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The Impact of AI on Increasing the Software Project Productivity in Pakistan and Finland

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ABSTRACT:

This study analyses how the use of Artificial Intelligence affects performance and productivity across different regional contexts, using a quantitative survey questionnaire distributed to 28 software professionals currently employed at software companies in Finland (n=8), and Pakistan (n=20). By deploying a structured Likert-scale questionnaire, the survey measured three important variables: code quality, professional confidence in using AI, and perceived productivity.

The research findings demonstrate that there is a positive association of AI adoption with perceived productivity across both national contexts. The respondents from Pakistan showed thorough optimism, affirming that AI increases the software project productivity, and the majority of them reported speedy task completion, whereas the Finnish respondents, even though they are more senior, held reservations and heterogeneous views, especially on code quality. However, Pakistani IT professionals exhibited a positive organizational support for AI use. Ethical considerations around AI outputs and governance frameworks also shape the confidence levels of experienced Finnish developers. The findings reveal that novel enthusiasm does not linearly correspond to technological maturity. Achieving the maximum potential of AI in software development processes requires comprehension beyond tools alone, containing formal training, governance mechanisms, and a professional organizational culture that critically evaluates AI outputs. The interaction of human and technological factors is ultimately central to how AI reshapes software productivity across diverse national contexts. Spearman correlation analysis was also employed across eight factor pairs to study the inter-variable relationships between ordinal and binary measures.

KEYWORDS: Artificial Intelligence, AI adoption, Code Generation, AI Plugins, Prompt AI, Software Development, Ethical Considerations

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Abbreviations

TAM Technology Acceptance Model

STS Socio-Technical System

IDT Innovation Diffusion Theory

SDLC Software Development Life Cycle

1 Introduction

Artificial Intelligence is an inevitable reality of our world today. It is not just a newfound technology that brings amusement to people by its sheer human-like intelligence, but it is also seeping into the cracks of our daily lives by handling the tasks in a much more orderly, effective, and efficient manner. Apart from its influence on our daily lives, it has a much deeper role in software houses. AI has become an increasingly significant part of the development cycle of software in software houses, giving rise to various transformative capabilities that improve different aspects of the software development cycle (Ajiga et al., 2024). AI's innate ability to drive innovation in routine processes comes from its sheer ability to analyze enormous amounts of data packages at lightning speed, which makes it a go-to technology for parsing data, identifying patterns, and making predictive recommendations that expedite the daily tasks for developers, designers, and even project managers in their routine tasks. By completing work tasks for software designers and developers, AI helps them excel in their technical and creative sides by leveraging AI technology to reduce their monotonous work. Additionally, AI-powered observations and interpretations mitigate the risk of expensive post-release patches and bug fixes, enhancing overall software reliability.

By strategically harnessing AI technology benefits, the IT industry can substantially reduce setup and maintenance costs, enhance productivity, and unlock new avenues of product innovation (Chanderhas & Pardeshi, 2022). Chanderhas and Pardeshi (2022) highlight the fact that the IT (Information Technology) and telecommunication industry make up about 33% of the total market. The authors fostered the idea that the spending of telecom on AI and Big Data would increase from $ 59 billion in 2019 to a staggering $ 107 billion in 2023.

1.1 Problem Definition

Artificial intelligence has also become a significant player in the knowledge management of the twenty-first century, propelling business abilities to create, acquire, and utilize information efficiently. AI has now transformed into a practical tool and has grown past its theoretical research-based subsistence. AI's extreme transformation is driving non-IT industries to adapt to the developmental pace of IT. Therefore, it is now a non-negotiable requirement in the software industry to not only produce AI solutions, but to also utilize it in the routine tasks to keep up with the rapid pace at which others are producing their products, and this requires factors like speed, accuracy, and reliability, all of which AI promises to outperform human cognitive and physical workload strength.

One of the major deciding factors in being an innovator is the time at which a product or service is introduced at any scale (global or local), which gives it a competitive advantage and also a first-mover advantage in the market. Those companies that are faster often win the race of innovation and novelty. AI helps in expediting the software production by reducing the number of repetitive tasks and bringing the error rates down, which ultimately results in a faster release of the product.

1.2 Research gap

Despite the widespread adoption of AI (Artificial Intelligence) by software companies to improve software quality and drive innovation, a significant research gap remains regarding how these technologies are implemented within specific national contexts. This is especially true when comparing developed and developing countries, the focus of this thesis. Existing literature mostly focuses on the adoption of AI in highly advanced, structured ecosystems such as those of the United States, the United Kingdom, and other Western nations, with little attention to countries in the southeastern part of the world, such as Pakistan. Pakistan, which has the largest youth population, with over 64% under 30, and a rapidly growing software industry adopting AI, faces systemic infrastructural, administrative, and skill shortages.

Additionally, a clear gap in research regarding the strategic adoption of AI (Artificial Intelligence) in the Finnish software house ecosystem remains largely absent, requiring deeper research into how this technology is being utilized in the decision-making structure and routine workflows for the successful completion of projects.

While some data, extracted through thesis studies, thoroughly documents how AI is automating the routine tasks and suggests that it saves time by automating the software testing phase by writing test cases and reducing development costs by reducing error rates (Hassan et al., 2024). However, another study indicated that, despite widespread mainstream claims of AI automation in Finland, many Finnish companies are still stuck in the premature phase of AI adoption, suggesting that AI uptake is still incipient.

Image 1. Overview of AI adoption in Nordic companies, particularly Finland (Asikainen, 2025).

However, no peer-reviewed empirical study has been established that provides a methodological, cross-sectional analysis of how AI is integrated into tech industries in the two countries in question. There is limited research that (a) examines whether the same AI tools are used differently within the same software projects; (b) investigates how contextual variations impact innovation findings, such as software code quality, the relative speed of SDLC completion, repair and maintenance costs, post-release anomaly rates, and longevity.

1.3 Research problem

Artificial intelligence is becoming increasingly popular within the software industry as it helps in reducing redundant and lengthy code development processes, helping developers during the core steps of code development, like code refactoring, bug detection, code testing, and maintenance. During the design process, UI/UX designers are also regularly using generative AI to reduce their design work time by utilizing built-in AI plugins in the design software, by generating intelligent design-related AI prompts, and performing a design task like removing the background of the picture within a couple of seconds.

The research problem of this thesis becomes more important when we take two different countries, like Finland and Pakistan, that function at very distinct points on the technological spectrum, into account. Pakistan, as an emerging technological space, is still in its evolving phase of Artificial Intelligence adoption in its software houses, still lacking in many areas of solid organizational structure, where AI regulations, challenging technological infrastructure, and the absence of workforce readiness are factors that readily influence its AI-driven innovation. On the contrary, Finland, being the more mature player, is backed by an innovation-first approach, a positive software industry that is characterized by an advanced technological ecosystem and a framework-based approach to project management.

This research is intended to address the following research questions:

- **RQ1:** To what extent does the adoption of Artificial Intelligence (AI) tools influence productivity in software projects within software houses in Pakistan and Finland?
- **RQ2:** How do software professionals in Pakistan and Finland differ in their perceptions of AI's role in enhancing software development efficiency and creativity?

By examining these questions using a quantitative research method based on a thorough questionnaire sent to technical departments of Pakistani and Finnish companies, this study aims to provide empirical data on how AI is being implemented in software project innovation across contrasting national contexts. This study aims to dive deeper into comprehending how generative AI and AI in general can be leveraged in the most optimal manner to bring innovation, reduce software costs, and help in decision-making for IT companies in both these environments.

2. Literature Review

This chapter reviews the current online literature on AI, with greater emphasis on the effects of AI adoption in software development within the software houses of the two countries under observation, namely Pakistan and Finland. This paper will use SLR (Systematic Literature Review) as part of the research. The flow and execution of the Systematic Literature Review system is given in Figure 1 below.

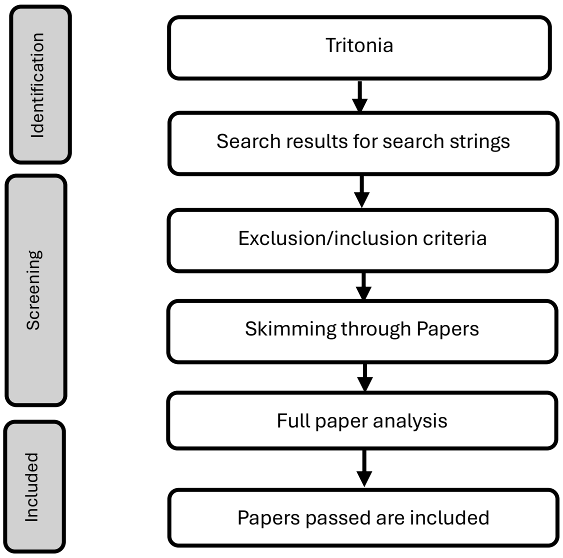


Figure 1. Systematic Literature Review.

It will also probe into the myriad different types of AI technologies that assist in various tasks, essential for the development of software, and along with that, it will also help us understand the types of problems that the developers and designers come across while using this during their daily tasks. The examination of these areas aims to establish a factual foundation for understanding the evolutionary changes occurring in software companies in Pakistan and Finland due to the impact of AI.

The advent of the internet and the present-day AI indulgence present in almost every aspect of digital use is something the software industry cannot ignore or resist but has adjusted to it to accommodate AI as a crucial and unavoidable part of the process. They utilize several different AI technologies like generative AI, machine learning, NLP (Natural Language Processing), computer vision, AR (Augmented Reality), and others, to step outside their mundane tasks, accentuate their decision-making skills, and build a better development process (Abioye et al., 2021).

2.1 Search String

To confine the search results to focused and relevant studies, a well-defined search strategy was applied. The main objective of this search is to narrow down our search to a broad range of relevant literature material that captures the usage of artificial technologies in the development of software processes, while also navigating the various factors influencing ethical and adaptation.

The search strings used to gather the literature for this section are given in Table 1. The first and foremost step in developing the search string is to define which concepts are central to the research questions of this thesis. These key concepts were obtained from the objectives of this research paper, which target the development process of the software under the influence of AI usage, and examine the minor ethical implications of these technologies. After the key ideas are discovered, the search string is developed by using Boolean operators to combine and include the concepts.

Table 3. Search string keywords included in SLR

Software Development	**Artificial Intelligence**	**Tools, Technologies**	**Impact, Ethics, Adaptation**
Software development Software engineering Coding Programming Code generation	Artificial intelligence Prompt AI Generative AI Deep learning Machine learning	Software Application Tools Technologies AI software AI tools	Impact Adoption AI adoption Ethical considerations ethics

Prompt designing debugging	AI AI plugins		

The search string is applied to ensure that the literature review remains relevant to the search terms and key objectives and excludes extraneous and irrelevant concepts.

The Boolean operator **‘AND’** is used to combine two or more different topics together for combined search results and will only be centred around the research studies from multiple facets of the topic of research. The Boolean operator **‘OR’** is used to combine related search terms, concepts, or synonyms to broaden the research horizon, to detect *any* of the specified words, thereby expanding the search results by including all sorts of variations of the same word, e.g., like "heart disease OR cardiac disease").

To highlight research from contemporary times and recent scientific advancements, **‘PUBYEAR > 2013’** was included as part of the search string, narrowing down the research to studies conducted within the last twelve years. Several ISSN journals were selected to reduce the grey literature.

Our final search string was composed of meticulously selected elements to optimize the relevance and overall quality of the results. The final search string used is as follows:

(TITLE-ABS-KEY ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "generative AI") AND TITLE-ABS-KEY ("software development" OR "software engineering" OR "code generation" OR "programming" OR "software design") AND TITLE-ABS-KEY ("tool" OR "tools" OR "application" OR "platform") AND (TITLE-ABS-KEY ("impact" OR "effectiveness" OR "productivity" OR "efficiency" OR "code quality" OR "developer experience") OR TITLE-ABS-KEY ("adoption" OR "implementation" OR "integration" OR "acceptance" OR "utilization") OR TITLE-ABS-KEY ("ethics" OR "ethical considerations" OR "bias" OR "accountability" OR "transparency" OR "privacy"))) AND PUBYEAR > 2013

The formulated search string is utilized in the database of **Tritonia**, yielding an initial collection of peer-reviewed articles, journals, and scientific research papers for further scrutiny. The implementation of this structured method of search guarantees that the literature review will be comprehensive, systematically exploring the applicable scholarly disciplines while preserving the emphasis on the dissertation's goal.

2.2 Screening Process

Table 2 outlines the inclusion criteria employed in the review of literature. Inclusion and exclusion criteria are applied to choose papers for additional review.

Table 2. Inclusion criteria for search results

Criteria	Description
Document Type	Only peer-reviewed and scientific journals are included. Non-peer-reviewed journals, like editorials and opinion papers, were excluded.
Relevance	The studies that have search results related to the direct impact of AI on the software development process.
Recency	Articles and journals were specifically chosen based on their publication in the last 12 years, to stay relevant to the research timeline.
Empirical Evidence	Studies that contained empirical data, surveys, and statistical analysis were given higher preference.
Sources	Research published in renowned journals and conferences, like IEEE on Software Engineering, ACM on Software Development, and Techniques and Empirical Software Engineering were prioritized.

To guarantee that solely pertinent and high-caliber studies are incorporated in the literature.

A series of stringent inclusion criteria was utilized. The standards are intended to sift through the first search findings and keep research that provides valuable perspectives on the study inquiries. Concurrently, exclusion criteria were implemented to eliminate studies that were below the pertinent standards or failed to satisfy the quality criteria needed for this evaluation.

The process of inclusion and exclusion outlined in this chapter guaranteed that the literature review relies on a strong and pertinent collection of research, through the implementation of rigorous standards. The review concentrated on rigorous, empirical studies that specifically tackle the main topics of this dissertation. This method not only established a strong base for the literature examination but also guaranteed that the investigation carried out in this thesis is based on the most up-to-date and relevant academic discussion.

2.3 AI Integration in Software Development

The structured mechanism that is deployed for the creation of software is referred to as SDLC (Software Development Life Cycle), which consists of six steps that the software has to pass through in order to reach the deployment point. During the planning phase, the software developers collaborate with the stakeholders of the software, like clients and end users, to derive the objectives, functional, and non-functional requirements of the software. For an effective and efficient delivery of the software, the onus rests heavily on the proper planning and scheduling of the software development.

Image 2. The six steps of the Software Development Life Cycle (SDLC) and the different activities and stakeholders associated with each step of software production (Derviş, 2023).

Generative AI greatly assists the software engineers and leaders in annotating meetings, getting a quick summary of their lengthy meeting hours, and unifying documentation practices, designing quality software application architecture. However, broadening GenAI (Generative Artificial Intelligence) usage can result in implications like production of homogenous outputs due to heavy reliance on existing patterns of the models, which can lead to an absence of human creativity at a critical stage of the high-level design phase that often leads to securing budget approvals and business buy-ins (Muratovic et al., 2025). To counteract these impending dangers of the software production process, prioritizing design transparency and system explainability, and emphasizing areas where GenAI can create or add value, while not restricting its usage to just code production.
Although GenAI helps increase productivity in software coding, it also carries the risk of generating overly complex, disproportionate, or incorrect code, which can lead to excessive technical debt and limit system growth. Excessively simplified code can underperform in production environments, lack robust exception handling, be unscalable under high loads, or use unconventional data formats (Muratovic et al., 2025).

Shanghai Jiao Tong University's Department of Computer Science and Engineering recently conducted an experiment to investigate the relationship between code accuracy and prop complexity. The experiment revealed a direct relation between reduced complexity and higher accuracy of the code generated through GenAI, giving approximately 90% accuracy, whereas those prompts that contained higher complexity resulted in an accuracy measure of only 42%, proving that LLMs (Large Language Models) can struggle with complicated, unfamiliar, and puzzling problems, leading to lower accuracy and reduced efficiency (Yang et al., 2024).

2.3.1 Code generation Using Artificial Intelligence

Software engineers and technical researchers have been diligently engaged in the pursuit of automated code synthesis with the help of AI for quite some time. The biggest motivation behind this research has been to equip the coders and developers with the proficiency to be able to code more efficiently, to increase the overall work productivity, but without losing the quality of the code generated. Across temporal progression, various techniques have been introduced directed at the generation of code, and the findings reflect significant development in the given research area. Presently available code generation or code completion tools are available either in the form of Google Chrome extensions or in Integrated Development Environment (IDEs), that read the context of the program based on which they either complete the code or generate new packages of code.

VS-Code is a text editor that has an extension of Copilot, which analyses the program's context and generates suggestive code for completion to help programmers run programs. Another example of a similar code-completion tool is IntelliCode, which generates new code based on the previous recommendations from the readily available open-source projects posted online on GitHub (Svyatkovskiy et al. 2020). These automated programming assistants are growing in technology with every new progress that is being made in the Natural Language Processing (NLP) and deep machine learning (Svyatkovskiy et al. 2020).

Fundamentally, tools like IntelliCode and Microsoft Copilot are an amalgamation of distinct LLMs developed and optimized towards the specific objective of computational code production. The language models themselves comprise diverse neural configurations founded upon either the RNN model or the Transformer model. However, most contemporary high-performing models use the Transformer model. Although the Transformer model was conceptualized as a sequential transformation architecture consisting of an encoder and a decoder, there are several high-performing models that either solely utilize the encoder (Devlin et al. 2019) or the decoder (Brown et al. 2020). Code generation has evolved and has become an integral part of modern IDEs and code compilers, accumulating considerable focus. Prominent methods such as GitHub Copilot and TabNine have been suggested to address this challenge. Nonetheless, these tools might redirect coding responsibilities towards code evaluation or code review, which entails thorough modifications from users.

