

ADDIS ABABA UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

SCHOOL OF COMMERCE

DEPARTMENT OF BUSINESS AND INFORMATION SYSTEMS

Measuring the Impact of AI Tools on the Productivity of Staff in the Case of World Bank Ethiopia Office

A Thesis Submitted to the department of business and information systems in Partial Fulfilment of the Requirements for the Degree of Master of Science in Business Information Systems

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I, the undersigned, declared that this research project is my own original work and has not been submitted for any award at any other university.

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Abstract

This study assessed the effect of Artificial Intelligence (AI) tools on the productivity of Staff of the World Bank Ethiopia Country Office. Data was collected from 70 employees to analyze the relationships between AI tool adoption, task features, AI literacy, organizational readiness and perceived performance impact. The study employed a quantitative cross-sectional survey design based on the task-technology fit (TTF) framework. From the data, we have witnessed the AI tools are making a big difference. They speed up and simplify routine tasks and which boost productivity.

The study identified key gaps in prompting and practical user skills as well as a disconnect between leadership goals and the training provided to staff. The findings confirm that AI literacy is a stronger predictor of productivity gains than frequency of use. Highlighting the importance of investing in human capital to maximize returns on technology. The study concludes with practical recommendations for the organization to address these gaps. And also strengthen AI's role in supporting knowledge work, including the development of transparent governance policies and tiered, skills-based training programs.

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Chapter 1: Introduction

1.1 Background of the Study

There is tremendous interest in how AI can increase people's productivity at work. To help meet this interest, in December 2023, Microsoft released the first AI and Productivity Report (Cambon et al. 2023) creating the results of many Microsoft studies on AI and productivity. These studies contributed to a large and growing literature from around the world.

When we see it from knowledge management view AI increases creation, sharing, and retrieval of systematic reviews. Artificial intelligence (AI) encompasses computational methods that teach data to assist or automate cognitive tasks. In knowledge-intensive organizations AI has shifted from experimentation to integration. For example, copilots summarize meetings, draft briefs, search large knowledge bases, and translate cross-lingual evidence. Randomized and experimental workplace studies show factual productivity gains typically double-digit and quality improvements with the largest benefits accruing to less experienced staff who can emulate best practice patterns raised by models (Brynjolfsson, Li, & Raymond, 2025; Dell'Acqua et al., 2023).

In creative knowledge work, AI reorients effort towards critical integration, to curate and evaluate model outputs against domain constraints, rather than production per se (Sarkar, 2023). In low- and middle-income countries (LMICs) inclusive AI needs foundations of affordable connectivity, computer, skills and local data. Assessment of global policies indicates a risk that without this AI could widen productivity and opportunity gaps (UNCTAD, 2025; International Labour Organization [ILO], 2024). Ethiopia's ecosystem is growing and there are use cases in agriculture, health and education, but capability constraints persist (GSMA, 2025). In this context, the World Bank Ethiopia Country Office (CO) has piloted AI to facilitate drafting, analysis and collaboration but evidence at the office level on impact on productivity is limited.

The purpose of this thesis is to measure the impact of AI tools on the productivity of Staff in Ethiopia CO and identify the types of workflows with the biggest potential gains and explain how AI literacy and organizational readiness set the conditions for such gains.

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1.2 World Bank Ethiopia Country Office

The World Bank Ethiopia CO located in Addis Ababa on Africa Avenue, Bole Road anchors a long-standing partnership with Ethiopia. Over two decades the Bank supported expanded access to essential services. The Bank works with the government of Ethiopia and partners across human capital, digital transformation, social protection, agriculture, climate resilience, and institutional capacity (World Bank, 2024; World Bank Africa Region, 2024).

1.2.1 World Bank and AI

The World Bank has comprised AI as part of its digital transformation strategy to improve service delivery and project outcomes. AI applications within the World Bank include data-driven policy analysis, automated translation tools, and predictive models for economic forecasting. These tools aim to support efficiency, reduce operational costs and support evidence-based decision making across global offices.

1.2.2 AI in World Bank Ethiopia Country Office

The World Bank Ethiopia Office is actively integrating AI into its operations. focuses include AI Powered Solutions for Development, Digital Public Infrastructure and AI Foundation, Human Capital and AI integration.

AI tools are being piloted to support and improve access to healthcare, education and financial services while enhancing disaster and climate resilience.

Digital Public Infrastructure and AI Foundations- as the backbone for digital transactions that can enable interoperability across sectors. AI is viewed as a major enabler for DPI, facilitating data-driven governance and inclusive digital services. Human Capital & AI Integration AI is used to improve human capital development with analytical and decision-making tools. The World Bank's Digital and AI for Human Capital team is leading the way in embedding AI into education and workforce planning.

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Local Context and Challenges

Ethiopia is ready for AI but faces challenges, including siloed approaches, gaps in infrastructure and limited technical capacity. These are being implemented by the World Bank Ethiopia Office through partnerships and capacity building programmes.

1.3 Statement of the Problem

Generative AI tools are universal today, but there is little empirical evidence for their effectiveness. Most of the existing work has focused on global technology companies or private sector services. Few studies currently measure outcomes at the clinic level. But the context of public development is quite different. The Ethiopia Country Office (CO) has its own specific challenges such as varied levels of infrastructure and skills and cannot depend on global studies. In this thesis, I estimate speed, quality and error reduction at the office level across prioritized workflows and test the specific roles of AI literacy and organizational readiness.

Mostly, people assume if you give someone AI powers, they will be more productive. But that misses the concept of task technology fit (TTF). Local policy writing, mission-driven stakeholder coordination, and the breadth of highly specialized work that staffs do in the Ethiopia Country Office. General-purpose AI tools just don't fit the nuanced needs of these specific workflows and if they don't, it's safe to say that the technology will almost certainly create friction and user frustration, not efficiency. So there's a big knowledge gap. "We need to know if AI is driving productivity here and how the software is addressing the needs of people's everyday work, and how that affects performance."

1.4 Why the World Bank Ethiopia Office?

The selection of the World Bank (WB) Ethiopia Country Office as the primary empirical site for this research is a deliberate methodological decision rather than a choice of convenience. To establish a robust case study, this selection is justified across three critical academic and practical dimensions: the low- and middle-income country (LMIC) socio-technical gap, the unique cognitive complexity of international development knowledge work, and the institutional readiness of the organization.

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First, this selection directly addresses the LMIC socio-technical gap in current literature. While empirical research on Generative AI (GenAI) and professional productivity is expanding rapidly it remains heavily concentrated within private-sector technology firms located in High-Income Countries (HICs). This geographic and sector-based concentration creates a significant empirical blind spot. The socio-technical landscape of a public international development organization in an LMIC like Ethiopia is fundamentally different, characterized by distinct infrastructural realities such as connectivity fluctuations localized cultural attitudes toward technology adoption and unique organizational workflows. By focusing on the Ethiopia Country Office this study tests the boundary conditions of Western-centric AI productivity theories in a challenging real-world development context.

Second, the nature of the knowledge work performed at the WB Ethiopia office provides an ideal laboratory for studying cognitive complexity. Unlike highly standardized digital tasks like basic customer support or routine software coding, which dominated early GenAI research World Bank staff manage a highly complex "hybrid" portfolio. Their daily responsibilities span a wide spectrum of cognitive demands, ranging from structured administrative compliance and routine reporting to highly unstructured, politically sensitive tasks. These complex tasks include drafting multi-sector project designs, formulating macroeconomic forecasts, and navigating delicate policy dialogues with government ministries. This diverse operational environment serves as a rigorous testing ground for the Task-Technology Fit (TTF) framework, allowing us to analyze how AI fits tasks of varying ambiguity and strategic importance.

Finally, the study is justified by the office's immediate institutional readiness and the practical need for a strategic baseline. The World Bank Group has actively pioneered institutional AI integration by provisioning secure, enterprise-approved tools, specifically Microsoft Copilot and their custom internal AI model, MAi. This deployment creates a rare "natural experiment" where staff have authorized secure access to advanced large language models within a protected data environment. However, because these tools were deployed recently, the Country Management Unit (CMU) lacks empirical localized baseline data to measure the actual operational return on this technology investment. This study fulfills a practical institutional need by providing the CMU with a diagnostic assessment to guide future training budgets, optimize user adoption and establish safe localized AI governance frameworks.

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1.5 Research Questions

1. What impact does adoption of enterprise approved AI tools have on the productivity of staff at the World Bank Ethiopia Country Office?
2. Which tasks are more likely to benefit from productivity gains from AI?
3. How much of the difference in staff productivity growth is due to AI literacy?
4. What is the moderating effect of organizational readiness factors (policy clarity, training, tools access, workflow fit) on the magnitude of productivity effects?

1.6 Objectives of the Research

General Objective: To investigate the impact of AI tools on productivity with a focus on addressing key research gaps such as ethical concerns, regional contexts, and long-term implications.

Specific Objectives:

1. Identify enterprise-approved AI tools currently in use in the Ethiopia CO and how frequently they are used by task type
2. Measure changes in productivity associated with the adaptation of these AI in the tasks identified Test whether AI literacy mediates productivity gains associated with AI tool use and explore challenges and opportunities for optimal productivity increase.
3. To examine the ethical and privacy implications of enterprise-approved AI tools adoption
4. Explain heterogeneity in productivity outcomes and identify enabling conditions and failure modes
5. Produce practical recommendations for responsible adoption in the Ethiopia CO
6. To generalize how development organizations can align AI tools with existing knowledge-sharing practices

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1.7 Significance of the Study

This study is significant both practically and theoretically in the context of measuring the impact of AI tools productivity. The results offer evidence-based insights to guide institutional decision-making regarding investments in AI-enabled tools, staff training and governance frameworks. By identifying high impact use cases and understanding the role of AI tools in productivity. The study showed that productivity is a function of the type of task and supports prioritizing resource allocations to the applications with the most operational value.

The findings support internal accountability through responsible and effective AI use. This will ensure compliance with ethical standards, developmental objectives and organizational policies. In theory, this study adds to the literature on AI in knowledge work by exploring the use of AI in an LMIC institutional context. This study says current research does not represent this enough. The study also provides insights into the roles of AI literacy and organizational readiness. Seeing the two as intervening variables in productivity outcomes. This will help to inform the measurement and conceptualization of productivity in AI supported KW environments. The contributions collectively advance scholarly knowledge and practical application of AI in international development organizations.

