UNIVERSITY OF GHANA

COLLEGE OF HUMANITIES

SCHOOL OF SOCIAL SCIENCES

DEPARTMENT OF PSYCHOLOGY

ARTIFICIAL INTELLIGENCE ADOPTION AND PSYCHOLOGICAL WELLBEING AMONG SOME SELECTED EMPLOYEES OF TECHNOLOGY-DRIVEN ORGANIZATION IN ACCRA

BY

SHEILA LUGUYARE

10937190

THIS THESIS IS SUBMITTED TO UNIVERSITY OF GHANA, LEGON IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF MASTER OF PHILOSOPHY DEGREE IN INDUSTRIAL AND ORGANIZATIONAL PSYCHOLOGY

MAY 2025

DECLARATION

I hereby declare that except for references to other people's works which I have duly cited and acknowledged, this thesis has been written by myself, and has not been submitted in previous cohorts or by anybody for another degree.

STUDENT
SHEILA LUGUYARE

SIGNATURE: ____________

DATE: __13/05/2025__

SUPERVISORS

DR. COLLINS BADU AGYEMANG

SIGNATURE:..................................

DATE: __13/05/2025__

(PRINCIPAL SUPERVISOR)

DR. RICHMOND ACQUAH-COLEMAN

SIGNATURE:

DATE: __14/05/2025__

(CO-SUPERVISOR)

DEDICATION

This thesis is dedicated to Almighty God, the source of wisdom and strength that guided me through the intricate paths of academia. I also dedicate this to my parents, Mr. & Mrs. Luguyare as well as my siblings; Joycelyn, Yvonne and Augustine Junior. I am internally grateful to them for their prayers, support, and encouragement throughout this journey of pursuing knowledge.

ACKNOWLEDGEMENT

I am extremely thankful to Almighty GOD for His unlimited mercy, compassion, love and support for seeing me through this thesis.

I owe profound gratitude to my two supervisors Dr. Collins Badu Agyemang and Dr. Richmond Acquah-Coleman for their untiring effort, commitment, guidance, and support in helping me write this thesis.

My next thanks go to my parents, Mr. & Mrs. Luguyare and my siblings for their love, encouragement, prayers, sacrifice and support throughout this journey.

I appreciate all organizations that welcomed me and allowed me gather data for this thesis, especially Zelus Technologies and COLDSIS Ghana Limited (CGL), without which, this study would not have been possible.

I also want to show appreciation to my friends and colleagues. These people were of immeasurable help and instrumental in the collection and gathering of data and analysis. Finally, to my colleagues and a whole lot of people I could not mention your names, I appreciate your participation and encouragement throughout this journey in diverse ways,

God richly bless you all.

Table of Contents

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
Chat GPT	Chat Generative Pre-Trained Transformer
CNN	Cable News Network
COVID-19	Coronavirus Disease
FinTech	Financial Technology
FM	Frequency Modulation
GDP	Gross Domestic Product
GPS	Global Positioning System
ICT	Information and Communications Technology
JD-R	Job Demands-Resource
KML AI	Keyhole Markup Language Artificial Intelligence
MTN	Mobile Telecommunications Network
PWB	Psychological Well-being
RAIA	Robotics, Artificial Intelligence and Automation
RQ	Research Question
SPSS	Statistical Product and Service Solution
TAM	Technology Acceptance Model

LIST OF TABLES

ABSTRACT

The study investigates the relationship between Organizational AI adoption and Psychological Well-Being (PWB). It also explores how some demographic factors (age and gender) moderate the relationship between AI adoption and psychological well-being, as well as views employees have towards AI adoption and potential challenges/effects of the adoption of AI in Greater Accra, Ghana. The Job Demands-Resource (JD-R) and Technology Acceptance Models (TAM) were used as underpinning theories for this study. Using an explanatory sequential mixed-method approach, a total of 202 participants (Quantitative= 189 and Qualitative= 13) were purposively sampled for this study. In Study 1, a regression analysis showed a positive relationship between AI adoption and PWB among technology-driven employees of Ghana. Personal growth predicted AI adoption than the other dimensions of PWB, although modestly. A hierarchical regression analysis was conducted to test how demographic factors (Gender, Age) affect AI adoption. Gender and Age did not moderate the relationship between AI adoption and PWB. In Study 2, participants expressed mixed-feelings viewing AI as a helpful challenge. Two sub-themes emerged from these mixed feelings (positive and negative sentiments) offering an understanding of the views held about AI adoption. Four key challenges/effects of AI adoption -Reduced interaction, unemployment, feelings of inadequacy, digital stress-emerged from the study. From this study, AI is seen as a helpful collaborator but with some potential challenges to employee wellbeing. The researcher recommends more advocacy on AI adoption in Ghana while prioritizing psychological interventions that could mitigate associated potential challenges. Study findings were integrated and discussed in line with theory and literature.

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

In today's rapidly evolving digital terrain, technology has deeply penetrated both individual and organizational levels of life, fundamentally transforming how we interact, work, live, as well as elevate human well-being in previously unimaginable ways (Uzir et al., 2023). The relationship between technology adoption and employee well-being has become increasingly important when it comes to employees' acceptance, adopting and using of technology, specifically Artificial Intelligence (AI), which has gained important attention in recent times (Ahumada-Tello et al., 2023; Sadeghi, 2024; Soulami et al.,2024). According to Soomro et al. (2024) nearly 80% of big organizations use AI. The World Economic Forum (2023) forecasts that AI automation might disrupt 14 million jobs, or about 2% of present employment, which is making workers extremely anxious about their future in the workforce and negatively impacting their wellbeing.