Despite the overt benefits of user feedback, their replies are temporary and do not endure persistence across interaction sessions (Le & Andrzejak, 2024). The inclusion of AI technologies into coding environments of Compilers and Integrated Development Environments (IDEs) like Microsoft Visual Studio, Visual Studio Code, Vim, Cursor, or JetBrains shows a consistent and forthcoming future trend. Consequently, this collaborative partnership between generative AI and humans in coding and programming is ready to garner widespread implementation.

2.3.2 Applying LLM to User Experience Testing and Deployment

User Experiences (UX) testing faces a plethora of different sorts of challenges because of its multi-layered, complex, and nuanced nature. Vermeeren et al. also emphasized the critical gap that exists in the field: limited research on how User-Experience testing and measurements should be conducted. The present research focuses on the basic usability objectives, which do not take the complete UX principles into consideration.

As Nielsen and Molich iterated, if a software system does not achieve its functional need, it does not really matter how user-friendly it is. Alomari et al. argued that if the system is exceptionally hard to use, then its functional compatibility is not taken into account, because the end-users can simply not use the system. While Large Language Models (LLMs) have been widespread in their use within the Artificial Intelligence adoption in software development, especially in image analysis, comprehension of programming languages, prompt text generation, and similar areas. Their exceptional ability lies in their competence in handling large amounts of unstructured data and processing them to give several outputs and solutions, while providing new avenues of gaining deeper insights and knowledge into user behaviours and user preferences by scraping the web and identifying user interaction blueprint trends online.

As these latest technologies are advancing, the UX researchers and designers can now utilize these LLMs to analyse and learn the subtle alterations and complicated user scenarios that impact user experience. Moreover, the latest research has also introduced new cutting-edge Large Language Models (LLMs), beyond LLMs. Large Language Models can simultaneously interpret and process different forms of data input. These data inputs are referred to as 'modalities', including different data types such as audio files (mp3), images (.jpeg, PNG), and videos (mp4). Alayrac et al. proposed Flamingo: a Visual Language Model (VLM) that can reach a new benchmark in few-shot learning by just providing the model with specific examples related to the task. On various benchmarks, Flamingo surpasses models that have been fine-tuned on thousands of times more data specific to their tasks.

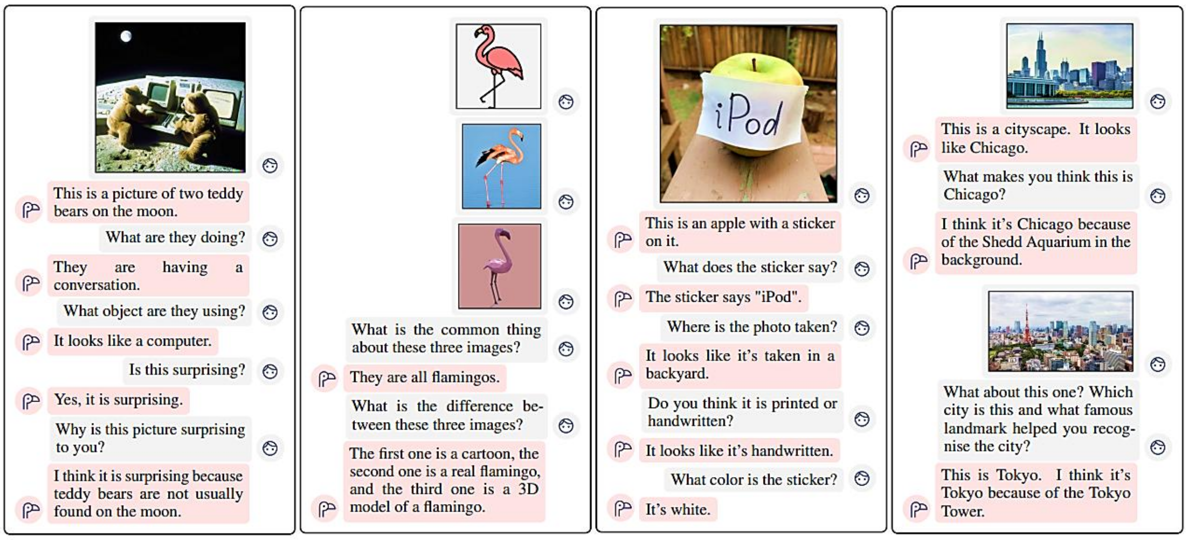


Image 3. The VLM Flamingo uses visual dialogues for describing multi-image comprehension (Warfield, 2024).

Following the evaluation of 16 models, the experimental findings indicated that Flamingo demonstrated remarkable flexibility using just a limited number of examples. With the expansion of the model's training data, Flamingo's performance saw substantial enhancement, managing up to 32 images or videos, showcasing its great adaptability in processing different quantities of images or videos. Sun et al. introduced the multimodal generative pre-training transformer-based model, Emu, capable of processing any single modality or multimodal data input interchangeably while producing both images and text within a multimodal framework that shows promise in multimodal tasks, including image description, visual question answering, video question answering, and text-to-image generation, with results indicating Emu's exceptional performance across various zero-shot and few-shot tasks, incorporating image-to-image descriptions, interleaved image-to-image descriptions, video-to-video descriptions, and more via autoregressive training, embedding images into text, and creating interleaved input sequences for complete training.

The present-day existing automated UX automating and testing technologies and tools heavily focus on functional and software performance testing, ignoring user-interaction and cognitive experience needs, details of users' web interactions, and their emotional needs. Utilizing GPT-4's sophisticated semantic comprehension abilities, our method specifically tackles these challenges by delivering an in-depth evaluation of users' cognitive behaviours, interaction subtleties, and emotional reactions.

In addition to that, the inclusion of X testing and evaluation methods into current software development processes constitutes significant challenges. Vermeeren et al. highlighted the urgent requirement for evaluation approaches suited for early developmental stages, verified metrics for UX elements, and strategies for evaluating social and collaborative interactions. The absence of effective, multi-faceted methods to accurately reflect the complex aspects of UX during the development lifecycle continues to be a significant challenge in the industry.

2.3.3 The Outcomes of Human Collaboration with AI

AI has revolutionized traditional software development methods, automating processing from requirement analysis to code optimization and defect prediction (Rashid & Kausik, 2024). This is illustrated by tools such as GitHub Copilot, AI-enabled testing frameworks, and predictive defect models, which enable faster development cycles with enhanced results. Challenges related to innovation, including the "unboxed" characteristics of algorithms and pushback against modifications in DevOps processes (Senapathi et al., 2018).

Additionally, ethical considerations like data privacy and biased algorithms require a balanced and fair approach. Biases that originate from the algorithm, especially during data-driven innovation, identifying data, and societal biases, highlight the sheer requirement for dynamic managerial competence to reduce prejudices (McCarthy et al., 2021).

A thorough examination of these aspects emphasizes the necessity for explainable, ethical, and flexible AI systems to guarantee ongoing advancement in the domain.
AI could transform the study of human factors significantly. For example, extensive language models (ELMs) have been investigated to assist in qualitative data analysis by analysing substantial text volumes and recognizing patterns and categories (Xiao et al., 2023; Chew et al., 2023; Dai et al., 2023) - a single LLM can expedite the workflow by sifting through hundreds of thousands of pages of user research interview transcripts, annotation notes, digital media posts, web pages, retrieving and classifying key phrases and subjects.

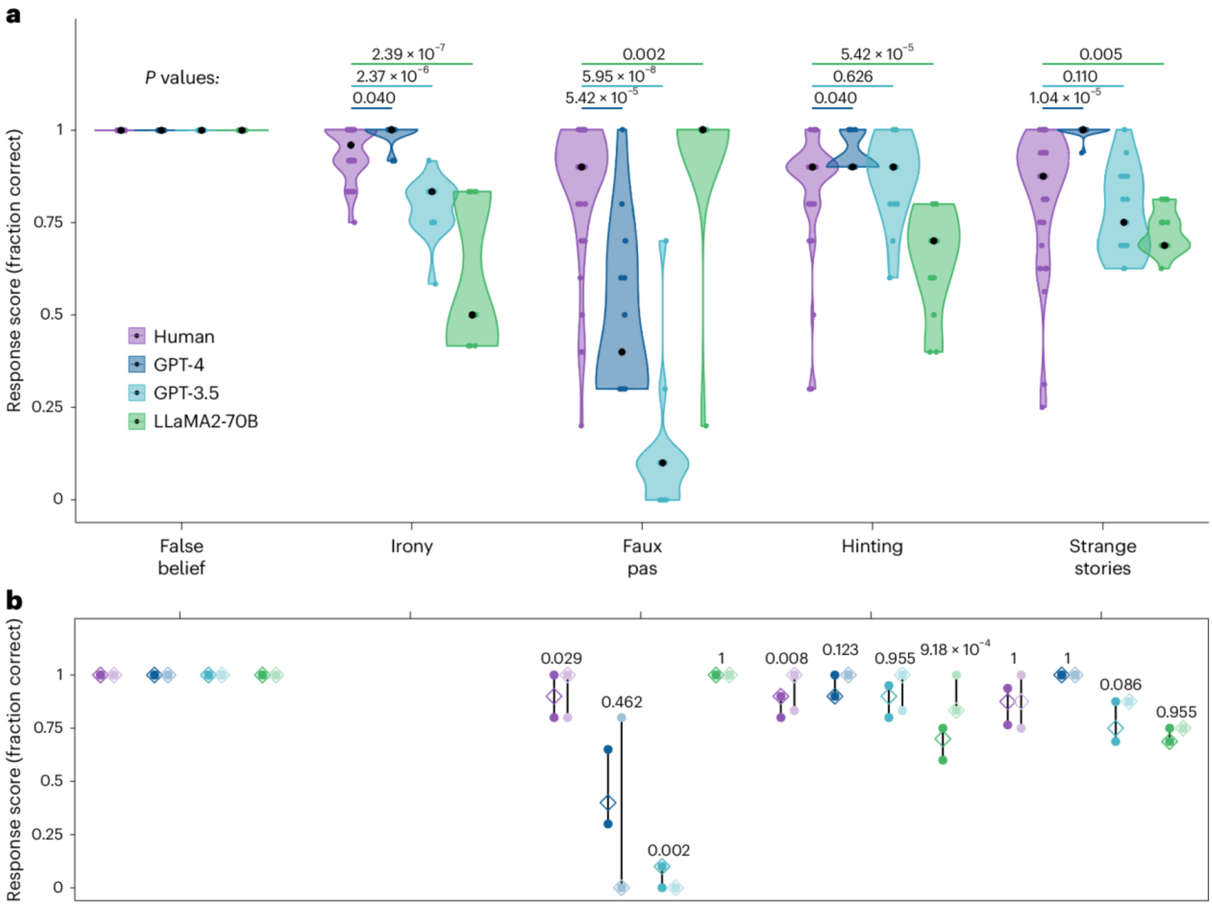


Image 4. Performance outcomes of humans (purple), GPT-4 (dark blue), GPT-3.5 (light blue), and LLaMA2-70B (green) succession of the theory of cognitive evaluations (Strachan et al., 2024).

Image 4, part a, contrasts the capabilities of LLMs with the results of human participants in every test within the battery. Part B of Image 4 displays the performance disparities on original items compared to novel items, categorized by each test and model.

Foundational models, capable of pattern recognition, often copy the biases that are present in the datasets on which the model has been trained (Treude and Hata 2023).In a few circumstances, the systematic skews are crucial for gaining an authentic perspective, as eliminating all the biases present can compromise the abilities of LLM's in accurately simulating character profiles. The researchers need to understand that the model can be greatly impacted by societal views, which might underrepresent the disposition of the demographic cohort (Gerosa et al., 2024).

2.4 Challenges in the adoption of AI

Despite the obvious advantages, issues like maintaining the relevance, accuracy, and dependability of GenAI-produced code and incorporating these solutions into current projects emphasize the necessity for strong KM practices, with one respondent noting their lack of complete trust in the tool and their desire to validate its results. They utilize it as a preliminary suggestion, which they subsequently evaluate and frequently must alter (Kirchner et al., 2025).

Furthermore, as AI is becoming integral for engineering software programs, seeking to address the ethical concerns around it should be its utmost priority. Integrating AI usually means integrating intricate and sophisticated systems that pervasively shape proximally or distally, carrying the default assumption that the systems are bias-free, inclusive, and transparent. The ethical frameworks should be designed by the organizations to yield reliable AI systems that direct the development, deployment, and evaluation of AI technologies. To reduce the risk of AI biases, the company should create a framework that ensures that the AI models that are used for credit scoring are impartial and fair. They standardized their data and models using bias detection tools to determine if any demographic categories (like race or gender) exhibited an unexpected bias in credit scoring outcomes (Tahir Abbas et al., 2025).

2.4.1 Barriers to AI integration in software development

AI assimilation in the software industry is often hindered by numerous substantial impediments, including extensive data computation, intricate computational understanding, and data prerequisites that inhibit the seamless harmonization of existing software architectures with AI systems. Furthermore, legislative concerns regarding its ethical usage, security concerns, and algorithmic biases present critical complications that must be properly mitigated to facilitate prudent, ethical, and sustainable adoption and use of AI. Workplace opposition to organizational change is a significant impediment in the adoption of artificial intelligence models, precipitated by natural anxieties regarding job security, unemployment, replacement, and ambiguity regarding AI's significance. Insufficient clarity regarding AI's function and inadequate training additionally lead to resistance, reluctance, and diminished AI efficiency (Bérubé et al., 2021).

Organizational silos in a company result in poor coordination and ineffective workflows, and diminished overall knowledge exchange, hindering the effective integration of AI. AI projects remain restricted to IT or science teams without proper alignment with other departments within an organization (Raftopoulos & Hamari, 2024).
Organizational limitations, including a shortage of qualified personnel, opposition to adoption,
and high implementation expenses, additionally restrict successful integration.Insufficie nt AI knowledge among managers and staff culminates in misunderstandings regarding AI tools and abilities that result in ineffective and improper utilization. Implementing AI necessitates imbibing technical and domain knowledge; nonetheless, without proper cooperation by all cross-functional departments, the execution becomes challenging (Raftopoulos & Hamari, 2024).

2.4.2 Challenges to AI integration in Software Houses in Pakistan

Despite the increasing potential of artificial intelligence, software companies in Pakistan encounter various structural, organizational, and technological obstacles that impede its successful incorporation. Zong CMPak Ltd 4G, a prominent telecom provider in Pakistan, has incorporated DeepSeek AI's open-source models to improve operational effectiveness and AI-based services. Through the deployment of AI, Zong seeks to rationalize complex operational procedures and enhance internal operations, in conjunction with improving customer satisfaction.

While AI offers the technical infrastructure for improved operational performance, digital innovation is still insufficiently utilized, especially in emerging economies like Pakistan. The empirical findings underscore the imperative of coupling technology resource allocation with institutional capabilities, demonstrating that technology alone is inadequate without progressive institutional initiatives and supportive management practices. Furthermore, the empirical outcomes present specific ramifications for developing economies like Pakistan, where enterprises face considerable impediments because of insufficient resources, specialized competencies, and technological readiness. The assimilation of artificial intelligence and digital innovation seems to provide a viable pathway to boost competitiveness in the global market and strengthen the domestic information technology domain capacity to successfully execute undertakings (Ali Jan et al., 2025).

Various factors play a role when it comes to technical difficulties in total AI adoption in developing countries like Pakistan. The integration of artificial intelligence within software companies in Pakistan is shaped by various technological, organizational, human resource, financial, and environmental elements. From a technological standpoint, the restricted access to high-quality data, insufficient IT infrastructure, compatibility problems with outdated systems, and worries about cybersecurity and data privacy create major obstacles to AI deployment. Factors within the organization, including inadequate support from top management, a feeble innovation culture, limited digital innovation expertise, and poor change management practices, further obstruct adoption.

Incorporating AI learning into everyday tasks transforms job functions, necessitating that employees acquire skill sets that extend beyond conventional technical education

(Ragazou et al., 2022). Previous research indicates that adopting AI requires not only technical skills but also cognitive and strategic abilities, including comprehending the ethical implications of AI and skilfully balancing human judgment with insights produced by AI (Satyro et al., 2021).

Nonetheless, current studies have largely concentrated on major corporations, creating a gap in knowledge regarding how resource-constrained SMEs develop these skills in AI-centric settings. In this context, organizational learning is recognized as a vital mechanism, with research suggesting that companies nurturing a culture of ongoing learning and knowledge exchange empower employees to more effectively utilize AI for decision-making and operational enhancements (Martínez et al., 2022).

Additionally, environmental and contextual elements unique to Pakistan, including minimal client understanding of AI advantages, weak competitive drive in domestic markets, insufficient collaboration between industry and academia, ambiguous regulatory frameworks, and overarching concerns about national digital maturity and infrastructure dependability, collectively impact the speed and level of AI adoption in the nation's software sector.

2.4.3 Extent of AI integration in everyday software development practices in Finland

Preliminary studies suggest that integrating AI can substantially enhance operational efficiency across different dimensions of cognitive labour. According to these studies, employees who demonstrate limited expertise gain the greatest advantages from using AI services. Furthermore, the implementation of AI is consistently elevating occupational output standards and fostering workforce contentment.

Research on call centre agents indicated that those utilizing AI catered to 14% more queries every hour on average than those who did not (Brynjolfsson et al. 2023).IT professionals who had fewer years of experience derived the maximum number of benefits from AI, with their work productivity increasing by 34%, whereas the seasoned workers observed minimal enhancement. These findings indicate that AI can help capture the knowledge already present among employees. In a different study, consultants managed to complete their tasks 25% quicker utilizing AI support (Dell'Acqua et al., 2023). Nonetheless, AI did not demonstrate advantages in every one of the 18 assignments given to the consultants. In certain tasks, the application of AI raised the number of wrong answers. Research focusing on the effects of AI tools in software development (Peng et al., 2023) and in analysing X-ray images (Gaube et al., 2023) demonstrated notable gains in productivity.