1.8 Scope of the Study

The study is geographically limited to the World Bank Ethiopia Country Office. The target population is staffs in different units who perform analytical, coordination and administrative tasks daily. The study employed a quantitative approach to measure productivity. This allows us to collect concrete results and user experiences . Key variables are the level of AI usage, staff literacy, organizational readiness and types of tasks.

We only employ enterprise-approved AI tools currently authorized by the World Bank. This includes meeting transcription tools, writing copilot tools, smart search for document retrieval and the like. Staff are increasingly turning to these tools to generate draft content, synthesize information. But this study is strictly limited to the office level operations. This makes the research feasible within the time constraints, while still providing practical insights for similar development organizations.

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The scope of this study is strictly limited to the analysis of enterprise-approved AI tools (e.g., Microsoft Copilot, MAi) that have been officially deployed and sanctioned for use by the World Bank. The exclusion of public-facing AI tools, often referred to as consumer tools (such as the free versions of ChatGPT or Gemini), was a deliberate and critical methodological boundary enforced by the institution's operational and security realities. The primary justification for this limitation is data confidentiality and risk management.

As a public international financial institution, the World Bank handles highly sensitive, non-public data, including government information, financial records, and confidential project documents. When data is entered into external, public AI tools, control over that data is lost, as it may be stored, processed and potentially used for model training outside the organization's secure environment. This creates a significant risk of data exposure and breach of confidentiality, which is unacceptable for an institution of this nature.

Secondly, the use of sanctioned tools is a matter of compliance and legal responsibility. The World Bank operates under stringent international regulations, internal governance protocols, and data protection standards comparable to GDPR. Utilizing unauthorized public AI platforms for official work could violate these data protection regulations and create legal liability. Enterprise tools like Microsoft Copilot and the internal MAi platform are deployed within a controlled, secure environment. They are integrated with existing World Bank systems and access rules, meaning the AI adheres to the same user permissions that govern all other institutional data. Critically, these enterprise solutions guarantee that internal data is not used to train public models and include built-in compliance features such as data encryption and audit logs.

Finally, by focusing exclusively on enterprise-approved tools, this study avoids the issue of "Shadow AI" the uncontrolled use of unapproved software by employees, which leads to data leakage and security blind spots. The institution's strategy is not just about controlling risk; it is also about providing tools that are practically integrated into daily workflows within applications like Microsoft Teams, Word, and Outlook. Therefore, by limiting the scope to these sanctioned tools, this research ensures that its findings are valid, relevant, and directly applicable to the real-world operational and security context of the World Bank Ethiopia Country Office.

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Chapter 2. Literature Review

2.1 Introduction

AI is increasingly transforming knowledge into intensive worksites by augmenting cognitive work such as drafting, summarization, analysis, information retrieval and decision support. With organizations increasingly relying on staff whose work is primarily interpretative and creative, the prospect of AI impacting productivity has become a concern in both academic research and organizational practice. Recent advances in generative AI machine learning and intelligent knowledge systems are accelerating the transition from experimental use of AI into daily workflows.

The literature on productivity gains from AI adoption is expanding. There is also evidence of unevenness to these gains. Outcomes vary depending on the type of task, the knowledge and skills of the worker, and the context within the organization. This variant is particularly pertinent for development organizations and offices operating in low- and middle-income countries (LMICs) where digital infrastructure, AI literacy and institutional readiness may vary widely from the private-sector settings of high-income countries.

This literature review is the foundation for the theories of knowledge work and productivity, the convergence between AI and knowledge management processes, and the empirical evidence of productivity effects of AI. It also provides the context of the findings in Ethiopia and LMIC context to contribute to the conceptual framework of the study.

Knowledge Management in the Era of AI and AI-Based Tools for Knowledge Workers

Digital age has changed how companies manage information using AI and knowledge management (KM). As discussed in the literature (2025), traditional KM has been hindered by old data, data fragmentation, and long manual processes. The old KM is being replaced by new dynamic ecosystems embedding integrated AI.

In these new systems, AI is not a data repository. But rather a thought partner for AI that actively transforms fragmented data into actionable insights. AI tools can automate repetitive KM tasks of

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knowledge workers such as document classification, and information retrieval. It changes organizations from information storage to knowledge synthesis. The application of AI in KM structures can substantially improve the efficiency of business processes by enabling knowledge creation, sharing, and utilization (Dash et al. (2025)). But this integration also brings new challenges. Challenges like the need to trust algorithmic decision-making and the technical challenge of integrating AI with legacy systems.

Ethiopia & LMIC Context for Knowledge Management (KM) & AI Integration

We can see the integration of AI in visible manner to improve KM systems in offices all over the world. But in LMICs such as Ethiopia implementation is largely led by structural and socio-technical realities. The KM infrastructure of Ethiopian organizations needs to be upgraded, and the successful integration of AI is contingent upon overcoming some local constraints. However, the deployment of AI-based KM in countries such as Ethiopia is often hamstrung by digital infrastructure gaps, data privacy concerns and lack of advanced digital skills (GSMA, 2025; UNCTAD, 2025). AI-based KM has been shown to help fill knowledge gaps in dispersed organizational units.

This emphasizes the need to carefully regulate the use of AI tools. so that we understand the regional differences as opposed to generalized Western data which is quite important in the Ethiopian development sector due to localized, context-heavy knowledge. The productivity gains of the integration of AI-KM for knowledge workers in the World Bank Ethiopia office are not only reliant on the technology itself but also on the organizational readiness on developing AI literacy and culture of knowledge sharing.

2.2 Theoretical framework

2.2.1 Knowledge Work and Knowledge Worker Effectiveness

The idea of knowledge workers provides a theoretical basis for understanding productivity in today's organizations. Drucker (1999) describes knowledge workers as people whose primary task is to create, apply and interpret knowledge rather than engage in physical labor. Productivity in

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knowledge work is more difficult to define and measure as it requires independence, decision making and problem solving skills unlike manual labor.

This supports Kelley's (1985) argument for the importance of creativity and problem solving to knowledge work, as quality and originality of output are as important as speed or volume. Davenport (2005) also notes that knowledge workers have different motivators, work processes and performance measure needs from other workers. As Davenport notes, effective management of knowledge work involves paying attention to task complexity, cognitive load, and the tools that help people think and work together.

Each of these views points to the multidimensional character of productivity in knowledge work, and that productivity cannot be reduced to simple counts of output. Productivity, instead, is best thought of as a combination of efficiency (time and effort), effectiveness (quality and accuracy) and learning or capability development over time.

2.2.2 Theories of AI and Knowledge Management Integration

The theory of knowledge management (KM) is a useful perspective to look at the impact of AI on the productivity of knowledge workers. The creation of organizational knowledge is a dynamic process of converting tacit and explicit knowledge through socialization, externalization, combination and internalization (Nonaka & Takeuchi, 1995). Alavi and Leidner (2001) use this model to identify systems and processes that facilitate the creation, storage, sharing and application of knowledge.

Within this theoretical tradition AI is conceptualized as an enabler of KM processes. AI-based systems can automate classification of documents, improve retrieval of information and accelerate access to relevant expertise. AI may enhance the efficiency and effectiveness of knowledge work by reducing search costs and cognitive overload.

According to Brynjolfsson and McAfee (2017), this interaction is part of a larger trend towards human–machine collaboration. In which digital technologies are used to supplement, rather than replace human capacity. Productivity gains from this perspective are achieved by successfully integrating the computational power of machines with human judgement, creativity and contextual understanding in organizations.

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2.2.3 Knowledge Management and AI Tool in the Context of LMIC and Ethiopia

In Ethiopia, AI and knowledge work are still in their infancy but growing rapidly. Many of Ethiopia's emerging AI use cases are macro-level in sectors like agriculture, health and public services, but face the challenge of existing gaps in digital infrastructure and technical skills (GSMA, 2025). Ethiopian knowledge workers, especially those working in international development organisations, academia and policy formulation, have specific contextual challenges in applying AI. AI models are mostly trained on Western-centric data and do not understand the localised Ethiopian contexts, socio-economic nuances or regional languages (e.g. Amharic data).

UNCTAD (2025) highlights that in LMICs the productivity gains of artificial intelligence may be severely constrained by gabs in connectivity, data availability and digital skills. Without intentional investments in organizational readiness and capacity building, the deployment of advanced AI tools could widen, rather than narrow, existing productivity gaps. The specific impacts of AI on Knowledge Workers (KWs) in LMICs therefore require a separate treatment in this context.

Analytical and creative work by knowledge workers requires constant access to information. In resource constrained settings, AI tools can be very helpful to overcome the traditional infrastructure bottlenecks through, for example, automating literature reviews, providing summaries of local field data, and translating complex policy documents quickly. The United Nations (2024) warns that the rapid uptake of enterprise AI could leave KWs in low-income settings behind if local skills development and AI literacy do not keep pace.

For the knowledge worker in Ethiopia, then, the "fit" of an AI tool is in large part a function of the tool's ability to address these local complexities. If an AI tool is not able to accurately synthesize development data specific to Ethiopia on the organization's KM system, the utility of the AI tool disappears. Therefore, these contextual factors are particularly relevant for organizational studies in Ethiopia. They find that the productivity implications for AI, the need for AI literacy and the requirements for Task-Technology Fit are likely to be very different from those that have been observed in high income private sector environments.

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2.2.4 Theory of Measurement of Productivity

Knowledge worker productivity is typically measured through output quality, speed of task completion, volume of deliverables produced and accuracy and decision-making effectiveness (Nonaka, 1995; Yang, 2024). AI tools impact these indicators by reducing time burdens, improving accuracy, and improving task quality.

2.2.5 AI in Knowledge Work

The recent literature stresses that AI is not only a tool for automating routine work but also for reconfiguring creative and analytical work. As noted by Sarkar (2023), AI-altered creative work is a shift of effort from initial production to critical evaluation, integration and refinement of outputs. AI is not a replacement for creativity but it changes the nature of creative work and AI is a thinking partner that provides alternatives, finds patterns and offers exploration.

This finding is consistent with the importance of user skill to productivity gains. AI can accelerate and enhance quality if knowledge workers can critically evaluate and contextualize AI outputs. Poor skills or too much reliance on AI can degrade quality and judgment. This result has direct implications on the mediating role of AI literacy on productivity outcomes.