The well-being of employees in the era of adoption of new technologies (AI) impacts mental health (Johnson et al., 2020), job satisfaction (Chang, 2024) and overall productivity (Page & Vella-Brodrick, 2009). On one hand, the rapid adoption of technology can introduce new challenges like stress, mental fatigue and job insecurity (Nazareno & Schiff, 2021), on the other hand it can improve general health and job satisfaction while lowering stress levels by relieving workers of monotonous task, and allowing them to concentrate on strategic and reflective work (Soulami et al., 2024). Recent studies thus highlight a complex relationship in the subject area of AI Adoption and well-being.

Conceptualization of Artificial Intelligence (AI) and Adoption

One of the most significant technological advancements in recent years is Artificial Intelligence (AI). According to Kurup and Gupta (2022) there is some element of AI in almost everything; from people utilizing smartphones or the Google search engine to organizations optimizing their operations- AI is at work. AI broadly refers to computers, robots, and other devices that can think and solve issues similarly to humans (McPherson, 2018, p. 4). It includes automation, machine learning, robotics and deep learning, all of which are subsets of AI (Amponsah & Kaur, 2021). Simply put, AI is a popular term that involves using a computer to model intelligent behavior with minimal human intervention (Wijayati et al., 2022).

Adoption is explained as the act of embracing something as one's own, it can also refer to the act of embracing ideas or habits (Vocabulary.com, n.d.). According to Yigitcanlar and Cugurullo (2020) AI adoption is the rapid growth of AI applications in various areas. 'Artificial Intelligence Adoption' is thus operationally defined and it refers to a complex undertaking that involves the purchase or use of AI software and hardware, as well as the use of appropriate infrastructure and resources embedded with AI algorithms for completing a task, work or an activity.

For this study, 'Artificial Intelligence Adoption' is operationally defined as the intentional implementation and use of AI technologies by both organizations and individuals. This includes the acquisition of AI software/hardware and the utilization of infrastructure and resources embedded with AI algorithms for completing specific tasks, work processes, or activities.

AI Adoption is an ongoing process rather than an activity carried out at a single point in time (Neumann et al., 2024). This study focuses primarily on organizational AI adoption and its effects on employee psychological well-being. Organizational AI adoption refers to the employer's decision to implement AI technologies within company operations, processes, and strategies

(Autor, 2015). While individual employee adoption (personal acceptance and use of AI) is relevant, the primary focus is how organizational implementation of AI technologies affects employee well-being. Kim and Lee (2024), captures that the success of new technology adoption relies on human variables and factors, including the wellbeing of the workers who are expected to deal with the AI technologies. Well-being becomes a crucial variable which requires further exploration.

AI Adoption in Organizations

One of the keys to achieving successful business outcomes is the adoption of new technologies (Syeda, 2018). In recent years, several organizations have begun to adopt AI in their operations (PwC, 2018). Research shows (Banerjee et al., 2023; Dwivedi et al., 2021; Stone et al., 2022) that by 2030 several organizations will adopt AI. For example, Dwivedi et al. (2021) mentions that it is predicted that AI technologies will spur economic expansion, revolution and innovation, generating 133 million new jobs worldwide by 2022 and accounting for 20% of China's GDP by 2030. AI adoption is reshaping industries globally, as organizations integrate these technologies to streamline operations, improve decision-making, and innovate service delivery (Braganza et al., 2021). This growing reliance on AI in workplaces has sparked interest in its impact on employees (Clifton et al., 2020).

AI technologies offer unprecedented opportunities for improving efficiency, increasing productivity, and driving innovation (Modhoriye, Yadav & Jadhav, 2023; Wamba-Taguimdje et al., 2020;). From recruitment processes (Hunkenschroer & Kriebitz, 2023) to customer service (De Andrade & Tumelero, 2022), AI adoption is transforming traditional job roles and organizational structures (Sharma & Sehgal, 2023). Hunkenschroer and Kriebitz (2023) captures that organizations are using AI recruiting tools more and more to increase the applicant recruitment process's speed and effectiveness.

The AI Adoption landscape in Ghana

In the Ghanaian context, AI adoption is still emerging, but the country has made significant strides in embracing digital technologies. Over the past two decades, Ghana has undergone major digital transformations in sectors like finance, education, and government services (Dzisah, 2022). This transformation has been particularly evident in the financial sector (Ofori-Acquah, Avortri & Preko, 2023), where the emergence of mobile banking (MTN Momo, Telecel cash, etc), and fintech solutions has extended financial services to remote areas. The financial sector is adopting AI for fraud detection, credit scoring, and customer service automation through chatbots (Danso & Hanson, 2023). Mobile network operators like MTN Ghana have integrated AI into their customer service platforms to improve user experience (Ofori-Acquah et al., 2023).

Most recent studies in Ghana present varying findings in the awareness, perception and integration of AI adoption and how this affects employees. For example, Ampofo et al. (2023) assessed the degree of understanding and awareness regarding AI and its potential applications in medical imaging. Result showed that almost two-thirds (65%) said that the use of AI in medical imaging technology made them feel threatened or uneasy about their job security. Relying on the TAM framework, Ankamah et al. (2024) revealed that over half of those surveyed (50.4%) reported they understood the concept of AI well enough and were somewhat aware of AI-assisted technology. However, Acheampong et al. (2025) found uncertainty about AI outcomes and value.

Recent COVID-19 pandemic accelerated the adoption of technology-assisted options. In healthcare, telemedicine platforms emerged as essential tools for remote consultations, reducing patient exposure to healthcare facilities during lockdowns (Clipper, 2020), for example, automated prognostics, forecasts, and diagnoses are provided by MinoHealth AI Labs in Ghana (Eke, Chintu & Wakunuma, 2023). Similarly, education saw a massive shift to online learning, with virtual classrooms and e-learning resources becoming the norm for millions of students (Chinnaswamy, 2021). Businesses also embraced digital tools like video conferencing, collaboration platforms, and AI-driven automation to ensure operational continuity amidst physical distancing measures (Eke et al., 2023).