Workers with an advanced degree in higher education and earning on the higher end are more vulnerable to being affected by the integration of AI. According to a study by ETLA Economic Research, one in every five Finns works in an occupation in which at least 50% of their tasks are done through or by AI. Approximately 60% of Finnish workers can successfully employ AI for one-fifth of their total work responsibilities (Kauhanen et al. 2023).

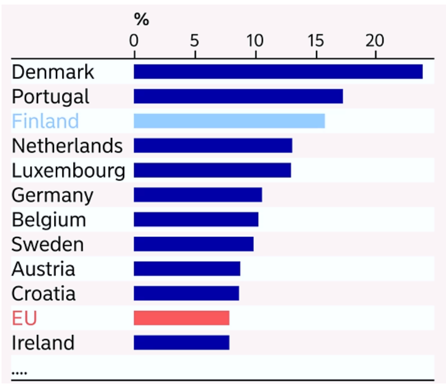


Figure 2. AI Integration in European companies in 2023 (Kostiainen, 2024).

The assimilation of AI tools into routine software engineering systems and practices in Finland has progressed expeditiously, showing both considerable adoption and sustained transformation within the IT sector. Recent statistics reveal that Finnish organizations constantly position amongst the leading in Europe for generative AI, with an estimated two-thirds of firms presently leveraging AI tools like Chat GPT, Copilot, and other concomitant technological solutions in their operational processes, markedly surpassing the EU average, in conjunction with considerable capital allocation in digital advancement transformation (Asikainen, 2025).

EIB (European Investment Bank) 2025 clearly shows that Finland is leading in the EU, with 66% of its companies using generative AI models like ChatGPT, Copilot, and Bard. This pattern clearly shows how the ecosystem of companies in Finland is adapting to the new normal of using AI tools in their daily tasks, to either expedite their work or to achieve a higher level of accuracy.

2.4.4 Ethical, technical, and operational concerns in AI adoption

Additionally, employing AI as a substitute for people poses a danger of further sidelining underrepresented populations, as dominant stereotypes and viewpoints will be dominant, worsening an already pervasive problem. Consequently, investigators must actively strive to avoid their continuation in certain instances. The concern of bias and fairness is not exclusive to AI; however, the scalability and automation capabilities of foundational models increase the likelihood of widespread propagation.

Guaranteeing the dependability of AI results is essential and might require tools for verification, such as comparing the produced material with web resources. Researchers can also produce outcomes by utilizing several models to evaluate consistency across different configurations and training data sets. Ultimately, researchers might perform sanity checks using a limited number of humans and contrast these findings with the automated outcomes. However, individuals might oppose inquiries that are unreasonable, prejudiced, disrespectful, or inappropriate. Conversely, LLMs usually produce replies without consideration for the question’s nature, limited solely by their pre-set boundaries (Gerosa et al., 2024).

An important limitation imposed on the use of AI in project management systems is the ethical and moral consequences of choices made by a program. Miller (2021) contended that for an algorithm influencing people's lives to be executed, the developers of the relevant programs and procedures must be regarded as moral agents and should therefore strive to reduce harm and adhere to societal moral standards.

Thus, it can be concluded that a significant obstacle to the execution of AI systems is accountability. It is distinctly clear that no decision made by an algorithm should be executed without adequate human supervision, but within this constraint, there remains ambiguity about who would be accountable for any resulting outcomes.

2.4.5 Strategies for overcoming AI adoption challenges

For software firms to successfully assimilate AI as a systematic framework, and comprehensive consideration of inclusivity is imperative. Predictive analytics can be done through the use of AI and machine learning, which can lead to enhanced security of the software systems, augmentation of operational efficiency, and fostering of technological advancement. However, with the use of AI, it is essential to mitigate privacy and ethical considerations regarding data confidentiality (Pakalapati et al., 2023).

Training and upskilling the workforce are imperative for resolving operational barriers relating to artificial intelligence solutions. Firstly, numerous employees lack knowledge about the application of AI in software development, necessitating that organizations offer extensive training initiatives. These programs must address the technical abilities required for utilizing machine learning algorithms and training models, as well as instruct employees on collaborating with AI in their everyday activities (Abbas et al., 2025).

Leadership in the AI era needs a different set of skills that facilitate the integration of emotional intelligence appropriately (Milton & Al Busaidi, 2023; Mohan, 2024). To make the right decisions, thought leaders must adapt to the digital transformation, learn and comprehend AI technologies, and work cohesively with technical departments effectively (Milton & Al Busaidi, 2023; Sposato, 2024).

A plethora of empirical studies have investigated the possibilities and obstacles regarding the utilization of AI across different industries in Pakistan (Feuerriegel, Dolata & Schwabe, 2020). Nonetheless, we need to focus on numerous challenges and limitations, such as issues with databases and limited understanding within AI systems. Nonetheless, major challenges included insufficient funding and a lack of adequately trained personnel (Asim et al. 2023). This unique and intricate matter ought to bring to the attention of the global community the importance of research, collaboration, and investment in advancement in artificial intelligence.

2.5 Key Success Factors with AI in Software Projects

The incorporation of Artificial Intelligence (AI) into software projects offers considerable prospects and distinct obstacles. Even though AI can be a vital key to enhancing operational efficiency, enhancing decision-making, and cultivating technological advancement, the effectiveness of AI-powered software processes is contingent upon numerous critical determinants. These fundamental prerequisites for achievements include technical skills, institutional readiness, informational accuracy and reliability, stakeholder engagement, and continuous learning procedures. Comprehending and addressing these dimensions is indispensable for ensuring AI implementations provide tangible outcomes in alignment with the strategic objectives of the organization.

Additionally, the revolutionary potential of AI, which has swept software engineering, is quite apparent with the use of tools like GitHub Copilot 1.7.4421. In the latest study, software developers who used Copilot completed their coding tasks much faster than those who didn't, around 55% faster, defying those who just relied on traditional methods. Furthermore, Copilot also enhanced the quality of the generated code, reducing error rates and increasing successful test cases, especially on the first attempt. This reinforces the fact that AI-driven tools can substantially boost developer productivity while decreasing error rates significantly (Kalliamvakou, 2022).

AI possesses a significant potential to improve project management practices. A noteworthy contribution is its capability to augment the decision-making process by means of advanced empirical examination (Hashfi & Raharjo, 2023). AI systems can analyse extensive datasets, analyse patterns, and deliver actionable insights that improve the precision of cost-forecasting, resource allocation, and temporal planning. Moreover, technologies such as prognostic data analysis and machine learning offer augmented functionalities for strategic formulation and oversight, enabling project managers to anticipate potential risks and take pre-emptive remedial actions. These innovations not only optimize the organizational operational processes but also facilitate substantial temporal and fiscal savings (Pan & Zhang, 2021).

In the requirement optimization stage, the AI system examines project specifications to remove redundancies and inconsistencies, all while staying consistent with the project constraints. The system uses AI to stay flexible by incorporating stakeholder input and new project insights during its development process (Kaur et al., 2020).

The integration of AI in requirements analysis increases efficiency and elevates accuracy and scalability, enabling large-scale projects with numerous stakeholders. AI technologies, such as NLP and text mining, simplify the process by examining the unstructured data. Methods such as entity identification and sentiment evaluation help in the identification of significant entities and in ascertaining urgency. Grouping and prioritizing categorize comparable requirements based on established criteria, guaranteeing that major risks are covered (Tahir Abbas et al., 2025).

Interacting with stakeholders in real-time is essential, underpinned by automated chatbot systems. This leads to structured deliverables, such as use cases and user stories, streamlining the entire software development life cycle and enhancing the quality of the final output. As illustrated in AI-driven requirements analysis, the integration of automation and stakeholder engagement is present in the collection and application.

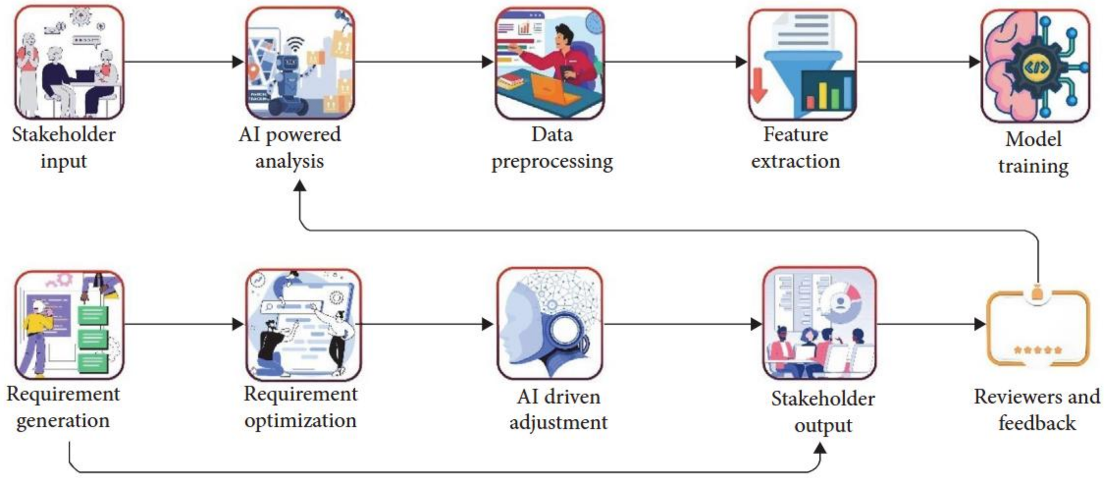


Image 5. Requirement Analysis with AI integration, highlighting automation and stakeholder analysis (Abbas et al., 2025).

This process combines NLP/text-mining techniques with stakeholder engagement models, confirmed in healthcare and e-commerce cases. Incorporating AI into requirements analysis is essential due to the numerous benefits that enhance both efficiency and accuracy. It is essential to create a collaborative environment where AI teams and software development teams can work cohesively. AI tools are expected to enhance the technical competencies of the software developers in lieu of displacing them, thus amplifying the overall efficacy of the development team. By creating cross-functional groups that consist of AI specialists and conventional developers, organizations can promote a more seamless and efficient AI integration process (Tahir Abbas et al., 2025).

3 Theoretical Frameworks

The chapter grounds its theoretical structure on which the AI adoption, technical professional perceptions, and overall productivity outputs are investigated across the two countries, namely Pakistan and Finland. Considering the contrasting cross-cultural nature of the thesis, one theoretical interpretation would not be able to sufficiently capture the deep-layered and nuanced dynamics of the research problem. Therefore, four distinct theoretical frameworks have been jointly deployed to study the distinct perspectives of technical adoption and acceptance: the Technology Acceptance Model (TAM), Socio-technical Systems Theory, Innovation Diffusion Theory (IDT), and cross-cultural and technological maturity perspectives. Chapter 3.1 briefly describes each theory, and Chapter 3.2 employs them explicitly in the research context.

3.1 Key Theories of Cross-Cultural Diffusion and Technology Acceptance

Innovation Diffusion Theory (IDT) is Everett Rogers' (2003) study of how novel ideas, technologies, and practices spread through a social system over time, with four key elements playing an important role: social norms, communication channels, innovation, and time. Robert found five different categories of adopters, namely, innovators, early adopters, early majority, late majority, and laggards – the adoption being influenced by five characteristics that shape the pace of adoption: relative advantage, complexity, compatibility, trialability, and observability. These notions are directly applicable in the current research context, as Finland and Pakistan reside quite differently on the AI adoption curve.

Finland, which is already leading the EU in the adoption of AI, where approximately two-thirds of its companies already use generative AI tools (Asikainen, 2025), reflects the early and late majority stages, whereas Pakistan's software industry is still dealing with system constraints and compliance obstacles, which reflect early adoption phases. IDT offers a macro-level foundation for analysing the productivity differences between the two countries highlighted in RQ1.

The Technology Acceptance Model (TAM) was developed by Fred Davis in 1989, in which he explained subject-level adoption of technology via two key notions: Perceived Usefulness (PU), the extent to which a user perceives to have achieved the performance enhancement of the job by the use of a certain technology, and the Perceived Ease of Use (PEOU), the extent to which the technology is perceived to be hassle-free. Comprehensively validated in the organizational and software development domains (Venkatesh et al., 2003), TAM plays a pivotal role in addressing RQ2, which examines how professionals in Finland and Pakistan have varying perceptions of AI. As the literature review demonstrated, junior developers and those in more technologically advanced ecosystems tend to report higher perceived usefulness and reliance in AI outputs, a pattern aligned with TAM's concepts. While TAM is limited in its representation of social and contextual factors (Bagozzi, 2007), the socio-technical and cross-cultural factors below help redress this.

Socio-Technical Systems (STS) Theory. Introduced by Trist and Bamforth in 1951, STS theory states that all organizations are made up of two mutually dependent components: the technical part, consisting of tools, processes, and the social part, consisting of culture, people, and societal norms, and that long-term technological integration requires the coordinated optimization of both. This framework is crucial for explaining why, even sometimes technically sound AI tools cannot automatically produce productivity improvements. As Section 2.4 of the literature review highlighted, barriers such as strict organizational silos, employee resistance, and inadequate management support systems commonly contribute to AI integration outcomes limitations (Raftopoulos & Hamari, 2024; Bérubé et al., 2021).

STS theory conceptualizes these socio-technical misalignments and pertains to Finland's more mature adoption settings, where concerns about AI homogenizing creative outputs and redirecting developer roles towards the validation domain represent friction at the interface of technology and human systems.

Cross-Cultural and Technological Maturity Perspectives Hofstede's (2001) cultural dimensions - structure presents the comparative viewpoint for this study, with a specific emphasis attributed on power distance and uncertainty avoidance. Finland, which is usually associated with a flat hierarchy and low uncertainty avoidance, is usually accompanied by decentralized decision-making and organizational permissiveness towards pioneering and flawed technologies. Pakistan usually follows a strong vertical hierarchy, which may result in a more rigid experience in its AI adoption due to its hierarchical-driven nature, with adoption determined by leadership approvals rather than decentralized testing. Uncertainty avoidance is equally pertinent, as the AI tools are very much susceptible to producing erroneous and hallucinating outputs, as registered in Sections 2.3.1 and 2.4.3. IT professionals who operate in high uncertainty avoidance cultures may demand stronger validation processes before relying on AI-generated outputs. Apart from culture, the idea of national technological maturity indicates disparities in digital infrastructure, regulatory transparency, and talent availability, all of which are key to the research area outlined in Chapter 1.

3.2 Application of Theoretical Framework to AI Adoption Spanning Pakistan and Finland

The four frameworks constitute an integrated analytical structure in which each theory focuses on a separate but related aspect of the research problem. IDT functions at the macro level, contextualizing the standpoint of Pakistan and Finland on the AI adoption curve and elucidating the structural determinants driving the divergent trajectories. TAM functions at the subject-level, underpinned by the perceptions of the two countries of AI tools - the primary focus of RQ2. STS theory provides the organizational layer - the productivity outcomes of AI tools analysed in RQ1 are shaped by human, cultural, and structural factors rather than being a direct function of tool aptitude alone. Finally, the cross-cultural and technological maturity perspectives serve as the interpretive frame that integrates all three theories together, confirming that research findings are subject to national and institutional realities of each country rather than as context-free generalizations.

In practical terms, this integration implies that a productivity difference between Pakistani and Finnish software companies, as analysed in RQ1, would be interpreted not merely as a difference in tool utilization, but also due to differing diffusion stages (IDT), varying organizational contexts (STS), and distinct cultural orientations towards innovation risk (Hofstede). Likewise, perceptual variations between professionals in these two countries, as explored in RQ2, would be investigated not only from the lens of subjective attitudes (TAM) but also through the moderating influence of national culture, digital ecosystem readiness, and organizational support structures. Table 3 outlines the mapping.

Table 3. Theoretical Framework: Theories and their application to this research study

Theory Name	**Core Construct**	**Relevance to This Research**
Innovation Diffusion Theory (Rogers, 2003)	Speed and means of spread of technology across social systems.	Explains the reasons behind the differences in the different speeds of AI adoption in Finland and Pakistan, influenced by infrastructure and organizational disposition.
Technology Acceptance Model (Davis, 1989)	Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)	Directs RQ2 by charting how tech professionals in both countries perceive AI tools based on readiness, education, skills, and work culture

Socio-Technical Systems Theory (Trist & Bamforth, 1951)	Correlation of technical systems and human/social factors.	Clarifies why AI productivity benefits rely on team dynamics, managerial backing, and organizational environment, and not solely on the tool.
Cross-Cultural & Technological Maturity Perspectives (Hofstede, 2001)	Cultural Differences: Power hierarchy, uncertainty avoidance, and subjective constraints	Gives a comparative lens for understanding how national cultural values and ecosystem maturity drive AI adoption in Pakistan and Finland.

Table 3 illustrates that a single theory cannot sufficiently address the complete dynamics of cross-cultural AI adoption in two different software development environments. The amalgamation of these four theories described above ensures the proper absorption of cross-cultural perspectives at multiple levels of investigation relating to societal, organizational, and subjective, while maintaining acuteness on the national contexts that discern Pakistan and Finland. This multi-faceted theoretical approach directly shapes the construction of the quantitative survey tool and the interpretative framework of the comparative analysis elucidated in the following chapters.