2.3 Empirical Review

2.3.1 Empirical Evidence on AI and Productivity

There is a growing body of empirical evidence that the adoption of AI can result in large productivity gains in knowledge intensive work. Brynjolfsson, Li and Raymond (2025) analyze large scale workplace data and find that access to generative AI tools leads to a large increase in worker productivity, especially for less experienced workers. They also observe heterogeneity in outcomes by skill and task type.

For example, Dell'Acqua et al. (2023) provide experimental evidence in professional services that AI can help increase both quantity and quality of output but with different effects depending on the nature of the task and the experience of the worker. Their results also reveal a "jagged technological frontier" where AI works well for some tasks but not for others, underscoring the need for human oversight.

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Large gains are found for tasks completed by workers using AI coding assistants, according to Cui et al. (2025), using randomized controlled trials at Microsoft, Accenture and a large firm. Again, this effect is strongest for less experienced workers and shows that AI can be a capability equalizing tool, embedding best practices into workflows.

Results are confirmed by other studies. Birhan (2024) finds positive links between the use of AI and productivity outcomes, and Sabina et al. (2024) finds that, at the firm level, productivity is higher when AI tools are more embedded in organizational processes. All in all, this evidence points to the fact that AI can improve productivity, but the size and quality of the gains will depend on the way and the users of AI. Taken together, the empirical findings support strongly the central proposition of the TTF theory.

The empirical findings strongly support the core proposition of TTF theory. Empirically, the 'heterogeneity in outcomes' across task types (Brynjolfsson et al., 2025) and the 'jagged technological frontier' (Dell'Acqua et al., 2023) demonstrate that productivity gains are not automatic but only occur when there is a strong alignment or 'fit' between the capabilities of the AI tool and the specific demands of the task being performed.

2.3.2 AI Literacy, Skills, and Human Capital

AI literacy is the knowledge, skills and attitudes needed to use AI systems responsibly and effectively (Hönigsberg et al., 2025). They find that the more AI-literate a user is, the more they translate access to AI tools into performance gains. In today's world, the productivity of people depends largely on their ability to understand and use AI.

Results support the inclusion of AI literacy as a mediating variable between AI use and productivity. Especially in sectors where digital skills are unevenly distributed. The International Labor Organization (2024) stresses that the implementation of AI without the necessary skills development may increase existing inequalities rather than enhancing productivity. in relation to human capital and labour. Where workers are not trained or not aware, they may not be able to use AI well, limiting the organization's returns on AI investments (International Labor Organization, 2024).

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In the TTF theory, AI literacy is the enabler of the operation and even if the task-technology fit is high, workers who lack AI literacy are not able to utilize this fit effectively and cannot convert the technology potential into actual performance enhancement.

2.3.3 Labor Productivity and AI theories

Theoretical explanations for the productivity effects of AI include:

a) Automation Theory - AI takes over routine cognitive tasks, freeing up workers to engage in higher-level conceptual tasks (Acemoglu & Restrepo, 2019).
b) Augmentation Theory AI destroys human skills Easier access to information Better insight extraction Better quality output (Brynjolfsson & McAfee, 2017)
c) Human-AI Collaboration Theory - The "Cyborg" and "Centaur" models (Dell'Acqua et al., 2023) exhibit productivity gains when humans strategically collaborate with AI Centaurs divide the labor between them and AI Cyborgs integrate AI into their workflow
d) Capability Theory and Digital Divide - Productivity gains in low income settings require infrastructure, skills and access (UN, 2024; GSMA Ethiopia, 2025). This is particularly true in Ethiopia.
e) Task-Technology Fit (TTF) Theory - The positive impact of technology adoption on individual performance depends on the fit between the capabilities of the technology and the specific demands of the user's tasks (Goodhue & Thompson, 1995). This theory is the main theoretical basis of the conceptual framework of this study, explaining why the above theories (automation, augmentation and collaboration) work or do not work depending on the underlying "fit" between AI tools and knowledge work.

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2.4 Conceptual Framework of the Study

The conceptual framework for this study, illustrated in Figure [X], is built upon an adapted version of the Task-Technology Fit (TTF) model (Goodhue & Thompson, 1995). This model was chosen over alternatives like TAM or UTAUT because it focuses on performance outcomes rather than just user acceptance, and its central emphasis on "Task Characteristics" is essential for testing this study's core hypotheses.

The framework maps the causal path from the initial inputs (the technology and the work) to the outcome (productivity), while also accounting for the contextual factors that moderate this process. The variables are organized into four distinct roles: independent, mediating, moderating, and dependent.

2.4.1 The Main Causal Path: From Inputs to Outcome

The core of the model explains the process through which technology impacts performance.

- Independent Variables (The Inputs): The process begins with two independent variables:
    1. Technology Characteristics: The features and capabilities of the AI tools.
    2. Task Characteristics: The demands and nature of the employee's work. These two variables interact to determine the level of perceived alignment.
- Mediating Variables (The Process): The effect of the inputs on the outcome is not direct; it is explained by a two-step mediation process:
    1. Task-Technology Fit (TTF): This is the primary mediator and represents the employee's cognitive perception of how well the technology's features match their task demands.
    2. Utilization of AI Tools: This is the secondary mediator and represents the employee's actual behavior. A strong perception of "Fit" leads to higher and more frequent "Utilization" of the tools. This path from Utilization to the final outcome is tested in Hypothesis 1 (H1).
- Dependent Variable (The Outcome): The final variable in the causal chain is:

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- Performance Impact (Productivity): This is the ultimate outcome of the model, representing the measured effect on an employee's work efficiency and effectiveness.

2.4.2 The Contextual Factors: The Moderating Variables

The model acknowledges that the main process does not occur in a vacuum. The strength of relationships in the causal path is influenced (or "moderated") by key contextual factors.

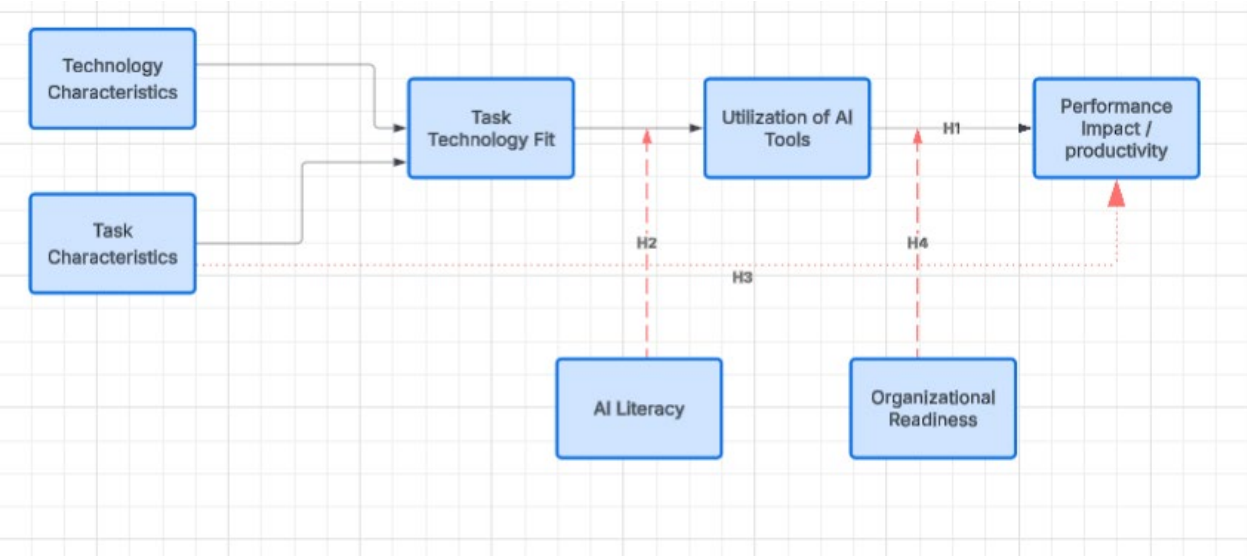
- AI Literacy (Moderator for H2): This variable represents the employee's practical skills, such as prompt engineering. As shown in the diagram, it moderates the path between Task-Technology Fit and Utilization. The theory posits that even with a perfect fit, an employee with low AI literacy will not be able to effectively utilize the tool, thus weakening this link.
- Organizational Readiness (Moderator for H4): This variable represents the institutional environment, including training and policies. It moderates the path between Utilization and Performance Impact. The theory posits that even high utilization will not lead to optimal productivity if the organization fails to provide adequate support, leading to errors or inefficient use.

2.4.3 The Final Hypothesis

- Task Heterogeneity (H3): This hypothesis is not represented by a single arrow but is tested by comparing the final Performance Impact across different groups defined by the initial Task Characteristics variable (i.e., comparing the outcomes for employees with "High-Routine" tasks versus those with "Low-Routine" tasks).

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Conceptual Framework



Description of the conceptual framework

Independent Variables: Technology and Task Characteristics

You have two independent variables in interaction and they deliver results. The first independent variable is Technology Characteristics (AI Tools). These include generative AI applications (MAI, Microsoft Copilot) in World Bank Ethiopia Office, document summarization, translation technologies, data analysis tools and AI enabled knowledge management systems. What gives them power? They can automate, augment human judgment, be easily integrated and satisfy data security standards.

The second independent variable is Task Characteristics. This reflects the nature of the specific knowledge work that staff are doing. This reflects the complexity, routineness and context sensitive needs of development work such as localized policy making, data analysis and information processing.

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Mediating Variables: Task-Technology Fit and Utilization

The existence of AI tools is related to productivity through two main mediators. The central mediator is Task Technology Fit (TTF) which is the degree to which the capabilities of the AI tools meet the demands of the user's tasks. The theory suggests that a high fit is directly associated with the second mediator, Utilization. Utilization is the behavioral dimension and refers to how often and how intensely employees actively use AI tools in their daily workflows.

Dependent Variable: Productivity

The final dependent variable of this study is the productivity (Performance Impact) of the staffs. Productivity is assumed as the efficiency and effectiveness of how well the employees perform knowledge intensive tasks. It can be measured by a few indicators such as time saved on routine tasks, the speed at which tasks can be completed, the quantity of output generated, the reduction in errors and the overall quality of analytical reports and written outputs.