Despite these digitalization efforts, the adoption of AI in Ghana is still at an embryonic stage. Several industries in Ghana are beginning to experiment with AI technologies. Yet, the implications of these technologies on employee well-being remain underexplored. As AI adoption increases, it is essential to examine how these technologies impact employees' well-being, especially in industries that are rapidly transitioning to AI operations (Eke et al., 2023).

Connecting AI Adoption and Employee Psychological Well-being.

The relationship between organizational AI adoption and employee psychological well-being is complex and multifaceted. When organizations implement AI technologies, employees experience various psychological effects that directly impact their well-being (Vyas-Doorgapersad, 2023). These effects can be both positive and negative, influencing multiple dimensions of psychological functioning.

On the positive side, AI adoption can strengthen employee psychological well-being by: reducing repetitive, mundane tasks, allowing for more meaningful work (Soulami et al., 2024); creating opportunities for skill development and career advancement (Malik et al., 2021); improving work-life balance through increased efficiency and flexibility (Ali, Warraich & Butt, 2024).

Conversely, organizational AI adoption can negatively impact psychological well-being through: increasing job insecurity and fear of technological replacement (Nazareno & Schiff, 2021); creating pressure to continuously adapt to new systems (Johnson et al., 2020); reducing autonomy through algorithmic management and decision-making (Brynjolfsson & McAfee, 2014).

This dual nature of AI's influence on employee psychological well-being necessitates careful examination of the specific dimensions of well-being that are affected which this study aims to explore.

Psychological Well-being in Technology-driven Organizations and AI Adoption

Psychological well-being (PWB) is a multifaceted concept that reflects an individual's emotional, psychological, and social health (Zhang & Chen, 2019). The term "psychological well-being" refers to a psychological health image based on a person's ability to perform psychological functions (Muqodas et al., 2020). Ryff's model and assessment of PWB is one of the most frequently employed literatures (Matud et al., 2019). Ryff (1989) emphasized positive psychological functioning, and as a result, took a eudaemonic viewpoint (Jackman & Sisson, 2022).

The Ryff (1989) model conceptualizes PWB through six key dimensions. The first is **self-acceptance**, which involves being positive about oneself and one's previous experiences, as well as acknowledging and embracing one's traits. The second dimension is **positive relations with others**, characterized by having genuine, warm relationships and being concerned about others' well-being. The third, **autonomy**, refers to being self-determining and independent in one's decisions and actions. **Environmental mastery** is the fourth dimension, which entails effectively managing one's environment and utilizing opportunities it provides. The fifth, **purpose in life**, involves having goals and a sense of direction that makes life meaningful. Lastly, **personal growth**, refers to the feeling of continuous development and the realization of one's potential.

These dimensions provide a comprehensive framework for examining how AI adoption might differentially impact various aspects of employee psychological functioning (Matud et al., 2019).

In technology-driven organizations, where employees must continually adapt to new AI tools and technologies, PWB becomes a crucial factor. Research suggests that technological changes in the workplace can affect employees' autonomy, environmental mastery, and sense of purpose (Othman et al., 2022). While AI offers opportunities for skill development and personal growth, it may also cause stress, anxiety, and job dissatisfaction due to the constant need for adaptation and fear of obsolescence (Malik et al., 2021). Therefore, understanding the relationship between AI adoption and PWB is crucial for creating supportive work environments in technology-driven organizations.

AI adoption directly influences each dimension of Ryff's psychological well-being model: Regarding **autonomy**, AI systems may reduce employee decision-making authority in some areas while enhancing it in others by providing decision support tools (Brynjolfsson & McAfee, 2014). For **environmental mastery**, AI adoption requires employees to develop new skills to effectively collaborate with intelligent systems, which can either enhance or diminish their sense of competence, depending on the context and the individual (Othman et al., 2022).

In terms of **personal growth**, AI implementation creates opportunities for new learning experiences. However, it may also lead to stress due to the continuous adaptation requirements (Malik et al., 2021). With respect to **positive relations**, AI can influence workplace social dynamics by altering communication patterns and collaborative workflows, thereby reshaping how employees interact (Zhang & Chen, 2019).

When it comes to **purpose in life**, the automation of routine tasks by AI can lead employees to question their value and contribution, or alternatively, find or seek more meaningful work (Johnson et al., 2020). Finally, **self-acceptance** may be affected by changes in performance evaluations and shifts in job roles resulting from AI integration, which could impact employees' self-perception and professional identity (Ford, 2015).

Demographic Characteristics in AI Adoption and Well-being

Demographic factors have been studied in the technology adoption literature (Jain, 2017; Kusuma et al., 2020; Rojas-Mendez et al., 2017). These factors play a significant role in moderating how AI adoption affects psychological well-being, as different demographic groups may experience technology changes differently (Løvik, 2024). Studies suggest that older employees may find it more challenging to adapt to new AI tools compared to younger employees, who are generally more familiar with digital technologies (Marquis et al., 2024; Meyer, 2008). This generational gap may lead to increased stress, reduced job satisfaction and overall impact on the wellbeing of older workers. Gender is also a relevant factor, as research shows that men and women may experience AI adoption differently (McClure, 2018; Nouraldeen, 2023; Ofosu-Ampong, 2023; Yu et al., 2023).

Age-related differences in AI adaptation have been observed in several studies. Younger employees, often referred to as digital natives tend to exhibit greater comfort and ease when engaging with new technologies (Marquis et al., 2024). In contrast, older employees may experience heightened levels of technostress and anxiety, particularly during periods of technological transitions (Meyer, 2008). Additionally, differences in learning styles and capacities based on age can influence the effectiveness of training programs for AI systems, potentially impacting how well different age groups adapt to technological change (Løvik, 2024).

Gender differences also shape individuals' experiences with AI in the workplace. Research shows that men and women may display varying levels of technological self-efficacy, which can influence their confidence and willingness to engage with AI tools (Nouraldeen, 2023). Furthermore, men and women may adopt and use AI in different ways, leading to distinct patterns of technology interaction (Ofosu-Ampong, 2023). Gender can also influence how employees perceive job security in relation to automation, with some evidence pointing to differing levels of concern about the potential for job displacement (Yu et al., 2023).