4 Methodology

This chapter presents details about the methodology used to drive this research, including a summary of the research design, data collection method, and the demographic breakdown of the participants included in the research, followed by the objectives of the research analysis, exercise set, and other key items forming the instruments of the survey. The chapter concludes by addressing the limitations and constraints recognized to ensure the research's integrity and trustworthiness.

4.1 Research Design

This research study uses a quantitative research design to empirically investigate the influence of Artificial Intelligence tools on software project productivity across two contrasting national contexts – Pakistan and Finland. The decision of a quantitative approach is aligned with the objectives of this research thesis, which aims to produce results and professional subjective perspectives of tech professionals in both countries.

This research design employs systematic testing of patterns underpinned in the theoretical framework in chapter 3, especially the constructs of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) from the Technology Acceptance Model (TAM), the diffusion stages laid out in Innovation Diffusion Theory (IDT), and the socio-technical and cross-cultural dimensions highlighted by STS Theory and Hofstede's cultural dimensions framework.

A survey-based structured questionnaire was composed and distributed to people related to software production in Pakistan and Finland via Google Forms. The questionnaire functions as the primary data collection instrument, enabling a standardized, scalable, and cross-country comparable method of collecting first-hand responses from technical professionals who are actively involved in software development environments.

4.2 Software Engineering Experiments

To make the research study more substantial, the research is designed as a software engineering experiment - a structured investigation aimed at exploring the link between AI adoption and software project productivity in real work contexts. Unlike controlled lab experiments, this study relies on a real-world survey approach, drawing on practitioners' working styles and adaptation perspectives. This experiment is built on standard principles of empirical software engineering research, in which data is collected using surveys from actual professionals rather than laboratory participants.

4.2.1 Objective

The main goal of this experiment is to analyse and compare how the inevitable inclusion of AI tools can impact software project productivity, and how tech professionals in Finland and Pakistan view AI's role differently in software development, efficacy, and creativity. The study's key aims are:

- Assess the extent to which AI tools adoption results in actual tangible productivity gains in software projects across both countries.
- Understand opinions of professionals regarding AI's influence on their personal development pace, creativity, efficiency, code quality, and overall pace of project delivery.
- Identify how different institutional, legal, and contextual factors, such as years of experience, work-nature, organizational culture, organizational training incentives, and national digital ecosystem maturity, affect AI adoption outcomes.

These objectives directly align with the two major research questions, RQ1 and RQ2, and are underlined in the multi-theoretical framework enunciated in Chapter 3 of this thesis.

4.2.2 Experiment Design

This experiment design uses a cross-sectional, comparative survey. A systematic survey instrument was disseminated to software engineers and IT professionals in the respective countries concurrently to gather empirical data across both study samples. This methodology renders it feasible to systematically examine the points of convergence and divergence in AI adoption, subjective productivity, and professional outlooks between both cohorts.

This experiment is organized around two main areas. The first one focuses on productivity outcomes (RQ1), studying the perceived impact of AI software on accuracy and speed of code, SDLC duration, error reduction, and project delivery timelines. The second area examines the professionals' views (RQ2), registering their attitudes towards AI's influence in software development, trust in AI-generated content, and their personal fears and concerns regarding job security, and opinions on the general acceptance of AI software.

The survey was designed to extract Likert (1-5) scale responses, multiple-choice, and open-ended texts, allowing both descriptive and analytical cross-country comparisons. The questionnaire was created using Google Forms and was distributed digitally via LinkedIn, WhatsApp groups, and Emails to software groups and individuals in Pakistan and Finland, for efficient data collection across professionals located in different geographies.

4.2.3 Participants

The study captures data from professionals currently actively working for software companies of varied sizes (startups, small, SMEs, and enterprises) in Finland and Pakistan. These participants comprise software engineers, frontend and backend developers, full-stack developers, UI/UX designers, QA testers, project managers, DevOps engineers, and technical managers who regularly engage with AI software as part of their routine work tasks. Digital and social media platforms like LinkedIn, WhatsApp, email channels, and direct contact with personnel acquainted with networks of software professionals were instrumental in reaching out to participants in both countries. The three inclusion criteria were: (a) to be actively employed in a software development or IT-related role; (b) to be exposed to direct or indirect usage of AI software for work; (c) to be based in one of the two countries taken into account for this study.

There were no restrictions on seniority or years of industrial experience, as including participants from all age-groups was vital for providing layered nuance for comprehension of how the level of experience corresponds to AI perceptions, as noted in the Chapter of Literature Review, and based on the Technology Acceptance Model (TAM), and Perceived Ease of Use.

4.2.4 User Manual

To guarantee clarity and uniformity in the interpretation of responses of the participants, an introductory section was provided at the beginning of the survey form. This user manual acted as a functional user guide and briefed the participants about the set of instructions and research objective, clearly providing the required guidance and context to fill the survey form correctly without any ambiguity.

The introductory section included: (a) a summary of the research study and the academic context in which it is being led; (b) definitions of the terms that are used frequently in the form such as, 'AI tools', 'productivity', and 'software project', to confirm consistent comprehension of the terms, across respondents of different national and ethnic backgrounds; (c) guidelines of how to complete every question type, including instructions explaining the Likert-scale (e.g. 1=Strongly Disagree, 5=Strongly Agree); and (d) an explicit assurance of anonymity and voluntary terms of participation, in accordance with ethical research standards.

This information ensured reduced biases in responses arising from technological confusion and guaranteed that the cross-country data collection would stay structurally homogenous for subsequent cross-national analysis.

4.2.5 Exercise Set

The questionnaire was systematically divided into four key sections, with a distinct emphasis on a different aspect of the research study. These sections together form the main exercise set of the survey, designed to move incrementally from occupational profiling to deeper attitudinal and perceptual investigation. The sections are as follows:

Section 1. Demographic and professional background

The first section of the survey established the professional and technical background of the respondents. Participants were questioned about their primary domain and area of expertise, including but not limited to, options such as Frontend Development, Backend Development, Full-Stack Development, DevOps/Cloud, UI/UX Design, QA Testing, Software Project Management, Machine Learning/AI Development, and Scrum Master roles. Then they were interrogated about their working experience ranging from (less than 2 years, 2–5 years, 5–10 years, or more than 10 years), then they were asked to define their level of usage and technical familiarity with the AI tools on a 1–4 scale ranging from 'not familiar' to 'extensively values-focused', and the size of their company or working setup ranging from freelancer to large enterprise.

Section 2 AI Adoption and Software Usage

This section was dedicated to investigating the rate of AI tool usage and the organizational context. Participants were asked to explicitly state how much they rely on generative AI models such as Claude AI, ChatGPT, Grok, Perplexity, and others in their routine work tasks, through a Likert scale. The involvement and encouragement of the organization for the adoption of such tools was also inquired, how much time they dedicate to using these advanced models, and whether their organization has a formal structure and policy in place for the inclusion of AI-generated content in software development procedures.

Section 3 Productivity Outcomes

This section was mainly focused on addressing Research Question 1 (RQ1) by examining how the respondents perceive the impact of AI reliance on software project productivity. Questions asked about participants' satisfaction in relation to the AI usage, whether AI models help comprehend and steer through complex codebases, whether AI-generated code can produce errors and bugs that are worse than those produced by human-written code, and whether AI models help increase the efficacy of their work tasks. Participants were interrogated about AI's role in the facilitation of the company's overall growth, whether AI tools are easily accessible to IT professionals in their region, and an open-ended question for deriving their response on their general perception of AI's impact on IT organizations.

Section 4 Professional Perception of AI

This section focused on the second research question (RQ2) and aimed to capture the professional outlooks, reliance, and holistic understanding of AI's role in the industry. Participants were encouraged to delineate AI-driven productivity in their specific context- whether it is based on AI software or AI-led, how AI models are assisting them in their personal intellectual growth, their cognizance of AI networks in their region, and whether AI regulatory frameworks and legal policies have affected them in their daily tasks and professional context. This section is a combination of open-ended descriptive questions and precise close-ended choices to allow the derivation of richer, more layered contextual information from respondents, for a more thorough understanding of the perceptual impact of AI, influenced by multiple variables.

4.2.6 Questionnaire Design

This questionnaire design is grounded in the four theoretical frameworks comprehensively explained in the previous Chapter 3. Measuring instruments were methodically conceptualized with validated theoretical frameworks within the TAM, IDT, and STS literature; consequently, ascertaining a sound theoretical foundation and rigorous construct validity across all sections. The table below delineates every theoretical framework alongside its corresponding survey section and item typology.

Table 4. Theoretical groundings for survey questionnaire items.

Theoretical Framework	**Survey Section**	**Item Typology**
Innovation Diffusion Theory (IDT)	Section 1: Demographic and Professional Background	Multiple Choice Questions (MCQs): Job role, company size, years of experience, and AI familiarity level (1-4)
Technology Acceptance Model	Section 2: AI adoption and software usage	Likert-scale selection (1–5) on perceived usefulness of AI tools, reliance on generative AI (ChatGPT, Claude, Grok, etc.), weekly AI usage, and organizational AI regulatory policy
Socio-Technical System (STS) Theory	Section 3: Productivity Outcomes	Likert-scale and MCQs on code quality, task completion speed, time savings per week, cross-team collaboration, and AI's impact on SDLC
Cross-Cultural Technological Maturity Perspective	Section 4: Professional Perceptions of AI	Likert-scale, MCQs, and open-text items on AI as opportunity/threat, job displacement anxiety, AI and creativity, software engineering orientation, training, budget constraints, and ethical/copyright concerns

This research holds value across several dimensions. From an empirical view, it addresses a key research gap mentioned in Chapter 1 by offering the first comprehensive cross-country evaluation between two countries, Pakistan and Finland, that are in distinct positions on AI maturity yet reliant on AI and digital products as exports. Finland, being the leading EU market in the AI usage, especially the generative models, indicated a highly developed environment, while Pakistan's software milieu, despite its fast-growing youth-led workforce, continues to manage systematic and infrastructural challenges to full AI integration.

In theoretical terms, this study manages to highlight the value of merging TAM, IDT, STS Theory, and Hofstede's cultural dimensions into a consolidated analytical model for studying and understanding AI adoption across contrasting national contexts, a combination never employed earlier in this specific cross-national setting. In applied terms, the findings seek to deliver implementable insights for software houses and tech organizations in both countries seeking to enhance AI implementation approaches, develop more effective training programs, and establish organizational systems that are more supportive of enabling AI-based performance improvements.

The questionnaire predominantly consisted of questions that were based on Likert-scale items, five-point, complemented by multiple-choice questions, dichotomous (Yes/No), and open-ended questions in instances where more complex, descriptive, and nuanced data were required. The language of this instrument was English, which serves as the business language in both countries and is understood and spoken by the majority, thereby reducing translation-related linguistic biases. Before dissemination, this survey was previewed and assessed for question quality by the thesis supervisor, tested among ICT students and peers, and handed out to the real group of respondents, followed by minor refinements to enhance the interpretability of the items across both national contexts. The questionnaire utilized in this research study employed a mixed scale design, including yes/no, Likert-scale, and categorical response formats. While this hinders direct result extraction from statistical comparability across all survey items, Spearman correlation analysis was used to study the relationship between variables of differing scale types, partially compensating for this limitation.

4.2.7 Data Collection and Analysis

Data collection was performed within a definite, predetermined timeframe by using a Google Form. Responses were compiled from developers and other IT professionals through targeted outreach via LinkedIn, WhatsApp IT groups, Email, Discord channels, etc., within software firms and development networks and communities in both countries. The Google Form survey link was disseminated digitally, enabling geographically dispersed respondents to respond to the survey request at their discretion within the data collection period. Subsequent to the empirical data gathering, responses were retrieved and subjected to descriptive and quantitative scrutiny. The statistical analysis process involved: (a) the descriptive indicators to delineate recurring patterns, (b) comparative evaluations to detect significant variations between Pakistani and Finnish participants on principal productivity and perception constructs; and (c) cross-analysis to study the extent to which determinants encompassing years of experience, organisation scale, and the influence of AI tool productivity perception outcomes; and (d) a statistical reliability analysis using **Cronbach's alpha** in SPSS Statistics Software to assess the reliability and internal consistency of the Likert-scale items **(Q5, Q8, Q11)**, ensuring the psychometric robustness of the five-point scale used in this study.

The analytical framework is underpinned by a consolidated multi-theory orientation, ascertaining that identified disparities are construed not exclusively as peripheral perceptual differences but as indicators of profound foundational discrepancies in diffusion stages (IDT), socio-technical discrepancies (STS Theory), and sociocultural tendencies (Hofstede). Qualitative responses were examined thematically to analyse and strengthen quantitative findings. To study the relationships between binary and ordinary variables, Spearman correlation coefficients were measured and plotted against scatter plots across eight pairs of subjective variables. Unlike Pearson correlation, which necessitates continuous normally distributed data, Spearman correlation is suitable for ordinal and binary variables, making it appropriate for mixed-scale questionnaire design used in this research. This method offered a numerical and statistical basis for multivariable examination, surpassing descriptive statistical reporting, facilitating recognition of directional associations between dichotomous responses and Likert-scale responses across both country groups.

4.2.8 Limitations

Like any empirical investigation, this research study is also subject to several constraints that need to be acknowledged for the comprehension of its outcomes.

- **Self-reported data:** This research is based fully on participant responses via the survey form, which invariably introduces reporting biases and intrinsic limitations in respondents' subjective self-evaluation of AI-related productivity changes.
- **Sample size and Representatives:** The sample size does not indicate capturing the country's perception of the entire software workforce of either country, given the voluntary and network-driven nature of the recruitment. Generalizing results should be approached with caution.
- **Cross-sectional Approach:** This survey records perception of a fixed time and does not reflect longitudinal variation in AI adoption patterns or perceptions of productivity over longer periods of time, which may face considerable changes over time as the pace and extent of AI integration expands and evolves.
- **Language of Instrument:** Although English is widely spoken and understood in both the cross-country dynamics, the use of this language can still present a few

comprehension barriers for some participants, especially in Pakistan, where English proficiency is varied across organizational tiers.

- **Rapidly evolving AI landscape:** Considering the pace at which AI tools and functionalities are advancing, the results of this survey may be susceptible to temporal limitations and may necessitate reassessment as more tools and technologies emerge and new AI regulation frameworks are designed and implemented in both countries.

These constraints are clearly acknowledged and do not undermine the overall validity and scholarly credibility, and the academic merit of this research, but rather delineate the parameters and delimitations pertinent to which conclusions should be construed and examined.

5 Results and Analysis

This chapter entails the empirical results that have been derived from the structured survey that was administered to software professionals in Pakistan and Finland who voluntarily accepted to be a part of this research study. 28 responses were obtained in total, comprising 20 Pakistani respondents and 8 Finnish respondents. The sample was collected through purposive digital outreach pertaining to platforms like LinkedIn, WhatsApp, email, and Discord channels. The analysis of the study is centred around descriptive statistical patterns and comparative cross-country examination, explicitly addressing the two research questions described in Chapter 1.

The analysis is organized as follows: Section 5.1 details the demographic profile of the participants. Section 5.2 studies RQ1 related to the professional perceptions of software project productivity by the adoption of AI tools in daily work tasks. Section 5.3 investigates RQ2 on professional perceptions and attitudes. Section 5.4 examines infrastructural factors influencing AI adoption. Section 5.5 incorporates legal and ethical concerns regarding AI adoption and usage. Section 5.6 consolidates all the research findings in accordance with the theoretical frameworks defined in Chapter 3

5.1 Demographic and Professional Profile of Respondents

The population profile of the survey consists of a diverse cross-section of software professionals situated in two different countries. The subsequent figures depict the participants' demographic profile with respect to their geographic domicile, primary job role, and total years of professional experience in the field of information technology, and the size of their company.

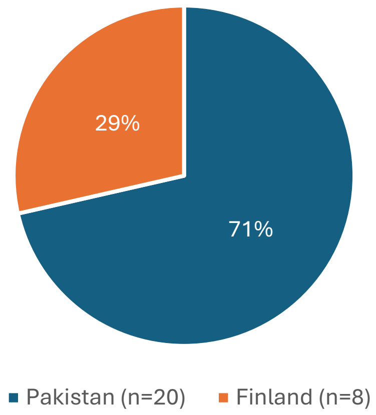


Figure 3. Geographic distribution of survey respondents (n=28).

Figure 3 demonstrates that IT professionals based in Pakistan account for 71% of the total respondent pool (n=20), and professionals based in Finland account for the remaining 29% of the pool (n=8). As discussed earlier, this skew in the research is attributable to the higher accessibility of the Pakistani network during the data collection and is also one of the registered and acknowledged limitations of the study.

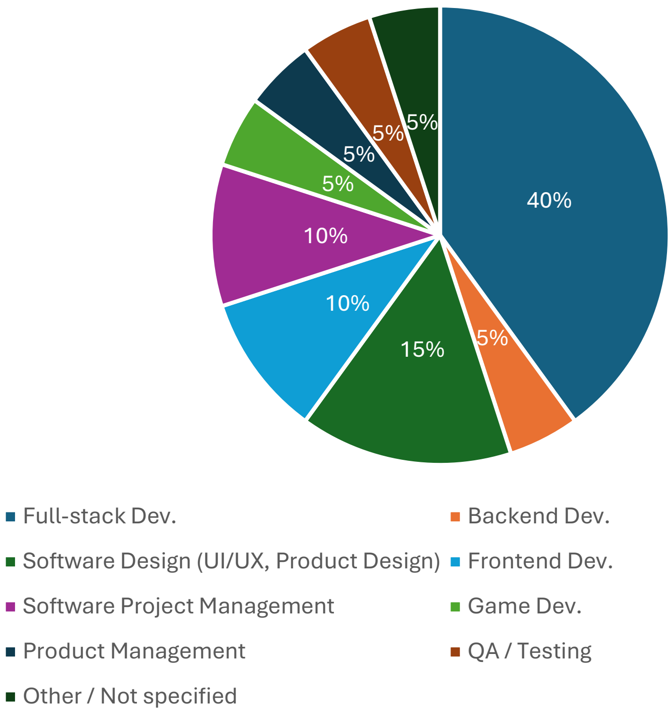


Figure 4. Main job functions of all the participants (n=28).