Moderating Variables: AI Literacy and Organizational Readiness

There are a few variables that moderate these pathways and influence their direction and strength. Digital Skills and AI literacy are an important moderator between TTF and Utilization. But even with a high fit, employees need digital literacy to identify and use the tools well. another related factor moderating the Utilization-final Productivity relationship are: Organizational Readiness (leadership support, clear AI policies), Infrastructure Quality (reliable internet, computing resources), and Work Experience Level (less-experienced workers benefit from greater capability-equalizing effects of AI than highly experienced staff).

TTF Theory: Theory Background

The framework is structurally aligned with the Task-Technology Fit (TTF) theory (Goodhue & Thompson, 1995) to provide a robust theoretical base. TTF theory suggests that productivity gains are not only a function of the provision of AI tools but also a function of the "fit" of the technology with specific needs of knowledge work. A dependent variable (productivity) and a high fit results in an active use of the tools. The main contextual mechanisms in the model are the moderating variables that govern a worker's ability to recognize a good technological fit and whether that

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utilization can be translated into measurable performance gains in the organizational environment. An employee can evaluate if there is a good technological fit or not, and whether the organizational environment will allow that fit to translate into measurable performance gains.

2.5 Hypotheses of the Study

H1: Staffs are expected to gain productivity from AI tools. The more frequently employees use AI tools, the faster they will be able to complete tasks, the less iteration they will need and the fewer mistakes their outputs will have compared to the outputs of employees who use AI tools less frequently.

H2: AI literacy is anticipated to influence the degree of utilization of AI tools by employees. Employees with more skills and knowledge of AI are likely to benefit more in terms of productivity from using these tools.

H3. The impact of AI tools on productivity will depend on the nature of the task performed. AI is likely to deliver bigger gains in routine work – drafting, summarizing and information retrieval – than in complex analytical work that requires deeper judgment and interpretation.

H4: The efficacy of AI adoption is hypothesized to be affected by organizational readiness. AI tools are likely to drive productivity more in units where training is easier to obtain, there are clearer rules around the use of AI and there is more support for technology.

2.6 Definition of Terms / Concepts / Constructs

Conceptual Definitions:

1. *Knowledge Worker:* employees whose major tasks include cognitive, analytical and creative work (Sarkar, 2023).
2. *AI tool:* software that uses machine learning or generative models to help with drafting, summarizing, analysis, or search (Yang, 2024; Hayouni et al., 2024).
3. *AI literacy*: the knowledge and skills required to use AI effectively and responsibly (prompting, evaluation, citing) (Hönigsberg et al., 2025).
4. *Productivity:* task output and efficiency- speed, quality (expert/peer ratings), throughput and error rate (Brynjolfsson et al., 2025; Dell'Acqua et al., 2023)

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Operational Definitions:

1. *Tasks per hour:* the number of tasks you complete within an hour on standard office workflows (e.g. short memos, emails, notes)
2. *Turnaround time:* is the number of minutes from the start of a task to the completion of a draft.
3. *Revision cycles:* number of rounds of review needed to achieve acceptable quality.
4. *Perceived quality:* self- and peer-rated quality (Likert scale). Optional expert panel rating on sampled outputs.

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Chapter 3. Research Methodology

3.1 Research Methodology

The hypotheses will be empirically tested by means of a quantitative cross-sectional survey. We will use the Task-Technology Fit (TTF) conceptual framework. This approach is very suitable for the study as it allows collecting data on all variables of interest. from the target population at a point in time. The main aim is to investigate the relationships between characteristics of technology, characteristics of task, task-technology fit, use of AI tools, and productivity of staff.

This study will use a census approach as the target population is clearly defined, accessible and of manageable size. The method of a census is to survey every person in the population. This approach eliminates sampling error and provides a highly accurate dataset. This ensures that the results reflect the actual state of the variables across rather than an estimate based on a sample.

3.1.1 The Definitive Rationale for Using the Task-Technology Fit (TTF) Model

The selection of a theoretical framework is a critical decision that underpins the entire validity of a research study. For this thesis, the Task-Technology Fit (TTF) model was deliberately chosen over alternative frameworks like the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT) for three specific and compelling reasons.

1. *Focus on Performance, Not Just User Acceptance:*

Models like TAM and UTAUT are primarily designed to predict a user's intention to adopt a new technology, focusing on factors like "Perceived Ease of Use" and "Perceived Usefulness." However, the research problem of this thesis is not about adoption. The World Bank has already deployed these tools. The core objective is to measure the impact on actual job performance and productivity. The TTF model is specifically designed to evaluate performance outcomes, making it the most appropriate framework to answer the research questions.

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2. *The Centrality of the "Task" to the Core Hypothesis:*

A central inquiry of this study, formalized in Hypothesis 3 (H3), is to investigate whether the impact of AI differs between routine vs. complex tasks. The TTF model is the only major information systems framework that explicitly places "Task Characteristics" at the very center of its causal structure. Alternative models do not provide a strong theoretical basis for analyzing this task heterogeneity. Therefore, TTF was the necessary and most rigorous choice to empirically test this crucial aspect of the research.

3. *The Unique Context of the World Bank's Work:*

The work performed at the World Bank Ethiopia Country Office is highly specialized, sensitive, and context heavy. In such an environment, the simple "usefulness" of a tool is insufficient. An AI tool might be easy to use, but if it produces generic or "hallucinated" outputs that do not align with the strict analytical and ethical demands of development policy work, it creates operational friction and reduces productivity. The TTF model, with its emphasis on "Fit," is uniquely capable of capturing this critical nuance, the degree of alignment between a general-purpose technology and a highly specialized professional environment.

3.2 Population and Sample of the Study

3.2.1 Target Population

The target population for this study is the 80 staff in the Bank. The population is precisely defined as full-time employees with formal access to the enterprise-approved AI tools. The population is made up of a variety of professional occupations. Roles include program leaders, economists, operations analysts, sector specialists and administrative support. This will provide a holistic view into the implementation of AI tools across various functions.

3.2.2 Sample Size Justification

This is a census study, so there is no sample. The study is applied to the entire population of 80. To statistically prove the effectiveness of this approach, we computed the minimum sample size required to reach statistical significance. The calculation is made according to the widely accepted formula of Yamane (1967). In this calculation, it is confirmed that the census approach is above the minimum threshold for generalizability.

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The formula is as follows:

n = N / (1 + N * e^2)

Where:

- n = Minimum required sample size
- N = Total population size (80)
- e = Level of precision or margin of error (set at 0.05 for a 95% confidence level)

Calculation:

n = 80 / (1 + 80 * (0.05)^2)

n = 80 / (1 + 80 * 0.0025)

n = 80 / (1 + 0.2)

n = 80 / 1.2

n ≈ 67

This calculation indicates that a minimum of 67 respondents is needed to arrive at the findings. The census-based approach employed in this study will provide a wealth of data for future statistical analyses. This approach will also provide high credibility and detailed understanding of the phenomena.

3.3 Operationalization of Variables

To bridge the conceptual framework with the empirical data collection, this section provides an explicit and detailed breakdown of how each variable in the model is defined, its role within the causal chain, and how it was measured using the survey instrument.

3.3.1 Independent Variables: The Primary Inputs

These variables constitute the foundational elements that initiate the causal chain in the structural model.

- Technology Characteristics
    - *Conceptual Definition:* This variable represents the specific capabilities, features, and inherent qualities of the AI tools being studied (e.g., Microsoft Copilot, MAi).

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- *Role in the Model:* It represents the "supply" side of the equation, defining what the tool is functionally capable of doing, including its capacity to automate, summarize, translate, and integrate into existing workflows.
- *Measurement:* This was operationalized by asking respondents to rate specific tool features, such as "reliability" and "ease of integration," using a 5-point Likert scale, alongside tracking which specific tools were accessed.

- Task Characteristics
  - *Conceptual Definition:* This variable represents nature, complexity, and demands of the daily work performed by World Bank staff.
  - *Role in the Model:* It acts as the "demand" side of the equation, defining what the job requires. In the context of the World Bank Ethiopia Country Office, this involves a "hybrid" workload characterized by high demands for both complex analytical synthesis and routine administrative tasks.
  - *Measurement:* This was operationalized by asking respondents to rate statements regarding their work profile, such as "My work requires complex analytical thinking" and "My work involves a high degree of routine and repetitive tasks."

3.3.2 Mediating Variables: The Functional Mechanisms

These variables explain the mechanisms through which the independent inputs are converted into dependent outputs.

- Task-Technology Fit (TTF)
  - *Conceptual Definition:* TTF is a cognitive/perceptual variable representing the employee's mental evaluation of how well the capabilities of the AI tools align with their specific task requirements.

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- *Role in the Model:* It serves as the primary mediator. It explains the motivation behind tool adoption, operating on the premise that a strong perceived fit encourages behavioral action.
- *Measurement:* This was operationalized through specific Likert-scale questions in Section C of the survey, utilizing items such as "The AI tools' features are a good match for my daily tasks."

- Utilization of AI Tools
  - *Conceptual Definition:* This is a behavioral variable representing the actual, observable act of engaging with the AI tools.
  - *Role in the Model:* It acts as the secondary mediator and the behavioral bridge in the model. It translates the positive perception of "Fit" into concrete action, proving that the technology is being actively applied to workflows.
  - *Measurement:* This was measured through behavioral self-reporting in Section B of the survey, capturing the frequency (e.g., "Daily," "Weekly") and duration ("Hours per week") of AI tool usage.

3.3.3 Moderating Variables: The Contextual Influencers

These variables represent the individual and environmental factors that strengthen or constrain the relationships within the primary causal path.

- AI Literacy
  - *Conceptual Definition:* This represents the employee's specific cognitive and technical skills required to use generative AI effectively.
  - *Role in the Model:* AI Literacy moderates the path between TTF and Utilization. Even if a tool presents a perfect fit, an employee lacking practical skills (e.g., prompt engineering) cannot effectively utilize it, thereby weakening the adoption chain.

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- *Measurement:* This was operationalized by evaluating and comparing mean scores for conceptual awareness (e.g., awareness of AI ethics) against practical application skills (e.g., the ability to write effective prompts).