These findings call attention to the importance of considering demographic factors in understanding AI adoption and their potential impact on employees' PWB, which could inform future research and the development of targeted interventions. This study will explore gender and age as potential moderators of the influence of AI adoption on PWB.

1.2 Statement of the Problem

In recent times, the proliferation of AI dominates headlines and discourse, with debates over its implications reverberating across media outlets such as CNN and Al Jazeera (Zhao et al., 2022). In Ghana, for instance, Unique FM's morning show has dedicated a 3 to 5 minutes time slot to update their listeners on tech news, of which AI is mostly discussed. The swift incorporation of artificial intelligence (AI) into technologically advanced companies has revolutionized work procedures, providing advantages including increased efficiency and productivity (PwC, 2018; Tai, 2020). However, this shift has also raised concerns about its psychological impact on employees. While AI adoption can reduce repetitive tasks, it may also lead to job insecurity, skill obsolescence, and increased stress due to constant adaptation to new technologies (Brynjolfsson & McAfee, 2014; Ford, 2015). Despite the growing adoption of AI in organizations, research examining its specific impacts on employees' psychological well-being remains limited, particularly in the Ghanaian context.

Current literature reveals several important gaps in understanding the relationship between AI adoption and employee well-being. To begin with, there is a lack of comprehensive studies that systematically analyze how the adoption of AI within organizations affects each specific dimension of psychological well-being among employees. While some research has touched on general impacts, few have explored these effects in a detailed and multidimensional manner. Additionally, there is limited exploration of how demographic factors, such as age and gender, moderate the relationship between AI adoption and psychological well-being. This oversight prevents understanding of how different groups of employees may be uniquely affected by technological changes in the workplace.

Moreover, little is known about how workers in Ghana specifically perceive and respond to the integration of AI in their work environments. Given the unique socio-cultural and economic context of Ghana, it is important to understand local perspectives to ensure relevance and effectiveness in organizational strategies. Finally, the literature offers few evidence-based recommendations for implementing AI in ways that support, rather than undermine, employee well-being. There is a clear need for practical, research-driven guidance to help organizations adopt AI responsibly while safeguarding the mental and emotional health of their workforce.

This research gap is significant because poor psychological well-being among employees can lead to decreased productivity, higher turnover rates, increased absenteeism, and elevated healthcare costs for organizations (World Health Organization, 2022). Without proper understanding of AI's psychological impacts, organizations risk implementing technologies in ways that inadvertently harm employee well-being and ultimately undermine the very productivity gains they seek.

In the Ghanaian context specifically, the relationship between AI adoption and psychological well-being takes on additional importance. As a developing economy actively embracing technological advancement, Ghana's organizations are increasingly incorporating AI systems. However, this technological transition occurs within a unique cultural, economic, and social environment that may influence how employees experience and respond to AI implementation (Eke et al., 2023).

The COVID-19 pandemic accelerated Ghana's digital transformation across various sectors, from financial services to healthcare and education (Dzisah, 2022). This rapid shift has created an urgent need to understand how these technological changes affect the psychological well-being of Ghana's workforce. Without this understanding, organizations risk implementing AI in ways that are not culturally appropriate or responsive to the specific needs of Ghanaian employees, potentially leading to resistance, reduced productivity, and poor mental health outcomes.

1.3 Aims/Objectives of the Study

1. To investigate the relationship between organizational AI adoption and specific dimensions of employees' psychological well-being (PWB), including self-acceptance, positive relations with others, personal growth, autonomy, environmental mastery and purpose in life, within technology-driven organizations.
2. To determine how demographic factors (age, gender) moderate the relationship between organizational AI adoption and Employee PWB.
3. To understand employees' views of AI adoption in technology-driven organizations.
4. To understand the potential challenges/effects with regards to AI adoption on employees to provide recommendations for managers on implementing AI technologies in ways that support employee well-being.

1.4 Relevance of the Study

Psychological Context

The rapid incorporation of AI technologies in the workplace has far-reaching implications, particularly in technology-driven organizations where employees are frequently interacting with AI systems. AI is increasingly been woven into daily functions across sectors-from virtual assistants and automated decision-making to personalized healthcare and education (Zhao et al., 2022). Given this widespread adoption, understanding how AI influences employees' PWB is critical to developing workplaces that foster mental health and positive employee experiences.

This study focuses to bridge a significant gap in existing research by probing into the psychological dimensions of AI adoption in organizational settings. By examining how employees interact with and perceive AI technologies, this research provides insightful information about the emotional and cognitive effects of AI, thereby advancing the understanding of human-technology relationships. Such understanding is especially relevant to psychology, as it offers a foundation for mental health professionals and researchers to explore how AI interactions may influence stress levels, autonomy, and employees' sense of purpose within AI-driven work environments.

This study also contributes to the on-going ethical and psychological discourse on AI adoption, emphasizing the human-technology relationship within organizations. While earlier studies have concentrated largely on the technical and economic advantages of AI, this study shifts the focus to psychological and well-being considerations. By doing so, it provides insights that can help mental health practitioners, psychologists, and organizational leaders understand the emotional and cognitive implications of AI use, fostering a more comprehensive approach to supporting mental health in technology-driven workplaces.

Technological Context

In addition, it is important to weigh the potential long-term influence of AI technologies adoption on society as a whole. For instance, Musikanski et al. (2020) explored community well-being and AI, where they conclude with important interdisciplinary and system-based approaches to research in this area. Understanding how AI may impact our PWB can inform ethical and policy formulations related to the development and deployment of AI for technology workers as well as workers from all walks of life. Overall, the study of AI adoption and PWB can help us identify opportunities for AI to positively impact psychological/ mental health care and help mitigate any potential negative effects, misconceptions and myths, while providing a guide to policy and law makers.