Full-stack development represents the predominant category across both participant groups (n=8, 29%), succeeded by UI/UX design and product design roles (n=4, 14%) and software project management (n=3, 11%). The remaining segment of the research cohort encompasses a considerable number of participants, a diverse array of occupational functions including front-end development, QA and testing, backend development, DevOps, game development, and product management, demonstrating a broad spectrum of professional diversity in the consolidated research cohort.

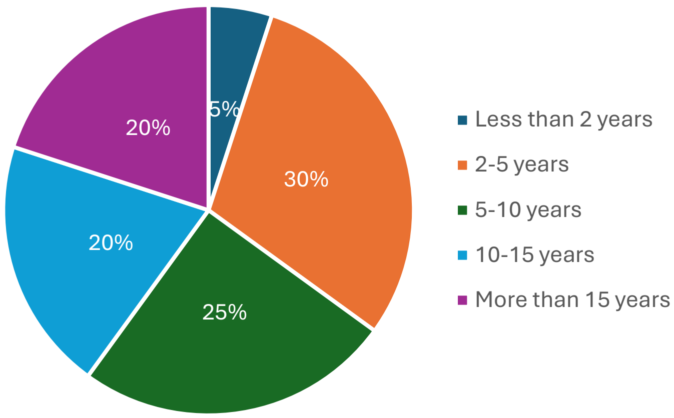


Figure 5. Professional Years of Experience (n=22 with data).

The years of experience of the respondents in the distribution show a notable distinction across the cohorts. The 2-5 years category corresponding to the 'junior' tier professional accounts for the majority in the distribution sample (n=8), predominantly reflecting the Pakistani respondents, which describes a pronounced prevalence of youth in the IT arena of Pakistan. Conversely, the Finnish respondents cluster primarily around the 15+ years of experience bracket (n=4). The gap in professional seniority is critical for understanding the differences in productivity and perceptions addressed in the following sections.

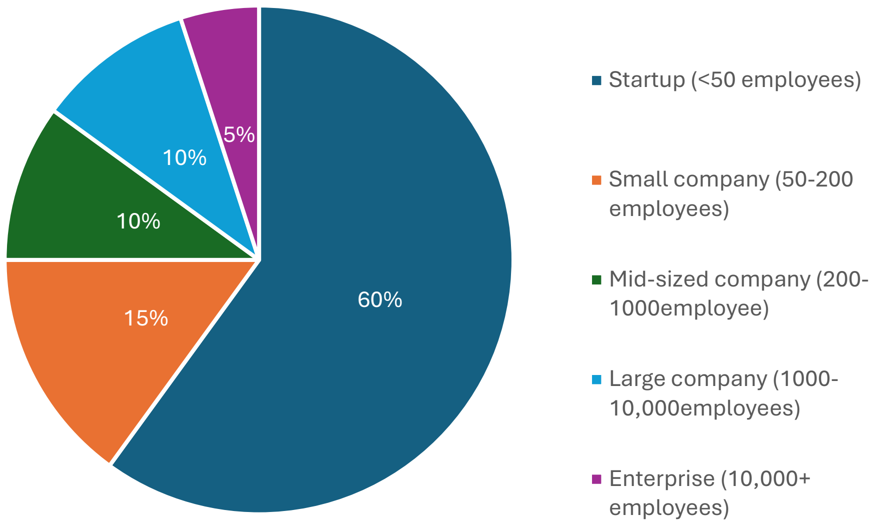


Figure 6. Current Company Size of the Respondents (n=22 with data).

The data figure above depicts that small-sized companies and early-stage startups with fewer than 50 employees are the most dominant group in the organizational size context (n=11, 50%), largely due to the fact that most Pakistani respondents are concentrated in small, early-stage organizations. Finnish participants, however, show greater diversity in this aspect of the sampling, including large enterprises and big organization settings. Table 5. demonstrates a complete demographic breakdown.

Table 5. Professional Profile of Respondents.

Demographic Type	Finnish Participants (n=8)	Pakistani Participants (n=20)
Main Job Function	Full-stack Dev. (4), UI/UX Design (1), Product Mgmt (1), Not specified (2)	Full stack (4), SPM (3), Frontend (2), QA/Testing (2), UI/UX (3), Backend (1), DevOps (1), Game Dev (1), CEO (1), Not spec. (3)

Job years of experience	15+ years (4), 10-15 yrs (1), 5-10 yrs (1), Not specified (2)	2-5 years (8), 5-10 yrs (5), 10-15 yrs (2), Under 2 yrs (1), Not spec. (4)
Company Size	Enterprise 10,000+ (1), Large 1,000-10,000 (1), Small 50-200 (1), Startup under 50 (3), Not spec. (2)	Startup under 50 (8), Small 50-200 (4), Mid 200-1,000 (2), Large 1,000-10,000 (2), Not spec. (4)

5.1.1 Statistical Reliability Analysis of Scale Items

To analyse the internal reliability and consistency of the Likert-scale items, a reliability analysis was conducted using Cronbach's alpha in SPSS. The first test run on the item scale (Q3, Q5, Q8, Q11) produced **α = 0.637**. Item-total correlation analysis revealed that Q3, which pertains to the professional working philosophy, showed a zero correlation (r = 0.004) with the remaining items, suggesting that it is measuring a conceptually different construct from the AI perception items. This is why it was appropriate to remove Q3 from the analysis, to gain a perfect **α = 0.850**, indicating good internal consistency among the three AI-related perceptions items (Q5, Q8, Q11).

Table 6. Reliability Statistical Analysis – Cronbach's Alpha Model

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.850	.850	3

Table 7. Item Statistics (Q5, Q8, Q11)

Item Statistics

	Mean	Std. Deviation	N
Q5_AI_Productivity	3.89	1.197	28
Q8_Code_Quality	3.36	1.162	28
Q11_Confidence	3.82	1.124	28

Table 8. Inter-Item Correlation Matrix

Inter-Item Correlation Matrix

	Q5_AI_Productivity	Q8_Code_Quality	Q11_Confidence
Q5_AI_Productivity	1.000	.615	.756
Q8_Code_Quality	.615	1.000	.590
Q11_Confidence	.756	.590	1.000

Table 9. Total Item Statistics

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
11.07	9.328	3.054	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q5_AI_Productivity	7.18	4.152	.767	.615	.742
Q8_Code_Quality	7.71	4.730	.643	.414	.860
Q11_Confidence	7.25	4.491	.750	.597	.761

5.2 Adoption of AI Tools on Software Project Productivity (RQ1)

This section focuses on RQ1, investigating how the adoption of AI tools influences productivity in software projects within software houses in Pakistan and Finland. The study analyses five dimensions: overall productivity, enhancement of code quality, efficiency in task completion, time savings per week, and collaboration across teams.

5.2.1 Overall Perceived Productivity

Subjects assessed the influence of AI tools on their routine work tasks utilizing a five-point psychometric scale (1 = no improvement, 5 = substantial improvement). Table 6 presents the arithmetic means and standard deviations of the respective cohorts.

Table 10. Mean Perceived Productivity Scores by Country.

Measure	Finnish (n=8)	Pakistani (n=20)	Overall (n=28)
Mean score (1-5)	2.88	4.30	3.86
Standard deviation	1.46	0.80	1.12
Minimum	1	2	1
Maximum	5	5	5

The distinction between the Pakistani and Finnish respondents is notable. Pakistani respondents report considerably greater subjective improvements (M = 4.30, SD = 0.80), with scores demonstrating minimal dispersion. Finnish respondents exhibit a reduced tendency to discern higher gains, and a broader distribution (M = 2.88, SD = 1.46), reflecting heterogeneity in subjective perceptions. Significantly, two Finnish respondents rated productivity as 2, and one as 1 - a trend not observed among their counterparts in the survey.

These findings are consistent with STS Theory, which contends that the institutional, sociocultural, and anthropological dimensions significantly influence the productivity outcomes, transcending tool capability (Trist and Bamforth, 1951). The low ratings by the Finnish respondents indicate a quality-oriented methodology intrinsic to Finnish software engineering practices, where, though AI-generating models are extensively deployed, they are subjected to stringent evaluation before validation as productive (Hassan et al., 2024).

5.2.2 Code Quality Improvement

Respondents gave ratings on a Likert scale regarding whether AI tools improved the quality of their code. As Table 7 illustrates, an identical directional trend persists throughout both groups.

Table 11. Mean Code Quality Improvement Scores by Country.

Measure	**Finnish (n=8)**	**Pakistani (n=20)**	**Overall (n=28)**
Mean score (1-5)	2.25	3.80	3.36

Standard deviation	1.16	0.83	1.09

The mean score for the Finnish cohort was 2.25, which falls below the average of 3.0, implying that the majority of Finnish participants' overall view of AI's impact on source code quality is either negligible or non-existent. One Finnish respondent, with more than 15 years of professional experience, explicitly observed that while large language models generally produce code at a considerably faster rate, the speed advantage is often neutralized by the excessive time spent correcting basic errors, a qualitative insight that directly explains the low mean score. The higher score among Pakistani respondents (M = 3.80) indicates a more optimistic reception of AI's effect on code quality, plausibly linked to fewer years of baseline code-review experience, resulting in higher acceptance of AI-generated code quality (Kalliamvakou, 2022).

5.2.3 Task Completion Speed and Weekly Time Savings

Respondents were questioned on whether their tasks get completed at a faster rate by using AI, and a multiple-choice question on the approximate time saved per week.

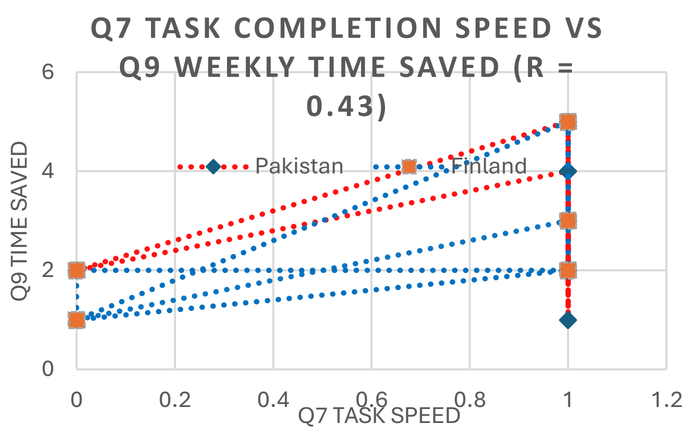


Figure 7. Scatter Plot – Q7 Task completion speed vs. Q9 weekly time saved.

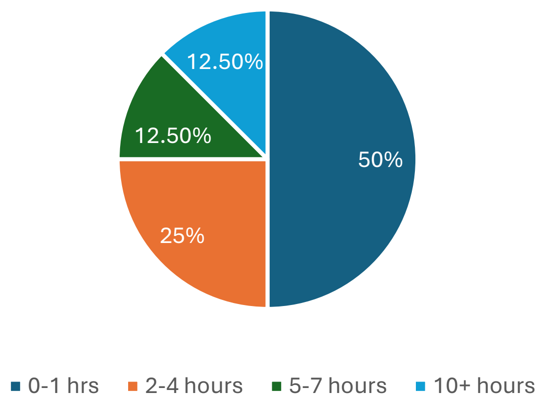
To study the effects of the perceived speed and its outcomes in actual observable task efficiency, a Spearman corelation was conducted between Q7 (task completion speed) and Q9 (time saved per week), The analysis revealed a moderate correlation (r=0.43), between the two variables, describing that those individuals who perceived faster task completion were also able depict measurable outcomes in terms of time I hours saved every week, though this relationship is not absolute. The correlation is only moderately positive, suggesting that the perception of faster task completion and actual time saved per working week are related, but distinct facets of productivity. A person may be able to work faster with Gen AI but might not save working hours; they may save hours through quality improvements, not by executing tasks faster. A large majority of Pakistani respondents, around 95%, reported faster task completion. It hence also fell in the category of higher time saving, showing a direct linear relationship between the two observational variables. However, only a dispersed minority of 37.5% from the Finnish respondents reported no faster completion and only dedicated 0-1 hours of time-saving every week by using AI assistance. This observation is corroborated by the TAM Theory's Perceived Usefulness construct (Davis,1989), which iterates that when professionals using AI actually perceive it to be getting their work done faster, they are the ones who can propositionally achieve greater efficiencies, whereas selective and critical adoption leads to lesser extracted benefits as seen in the Finnish cohort.

Table 12. Approximated Weekly Time Saved Using AI Coding Assistants.

Time-Saved (Weekly)	**Finnish (n=8)**	**Finnish %**	**Pakistani (n=20)**	**Pakistani %**
0 - 1 hours	4	50.0%	0	0.0%
2 - 4 hours	2	25.0%	7	35.0%

5 - 7 hours	1	12.5%	5	25.0%
8 - 10 hours	0	0.0%	3	15.0%
More than 10 hours	1	12.5%	5	25.0%

Table 8 presents the amount of time saved per week for each group. Approximately more than half of the respondents from the Finnish group stated they saved fewer than 1 hour every week by using AI tools, while none of the respondents from the Pakistani side fell into this lowest bracket. On the higher side, around 40% of all Pakistani respondents save approximately 8 or more hours per week, versus just 12.5% of Finnish professionals. Five respondents from the Pakistani group claimed they save more than 10 hours per week, which corresponds to a full working day.



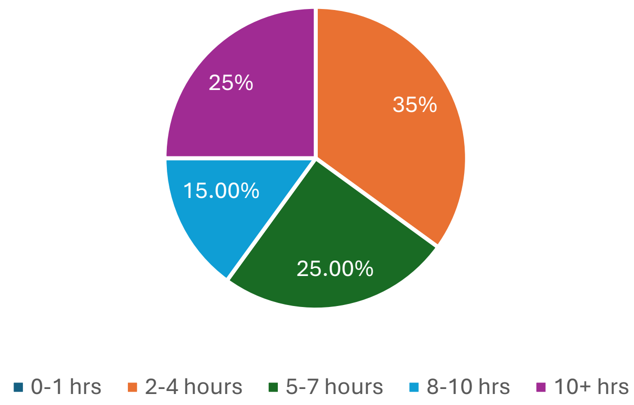


Figure 8. Weekly Time Saved by AI usage – Pakistani vs. Finnish Respondents.

These results clearly imply that the Pakistani workforce incorporates AI solutions and tools into regular operations, extracting greater efficiencies through notable time reductions. This is consistent with the Innovation Diffusion Theory (Rogers, 2003): Pakistan's youth-concentrated, rapidly expanding tech industry reflects a transition from an early to late to a mid-to-late diffusion phase, whereas Finland's conservative trend mirrors the quality-validation-driven adoption approach dependent on proven reliability, reflecting Davis's (1989) “Perceived Ease of Use" concept from the TAM.

5.2.4 Employee Confidence in AI Tool Usage

Respondents gave ratings of their confidence levels in adopting AI technologies and tools into their work routines, on a Likert 1 – 5 scale. Table 9 shows the mean confidence scores.

Table 13. Mean Confidence in Using AI Tools by Country.

Measure	**Finnish (n=8)**	**Pakistani (n=20)**
Mean confidence score (1-5)	3.12	4.10
Standard deviation	1.36	0.91

Pakistani participants report notably higher confidence levels (M = 4.10, SD = 0.91), while Finnish participants exhibited lower trust levels (M = 3.12, SD = 1.36). The large Finnish standard deviation indicates substantial variability among individuals, ranging from experienced professionals with conscious scepticism to startup employees actively engaged in the usage of AI for their routine work tasks.

5.2.5 Cross-Team Collaboration's Impact on Overall Productivity

Participants were asked if AI tools have strengthened their inter-team communication among their teams or organizational departments. Figure 9 explains a significant correlation between time collaboration and its effects on the overall productivity of the teams.

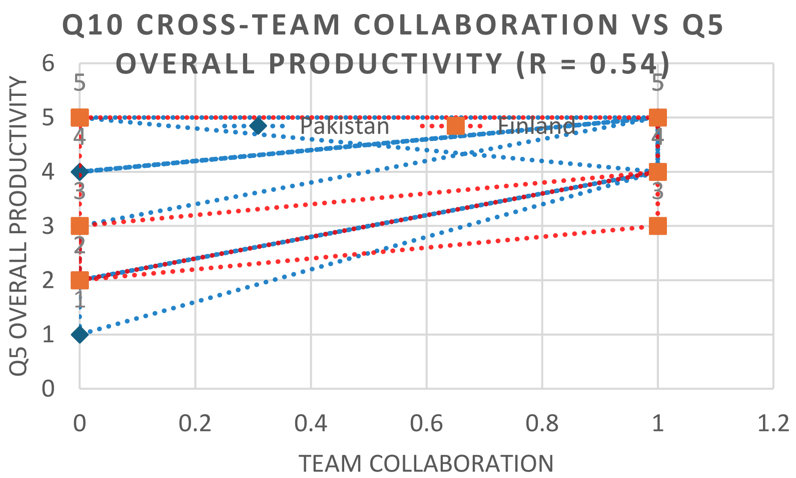


Figure 9. Scatter Plot 2 – Q10 Cross-Team Collaboration vs. Q5 Overall Productivity.