- Organizational Readiness
    - *Conceptual Definition:* This represents the institutional environment within the Country Management Unit, encompassing leadership support, governance policies, and training resources.
    - *Role in the Model:* It moderates the path between Utilization and Performance Impact. Frequent utilization of a tool without adequate organizational support (e.g., clear data guidelines or training) can lead to misuse and errors, thereby suppressing ultimate productivity gains.
    - *Measurement:* This was operationalized by comparing mean scores measuring strategic support (e.g., "Leadership encourages AI use") against operational support (e.g., "Received adequate training").

3.3.4 Dependent Variable: The Final Outcome

This is the ultimate performance metric that the structural model seeks to explain.

- Performance Impact (Perceived Individual Productivity)
    - *Conceptual Definition:* This is the self-assessed, measured effect of generative AI integration on an employee's professional output.
    - *Role in the Model:* It serves as the final dependent variable the ultimate outcome that all independent, mediating, and moderating variables interact to influence.
    - *Measurement:* This was operationalized by asking respondents to rate the perceived impact of AI on specific work dimensions, such as "Speed of completing routine tasks" and changes in the "Level of innovation and creativity" applied to their deliverables.

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3.4 Data Collection Instrument and Procedure

The study will collect data through the online questionnaire survey that will be conducted electronically. The survey instrument has been rigorously developed to operationalize the constructs from the conceptual framework of TTF. It comprises different sections of close-ended questions on the 5-point Likert scale (1=Strongly Disagree to 5=Strongly Agree) to measure the perceptual variables.

A secure online link will be used to distribute the questionnaire to the entire population of 80 staff. An introductory statement will explain the academic nature of this study and the promise of strict confidentiality and anonymity of data collection so that responses can be honest and open.

3.5 Data Analysis Plan

Once data collection has been completed, the quantitative data will be exported, cleaned, and coded for analysis using SPSS statistical software. The data will be analyzed in a systematic way as follows

1. Descriptive Statistics Descriptive analysis including calculation of frequencies, means and standard deviations will be performed for all variables. This will be used to summarise the demographic profile of the respondents. It will give an overview of the basic constructs.
2. Inferential Statistics: Hypotheses will be tested empirically by hierarchical multiple regression analysis. This technique will allow to test the direct effects proposed in the TTF model (e.g. the effect of TTF on Utilization, and Utilization on Performance Impact).
3. Moderation Analysis: Moderation analysis will be carried out to explore the moderating effects of AI Literacy and Organizational Readiness. This will involve creating interaction terms between the moderators and the independent/mediating variables. Entering them into regression models to determine if they have a statistically significant effect on the relationships. A p-value of < 0.05 will be the established threshold for determining statistical significance.

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Chapter Four: Results and Discussion (Data Presentation, Analysis, and Interpretation)

4.1 Introduction

This chapter presents the summary of the empirical findings and results of the study. It is presentation, analysis, and interpretation of collected primary data. We will also examine the impact on this chapter. In this chapter we explore the survey responses to show how staff are currently using AI. The productivity gains being captured and the factors underpinning this technological integration answer the fundamental research questions set out at the beginning of the study.

The data is presented in the beginning of the chapter and there is a detailed data analysis section which empirically tests the hypothesis of the study. The first data presentation is descriptive statistical analysis which provides a complete baseline profile of the respondents. Next, the complexity or routine of their daily tasks, their current use of AI tools and the frequency of such use, and their self-rated AI literacy are described.

The statistical tools employed are Spearman's rank order correlation and One-Way Analysis of Variance (ANOVA). Methods are discussed in Chapter 3. The analytic approach facilitates a more detailed analysis of the relationships between the core variables that impact the statistical significance and magnitude of the associations between AI use, organizational preparedness, individual skill levels and the resulting productivity outcomes.

This chapter ends with a discussion and analysis of the statistical results. This section is organized according to the research guidelines and refers to the literature review of chapter 2 and the conceptual framework of TTF (Task-Technology Fit). The discussion contextualizes the empirical evidence of the study.

With reference to AI adoption, academic research, automation theories, and global industry benchmarks. It takes the quantitative metrics and turns the "why" of the data, such as the identified skill gaps and organizational training deficits, into relevant academic insights that will inform the conclusions and recommendations of Chapter 5.

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4.2 Response Rate

Producing the response rate is an essential first step in data presentation as it determines the extent to which the collected data represents the target population which ensures the reliability of the analyses. In association with the research methodology established in Chapter 3 the primary data for this study was collected using an online questionnaire designed and distributed via Microsoft Forms. The questionnaire link was electronically distributed to a target sample of 80 staff within the World Bank Ethiopia Country Office.

By the conclusion of the data collection period, a total of 70 participants completed and submitted the online form. Following a preliminary screening for data integrity and completeness, all 70 responses were found to be valid and were retained for the final quantitative analysis.

Table 4.1: Questionnaire Response Rate

Category	**Frequency (n)**	**Percentage (%)**
Total Questionnaires Distributed (Target Sample)	80	100.0%
Returned and Valid Questionnaires	70	87.5%
Unreturned/non-responsive	10	12.5%
Total Response Rate	70	87.5%

4.3 Descriptive Analysis of Key Dimensions

This section is the basic step of getting to know the dataset before going into inferential hypothesis testing. The purpose of this section is to provide a detailed quantitative summary of the survey responses. The responses are presented as frequencies, percentages, means and standard deviations.

The data are presented and the analysis is organized in accordance with the main theoretical dimensions as defined in the conceptual framework of this research. This section starts by presenting the Professional Profile of the respondents, analyzing their job role and years of

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professional experience to validate the representativeness of the sample. Then the features of their tasks are discussed. It is highlighted by the combination of the routine tasks and the complex unstructured knowledge work. Next, Current AI Tool Adoption and Technology Characteristics are presented, including descriptions of the tools used, frequency of use, and staff perceptions of the quality of the tools.

With this model context in place, the analysis turns to the assessment of the core constructs of the research model. The basic element of the Task-Technology Fit (TTF) is explored to evaluate the respondents' perception on the suitability of the current AI tools. for the specific daily job needs of the respondents. The section also discusses the data on the two main moderate variables of the study.

The first one is the employees' self-rated AI Literacy and the second Skills such as prompting ability and awareness of ethics and their perception of Organizational Readiness. The descriptive analysis ends with the description of the dependent variable, Perceived Impact on Productivity. It reflects the reported effect of AI on speed of work, volume of output, and quality. In this section we provide a detailed empirical overview of the current AI landscape in the Bank. We cover each of these dimensions in detail.

4.3.1 Professional Profile of Respondents

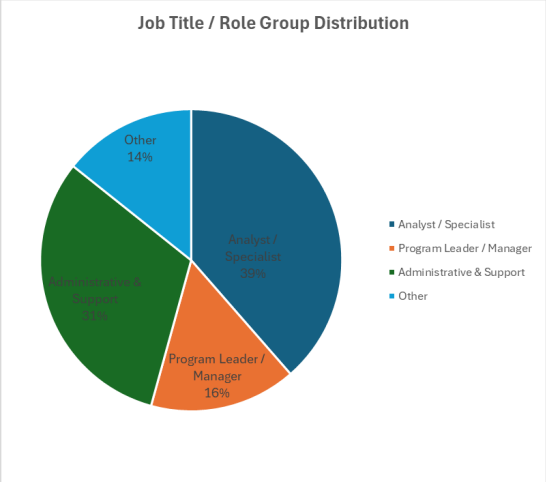
Analysis of the professional characteristics of the respondents is an important step in contextualizing and assessing the generalizability of the study results.

Table 4.2: Distribution of Respondents by Job Title/Role Group (N=70)

Job Title / Role Group	Frequency (n)	Percentage (%)
Analyst / Specialist	27	38.6%
Administrative & Support	22	31.4%

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Program Leader / Manager	11	15.7%
Other	10	14.3%
Total	70	100.0%

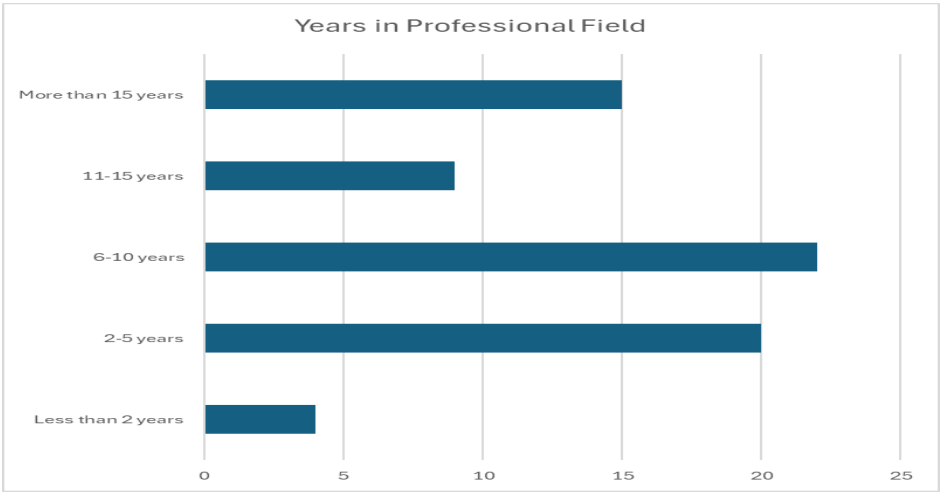


This sample contains the demography of ‘Analyst / Specialist’ profiles in all functions of the org. The largest group is “Analyst / Specialist” with 38.6%. ‘Administrative & Support’ (mostly routine and procedural work) at 31.4%. , ‘Program Leader / Manager’ roles at 15.7% of the sample, with the rest being other roles such as Team Leads and Drivers. The analysis allows us to quantify the impact of AI across various task categories, ranging from highly analytical to more structured support roles.

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Table 4.3: Distribution of Respondents by Years in Professional Field (N=70)

Years in Professional Field	Frequency (n)	Percentage (%)
Less than 2 years	4	5.7%
2-5 years	20	28.6%
6-10 years	22	31.4%
11-15 years	9	12.9%
More than 15 years	15	21.4%
Total	70	100.0%



The largest respondents (31.4%) have 6-10 years of experience and a big portion (21.4%) have more than 15 years of experience. In total over two-thirds of the sample (65.7%) possess more than 6 years of professional tenure. This level of experience has a significant factor since it

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suggests respondents are evaluating AI tools not as learners but against a backdrop of well-established traditional work processes.

4.3.2 Task Characteristics

Respondents rated the nature of their work on a 5-point scale (1=Very Little Extent, 5=Very Great Extent).

