric, workflows with dynamic, hybrid ones, where humans and AI agents distribute and share work, exchange information, and complement each other. The PMO needs to establish conditions where the agentic systems are being operated as consistent working partners and not as a stand-alone instrument.

The fourth suggestion is that there should be ethical, transparent and auditable governance systems. As AI agents and predictive models gain more and more autonomy in their operations, the PMO should make sure that decisions are explainable, accountable, and in line with organisational values. Governance structures must accommodate escalation procedures, validation loop and human controls gateway.

Lastly, PMOs will need to have a strategic stance toward AI. PMOs should understand that AI is a competitive need, rather than a technical improvement. Those organisations that successfully integrate AI will outshine and eventually outcompete organisations which do not. PMOs are hence recommended to be proactive agents of AI-enabled change, which makes sure that the organisation can keep up with a fast-paced global ecosystem.

7.3 Closing Reflections

Overall, the discussion indicates that the PMO is at a crossroad. Combination of AI and emergence of agentic systems present new opportunities to improve organisational intelligence, speed up project delivery, and strategic alignment. These opportunities, however, also have risks associated with them to PMOs that are not able to adjust. The Seven Layer PMO Transformation Architecture will offer a solid and practical roadmap to help navigate this new landscape. The future PMO will be smart, flexible and highly integrated with AI and only through this change the PMO will be relevant and strategic to the AI driven organisation.

8 Summary and conclusion

This thesis also sought to examine how the Project Management Office (PMO) could transform and rebrand itself in a period characterized by the fast-evolving artificial intelligence features. The research motivation was triggered by the fact that there is a visible change in global organisations: AI is no longer a niche technology that is applied to specific functions and is a general force that is changing business models and operational structures, as well as strategic processes. It is on this backdrop that PMOs, with their core responsibilities of coordination, governance and organisational alignment are confronted with unprecedented challenges and unique opportunities. This thesis was meant to investigate these forces and determine the gaps that existed in current PMO research and present an organized, evidence based transformation architecture that could lead PMOs through the changing AI landscape.

The study started with six significant knowledge gaps in the literature. These were a lack of empirical PMO specific AI studies, conceptual vagueness of role evolution, the lack of AI competency frameworks, the lack of focus on human AI collaboration, and a great discrepancy in AI maturity across industry and functions. To fill these gaps, the research engaged in convergent mixed methods approach whereby quantitative descriptive analysis of seven worldwide AI datasets was used alongside qualitative thematic analysis of scholarly and practitioner literature. This approach was used to ensure the findings were empirically as well as conceptually sound.

The findings indicated a number of significant findings. The use of AI has increased tremendously, nearly doubling to 88 percent in 2025 (up from 55 percent in 2023), and generative AI is increasing at an even greater rate. The adoption patterns in industries and organisational functions differed significantly, which means that AI maturity is distributed. The feeling of the people is no less varied, and there is optimism and anxiety on a balance in world trends. Regional variation in investment also demonstrates the organisational readiness as shaped by structural forces. Collectively, these results affirm that the environment within which PMOs have to operate is experiencing a fundamental shift, which is characterized by a growing complexity, more demands and a faster moving interaction between technology, people, and strategy.

These findings were discussed in the chapter on discussion and demonstrated how they all lead to the development of what could be defined as an Intelligent or Agentic era. The older AI tools, the ones that primarily aid in discrete tasks, are being replaced by autonomous AI Agents with the ability to plan, execute and coordinate multi step workflows. Such agentic systems can completely transform the process of the project and shift the PMO towards the manual performance of coordination functions to the management of autonomous digital actors. The PMO does not only assume the role of a human team manager but also a manager of machine-based processes. This observation expands the applicability of the study outside of traditional digital transformation narratives, and shows that PMOs need to look forward to a future where AI is no longer a helper to the PMO, but a part and parcel of its operational ecosystem. Based on empirical and theoretical insights of the study, the Seven Layer AI Enabled PMO Transformation Architecture was proposed as the key contribution of the current thesis. This architecture acknowledges that transformation of PMO is multidimensional and should be implemented in a cascading and combined fashion. The seven layers include organisational context, AI and data infrastructure, human capability development, AI enabled processes, governance and ethics, PMO outcomes, and strategic impact, that can be used as a complete transformation roadmap. The architecture provides an organised means of navigating the complexity of the AI integration, and also provides the PMOs with a responsible, sustainable and strategically aligned evolution.