Organizational Context

From an organizational perspective, this research offers practical value by providing evidence-based insights for implementing AI in ways that prop up employee psychological well-being. Organizations investing in AI technologies need guidance on how to manage the human side of technological change, particularly regarding: Developing effective change management strategies that consider psychological impacts; Creating training programs that address the different needs of diverse demographic groups; Designing AI implementation processes that minimize negative psychological effects while maximizing benefits; Establishing supportive organizational cultures that help employees adapt to AI integration.

By addressing these organizational needs, this study contributes to more effective and sustainable AI adoption practices that benefit both organizations and employees.

1.5 Scope and Organization of the Study

This study was conducted systematically, following a structured approach to ensure valid and reliable results that accurately reflect participants' responses. All participants were fully informed about the study's purpose and relevance, enabling them to make an informed decision about their involvement. Participation was entirely voluntary, with participants given the freedom to withdraw from the study at any point without coercion. The research is organized into five chapters: Chapter One presents an introduction to the study; Chapter Two reviews relevant literature; Chapter Three outlines the methodology; Chapter Four details the results; and Chapter Five offers a discussion of the findings and their implications.

Chapter 1 provides an overview of the study, including the background, problem statement, aims, and objectives, along with the study's anticipated contributions. Chapter 2 presents the theoretical foundations of the study, followed by a comprehensive review of relevant literature within the global, African, and Ghanaian contexts. This chapter also includes the rationale for the study, defines key variables, outlines the research hypotheses, and provides operational definitions pertinent to the research.

In Chapter 3, the methodology is thoroughly described. The researcher justifies and explains the chosen research approach, detailing the study's design, target population, sample, and sampling techniques. Chapter 4 reports the research results, presenting detailed findings of study 1 and study 2 including descriptive statistics (mean, standard deviation, skewness, kurtosis), reliability analyses (Cronbach's alpha), hypothesis testing, and all other analyses conducted. Chapter 5 includes a comprehensive discussion of all hypotheses and research questions that were tested in the study, it also discusses the themes that were derived from the qualitative data. The implications of the study (theoretical and practical implications), addresses its limitations and offers recommendations for future research. The thesis concludes with a summary of key findings.

References are formatted according to APA style, and appendices (including the questionnaire, budget, timetable, and analytical outputs) are provided at the end of the thesis.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter includes a review of studies conducted by various authors and researchers on the subject matter. The significance of the literature review section in every research paper is to understand what has already been done in a particular field of interest in order to avoid repetition. It narrows gaps and expands on earlier research by relating the study to the broader discussion taking place in the literature (Creswell & Creswell, 2018). This chapter presents the theoretical background of the study as well as reviews the relevant literature that applies to the study. The first part explored theories upholding the study, and the second and subsequent sections focused on review of related studies, hypotheses, key variables and operational definition of terms. The section also highlights the relevance and rationale of the study respectively.

2.1 Theoretical Underpinnings

Several theories have been propounded and adopted to study either AI adoption or PWB. It is challenging to apply any existing adoption model in the context of AI adoption, as it is a complicated technology (De Graaf, 2016 as cited in Chatterjee et al., 2021). For this research, two theoretical frameworks were integrated to provide a comprehensive foundation: the 'Job Demands-Resources (JD-R) model' which helps explain how AI adoption affects psychological well-being, and the 'Technology Acceptance Model (TAM)' which addresses the factors that influence organizational AI adoption.

2.1.1 Job Demands-Resources Model

According to Scholze and Hecker (2024), the Job Demands-Resources Model (JD-R) was introduced by Demerouti et al. (2001) and has since undergone several refinements, including contributions from Bakker and Demerouti (2007, 2014, 2017), Demerouti and Bakker (2011), and Demerouti and Nachreiner (2019). The JD-R model offers a thorough framework for comprehending how job characteristics influence employee well-being and performance by categorizing workplace factors into *job demands* and *job resources*. **Job Demands** refer to aspects of a job that require sustained effort and are linked to psychological or physiological costs, such as workload, time pressure, and adapting to new technologies. On the other hand, **Job resources** are factors that assist workers in reaching their objectives, mitigate job demands, and foster personal development, including autonomy and social support (Bakker & Demerouti, 2007). While excessive job demands can lead to stress and burnout, the presence of adequate job resources can enhance work engagement and improve overall well-being.

The JD-R model offers a valuable framework for comprehending the relationship between organizational AI adoption and employee psychological well-being. When organizations implement AI technologies, these implementations can function as both job demands and job resources:

As job demands, AI adoption may: Create pressure to acquire new skills, abilities and adjust to evolving job procedures (Morandini et al., 2023); Generate fear of job displacement or role changes (Raj, 2024); Increase monitoring and performance expectations (Malik et al., 2021); Produce technostress from continuous technological changes (Soulami et al., 2024).

As job resources, AI adoption may: Reduce repetitive tasks, allowing workers to focus on more meaningful work (Sharma & Sehgal, 2023); Provide tools that enhance decision-making and problem-solving capabilities (Baabdullah, 2024); Create opportunities for skill development and career advancement (Chuang et al., 2024); Improve work efficiency and work-life balance through automation (Dalisaymo & Patalay, 2024).

According to the JD-R model, when AI-related job demands exceed available resources, employees may experience stress, burnout, and diminished psychological well-being across various dimensions of Ryff's (1989) framework. Conversely, when AI implementation provides adequate resources to meet or exceed demands, it may enhance psychological well-being by supporting personal growth, environmental mastery, and purpose in life. Recent research by Scholze and Hecker (2024), Kim and Lee (2024), and Lee (2019) confirms these theoretical relationships, making the JD-R model particularly appropriate for examining AI adoption's psychological impacts.

Having understood how the JD-R offers a robust framework for understanding how AI functions as both a demand and a resource affecting employee well-being, the Technology Acceptance Model (TAM) complements this perspective by shedding light on the cognitive and attitudinal factors that impact how employees view and engage with AI technologies.