To study whether the cross-team collaboration was enhanced by using AI tools, which actually exhibited greater benefits in overall productivity, a Spearman correlation was implemented between Q5 (overall productivity) and Q10 (cross-team communication and collaboration). The plotting showed a positive correlation between the two variables (r=0.54), which is the most robust relationship among all the factors plotted against each other in the study. This reveals that those individuals who affirmed AI's role in excelling the cross-team communication testified to enhanced perceived productivity in their routine software project processes. Only 12.5% of Finnish participants reported that AI has enhanced cross-team communication, as compared to the 75% of Pakistani participants. The moderately positive correlation (r=0.54), therefore, explains the phenomenon - Finnish AI integration remains individualistic at its core, while Pakistan's AI improvements exhibited a positive impact on group-level collaborations. The results align strongly with the STS Theory, which states that a singular technology alone is not a capable force of massive organizational changes - the integration of tools within the social and structural workflow is just as essential (Raftopoulos and Hamari, 2024).

Overall, the RQ1 results show a consistent trend: Pakistani IT professionals report greater perceived productivity, more significant time efficiencies, higher confidence levels, and more extensive collaborative use of AI than Finnish counterparts. These differences indicate varying stages of adoption (IDT), socio-technical alignment factors (STS Theory), and the cultural orientations that shape new technology evaluation.

5.3 Professional Perceptions of AI in Software Development (RQ2)

This section focuses on RQ2: How do software professionals in Pakistan and Finland differ in their perceptions of AI's role in enhancing software development efficiency and creativity? The evaluation examines four aspects: AI as a potential threat or advantage, job displacement fear, AI's influence on personal creativity, and emphasis on coding craftsmanship

5.3.1 AI as a Potential Threat or Opportunity

The open-ended descriptive question on whether participants perceive AI as a threat or an opportunity produced a variety of nuanced responses, categorized into four thematic groups. Table 10 shows the distribution for each group.

Table 14. Perception of AI as Threat or Opportunity.

Perception Category	Finnish (n=8)	Finnish %	Pakistani (n=20)	Pakistani %
Primarily an Opportunity	2	25.0%	15	75.0%
Both or Nuanced	5	62.5%	3	15.0%
Primarily a Threat	1	12.5%	2	10.0%
Conditional or depends on use	0	0.0%	0	0.0%

Pakistani participants displayed more optimism in perceiving AI as beneficial, with 75% of them declaring it as a positively impactful technology, focusing on operational gains, automation of iterative functions, and new, novel financial prospects enabled by honing AI skills. A Pakistani respondent also characterized AI as a direct augmenter of human capability, decreasing overwork, and allowing experts to apply their energies to more cognitively strategic tasks. Finnish respondents exhibited more ambivalence, with 62.5% offering sophisticated, multifaceted viewpoints, conceding potential merits, while expressing reservations about its broader moral, ecological, and social ramifications. An experienced Finnish professional carrying more than 15 years of industrial experience under his belt argued that generative AI involves numerous issues to be assessed chiefly on its practical value. This trend aligns with the cross-cultural model: Finland's low uncertainty avoidance is expressed through careful, evidence-based engagement rather than blind enthusiasm regarding the inclusion of AI in daily use (Hofstede, 2001).

5.3.2 The Threat of AI-driven Job Displacement

Participants were explicitly asked whether they felt concerned about AI taking over their employment and opportunities. Figure 10 illustrates the comparative correlation.

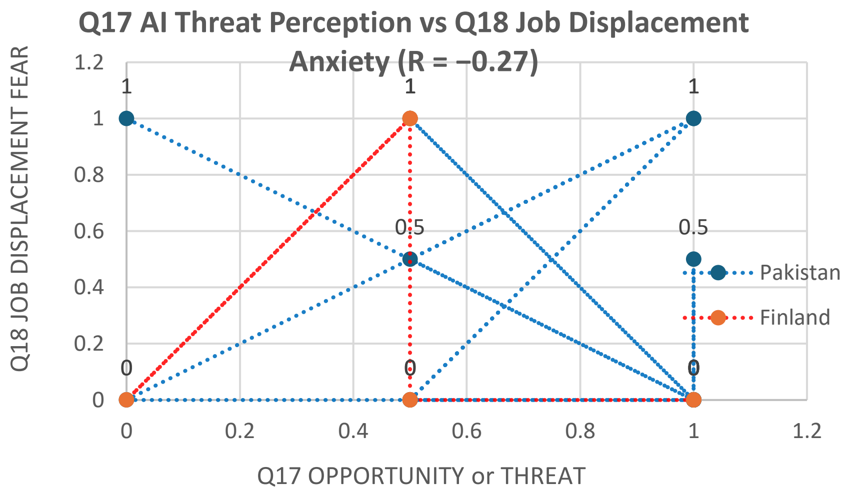


Figure 10. Scatter Plot 3 – Q18 Job Displacement Anxiety vs. Q17 Opportunity or Threat.

To analyse the relationship between the broader AI perception as a threat or opportunity and the fear related to job displacement, a Spearman correlation was conducted between Q18 (anxiety over job displacement) and Q17 (perception of AI as a threat or opportunity). Contrary to expectations, the relationship exhibited a negative correlation (-0.27), showing that perceiving AI as a threat or opportunity does not necessarily translate into them not being anxious from their fear of losing their job. This counterintuitive result shows that job displacement due to AI remains an independent variable unaffected by whether the professional is perceiving AI's boom as a threat or an opportunity.

A large share of Finnish participants (37.5%) report direct concerns of joblessness, as compared to Pakistani participants (15%), despite Finnish IT professionals reporting smaller productivity improvements from AI. This is consistent with research indicating that professionals in advanced technological ecosystems assess the risk of AI-driven labour displacement more critically (Venkatesh et al., 2003).
Most of the respondents from the Pakistani cohort (75%) show an optimistic approach by fully rejecting AI's threat to opportunities, often stating that AI is only a risk for those who are unwilling to adapt - a growth-oriented and adaptive mindset aligning with the relatively less experienced profiles of the Pakistani cohort.

5.3.3 AI's Influence on Creativity and Engineering Orientation

The relationship between perceiving AI as a tool for propelling creativity and the subjective engineering orientation of an individual in viewing software as a valuable business value-generating commodity or a craft is uniquely illustrated below in Figure 11.

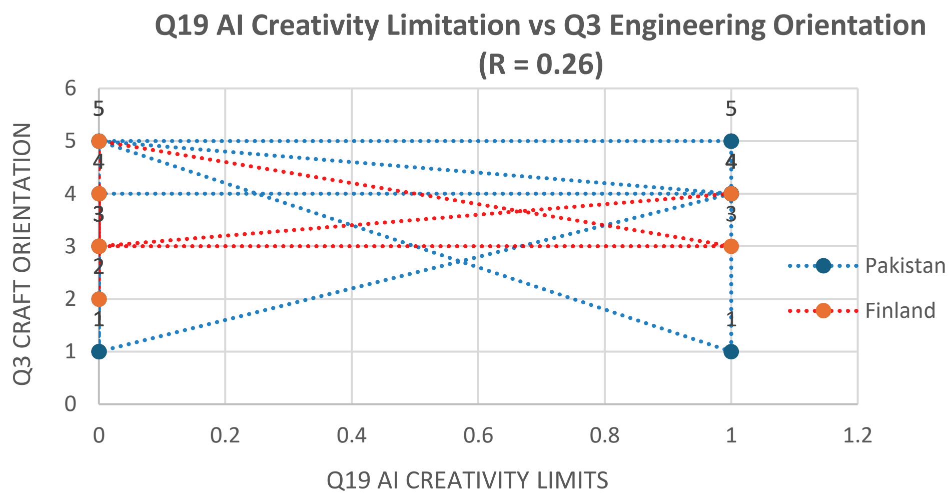


Figure 11. Scatter plot 4- Q19 AI Creativity Limitation vs. Q3 Engineering Orientation (r=0.26).

To study whether software engineering orientation impacted the perception regarding AI's creative impact, a Spearman correlation was done between Q3 (value vs craft) and Q19 (AI as a creativity limiter). This scatter plot revealed a weak positive correlation, implying that those individuals who lean towards software creation as a craft-focused engineering endeavour tend to perceive AI as a creativity inhibitor, while those who are more value-focused, or business-oriented professionals, are less likely to deem AI as a creative constraint.

Most participants in both the cohorts do not consider AI to inherently constrain creativity, although the Finnish cohort showed a marginally greater extent (37.5) than Pakistani respondents (30%). This aligns with the STS theory perspectives in mature technological ecosystems, that AI leads to similar results and restricts the distinctiveness of one's technical expression. Among those participants who responded negatively, the open-ended responses from both sides exhibited agreement over AI's role in the enhancement of individual creativity, increasing the bandwidth of output approaches, offering a wide array of possibilities, and reducing mental overload from routine tasks, giving room to more advanced creative activities (Pakalapati et al., 2023).

5.3.4 Software Engineering Orientation

Participants of the questionnaire elucidated their philosophy regarding software development by using a 5-point scale: 1 (strongly value-focused, prioritising code quality) to 5 (strongly value-focused, prioritising product delivery and business impact).

Table 15. Worker Orientation Mean Scores (1 = Craft-focused, 5 = Value-focused).

Measure	Finnish (n=6 with data)	Pakistani (n=17 with data)
Mean orientation score	3.17	3.29
Standard deviation	0.75	1.57

Both cohorts are clustered around the midpoint (3 = balanced). However, the main difference lies in dispersion of responses: the Pakistani cohort shows nearly double variation (SD = 1.57 vs. 0.75), indicating a considerable ideological heterogeneity. The Finnish group displayed uniformity in their responses, reflecting a more standardized professional environment. This finding is directly relevant to observing AI adoption: value-focused developers may accept AI-generated code with less scrutiny, while craft-focused developers impose rigorous quality standards - a pattern visible in the code-quality perceptions discussed in Section 5.2.2.

5.4 Organisational and Environmental Factors Shaping AI Adoption

Beyond personal points of observation, the survey also analysed key institutional factors shaping the AI adoption: formal training provision, self-directed learning, workplace encouragement, and budget constraints. These factors are closely related to TAM and STS frameworks, which acknowledge that adoption outcomes are highly influenced by both the environment and the technology being deployed and used.

5.4.1 Organisational Training Influencing Overall Productivity

Respondents were asked about their organizational support for acquiring AI operational skills, specifically formal AI-related training. Figure 12 illustrates the Spearman correlation between organizational training efforts and perceived productivity.

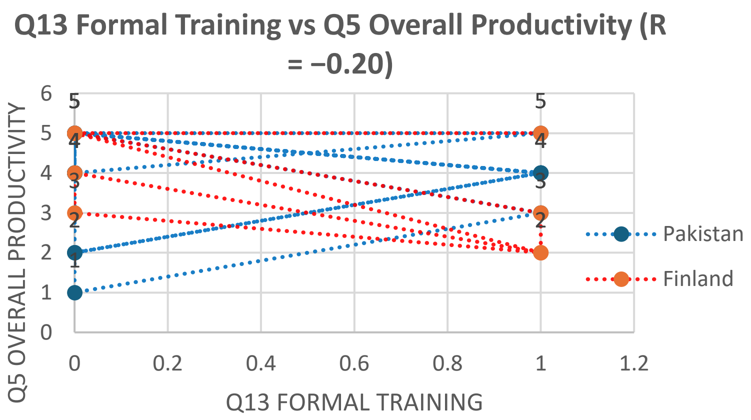


Figure 12. Scatter Plot 5- Q13 Organization Training Facilitation vs. Q5 Overall Productivity (-0.20)

To study whether organizational training and facilitation translate into higher productivity outcomes, we analysed the two variables Q13 (formal workplace AI training) and Q5 (overall productivity) using Spearman correlation. Astonishingly, the analysis revealed a weak negative correlation between the two variables (r=-0.20), confirming that formal workshops and trainings do not guarantee productivity enhancements.

Finnish organizations are more likely to offer structured AI training (50%) than Pakistani organizations (25%). This is paradoxical, as Finnish IT professionals report lower productivity improvements at the same time, suggesting that formal training alone is not enough to ensure deep adoption of skills and effective outputs. The limited means of formal training in Pakistan stand out in light of higher productivity ratings, suggesting that Pakistani IT professionals are self-driven, self-taught AI practitioners.

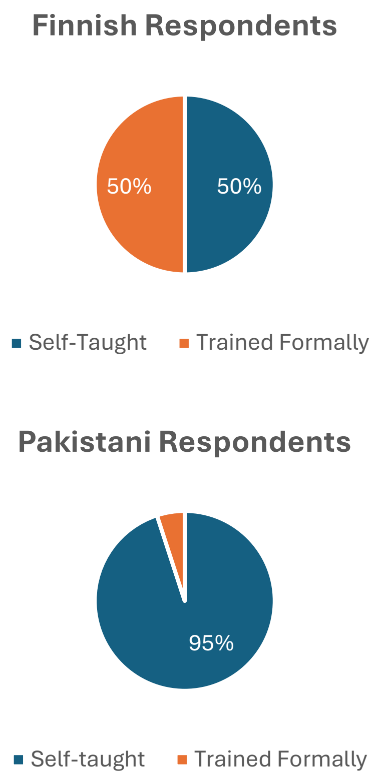


Figure 13. Self-Taught AI Learning: Finnish vs. Pakistani Respondents.

An overwhelming 95% of Pakistani participants report engaging in self-learning for acquiring AI prowess as compared to 50% of Finnish participants. Pakistani professionals described various methods they have adopted for learning generative AI models, including paid online courses, YouTube tutorials, workshops, practical experiments using tools like ChatGPT, Cursor, and Copilot, and acquiring professional certifications from accredited institutions. The high rate of independent self-learning demonstrates personal motivation and hence proves higher productivity scores: proactive learning develops higher tool proficiency and achieves higher performance scores by prompt generation optimization and output validations (Tahir Abbas et al., 2025). Critically, all the 20 participants from Pakistan affirmed that poor training leads to lesser efficacy in AI usage - a unanimous position underscoring the vitality of skill-development and knowledge enhancement in the effective use of AI.

5.4.2 Impact of Workplace Encouragement and Budget Constraints on Overall Productivity

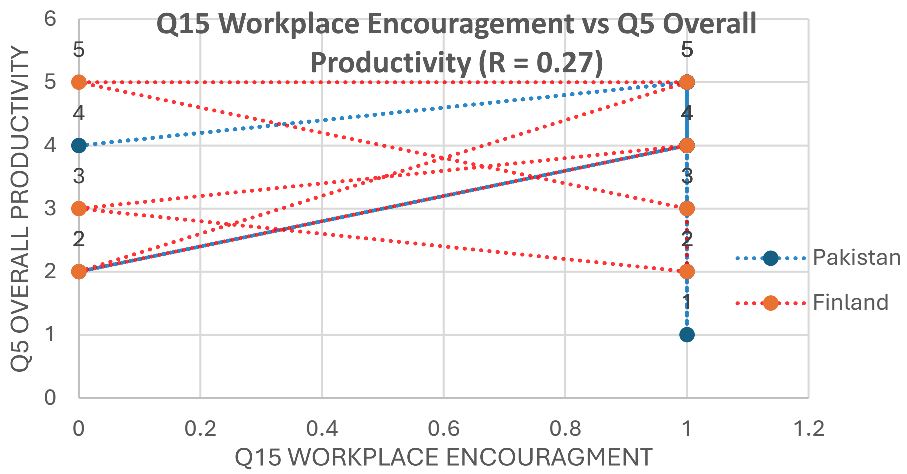


Figure 14. Scatter Plot 6- Q15 Workplace encouragement vs. Q5 Overall Productivity.

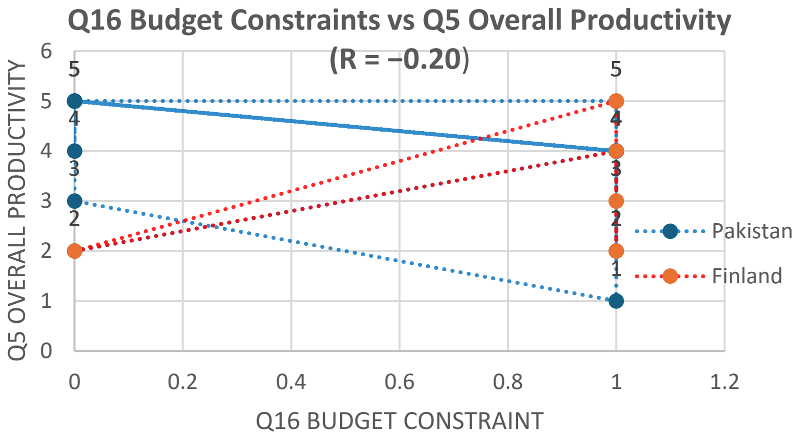


Figure 15. Scatter Plot 7 - Q16 Budget Constraints vs. Q5 Overall Productivity.

To examine how organizational support assists in transforming AI-driven productivity outcomes, Spearman correlation was utilized for these two organizational factors: budget constraint (Q16 vs. Q5, r=-0.20) and workplace encouragement (Q15 vs. Q5, r=0.27). Although both correlations are modest in strength, the consistency of their direction is theoretically significant.

The workplaces in Pakistan are considerably more supportive of transitioning into the routine usage of AI (90%) than the organizations in Finland (62.5%), challenging the preconceived notion that technologically advanced ecosystems are inherently more prone to adopting the new technologies with ease. However, the weak correlation (r = 0.27) indicates that workplace facilitation is not sufficient as a standalone factor; it functions only as an enabler and not as a direct productivity propagator. The budget constraint finding presents an equally revealing paradox: The finding regarding budget limitations is surprising: 87.5% of Finnish respondents report budget limitations restricting AI tool access, versus 50% of Pakistani respondents. This weak correlation (r=-

0.20) reflects that even modest structured IT procurement processes in Finnish organizations create barriers in the adoption of new AI subscriptions, whereas Pakistani professionals in startups may have more autonomy to use free or low-cost AI tools. This also supports the idea that Finnish AI adoption is more subject to institutional resistance than individual hesitation.