Strategically, the paper finds that PMOs are at the edge of a cliff. AI has significant potentials to increase efficiency, the quality of decisions, and improve the strategic relevance of PMOs. Such opportunities can be opened, however, to PMOs that are ready to dive into transformation. Failure to modernise PMOs can result in organisational bottlenecks in an environment where speed, data driven decision making and adaptive intelligence are required. On the other hand, PMOs that embrace AI actively and more so those that are embracing new agentic capabilities are well placed to be part of the key enablers of organisational competitiveness.

The results indicate that PMO can no longer be an administrative or compliance-driven organization. Instead, it needs to rebrand itself as an intelligence hub, coordinating human and AI interactions, agentic workflow operation, ethical and transparent governance, and align AI driven insights with organisational strategy. The future PMO

should be at ease with autonomous systems, and with the ability to make sense of algorithm results, and create governance frameworks that can balance automation and human judgement.

To sum up, the current thesis has shown that AI is transforming the PMO landscape in a transformative and challenging manner. The Seven Layer PMO Transformation Architecture offers organisations an effective and theoretically based way of negotiating this new reality. The PMO which will result out of such a transformation will not just deal with projects; it will deal with ecosystems of intelligence that will bring together humans, data, and autonomous agents to harmonious, strategically aligned results. Such PMOs will not only ensure they survive the AI revolution but they will be at the frontline in leading organisations through the revolution. The ones that do not move also run a risk of being left behind in a world where competitive advantage is more and more about the smart coordination of people, technology and strategic wisdom.

The research ends up supporting one and decisive conclusion: AI can bring tremendous benefits to the PMO, and only when it, in deliberate, strategic, and proactive ways, embraces change. The future competitive environment is of organisations whose PMOs become smart, agent enabled and strategically aligned organisations. The way to that future is not by choice it is necessity.

8.1 Future research options

Although this thesis offers a good and empirically supported basis to comprehend the AI enabled PMO transformation, there are still multiple avenues that can be explored in a future study. The empirical assessment of the Seven Layer PMO Transformation Architecture in the context of real organisations is one major direction. The framework provided in the study can be applied in future study longitudinally across various industries in order to estimate its effectiveness, versatility and influence on the performance of the organisations. The other opportunity is to explore how autonomous AI Agents can be integrated into PMO processes. As agentic systems develop it will be critical to know how AI agents will collaborate with human project teams, how governance systems will need to evolve to allow autonomous decision processes, and

what new types of risk come about as a result of delegating multistep processes to non-human actors. The ethics, psychological or cultural aspects of human collaboration with AI would also be an interesting research topic to further study especially in areas or sectors where the levels of AI anxiety are higher. Lastly, researchers can explore the ways that PMO roles and career trajectories will shift in highly automated workplaces, discovering new models of competencies and learning requirements to nurture the next generation of AI-fluent PMO practitioners.

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Appendices

Appendix 1. Datasets sources

Data Source	Provider	Year	Data Categories Covered	Scope	Access
AI Index Report	Stanford Institute for Human-Centered Artificial Intelligence (HAI), Stanford University	2024–2025	• Global AI adoption trends	Global, cross-industry, multi-regional	https://aiindex.stanford.edu
			• Industry-level AI maturity		
			• Public sentiment toward AI (via Ipsos)		
			• AI investment trends		
			• AI performance indicators		
Global Survey on AI (The State of AI)	McKinsey & Company (QuantumBlack)	2023–2025	• Enterprise AI adoption	Global enterprise and executive-level survey data	https://www.mckinsey.com
			• Generative AI adoption		
			• Functional AI usage across organizations		
AI in Project Management – Thought Leadership	Project Management Institute (PMI)	2021–n.d.	• Responsible AI principles	Professional project management standards and guidance	https://www.pmi.org
			• Governance and ethical guidance		
			• Outcome- and value-oriented project management practices		
Global AI Adoption Trends (2017–2025)	Mendeley Data	2026	<ul style="list-style-type: none"> • Longitudinal global AI adoption indicators • Cross-industry AI diffusion trends • Aggregated secondary adoption metrics 	Global, multi-industry sectors, Country, and Business Function	https://data.mendeley.com/datasets/dnm5jxgn2m/2