2.1.2 Technology Acceptance Model

The Technology Acceptance Model (TAM) is a model designed to ascertain users' acceptance or rejection of computer usage by Davis et al., 1989 (Oyman, Bal & Ozer, 2022). TAM is a theory that explains how humans accept and make use of technology (Malatji, Eck & Zuva, 2020). Davis (1989) developed the TAM model based on his research on The Theory of Reasoned Action by Ajzen and Fishbein in the 1980s and related studies. TAM puts forward that perceived usefulness (PU) and perceived ease of use (PEOU) shape people's attitudes and intentions toward technology, which in turn influences their behavioural intention to use it and ultimately their actual usage behaviour. (Davis, 1989). Studies such as Oyman et al. (2022); Fussell and Truong (2022) confirm the assumptions of this theory which is incorporated in the current study.

In the context of organizational AI adoption and psychological well-being, TAM provides critical insights into why employees may embrace or resist AI technologies. When employees perceive AI systems as useful (improving their job performance) and easy to use (requiring minimal effort to learn), they are more likely to develop positive attitudes toward the technology. They experience less stress during the adoption process, engage more fully with the new systems and experience enhanced psychological well-being through successful adaptation.

Conversely, when employees perceive AI as difficult to use or not useful for their work resistance to adoption increases. Also, stress and anxiety levels may rise, psychological well-being dimensions like environmental mastery and autonomy may suffer and the potential benefits of AI adoption may not be realized.

The TAM framework is particularly relevant for understanding how demographic factors like age and gender might moderate the relationship between AI adoption and psychological well-being. Research puts forward that perception of usefulness and ease of use often vary across demographic groups, potentially explaining differences in adoption experiences and well-being outcomes (Oyman et al., 2022).

The integration of TAM and JD-R models provides a comprehensive theoretical foundation for this study. TAM explains the cognitive and attitudinal factors that influence how employees respond to organizational AI adoption, while JD-R explains the mechanisms through which these responses affect psychological well-being. Together, these frameworks provide a comprehensive understanding of employee responses to AI implementation in the workplace. The Technology Acceptance Model (TAM) helps explain why employees may react differently to the same AI system, based on their individual perceptions of its usefulness and ease of use. These varied responses, in turn, influence psychological well-being (PWB) outcomes, as outlined by the Job Demands-Resources (JD-R) model, which links workplace demands and resources to employee stress and well-being. Demographic factors such as age and gender further moderate these relationships, shaping how different individuals experience and adapt to AI. Moreover, these frameworks highlight the crucial role of organizational support in shaping outcomes, showing how adequate training, communication, and resources can create pathways that enhance the positive effects of AI adoption while minimizing potential harm to employee well-being.

This integrated theoretical approach allows for a more meaningful examination of the multiplex relationship between organizational AI adoption and employee psychological well-being than either framework could provide alone.

2.2 Review of Related Studies

This literature review seeks to determine what is already known as well as discover gaps in order to fill in. The review was categorized under 4 subthemes;

2.2.1 General AI Adoption Review

Soomro et al. (2024) examined the relationship between AI adoption, employee well-being, and organizational support within SMEs in Pakistan. Using Affective Events Theory (AET) and Force Field Analysis (FFA) as frameworks, the research analyzed data from 324 employees to probe how AI anxiety impacts employee well-being, mediated by managerial capabilities and moderated by organizational support. Findings revealed that while AI anxiety negatively impacts employee well-being, managerial acumen and organizational support significantly mitigate these effects. Additionally, organizational support played a crucial moderating role, reducing the adverse impact of AI anxiety. The study highlighted the importance of strong managerial capabilities and organizational backing for successful AI adoption, emphasizing structured communication and training programs to alleviate employee concerns. Despite its contributions, the research's focus on a single industry and context limits its generalizability, suggesting the need for future research in varied organizational settings and cultural contexts.

Kim and Lee (2024) examined the mental health implications of AI adoption in workplaces, focusing on job stress, burnout, and the moderating role of self-efficacy in AI learning. Using a three-wave time-lagged methodology and data from 416 professionals in South Korea, the study discovered that AI adoption indirectly increases burnout through workplace stress rather than a direct effect. Self-efficacy in the learning of AI significantly influenced the connection between AI adoption and occupational stress, with higher self-efficacy mitigating stress levels. The research emphasizes a human-centered approach to AI implementation, recommending strategies such as stress management, transparent communication, and targeted training programs to enhance employee adaptability and well-being. Despite its contributions, the study's reliance on a single cultural and organizational context limits the generalizability of its findings.

In a study in South Africa, Moghayedi et al. (2024) investigated the impact of AI adoption on the social well-being of employees in South Africa's facilities management (FM) sector. Using a mixed-methods approach, the study identified 16 social well-being factors- grouped into job satisfaction, social relationships, and knowledge development- that are influenced by AI adoption. The research revealed that AI negatively impacts job security and social isolation but positively influences factors such as professional status and work-life balance. The study emphasized the critical role of organizational policies in managing these effects, proposing a hierarchical framework to prioritize interventions. While the findings provide a valuable roadmap for balancing the social costs and benefits of AI adoption, the study's focus on South Africa's FM sector limits its applicability across broader contexts.

Gikunda and Kute (2023) provided a comprehensive literature review on the adoption of AI in Africa, highlighting its transformative potential across various sectors, including healthcare, agriculture, finance, and education. They explored how AI-driven innovations enhance efficiency, accessibility, and inclusivity while addressing socio-economic challenges unique to the continent (Egypt, Rwanda, Mauritius). The authors discussed the role of indigenous AI advancements and international collaborations in shaping a distinct African AI ecosystem, emphasizing the need for local capacity-building and infrastructural development. It is apparent that Gikunda and Kunte (2023) were more interested in how AI enhances the main organizational efficiency but not how it affects employees' wellbeing.