Table 4.4: Perceptions of Work Characteristics (Mean Scores, N=70)

Statement	Mean Score	Std. Deviation
My work requires me to synthesize information from multiple sources.	3.84	1.18
My work involves a high degree of routine and repetitive tasks.	3.61	1.22
My work requires complex analytical thinking and problem-solving.	3.56	1.15
The tasks I perform daily are predictable...	3.49	1.23
I frequently encounter unstructured problems...	3.45	1.34
My work demands a high level of creativity and original thinking.	3.39	1.35
My work involves drafting, writing, or editing long and detailed documents.	3.20	1.45

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While tasks involving information synthesis (Mean=3.84) and routine/repetition (Mean=3.61) are prominent, the need for complex analytical thinking (Mean=3.56) is also high. This profile of the "staff" at the Ethiopia office is one who must manage both structured, predictable work and unstructured, analytical challenges. This duality makes the workforce an ideal population for studying AI's dual impact as both an automation tool (for routine tasks) and an augmentation tool (for complex analysis).

4.3.3 Technology Characteristics, AI Tool Adoption and Task-Technology Fit

This section deals with the use of AI in terms of the work done and the perspective of the tools.

Table 4.5: Frequency of AI Tool Usage (% of Respondents, N=70)

AI Tool	Daily	Weekly	Monthly	Rarely	Never
Microsoft Copilot	35.7%	22.9%	7.1%	10.0%	24.3%
MAi	32.9%	17.1%	4.3%	7.1%	38.6%
AI-powered Transcription	21.4%	21.4%	10.0%	11.4%	35.7%
Gemini	11.4%	12.9%	14.3%	5.7%	55.7%

From the analysis Microsoft Copilot is the most popular tool by far, used by 58.6% of staff at least once a week. Most likely it is because it is embedded within the Microsoft 365 system. In contrast, more than half of staff (55.7%) have never used Gemini. This clearly indicates a preference for enterprise embedded tools over external platforms.

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Table 4.6: Perceptions of Technology & Task-Technology Fit (Mean Scores, N=70)

Category	Statement	Mean Score
Task-Technology Fit	The AI tools' features are a good match for my daily tasks.	3.91
	Overall, the AI tools fit my job needs very well.	3.89
Technology Characteristics	The AI tools are easy to integrate into my existing software.	3.79
	The quality of the output from the AI tools is high.	3.70
	The AI tools are reliable and perform consistently.	3.66

The respondents perceived a high Task Technology Fit (Mean≈3.9) with the tools being relevant to their work. with the highest rated item “good match for my daily tasks” (3.91) and easy to integrate (3.79). However, perceptions of output quality (3.70) and reliability (3.66) are slightly lower. that indicating even if the tools are useful their outputs still require some human verification and refinement.

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4.3.4 AI Literacy and Organizational Readiness

This section is about the human and office environment and how it affects AI.

Table 4.7: AI Literacy and Organizational Readiness (Mean Scores, N=70)

Category	Statement	Mean Score
AI Literacy	I am aware of the Bank's ethical guidelines for using AI.	4.14
	I understand the potential limitations and biases of the AI tools I use.	4.11
	I feel confident in my ability to adapt my prompts...	3.76
	I can write effective prompts to get the best results.	3.73
Organizational Readiness	My leadership encourages the use of AI tools...	4.01
	My immediate supervisor supports my use of AI tools...	3.91
	The Bank has provided clear policies and guidelines on AI use.	3.61
	I have received adequate training and resources to use AI effectively.	2.91

First, there is a large gap in AI Literacy between conceptual awareness (ethical guidelines,

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Mean=4.14) and practical skill (writing effective prompts, Mean=3.73). Second, there is a large gap between leadership encouragement (Mean ≈ 4.0) and tangible support in Organizational Readiness. The provision of adequate training and resources was the lowest scoring item in the whole section (Mean=2.91) indicating that this is an area that requires improvement.

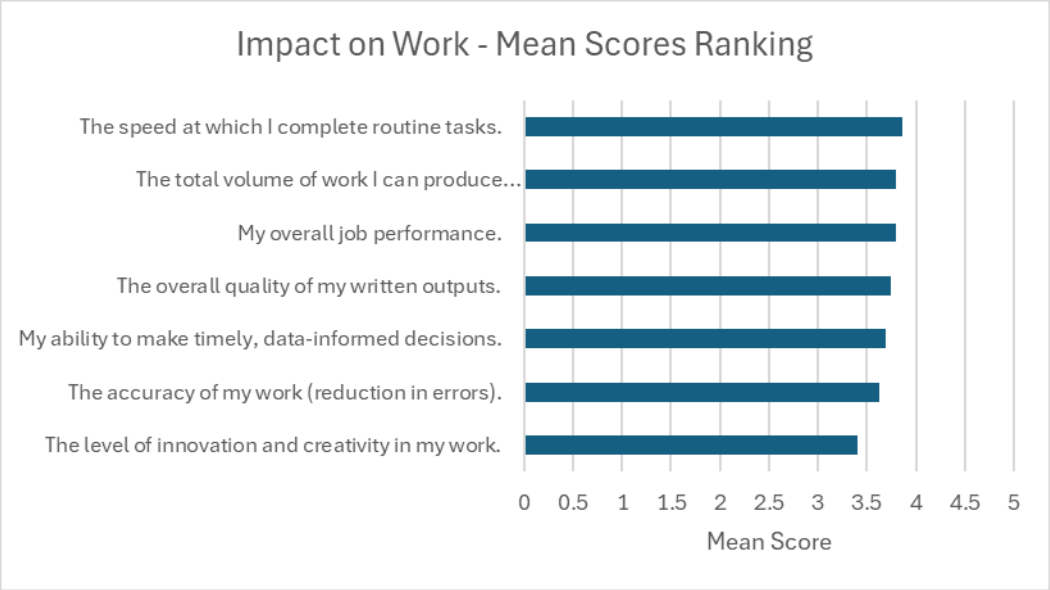
4.3.5 Perceived Impact on Productivity (Dependent Variable)

In this section we report workers' perceptions of how AI affects their performance.

Table 4.8: Perceived Impact of AI on Work Aspects (Mean Scores, N=70)

Aspect of Work	Mean Score	Std. Deviation
The speed at which I complete routine tasks.	3.86	1.13
The total volume of work I can produce (throughput).	3.80	1.07
My overall job performance.	3.79	1.03
The overall quality of my written outputs.	3.74	1.07
My ability to make timely, data-informed decisions.	3.69	1.10
The accuracy of my work (reduction in errors).	3.63	1.14
The level of innovation and creativity in my work.	3.40	1.18

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The most positive impact of AI was on speed (Mean=3.86) and volume of work (Mean=3.80) as reported by respondents. This points to the fact that AI is largely viewed as a way to automate and be more efficient. The least impact is felt in more qualitative areas such as innovation and creativity (Mean=3.40), but this is still rated positively .

4.4 Analysis of Inferences and Test of Hypothesis

In this section we discuss the relationships between AI adoption, user competency, organizational context and productivity outcomes. It shifts from the discussion of the data to an empirical test of the hypotheses presented in Chapter 2. By applying the statistical methodologies in Chapter 3 specifically Spearman's rank-order correlation and One-Way Analysis of Variance (ANOVA). All analyses are conducted on the valid sample of N=70 respondents.

4.4.1 Hypothesis 1: The Impact of AI Tool Use on Productivity

Hypothesis (H1): *The use of AI tools is expected to improve the productivity of staffs.*

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- Methodology: To test this hypothesis, a composite "Frequency of AI Use" score was created by averaging the ordinal responses for the usage of the four listed AI tools. A Spearman's rank-order correlation was then conducted to measure the association between this frequency score and the composite "Performance Impact" score.

Table 4.9: Correlation between Frequency of AI Use and Performance Impact

		Frequency of AI Use	Performance Impact
Spearman's rho	Frequency of AI Use	1.000	.591
	Performance Impact	.591	1.000
Sig. (2-tailed)	Frequency of AI Use	.	<.001
	Performance Impact	<.001	.
N		70	70

The analysis revealed a statistically significant, strong positive correlation between the frequency of AI use and the perceived performance impact ($\rho = .591$, $p < .001$). The strength of the coefficient (.591) indicates a substantial positive relationship. The p-value (<.001) confirms that this finding is highly unlikely to be due to random chance. Therefore, Hypothesis 1 is supported. Employees who report using AI tools more frequently are significantly more likely to perceive a positive impact on their overall productivity.

4.4.2 Hypothesis 2: The Influence of AI Literacy

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Hypothesis (H2): *AI literacy is expected to influence how effectively employees benefit from AI tools.*

Methodology: A composite "AI Literacy" score was created by averaging the six relevant Likert-scale items. A Spearman's correlation was conducted to assess the relationship between this score and the "Performance Impact" score.

Table 4.10: Correlation between AI Literacy and Performance Impact

		AI Literacy Score	Performance Impact
Spearman's rho	AI Literacy Score	1.000	.632
	Performance Impact	.632	1.000
Sig. (2-tailed)	AI Literacy Score	.	<.001
	Performance Impact	<.001	.
N		70	70

a statistically significant, strong positive correlation between AI literacy and performance impact ($\rho = .632$, $p < .001$). This is a strong support for hypothesis 2. Good relationship as indicated by coefficient (.632), even better than frequency of use. This key finding indicates that the perceived skill and knowledge of an employee in using AI tools effectively is a better predictor of productivity gains than frequency of use alone.

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4.4.3 Hypothesis 3: Variation by Task Type

Hypothesis (H3) Productivity gains from AI tools can vary depending on the type of task being performed.

Respondents were split into two groups based on the routine nature of their work. The Low-Routine group (n=36) included respondents who rated the statement "my work involves a high degree of routine and repetitive tasks" as 1, 2 or 3. Those who scored 4 or 5 on the statement were placed in the High-Routine group (n=34). The productivity scores of the two groups were compared by means of one-way ANOVA.

a statistically significant $F(1, 68) = 8.59$, $p = .005$. Staff in the High-Routine group scored noticeably higher on performance impact (M=4.15, SD=0.75) compared to those in the Low-Routine group (M=3.71, SD=0.82). The more repetitive the work, the more AI helps The more complex and varied the work, the less AI helps

Table 4.11: ANOVA Results for Performance Impact by Task Routine Type

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5.23	1	5.230	8.59	.005
Within Groups	41.40	68	0.609		
Total	46.63	69			

This p-value is significant (.005) and we reject the null hypothesis. This confirms hypothesis 3: employees in jobs with a higher degree of routine and repetition have a much more positive impact on their productivity from the use of AI tools. This is consistent with the automation theory that the most visible and tangible benefits of AI are from automating predictable tasks.