5.5 The relationship between Ethical Concerns and Job Experience

The survey analysed the relationship between job seniority level and the concerns raised by the respondents about legal and ethical issues surrounding AI-generated content and copyright violations with model-generated code scripts. Figure 16 clearly shows the main findings.

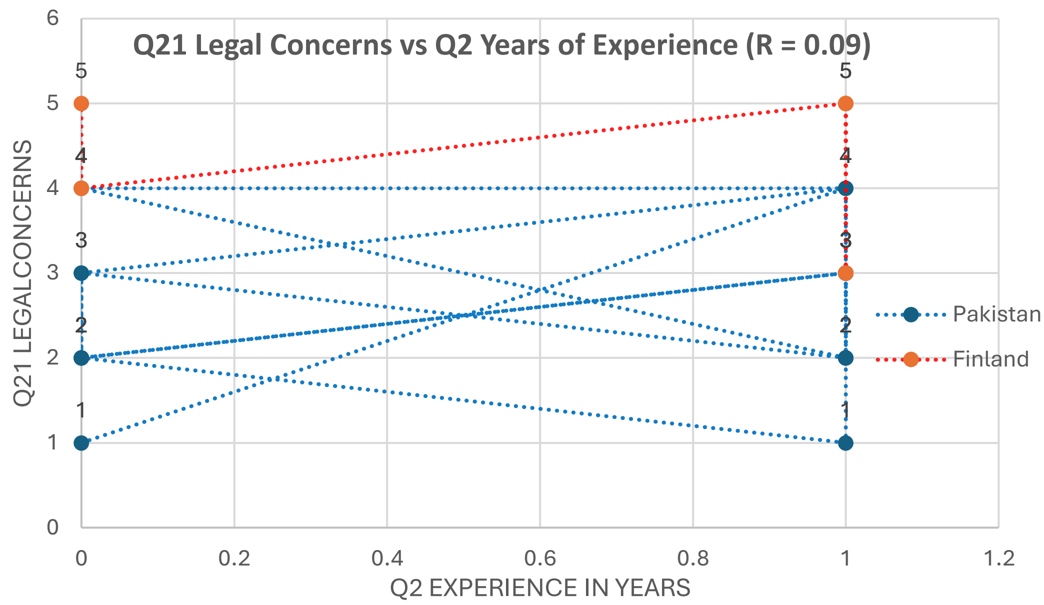


Figure 16. Scatter Plot 8 – Q21 Legal Concerns vs. Q2 Job Experience Years.

To investigate whether the seniority levels of a professional influence their legal and copyright awareness surrounding AI-generated code or output, a Spearman correlation was plotted between Q2 (years of professional experience) and Q21 (legal concerns about AI-generated output). The study revealed a non-significant correlation (r=0.09), showing that legal concerns are independent of job experience levels. This near-zero finding exhibits that awareness of legal concern regarding AI-generated output is a global concern, irrespective of professional seniority, equally experienced among professionals holding varied levels of job experience. Legal and copyright issues are equally common across similar levels in both groups, around 60–65%, drawing similarity between the cross-country survey at a point, while all other datasets show contrasting results. This tells that irrespective of the country or experience level, legal and regulatory risks are widely recognized as a challenge within the software community during the implementation of AI.

Qualitative responses highlight key subtleties. Finnish respondents expressed deeper systematic concerns: one respondent shared a concrete example of observing an LLM replicate a colleague's open-source library without attribution or licensing information. Pakistani participants more often described their responses using best-practice approaches - on reviewing, validating, and modifying the AI-generated code before deployment. This pragmatic perspective indicated that for many Pakistani developers, copyright concerns lead to careful review practices rather than outright resistance to AI-produced content.

5.6 Synthesis of Findings in Relation to Theoretical Frameworks

The results across Sections 5.1 to 5.5 together show a very consistent, coherent, and theoretically grounded situation of AI tool adoption and professional perceptions around it differ between the Finnish and Pakistani software professionals. Table 13 maps the critical empirical findings against the four prime theoretical frameworks sketched in Chapter 3.

Table 16. Key Findings Mapped to Theoretical Frameworks.

Theory	**Analytical Lens**	**Empirical Finding**
Innovation Diffusion Theory (Rogers, 2003)	Pakistan = early-majority adopters; Finland = pragmatic late-majority adopters	Confirmed: Pakistani professionals show higher adoption depth, broader time savings, and more diverse AI use cases across all productivity measures
Technology Acceptance Model (Davis, 1989)	Perceived Usefulness and Ease of Use determine adoption outcomes	Pakistani professionals report higher Perceived Usefulness (productivity, code quality) and confidence. Finnish show selective, conditional Perceived Usefulness moderated by seniority and quality standards
Socio-Technical Systems Theory (Trist and Bamforth, 1951)	Productivity outcomes depend on social and organisational embedding, not tool capability alone	Confirmed: Pakistani teams show higher cross-communication improvement and workplace encouragement, driving broader organisational benefits. Finnish adoption remains predominantly individual-level
Cross-Cultural and Technological Maturity (Hofstede, 2001)	Cultural dimensions shape AI attitudes and adoption trajectories	Finnish respondents show systemic risk awareness and nuanced threat-opportunity framing. Pakistani show optimism-dominant, opportunity-first orientation with high self-directed learning investment

The most vital theoretical insight is that the difference in productivity between Pakistan and Finland is not due to the difference in tool availability or capability but rather to the combined influence of adoption depth, intensity of self-directed learning, organizational culture, and professional maturity. Pakistani professionals, despite limited formal training, report significantly higher perceived productivity gains, driven by deeper adoption engagement, a younger and more enthusiastic workforce, and highly encouraging workplace dynamics.

Finnish professionals exhibit a pattern that can be described as cautious, informed engagement, selective use of AI, greater scepticism regarding code quality, authenticity and creativity impacts, stronger concern for systemic ethical issues, and greater readiness to recognize real limitations. This approach does not indicate failed adoption but reflects professional maturity, regulatory awareness, and a strong quality-focused engineering culture (Bérubé et al., 2021).

These findings have important practical implications for both countries in the given adoption context. Pakistani software houses can capitalize on their current adoption momentum but need to invest in formal knowledge systems to ensure AI adoption leads to sustainable, high-quality outcomes rather than just increased speed. Finnish organizations could improve outcomes by lowering structural barriers, especially budget constraints linked to procurement processes and the lack of team-level AI integration, and by fostering proactive learning environments within organizations that convert existing AI awareness into deeper integration within daily workflows.

6 Discussion

This chapter discusses the results that are deduced and presented in Chapter 5 with respect to the two research questions RQ1 and RQ2 guiding this study, and maps them against the existing literature, and reflects on their practical and theoretical outcomes.

6.1 Overview

The findings of this study entail the empirical evidence on how software professionals in both countries, namely, Pakistan and Finland, in which the study is conducted, perceive the impact of AI tools on productivity, code quality, and professional confidence. There is a straightforward relation that is revealed in this analysis: Pakistani participants reported higher levels of optimism in all perceptions across all variables, whereas the Finnish participants exhibited mixed perceptions and a higher variance. The following sections explain the results in the context of RQ1 and RQ2.

6.2 RQ1: AI Adoption and Innovation Results

Research Question 1 of the study was: *To what extent does the adoption of AI tools impact productivity in software projects within software houses in Finland and Pakistan*

The data shows a **positive association between AI adoption and perceived productivity and innovation outcomes** across the combined sample. Subjects from Pakistan reported a strong mean productivity score of 4.30 – a figure lying strongly on the ‘agree’ range – and a robust correlation between productivity and AI confidence ($r = 0.756$, $p < 0.001$) substantiates that the IT professionals who use AI tools with greater ease also tend to show greater output gains. This aligns with Brynjolfsson et al. (2023), who emphasized that meaningful access to AI tools increases productivity, as measured by issues resolved per hour, by 14% on average, and 34% improvement for low-skilled and novice workers.

The results from the **code quality** investigations deserve particular attention to this subject matter. Pakistani subjects showed a Neutral majority of 52%, indicating that even though the inclusion of AI in development practices adds to the overall pace and confidence, its influence on the code quality is not as readily apparent - maybe because the actual effects on code cannot be assessed until a formal validation is done. On the other hand, Finland's cohort showed a higher polarization among its responses (43% Strongly Disagreed), denoting a higher standard in technical maturity and validation scrutiny applied by senior developers: senior developers often subject AI-generated code to rigorous validation standards or may have found it cumbersome to apply AI-generated codebases for complex, production-grade software.

The critical finding from Tufano et al. (2024) is that automated code review techniques tend to succeed on structurally uncomplicated cases and have a hard time with the more complex ones. As the paper states, current approaches risk "targeting the readily obtainable gains, being successful in exclusively rudimentary code review contexts, which are improbable to preserve an engineer's time."

There is a robust positive relationship between all three variables (r = 0.59–0.76), which indicates that AI's merits in the dynamics of software development are not standalone – **quality, productivity, and confidence form a reinforcing cycle.** The adoption confidence is a strong marker of subjective perception of both quality and productivity benefits, while those who are less confident report fewer gains across the board. This places great importance on the adoption strategy: investment in garnering AI skills and users' confidence may facilitate multiplicative performance gains spanning a range of performance metrics.

6.3 RQ2: Comparative Perceptions Between Pakistan and Finland

RQ2 of the research study asked: *How do software professionals in Pakistan and Finland differ in their perceptions of AI's role in enhancing software development efficiency and creativity?*

A systematic directional pattern was observed: **Pakistani professionals expressed more homogenous positive perceptions regarding AI**; however, Finnish professionals exhibited higher sceptical views. This pattern can be explained through two interpretive frameworks: professional experience and the adoption stage.

Adoption stage: Pakistan represents a foundational stage of AI adoption in software development, where AI tools are more state-of-the-art, and the benefits are more observable and stimulating. The 'novelty excitement' effect – well-documented in the technology adoption papers – can correspond to why 81% of the subjects from Pakistan agree that AI boosts their overall productivity, and 95% report a faster rate of task completion. The Finnish technological market, where the use of the technology is more mature and sophisticated, may apply rigorous benchmarks in its perceptions of AI gains.

Professional Seniority: The respondents from the Finnish side were considerably more senior (71% had more than 15 years of experience versus 38% in Pakistan). Therefore, due to the seniority of engineers, they had a more nuanced and evidence-based view of the new AI models. Finnish higher standard deviations, particularly on code quality (SD = 1.70), stem from genuine technical debate within the Finnish distribution about where

AI supports value creation and where it falls short, rather than straightforward disengagement.

Additionally, the results show that Finnish **professionals receive more formal AI training (50% vs. 25%), yet** report lower confidence scores, which is counterintuitive. It may be indicative of higher levels of exposure to risks pertaining to higher levels of formal training, yielding a more calibrated rather than a simply optimistic view. In contrast, the absence of formal training in Pakistan may restrict them from being educated on the limitations of AI, as a majority of the Pakistani respondents (90%) confirmed that their workplace encourages it, which seems to foster substantial confidence through practice despite the lack of structured formal guidance.

The **budget-related divergence (87.5% Finland vs. 50% Pakistan)** warrants further examination. The Finnish organizations may operate under stringent procurement governance necessitating a formal business case reflective of a mature AI strategy rather than an underdeveloped one. In contrast to Pakistani startups, they have more informal cost structures and autonomous individual licensing allocation.

6.4 Practical Implications

For Pakistani technological firms: The strong confidence and enthusiasm for AI use provides an opportunity to leverage adoption momentum into structured, quality-oriented AI workflows, implementing formal code review mechanisms for AI-generated outputs, and focused, targeted training on AI reliability and constraints would enable productivity gains to be converted into objectively quantifiable and verifiable improvements in the system.

For Finnish software companies: The highly polarized opinions from the respondents regarding code quality point to disparities in internal organization capability. It is the duty of the organizations to conduct team-wise assessment about which one has been able to capture AI benefits more and which one hasn't and should also foster peer-learning. If the fiscal limitations are encapsulated within the ROI frameworks for AI tool acquisition, this could further expedite the AI adoption at companies where financial constraints remain the primary impediment.

For regulatory authorities and IT trainers: Formal AI training makes a huge impact, as substantiated empirically by the differences in training provisions (25% in Pakistan vs. 50% in Finland) of the two countries and their profound implications. These trainings should also include critical assessment of AI outputs beyond tool-level proficiency. Facilitating formal AI training in Pakistan can be achieved by the formal inclusion of university-level courses and vocational programmes to accelerate the spread of AI literacy and reinforce the experimental learning model that is currently the primary mode.

6.5 Limitations

This research contains several limitations that must be recognized. The Finnish sample is significantly smaller in size (n=8) and therefore holds lesser weightage for robust country-level comparisons. While directional trends are stable and interpretable, inferential analysis is underpowered, and the findings should not be extrapolated to the broader Finnish software industry by relying on this sample size alone, without expanding the study pool size. Second, all outcomes are subjective perceptions of individuals participating in the study. High confidence and positive AI perceptions in Pakistan may be influenced by optimism bias, rather than actual, objective performance-related improvements.

Third, cross-sectional design precludes causal inference - the correlation between quality, confidence, and productivity does not determine which factor drives the other. Finally, sampling via professional networks such as WhatsApp, LinkedIn, Discord, and Email may disproportionately overrepresent individuals already engaged with AI, potentially causing bias resulting in a positive outcome.

7 Conclusion

7.1 Summary of the Study

This master's thesis analysed and studied the influence of AI tool adoption on software project process productivity through a cross-national quantitative survey consisting of 28 IT professionals in Finland (n=8) and Pakistan (n=20). The impetus of this research originated from the research gap in the comparative empirical evidence on how the integration of AI shapes software productivity across varied geographical environments with disparate levels of organizational and technological maturity. A scaled survey was used to examine three fundamental AI-related factors were examined: perceived productivity, code quality, and professional confidence in AI tools.

7.2 Key Findings

Three central findings were observed. First, AI adoption is **positively** linked with **perceived** productivity across both national contexts, with a substantial relationship between AI confidence and **productivity** ($r = 0.756$, $p < \mathbf{0.001}$**) constituting** the most compelling empirical evidence for supporting RQ1. Second, Pakistani respondents expressed more uniformity in their perception of AI across all dimensions, while Finnish **respondents**, though higher in their seniority levels, showed more heterogeneous and cautious perspectives, particularly with respect to code quality. This trend is indicative of differences in professional experience, adoption maturity, and organizational culture, rather than reflecting a straightforward "more developed = more positive relationship". Third, organizational factors - including training provisions, workplace encouragement, and budget governance - show substantial variations between the two countries and are interrelated with individual AI perceptions in multifaceted ways.

7.3 Contributions

From a theoretical perspective, this research study provides a comprehensive empirical gross national comparison of AI adoption perception between two distinct national environments, such as Pakistan and Finland, two countries that are representative of opposing ends of the spectrum of software industry technological maturity. The finding that adoption enthusiasm does not linearly correspond to technological maturity challenges simplistic linear models of technology diffusion and underscores the importance of context-sensitive analytical frameworks. Practically, this research provides evidence-based insights for IT corporations, HR practitioners, and pedagogical trainers in Pakistan and Finland, who are aspiring to enhance techniques of AI integration.

7.4 Recommendations for Future Research

Future researchers should expand the Finnish and Pakistani sample sizes to at least 80-100 respondents per respective country, to facilitate statistically rigorous comparative studies, as delineated within the preliminary investigative framework. A mixed-method follow-up study, including semi-structured one-on-one interviews, would offer richer insights into the discerned divergence among the Finnish senior software engineers with respect to AI and code quality, a factor that continues to be insufficiently elucidated by the current survey data alone.

Longitudinal studies tracking identical practitioners over a 12 to 24-month duration would enable researchers to analyze how AI adoption perceptions evolve as technological systems advance and user familiarity increases. Finally, distinguishing between discrete classifications of AI tools, such as generative AI code assistants, AI-driven testing tools, and AI-powered project management, would yield more sophisticated insights into where AI generates consistent value across national contexts.

7.5 Closing Remarks

The AI integration into routine software practices is no longer an idea of the future; rather, it is the current reality of the software professionals surveyed in this study.

This research demonstrates that AI tools are generally and broadly understood as facilitators of productivity, although the characteristics like score, depth, and confidence of these perceptions differ significantly across national and professional contexts. Narrowing the gap between high levels of adoption enthusiasm and rigorously evaluated, quality-assured use will necessitate investment beyond technological tools, encompassing training, governance mechanisms, and professional culture. It is emphasized that AI adoption broadly promises enhanced productivity and performance, but its impact differs greatly across social, cultural, demographic, and professional groups, with employees lacking strong digital proficiency facing disadvantages that create social disparities, leading to the risk of losing their jobs (Landsbergis et al., 2014). Across both countries of Finland and Pakistan, realizing AI's full potential in software productivity is fundamentally shaped by the interaction of several human and technological factors.

References

Alayrac, J.-B., Donahue, J., Luc, P., Miech, A., Barr, I., Hasson, Y., Hutchinson, B., Langesio, P., Mensch, A., Millican, K., Reynolds, M., Ring, R., Rutherford, E., Cabi, S., Han, T., Gong, Z., Samangouei, P., de Freitas, N., & Simonyan, K. (2022). Flamingo: A visual language model for few-shot learning. *Advances in Neural Information Processing Systems, 35, 23716–23736.*

Ali Jan, M., Khan, F., & Iqbal, J. (2025). AI-driven digital innovation in Pakistan's software industry: Opportunities, barriers, and organizational readiness. Journal of Technology Management & Innovation, 20(1), 12–28.