Arboh et al. (2024) examined the influence of AI awareness on workplace well-being among healthcare workers in Ghana, applying the Job Demands-Resources (JD-R) model. The study, based on survey data from 420 employees across ten AI-integrated hospitals, discovered that knowledge of AI had a favourable impact on informal learning practices, which improved workplace wellbeing. The impact of AI awareness on informal learning was found to be strengthened by employee learning orientation, which was found to be a significant moderator. The findings suggest that AI awareness, when perceived as a challenge rather than a threat, can drive proactive learning and adaptation, mitigating workplace stress. While offering valuable insights into AI's psychological and behavioural implications, the study's reliance on self-reported data and its focus on Ghanaian healthcare settings limit its broader applicability, warranting further research across diverse contexts.

Ampofo et al. (2023) evaluated 225 second- to fourth-year medical imaging students from Ghanaian public universities' knowledge and awareness of artificial intelligence (AI) and its potential applications in medical imaging. According to the results of a cross-sectional quantitative study, almost two-thirds (65%) of respondents said that the use of AI technology in medical imaging equipment made them feel threatened or uneasy about their job security.

Similar findings were found by Ankamah et al. (2024), who used the TAM framework to examine medical students' awareness, use, and perception of AI-assisted technologies. Of the respondents, over half (50.4%) said they were only moderately aware of AI-assisted technologies and had a sufficient understanding of the concept.

Acheampong et al. (2025) evaluated key elements influencing the uptake of AI technologies in construction health and safety management within the Ghanaian industry, using a qualitative approach and later quantitative. Among his findings was uncertainty about AI outcomes and value.

The reviewed studies provide valuable insights into AI adoption and its impact; notable research gaps remain. Most studies focus on general organizational adoption rather than examining how adoption specifically affects psychological well-being across its various dimensions. Additionally, few studies have employed Ryff's (1989) comprehensive psychological well-being framework, which offers a more refined understanding of well-being beyond simple measures of job satisfaction or stress. Finally, research in the Ghanaian context remains limited, with existing studies focusing primarily on specific sectors like healthcare rather than technology-driven organizations more broadly.

Collectively, the reviewed literature under this sub-theme encompasses diverse aspects of AI adoption and its impact across various domains globally, in Africa and locally. In synthesis, while these studies collectively contribute to the understanding of AI's impact, future research should address data quality, practical implementation, and consider a broader range of perspectives and methodologies, which will be addressed in the present study.

2.2.2 Well-being of Employees amidst AI adoption

Jin, Jiang, and Liao (2024) scrutinized the impact of AI adoption on employees' work affective well-being, focusing on job stress as a mediator and psychological resilience as a moderator, using Conservation of Resources (COR) theory as a framework. Analysing data from 349 employees in manufacturing undergoing digital transformation, the study found that higher awareness of AI-driven job threats (STARA awareness) negatively affects well-being via increased job stress, while psychological resilience buffers this effect. Employing robust statistical methods, the findings highlight the need for organizations to address AI-related stress by fostering skill development and resilience. Despite its contributions, the study focused on manufacturing workers which limits its generalizability, prompting future research to explore diverse settings and mediating factors like gender and age.

Sadeghi (2024) explored the dual impact of AI integration in Human Resources (HR) on employee well-being, introducing an AI-Employee Well-being Interaction Framework. The study identified that while AI enhances efficiency and reduces bias, it also raises significant concerns regarding job security, fairness, and mental health. Transparency emerged as a critical factor influencing employee perceptions, with opaque AI decision-making processes leading to mistrust and dissatisfaction. The study emphasized organizational tactics to reduce negative effects and promote trust, including open communication, upskilling initiatives, and employee participation in AI deployment. A key finding was that AI-driven processes can simultaneously enhance and undermine well-being depending on implementation and employee perceptions. Although the paper provides actionable insights for HR leaders and a conceptual framework, its reliance on general employee perceptions and absence of empirical data limits its applicability across diverse organizational contexts. Future research could benefit from longitudinal studies and specific sector-focused analyses to explore the effects of AI on job satisfaction and mental health.

In a study conducted in Georgia, USA, Nazareno and Schiff (2021) investigated the "impact of automation and artificial intelligence on worker well-being." Based on data from the General Social Survey from 2002 to 2018, the researchers found that workers who are threatened by automation appear to be less stressed, but they also have worse health and little to no job satisfaction. The researchers contributed significantly to the AI/Automation and well-being literature considering prior work in that area. However, the study was based on previous/already existing data and hence may not capture current trends on the topic. Future studies should therefore explore the above topic by gathering contemporary data, and should consider mixed-methods approach for studies on the topic. The present study submits meaningfully by using a mixed-method study from an African context.

Thakur et al. (2025) critically examined the ethical implications of AI-driven HR practices in Indian universities, focusing on employee well-being. The study highlighted AI's dual impact; enhancing efficiency and personalized employee experiences while raising concerns about privacy, job security, and bias. Through a mixed-method approach across 15 universities, the research found that private institutions with high AI adoption experienced improved well-being and lower stress, whereas public institutions reported heightened anxiety due to lack of transparency and job insecurity. The study proposed an ethical framework emphasizing transparency, accountability, and employee involvement to mitigate adverse outcomes. It is heart-warming to see a close study on AI and well-being from an Indian context. This notwithstanding, the researchers concentrated on HR practitioners and this study targets employees in technology-driven organizations.

A critical analysis of these studies reveals that while they explore various aspects of employee well-being in relation to AI adoption, most rely on general well-being measures rather than examining psychological well-being from a eudemonic perspective as conceptualized by Ryff

(1989). This represents a significant gap in understanding how AI adoption specifically affects the six distinct dimensions of psychological well-being: autonomy, environmental mastery, personal growth, positive relations with others, purpose in life, and self-acceptance. The present study addresses this gap by applying Ryff's multidimensional framework to provide a more refined comprehension of AI's psychological impacts.