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4.4.4 Hypothesis 4: The Impact of Organizational Readiness

Hypothesis (H4): *Organizational readiness is expected to shape the effectiveness of AI adoption.*

Methodology: A composite "Organizational Readiness" score was created by averaging the six items of interest. A spearman correlation was run between this score and the "Performance Impact" score.

Table 4.12: Correlation between Organizational Readiness and Performance Impact

		Organizational Readiness	Performance Impact
Spearman's rho	Organizational Readiness	1.000	.538
	Performance Impact	.538	1.000
Sig. (2-tailed)	Organizational Readiness	.	<.001
	Performance Impact	<.001	.
N		70	70

The analysis shows a moderate to strong positive correlation between organizational readiness and performance impact ($\rho = .538$, $p < .001$) which is statistically significant. Hence, Hypothesis 4 is supported. The findings provide empirical evidence that a supportive organizational environment with leadership encouragement, clear policies, and adequate resources is a significant predictor of realizing productivity gains from AI. As seen in the descriptive analysis (Table 4.7) training and resources was the weakest component of organizational readiness and therefore a clear high impact area for institutional intervention.

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4.5 Primary Quantitative Findings

The analyses conducted on the data set N=70 offer deep quantitative insights that characterize the current state of AI adoption and its impact in the World Bank Ethiopia Country Office. The analyses provide several deep quantitative insights that go beyond simple frequencies and highlight important relationships between variables.

1. Speed and Volume over Innovation

The descriptive mean analysis of the dependent variable (Performance Impact) provides clear quantitative evidence for the current choice of AI. The data are clearly biased in favor of efficiency. The impacts most highly rated were speed in getting routine tasks done (Mean = 3.86) and total amount of work (Mean = 3.80). The lowest effectiveness rating was for innovation and creativity (Mean = 3.40). The quantitative difference implies that the workforce sees AI as an operational engine to get more done, faster, rather than a cognitive engine to generate entirely new or creative solutions.

2. The Strong Predictive Power of AI Literacy

What we learned from the data is about people, not tools. Results show a significant positive relationship between AI Literacy and Performance Impact ($r = .632$, $p < .001$). What is interesting is that this figure is higher than the correlation of frequency of use of AI by staff with productivity ($r = .591$). It's less about how much you use AI and more about how well you prompt it. Employees trained to prompt AI, validate its outputs, and use it responsibly will achieve better results than those who simply open up the tool and hope for the best.

3. The Statistically Significant Role of Task Routine

The One-Way ANOVA test confirms in a clear quantitative way that the effect of AI is not the same for all kinds of knowledge work and staff. This analysis showed a statistically significant difference in performance by type of task ($F = 8.59$, $p = .005$). Employees with high routine tasks ($M = 4.15$) had significantly higher means on impact than employees with low routine and high ambiguity (M

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= 3.71). The more predictable the task the greater the immediate measurable benefit of AI intervention. This quantitative data empirically supports the theory of automation in the organization.

4. The Quantitative Disconnect in Organizational Support

Finally, there appears to be a quantitative gap in the descriptive measures of Organizational Readiness. The workforce strongly agreed that leadership encourages the use of AI (M = 4.01). However, the availability of adequate training and resources had the lowest mean score of the entire study (Mean = 2.91) . The 1.10 point mean difference is a mathematical reminder of the gap between strategic intent and operational execution. The following inferential finding quantifies the opportunity cost of this gap: organizational readiness is strongly correlated with productivity (= .538). Failure to provide adequate training is statistically linked to lower overall productivity gains from technology.

4.6 Summary of the Chapter

The quantitative analysis presented in this chapter provides a multi-dimensional perspective of AI's impact in the Bank. The statistics show that the staff is quite experienced and mainly uses enterprise integrated AI tools. The inferential analysis statistically supported the 4 hypotheses of the study. The key findings indicate an indication of a strong association between AI adoption and increased perceived productivity.

Moreover, the effect is significantly moderated by individual AI literacy and organizational readiness. The major difficulties identified were a skills gap in the practical use of AI, particularly in prompting. Another organizational gap is that there is strong leadership encouragement but lack of training. These results will be discussed in more detail in the next chapter.

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Chapter five: Summary, Conclusions and Recommendations

5.1 Introduction

This Chapter consists of four major sections. The first section summarizes the main descriptive and inferential results. Section Two is the last logical conclusions on the summarized findings that evaluate how AI is functioning as an operation at the present time. The third part of the paper discusses the methodological and contextual limitations of the study, making the boundaries of the research transparent, and the final part concludes, translating the findings of the study into a set of very-detailed, real-world and actionable recommendations to help organizational leadership to optimize their AI integration strategy. This chapter seeks to synthesize the empirical evidence presented in chapter 4, and to convert the raw statistical data into meaningful academic and operational insights. The initial research objectives are associated with the empirical reality of the organization in chapter 3 by the conceptual framework of Task-Technology Fit (TTF).

5.2 Summary of Findings

The study achieved a valid sample of 70 respondents with a response rate of 87.5%. Data was analyzed using descriptive statistics (frequencies, percentages, means and standard deviations) and inferential statistics (Spearman's rank order correlation and One-Way ANOVA). The main findings are:

5.2.1 Task-Technology Fit and Productivity Impact

For the dependent variable productivity, the results were strongly in favor of efficiency. Perceived effects of speed of completing routine tasks (Mean = 3.86) and total work throughput (Mean = 3.80) were rated as most important. Impact of AI on innovation and creativity received the lowest rating (Mean=3.40). Respondents generally perceived a positive Task-Technology Fit (TTF), agreeing that the AI tools' features were a good match for their daily tasks (Mean = 3.91). However, perceived efficiency for complex analytical and synthesis tasks was rated lower (Mean = 3.59).

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5.2.2 Task Characteristics and AI Tool Adoption

The findings indicated that the hybrid working environment was complex. Respondents cited high needs for information synthesis from multiple sources (M = 3.84) and complex analytical problem solving (M = 3.56). This was in comparison with a high level of routine and repetitive tasks (Mean = 3.61). The workforce was deeply steeped in AI tools that were built into the enterprise through the lens of technology adoption. The most used platform was Microsoft Copilot, with 58.6% of the sample using it daily or weekly, while external platforms such as Gemini had little adoption (55.7% had never used it).

5.2.3 Professional Profile

The analysis confirmed that the sample had a substantial amount of institutional experience. A large majority (65.7 percent) had over six years of professional tenure. The respondents were well distributed across the major functions within an organization primarily divided between core analytical functions, Analyst / Specialist 38.6% and operational support functions, Administrative & Support 31.4%.

5.2.4 AI Literacy and Organizational Readiness

The descriptive analysis showed two major gaps in operation. Results show firstly high conceptual awareness of AI ethics and limitations in the AI Literacy construct (Means > 4.10. However, respondents expressed much lower confidence in practical skills, ability to write and adapt effective prompts (Means ≈ 3.75). Secondly, the actual provision of adequate training and resources had the lowest mean score in the whole study (Mean = 2.91) and there was a stark contradiction within Organizational Readiness, leadership encouragement on AI use scored high (Mean = 4.01).

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5.2.5 Inferential Hypothesis Testing

The inferential statistical analysis provided strong empirical support for all four central hypotheses of the study:

Hypothesis 1: A significant, positive correlation was found between the frequency of AI use and the perceived impact on performance ($r = .591$, $p < .001$).

Hypothesis 2: positive association with performance impact (= .632, $p < .001$) It was more than just the frequency with which they used the relationship.

Hypothesis 3: The impact on performance was significantly higher for employees with high routine tasks (Mean = 4.15) compared to employees with low routine tasks (Mean = 3.71).

Hypothesis 4: High perceived productivity gain from AI were significantly positively associated ($F = .538$, $p < .001$) with high organizational readiness.

5.3 Conclusion

Below are the conclusions reached on the integration and impact of AI tools at the World Bank

5.3.1 Management support on ground

Leadership has done a good job to create a pro-innovation culture but the strategic intent has not yet translated into operational support on the ground. The alarmingly low scores on provision of training and resources suggest that employees are expected to adopt highly disruptive technologies without the institutional instructional frameworks to do so effectively. This approach forces employees into expensive trial-and-error learning paradigms, which in turn limits the overall return on the organization's technology investments.

5.3.2 A practical "gap of prompting" limits task-technology fit

A skills gap exists between technology utility and human capability, the study finds. The workforce has a "prompting gap," even with advanced academic degrees and grasp of AI ethics. The quality of the output from generative AI is entirely dependent on the specificity of the natural

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language input by the user and the lack of confidence in writing and refining prompts severely limits the utility of the tools. This lack of practical skills also accounts for the result that the perceived Task-Technology Fit is significantly lower for complex synthesis tasks than for routine administrative tasks . Without prompt engineering skills, you cannot tap into the full theoretical capabilities of tools like Microsoft Copilot to deeply examine economic or policy issues.

5.3.3 Human Capital the final moderator of AI value realization

The study finds that human capital, especially digital literacy, is the most important driver of AI success. This finding that AI literacy is a stronger predictor of productivity than frequency of AI use supports the core assumption of the Task-Technology Fit theory. This enables sophisticated software which does not automatically offer performance. The user will be able to use the tool correctly. Therefore, upgrading the digital skills of the labour force is more relevant for productivity enhancement than the purchase of technology.

5.3.4 AI: accelerator, not thinking companion (yet)

The real world evidence is crystal clear. AI tools are doing good in understanding what staff productivity really looks like. This has very much an impact in automation and efficiency. The biggest benefits were in speed of task completion and volume of output. The productivity benefits were more likely to be added to routine workers (refer ANOVA results). The point here is that, AI is mostly just an operational efficiency multiplier. Technology excels at automating the routine parts of knowledge work. In this office it is not yet a sophisticated cognitive partner that can take high-level innovation or complex original thought generation to the next level.

5.4 Limitations of Study

Nevertheless, some limitations should be mentioned despite the rigorous applied research methodology.