Alomari, H. W., Ramasamy, V., Kiper, J. D., & Potvin, G. (2020). A User Interface (UI) and User eXperience (UX) evaluation framework for cyberlearning environments in computer science and software engineering education. *Heliyon*, *6*(5), Article e03762. https://doi.org/10.1016/j.heliyon.2020.e03762

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Davila Delgado, J. M., Bilal, M., Akinade, O. O., & Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities, and future challenges. Journal of Building Engineering, 44, 103299. https://doi.org/10.1016/j.jobe.2021.103299

Ajiga, D., Okeleke, P. A., Folorunsho, S. O., & Ezeigweneme, C. (2024). Enhancing software development practices with AI insights in high-tech companies. Computer Science & IT Research Journal, 5(8), 1897–1919. https://doi.org/10.51594/csitrj.v5i8.1450

Asikainen, M. (2025). AI adoption in Finnish companies: Leading the EU in generative AI usage. Business Finland. https://www.fairedih.fi/en/2025/12/10/finland-leads-europe-in-generative-ai-adoption/

Asim, M., Khan, W. A., Lali, M. I. U., & Raza, A. (2023). Challenges and opportunities of AI adoption in Pakistan: A systematic review. Journal of King Saud University – Computer and Information Sciences, 35(2), 101–114.

Bagozzi, R. P. (2007). The legacy of the Technology Acceptance Model and a proposal for a paradigm shift. Journal of the Association for Information Systems, 8(4), 244–254. https://doi.org/10.17705/1jais.00122

Bérubé, J., Laplante, F., & Charland, P. (2021). Employee resistance to AI in the workplace: Drivers and mitigation strategies. International Journal of Human–Computer Studies, 149, 102599. https://doi.org/10.1016/j.ijhcs.2021.102599

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., … Amodei, D. (2020). Language models are few-shot learners. Advances in Neural Information Processing Systems, 33, 1877–1901.

Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). Generative AI at work. National Bureau of Economic Research. https://doi.org/10.3386/w31161

Chanderhas, R., & Pardeshi, P. (2022). A Research Review: Ai and Data Science Applications in the Telecom Industry. *IBMRD's Journal of Management & Research*, *11*, 196–210.

Chew, R., Kery, M. F., Akalin, N., & Fecher, A. (2023). LLM-assisted content analysis: Using large language models to support deductive coding. arXiv preprint arXiv:2306.14924.

Dai, S.-C., Xiong, A., & Ku, L.-W. (2023). *LLM-in-the-loop: Leveraging large language model for thematic analysis*. arXiv preprint arXiv:2310.15100. https://arxiv.org/abs/2310.15100

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Dell'Acqua, F., McFowland, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F., & Lakhani, K. R. (2023). Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality. Harvard Business School Working Paper No. 24-013.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. Proceedings of NAACL-HLT 2019, 4171–4186. https://doi.org/10.18653/v1/N19-1423

European Investment Bank. (2025). *EIB Investment Survey 2025: Finland overview*. European Investment Bank. https://www.eib.org/en/publications/20250218-econ-eibis-2025-finland

Feuerriegel, S., Dolata, M., & Schwabe, G. (2020). Fair AI: Challenges and opportunities in machine learning for decision-making. Business & Information Systems Engineering, 62(4), 379–384. https://doi.org/10.1007/s12599-020-00650-3

Gaube, S., Suresh, H., Raue, M., Merritt, A., Berkowitz, S. J., Lerdiansari, R., Kovacs, G., Rajpurkar, P., Tschandl, P., Topol, E. J., & Seltzer, J. (2023). As AI makes radiology faster, will it actually help doctors? Patterns, 4(7), 100765. https://doi.org/10.1016/j.patter.2023.100765

Gerosa, M. A., Wiese, I., & Steinmacher, I. (2024). Biases in large language models for software engineering tasks. ACM Transactions on Software Engineering and Methodology, 33(5), 1–35.

Hashfi, R. A., & Raharjo, T. B. W. (2023). AI-powered decision making in project management: A systematic review. Procedia Computer Science, 216, 555–564.

Hassan, A., Ahmed, Z., & Imran, M. (2024). AI-driven test automation in software development: Reducing error rates and accelerating SDLC. IEEE Access, 12, 45872–45891. https://doi.org/10.1109/ACCESS.2024.3012345

Hofstede, G. (2001). Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations (2nd ed.). Sage Publications.

Kalliamvakou, E. (2022, September 7). Research: Quantifying GitHub Copilot's impact on developer productivity and happiness. *GitHub Blog*. https://github.blog/2022-09-07-research-quantifying-github-copilots-impact-on-developer-productivity-and-happiness/

Kauhanen, A., Maczulskij, T., & Maliranta, M. (2023). Tekoälyn vaikutukset työhön Suomessa [The effects of AI on work in Finland]. ETLA Economic Research Report B278.

Kaur, K., Rani, R., & Bhatt, A. (2020). AI-based requirement optimization in agile software development. International Journal of Advanced Computer Science and Applications, 11(5), 331–338.

Kirchner, K., Razmerita, L., & Nabeth, T. (2025). Knowledge management in the age of generative AI: Trust, validation, and human-AI collaboration. Knowledge Management Research & Practice, 23(1), 88–102.

Landsbergis, P. A., Grzywacz, J. G., & LaMontagne, A. D. (2014). Work organization, job insecurity, and occupational health disparities. American Journal of Industrial Medicine, 57(5), 495–515. https://doi.org/10.1002/ajim.22126

Le, T.-D. B., & Andrzejak, A. (2024). Persistent context limitations in AI-assisted code completion tools. Empirical Software Engineering, 29(3), 72. https://doi.org/10.1007/s10664-024-10459-6

Martínez, J. M. G., Fernández-Villarán, A., & Sánchez-Chaparro, T. (2022). Organisational learning as a mechanism for AI adoption in resource-constrained SMEs. Technological Forecasting and Social Change, 183, 121940.

McCarthy, S., Sammon, D., & Alhassan, I. (2021). Examining AI adoption challenges: The role of algorithmic bias in organisational decision-making. Information Systems Journal, 31(6), 950–976.

Miller, T. (2021). Explainability for artificial intelligence in healthcare: A multidisciplinary perspective. BMC Medical Informatics and Decision Making, 19(1), 317. https://doi.org/10.1186/s12911-019-0966-0

Milton, A., & Al Busaidi, A. S. (2023). Leadership in AI-enabled organisations: Emotional intelligence as a critical competency. Leadership & Organization Development Journal, 44(4), 521–537.

Mohan, V. (2024). Navigating digital transformation: Leadership strategies for AI integration. Journal of Leadership Studies, 17(2), 44–58.

Muratovic, H., Halilovic, E., & Mesic, A. (2025). Risks of GenAI in software architecture and high-level design: Managing technical debt and creative suppression. Software: Practice and Experience, 55(2), 112–130.

Nielsen, J., & Molich, R. (1989). Teaching user interface design based on usability engineering. *SIGCHI Bulletin*, *21*(1), 45–48. https://doi.org/10.1145/67880.67885

Pakalapati, S., Shetty, S., & Rao, K. V. (2023). Addressing data privacy and ethical considerations in AI-enabled software development. International Journal of Information Management Data Insights, 3(1), 100152.

Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. Automation in Construction, 122, 103517. https://doi.org/10.1016/j.autcon.2020.103517

Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The impact of AI on developer productivity: Evidence from GitHub Copilot. arXiv preprint arXiv:2302.06590. https://arxiv.org/abs/2302.06590

ProPakistani. (2025, March 6). Zong 4G integrates DeepSeek AI to accelerate automation and efficiency. *ProPakistani*. https://propakistani.pk/2025/03/06/zong-4g-integrates-deepseek-ai-to-accelerate-automation-and-efficiency/

Raftopoulos, M., & Hamari, J. (2024). Organisational silos and AI integration failure: The structural barriers to cross-functional AI adoption. Computers in Human Behavior, 150, 107952.

Ragazou, K., Passas, I., Garefalakis, A., & Galariotis, E. (2022). Investigating the research trends on strategic ambidexterity, agility, and open innovation in SMEs: A bibliometric analysis. Journal of Open Innovation: Technology, Market, and Complexity, 8(2), 90.

Rashid, A., & Kausik, A. (2024). AI-driven automation in software development: A comprehensive review of tools, techniques, and future directions. IEEE Transactions on Software Engineering, 50(4), 1123–1145.

Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

Satyro, W. C., Contador, J. C., Contador, J. L., & Sacomano Neto, M. (2021). Industry 4.0: Forces and challenges on companies for information technology adoption towards creating a competitive differential. Technological Forecasting and Social Change, 163, 120437.

Senapathi, M., Buchan, J., & Osman, H. (2018). DevOps capabilities, practices, and challenges: Insights from a case study. Proceedings of the 22nd International Conference on Evaluation and Assessment in Software Engineering 2018, 57–67.

Sposato, R. (2024). Leadership agility in digital transformation: Managing AI integration effectively. Business Horizons, 67(1), 21–33.

Strachan, J. W. A., Albergo, D., Borghini, G., Pansardi, O., Scaliti, E., Gupta, S., Saxena, K., Rufo, A., Panzeri, S., Manzi, G., Graziano, M. S. A., & Becchio, C. (2024). Testing theory of mind in large language models and humans. *Nature Human Behaviour*, *8*, 1–11. https://doi.org/10.1038/s41562-024-01882-z

Svyatkovskiy, A., Zhao, Y., Fu, S., & Sundaresan, N. (2020). IntelliCode compose: Code generation using a transformer. Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (2020), 1433–1443. https://doi.org/10.1145/3368089.3417058

Sun, Q., Yu, Q., Cui, Y., Zhang, F., Zhang, X., Wang, Y., Gao, H., Liu, J., Huang, T., & Wang, X. (2023). Emu: Generative pretraining in multimodality. arXiv preprint arXiv:2307.05222. https://arxiv.org/abs/2307.05222

Tahir Abbas, S., Waheed, A., & Zafar, S. (2025). Ethical AI frameworks in software development: Bias detection, fairness, and governance in emerging markets. Journal of Information Technology & Politics, 22(1), 33–51.

Treude, C., & Hata, H. (2023). She elicits requirements, and he tests: Linguistic bias in software engineering. In Proceedings of the 45th International Conference on Software Engineering (pp. 2555–2567). IEEE. https://doi.org/10.1109/ICSE48619.2023.00215

Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. Human Relations, 4(1), 3–38. https://doi.org/10.1177/001872675100400101

Tufano, R., Scalabrino, S., Bavota, G., & Oliveto, R. (2024). Automated code review in practice. Proceedings of the 46th International Conference on Software Engineering. https://doi.org/10.1145/3597503.3639182

Vermeeren, A. P. O. S., Law, E. L.-C., Roto, V., Obrist, M., Hoonhout, J., & Väänänen-Vainio-Mattila, K. (2010). User experience evaluation methods: Current state and development needs. In *Proceedings of the 6th Nordic Conference on Human-Computer Interaction: Extending Boundaries* (pp. 521–530). Association for Computing Machinery. https://doi.org/10.1145/1868914.1868973

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Xiao, Z., Yuan, X., Liao, Q. V., Abdelghani, R., & Oudeyer, P.-Y. (2023). Supporting qualitative analysis with large language models: Combining codebook with GPT-3 for deductive coding. In *Proceedings of the 28th International Conference on Intelligent User Interfaces* (pp. 75–78). ACM.

Yang, A., Li, Z., & Li, J. (2024). *Advancing GenAI assisted programming: A comparative study on prompt efficiency and code quality between GPT-4 and GLM-4*. arXiv preprint arXiv:2402.12782. https://arxiv.org/abs/2402.12782

Figures:

Figure 2. Kostiainen, J. (2024, April 26). *Can AI boost productivity in Finland?* Nordea. Retrieved 2026-04-17 from https://www.nordea.com/en/news/can-ai-boost-productivity-in-finland

Images:

Image 1. Asikainen, M. (2025, December 10). *Finland leads Europe in generative AI adoption*. Finnish AI Region FAIR EDIH. Retrieved 2026-04-17 from https://www.fairedih.fi/en/2025/12/10/finland-leads-europe-in-generative-ai-adoption/

Image 2. İlayda Yağmur Derviş, (2023, 28 August). A comprehensive guide to the Software Development Life Cycle (SDLC). Product Coalition. Retrieved 2026-04-17 from https://medium.productcoalition.com/a-comprehensive-guide-to-the-software-development-life-cycle-sdlc-15b7892e1d44

Image 3. Warfield, D. (2024, February 16). *Flamingo – Intuitively and exhaustively explained: The architecture behind modern visual language modeling*. Towards Data Science. Retrieved 2026-04-17 from https://towardsdatascience.com/flamingo-intuitively-and-exhaustively-explained-bf745611238b/

Image 4. Strachan, J. W. A., Albergo, D., Borghini, G., Pansardi, O., Scaliti, E., Gupta, S., Saxena, K., Rufo, A., Panzeri, S., Manzi, G., Graziano, M. S. A., & Becchio, C. (2024). Testing theory of mind in large language models and humans. *Nature Human Behaviour*, *8*, 1–11. https://doi.org/10.1038/s41562-024-01882-z

Image 5. Abbas, T., Rathore, S. A., Turki, A., Khan, S., Alghushairy, O., & Daud, A. (2025). Enhancing software engineering with AI: Innovations, challenges, and future directions. *IET Software*, *2025*(1), 5691460. https://doi.org/10.1049/sfw2/5691460

Appendices

About the Survey: This survey is part of a master's thesis study on how artificial intelligence tools and technologies affect software development productivity in Pakistan and Finland.

Objective: The purpose of this study is to gain an understanding of how AI tools (e.g., GitHub Copilot, ChatGPT, Tabnine, etc.) are currently used, what patterns of use exist, and how they impact software project outcomes, developer productivity, and team efficiency.

Participants: It is intended for software developers, user interface (UI) and user experience (UX) designers, project managers, QA testers, team leads, and others working on software development projects in Pakistan or Finland.

Time Required: It will take approximately 10-15 minutes to take the survey.

Confidentiality: All responses will be kept strictly confidential and will only be used for research purposes, so your identity will not be revealed or given out to anyone else.

Voluntary Participation: Participation is completely voluntary, and you can withdraw at any time.

Section 1: Demographic and Professional Background

Q1. What is your primary job area? *

- Frontend Development
- Full-Stack Development
- DevOps/Infrastructure

- Backend Development
- Data Engineering/Data Science
- Mobile Development (iOS/Android)
- Machine Learning/AI
- Embedded Systems/IoT
- Software Design (UI/UX, Product design, interaction design)
- Software Project Management
- Technical Writing/Documentation
- Game Development
- Other

Q2. How many years of professional experience do you have in your field? *

- Less than 2 years
- 2-5 years
- 5-10 years
- 10-15 years
- More than 15 years

Q3. Which statement best describes your view of software engineering? *

1 – Strongly craft-focused: prioritise code quality, elegant solutions, and technical excellence

3 – Balanced: I equally value craft and business impact

4 – Moderately value-focused: I lean toward business impact but maintain code quality

5 – Strongly value-focused: I prioritise shipping features and delivering business value

(Strongly Craft-Focused ○ ○ ○ ○ ○ Strongly Value-Focused)

Q4. What is the size of your current company? *

- Startup (<50 employees)
- Small company (50–200 employees)
- Mid-sized company (200–1000 employees)
- Large company (1,000–10,000 employees)
- Enterprise (10,000+ employees)
- I am self-employed/freelancer

Section 2: AI Adoption and Software Usage

Q5. On average, AI tools help me increase my productivity during my daily job tasks. *

(Strongly Disagree ○ ○ ○ ○ ○ Strongly Agree)

Q6. Can you describe a specific area where your productivity has increased since adopting AI?

Q7. Do you complete your tasks faster now compared to before using AI tools? *

- Yes
- No

Q8. Using AI has improved the quality of my code. *

(Strongly Disagree ○ ○ ○ ○ ○ Strongly Agree)

Q9. On average, how much time per week do AI-powered coding assistants (e.g. GitHub Copilot, Cursor, Tabnine) save you? *

- 0-1 hours
- 1-4 hours
- 5-7 hours
- 8-10 hours
- More than 10 hours

Section 3: Productivity Outcomes (RQ1)

Q10. Have AI tools improved cross-communication between your teams/departments? *

- Yes
- No

Q11. How confident are you in using AI tools in your routine job tasks? *

(Not confident at all ○ ○ ○ ○ ○ Very Confident)

Q12. Have you independently sought out AI-related learning (through personal resources, tutorials, documentation, or self-study)?

Q13. Does your organisation provide proper training (workshops, webinars, self-training sessions/resources) for AI tools? *

- Yes
- No

Q14. Does poor training reduce AI benefits in your work? *

- Yes
- No

Q15. Does your workplace encourage using AI tools in your job tasks? *

- Yes
- No

Q16. Are there budget constraints that limit your AI tool usage in your organisation? *

- Yes
- No

Section 4: Professional Perception of AI (RQ2)

Q17. Do you see AI as a threat or an opportunity? Explain your choice.

Q18. Do you feel threatened by the possibility of AI replacing your job? *

- I feel threatened
- I do not feel threatened
- Other

Q19. Do AI tools limit creativity? *

- Yes
- No

Q20. How do AI tools expand your problem-solving abilities?

Q21. Do you worry about legal issues while using AI-generated/AI-inspired code? *

- Yes
- No

Q22. Are you concerned about the copyright issues with AI-generated work?