5.4.1 Reliance on Self-Reported Perceptual Data

The limitation of the study is that the dependent variable is assessed by self-reported survey data. It measures the quality and the quantity of the work, speed and captures the perceived impact of

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AI. Then employees might overestimate the gains in efficiency, either because the technology is new or because they feel pressure to meet what they think are the expectations of the organization. The lack of objective, system-tracked "digital exhaust" data (e.g., real-time tracking logs, error-rate metrics) constrains the ability to quantify the precise and objective magnitude of productivity changes.

5.4.2 Design of the Cross-Sectional Study

The study was cross-sectional in design and data were collected at one point in time. Inferential statistics showed associative relationships between the variables but causality can not be determined by this method . (For example, high performers may be more proactive in acquiring AI skills per se, not that AI skills per se lead to high performance.) In order to follow learning curves and establish definite cause and effect over time a longitudinal study would have to be conducted.

5.4.3 These Findings Belong to a Single Organization

The study was limited to the World Bank Country Office in Ethiopia. The high response rates do add good internal validity to this population but the findings may not be generalizable to a wider readership. The World Bank has a very unique culture, its IT infrastructure is based on Microsoft 365 and its staff is highly educated. The results are not necessarily generalizable to other private sector organizations or to other World Bank offices in other technological and regional contexts.

5.5 Recommendations

The empirical findings are used to propose the following practical and realistic recommendations to improve the AI integration strategy better.

5.5.1 Build a Peer-Led AI Champions Network

It is important for the office to use peer-to-peer knowledge sharing as there is a strong correlation between organizational readiness and productivity. "It should be home in The Office and staff

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should be encouraged to share their AI skills," he said. "That's a recommendation that often works better than top-down dictates. Find AI power users to be champions. Let them coach their own students. The champions should have informal workshops. Workshops to demonstrate real world AI problem solving and feedback to the unit responsible on pain points on the technology side.

5.5.2 Transition to Real Productivity Measurement Systems

"The office needs safe tracking tools like Microsoft Viva that can track aggregated data on digital exhaust. Managers need to be able to monitor completion of routine reports. There are already insights in the Bank ecosystem, and can do this safely tracking aggregated patterns instead of individual behaviour. Are reports being completed more quickly? Are employees leaving work early? Are there other time blocks to work undisturbed? That's the kind of signal that tells a real story." Without that kind of data, AI training and tool resourcing decisions are basically a shot in the dark.

5.5.3 Create Clear Task-Specific AI Rules

The problem is the ambiguity and the risk of when is it OK to use AI and when it is not. The answer is simply a traffic light policy. This could solve the problem

a) Green-Light Tasks: AI can be used for low risk tasks like brainstorming or summarizing public documents.
b) Yellow-Light Tasks: Use of AI to draft external-facing reports, or to perform preliminary data analysis, as long as there is a documented "human-in-the-loop" verification process.
c) Red-Light Tasks: Don't use generative AI for jobs that involve sensitive and confidential information

Clear rules like these help clarify things for many staff who may be reluctant to use AI but also help mitigate the risk of misuse.

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5.5.4 Training for Specific Roles

Training of staff is far too rudimentary at this point in time. The office should offer ongoing skills-based training specific for certain job functions. “Admin staff should be trained in flow automation. How to create good prompts How to prepare standard letters How to format documents For analysts and specialists: training to be on advanced skills Chain of thought prompting skills How to combine multiple economic reports How to use AI to test human ideas

5.5.5 Develop a localized AI Center Resource Hub

Most of the trial and error learning happening right now exists because there is nowhere for staff to turn when they need help with AI. To improve the score on the provision of resources, the Bank should develop a new internal portal for the Eth Office. The portal should have a Library of prompts for staff on recurring Bank tasks. Standard Operating Procedure for checking AI generated data to reduce the risks of hallucinations

**Create new video tutorials that demonstrate and guide users on how to use AI tools integrated into the Bank system.

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APPENDICES

Questionnaire

Measuring the Impact of AI Tools on the Productivity of Staff in the Case of World Bank Ethiopia Office

Introduction

Thank you for participating in this research study that is being conducted as part of a master's thesis on the above-mentioned topic. The purpose of this questionnaire is to have an idea of how enterprise-approved AI tools are being used and how they affect your work based on the Task-Technology Fit model.

Participation is completely voluntary and all responses will be kept confidential and anonymous. The data will be aggregated for analysis, and no person will be identified in the final report. The survey should take approximately 15 minutes to complete.

Section A: Your Work Profile (Task Characteristics)

This section helps us understand the nature of your work, which corresponds to the "Task Characteristics" in the research model.

1. To what extent do you think the following statements characterize your main job activity?
Scale: 1 = Very Little Extent, 2 = Little Extent, 3 = Moderate Extent, 4 = Great Extent, 5 = Very Great Extent

Statement	1	2	3	4	5
My work involves a high degree of routine and repetitive tasks.	○	○	○	○	○
The tasks I perform daily are predictable and follow a standard procedure.	○	○	○	○	○
My work requires complex analytical thinking and problem-solving.	○	○	○	○	○
I frequently encounter unstructured problems that require novel solutions.	○	○	○	○	○
My work involves drafting, writing, or editing long and detailed documents.	○	○	○	○	○
My work requires me to synthesize information from multiple sources.	○	○	○	○	○

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My work demands a high level of creativity and original thinking.	◯	◯	◯	◯	◯

Section B: Use and Characteristics of AI Tools (Technology Characteristics & Utilization)

This section measures which AI tools you use, how you perceive their features, and for what purpose.

2. How frequently do you use the these AI tools in your work?
Scale: Daily, Weekly, Monthly, Rarely, Never

AI Tool	Daily	Weekly	Monthly	Rarely	Never
MAi	◯	◯	◯	◯	◯
Microsoft Copilot	◯	◯	◯	◯	◯
Gemini	◯	◯	◯	◯	◯
AI-powered Transcription (Teams)	◯	◯	◯	◯	◯

3. On average, how many hours a week are you actually using these AI tools?

- ◯ No time at all
- ◯ Less than 1 hour
- ◯ 1-3 hours
- ◯ 4-5 hours
- ◯ More than 5 hours

4. Please tell us how much you agree or disagree with the following statements about the features of the AI tools you use?
Scale: 1 = Strongly Disagree, 5 = Strongly Agree

Statement	1	2	3	4	5
The AI tools' are reliable and perform consistently.	◯	◯	◯	◯	◯
The quality of the output (e.g., summaries, drafts) from the AI tools is high.	◯	◯	◯	◯	◯
The AI tools are easy to integrate into my existing software and work processes.	◯	◯	◯	◯	◯

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Section C: Alignment with Your Work (Task-Technology Fit - TTF)

This is the most critical section, measuring the core variable of "Task-Technology Fit".

5. Please rate your agreement with the following statements about how well the available AI tools match your work.
Scale: 1 = Strongly Disagree, 5 = Strongly Agree

Statement	1	2	3	4	5
The AI tools' features are a good match for my daily tasks.	○	○	○	○	○
The AI tools are well-suited for the complexity of my work.	○	○	○	○	○
The functionality of the AI tools is sufficient to meet the demands of my work.	○	○	○	○	○
The AI tools effectively support my drafting and writing tasks.	○	○	○	○	○
The AI tools are useful for my analytical and synthesis tasks.	○	○	○	○	○
Using the AI tools available to me improves my performance in the tasks that are most important to my job.	○	○	○	○	○
Overall, the AI tools fit my job needs very well.	○	○	○	○	○

Section D: Your AI Skills (AI Literacy - Moderator 1)

This section assesses your familiarity and confidence with AI tools.

6. Please rate your agreement with the following statements about your personal AI skills.
Scale: 1 = Strongly Disagree, 5 = Strongly Agree

Statement	1	2	3	4	5
I can write effective prompts to get the best results.	○	○	○	○	○
I feel confident in my ability to adapt my prompts to get better outputs from AI tools.	○	○	○	○	○
I know how to critically evaluate the accuracy of AI-generated information.	○	○	○	○	○

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I understand the potential limitations and biases of the AI tools I use.	○	○	○	○	○
I am aware of the Bank's ethical guidelines for using AI.	○	○	○	○	○
I can effectively integrate AI content into a final work product.	○	○	○	○	○

Section E: Impact on Your Work (Performance Impact - Dependent Variable)

This section measures the core dependent variable: "Performance Impact" (Productivity).

7. How much has the use of AI tools affected the following?
Scale: 1 = Significantly Decreased, 2 = Decreased, 3 = No Change, 4 = Increased, 5 = Significantly Increased

Aspect of Work	1	2	3	4	5
The speed at which I complete routine tasks.	○	○	○	○	○
The overall quality of my written outputs.	○	○	○	○	○
The level of innovation and creativity in my work.	○	○	○	○	○
The total volume of work I can produce (throughput).	○	○	○	○	○
The accuracy of my work (reduction in errors).	○	○	○	○	○
My ability to make timely, data-informed decisions.	○	○	○	○	○
My overall job performance.	○	○	○	○	○

Section F: Organizational Environment (Organizational Readiness - Moderator 2)

This section explores the organizational environment.

8. Please rate your agreement with the following statements about the support for AI use in the Ethiopia CO.
Scale: 1 = Strongly Disagree, 5 = Strongly Agree

Statement	1	2	3	4	5
The Bank has provided clear policies and guidelines on AI use.	○	○	○	○	○

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I have received adequate training and resources to use AI effectively.	◯	◯	◯	◯	◯
There is a culture of learning and experimentation with AI tools in my team/office.	◯	◯	◯	◯	◯
My leadership encourages the use of AI tools to improve productivity.	◯	◯	◯	◯	◯
My immediate supervisor supports my use of AI tools for my work.	◯	◯	◯	◯	◯
The available IT infrastructure (e.g., internet speed) is sufficient.	◯	◯	◯	◯	◯

Section G: Demographics

This final section helps to contextualize the data.

9. What is your current job title/role group?

- ◯ Analyst / Specialist
- ◯ Program Leader / Manager
- ◯ Administrative & Support
- ◯ Other

10. How long have you been working in your current position?

- ◯ Less than 2 years
- ◯ 2-5 years
- ◯ 6-10 years
- ◯ 11-15 years
- ◯ More than 15 years

Thank you for taking the time to complete this questionnaire. Your feedback is important to this research.

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