Altogether, articles revealed under this theme shows that all studies contribute valuable insights, but limitations such as sample size, regional specificity, and methodological constraints must be considered, emphasizing the need for future research to address these gaps.

2.2.3 Psychological Well-being of Employees in Technology-driven Organizations

Zahoor et al. (2022) examined the relationship between technological innovation and employee PWB, emphasizing the moderating effects of employee learning orientation and perceived organizational support. The study highlighted that while technological advancements can enhance productivity and job satisfaction, they also introduce stress and uncertainty, affecting employee well-being. Findings suggested that employees with a strong learning orientation adapted better to technological changes, experiencing less psychological distress. Additionally, perceived organizational support played a crucial role in mitigating negative effects, establishing a more positive work environment. Despite its contributions, the study's reliance on self-reported data and its focus on specific organizational contexts limit its broader applicability. Also, employee PWB was conceptualized with a different model other than Ryff (1989). This calls for further research across diverse industries and cultural settings as well as introducing Ryff's model.

Using Ryff's six-factor model, Dissanayake (2024) examined how remote work affected the PWB of software workers in New Zealand. Employing a mixed-methods approach, the study combined qualitative information from 15 semi-structured interviews with survey data from 128 people. Findings indicated that remote work positively influenced autonomy, self-acceptance, and purpose in life, as employees valued flexibility and control over their work environment. However, challenges emerged in environmental mastery, personal growth and social interactions due to blurred work-life boundaries and limited in-person engagement. The study emphasized the need for organizational support, structured communication, and well-being initiatives to address these challenges. While offering valuable insights into the psychological effects of remote work, the study's focus on software professionals in New Zealand limits its generalizability, suggesting the need for further research across diverse industries and cultural settings.

Johnson et al. (2020) conducted a comprehensive review of how technology-driven workplace changes impact employee mental health and well-being. The study examined two major trends: automation and advanced technology reshaping job roles and tasks, and flexible work arrangements enabled by telecommunication advancements. While automation improves efficiency, it also increases job insecurity and work intensification, contributing to stress and burnout. Conversely, flexible work arrangements offer autonomy but blur work-life boundaries, potentially leading to social isolation and overwork. The study emphasized the need for well-designed workplace policies, participatory decision-making, and mental health support mechanisms to balance technological benefits with employee well-being. Although providing a robust research agenda, the review calls for longitudinal studies and interdisciplinary approaches to better understand long-term mental health implications across diverse work settings.

Park et al. (2021) explored the PWB and career development of remote e-workers during the COVID-19 pandemic, emphasizing the role of Human Resource Development (HRD) professionals in mitigating challenges. The study reviewed empirical and conceptual literature, identifying key psychological risks including social isolation, a lack of clear boundaries between work and life, and career stagnation due to decreased workplace visibility. While remote work increased autonomy and flexibility, it also heightened concerns regarding mental health and career advancement. The authors highlighted supportive factors, including organizational climate, managerial support, and structured communication, which can enhance PWB. Grounded in Social Cognitive Career Theory (SCCT), the study provided a framework for HRD interventions, such as e-mentoring and career development programs, to support remote employees. Despite its valuable insights, the study called for further research into long-term psychological effects and cross-cultural variations in remote work experiences.

While the above studies provide valuable insights into psychological well-being in technology-driven organizations, there remains a significant gap in research specifically examining the relationship between organizational AI adoption and employee psychological well-being using Ryff's (1989) comprehensive framework. Of the studies reviewed, only Dissanayake (2024) employed Ryff's six-factor model, but in the context of remote work rather than AI adoption. This highlights the novelty and importance of the present study in examining how AI adoption specifically impacts each dimension of psychological well-being within the Ghanaian context.

Together, the keyword search for this theme was 'psychological well-being', 'employee PWB', 'employee wellbeing', 'wellbeing' etc and close to 2407 papers where found. The reviewed literature on employee PWB in technology-driven workplaces highlights both benefits and challenges. However, limitations in generalizability, reliance on self-reported data, and varied PWB models suggest the need for future research across diverse settings, using interdisciplinary and longitudinal approaches, and incorporating Ryff's (1989) model for a more comprehensive analysis.

2.2.4 Demographic Factors in AI Adoption and Well-being

Medeiros (2024) examined global attitudes toward AI in the workplace, concentrating on demographic and geographic differences in perceptions. Using survey data from employees in the United States and India, the study explored variations in AI acceptance based on gender, age, and cultural background. Findings revealed that U.S. employees generally exhibited more positive attitudes toward AI, with greater trust in its ethical applications and competence compared to their Indian counterparts. Additionally, male respondents showed consistently higher enthusiasm for AI adoption than female respondents. Interestingly, generational differences had minimal influence on AI perceptions, challenging assumptions that older employees would be more resistant to technological change. The study emphasized the significance of customizing AI implementation strategies to account for cultural and demographic variations, providing managerial insights for improving AI acceptance. While offering valuable global perspectives, the study's limited sample size across multiple countries restricted broader generalizability, highlighting the need for future cross-cultural research.

Rojas-Méndez et al. (2017) conducted a cross-cultural analysis to examine how demographic and attitudinal variables influence technology adoption, using the Technology Readiness Index (TRI) framework. The study compared data from the United States and Chile, representing developed and developing countries, respectively. Findings confirmed the cross-cultural validity of the TRI, highlighting that education was the strongest demographic predictor of technology adoption, followed by age and gender. In the U.S., attitudinal variables, particularly technology-related insecurity, were more significant in predicting technology adoption, whereas in Chile, demographic factors, especially education, played a larger role. The study challenged conventional theories of attitude-behavior consistency, revealing that while pro-technological attitudes predicted adoption in the U.S., demographic variables were stronger predictors in Chile.

Despite its contributions, the research called for further studies to explore the interplay of cultural and socioeconomic factors in shaping technology adoption behavior across diverse global contexts

Using gender as a moderating factor, Nouraldeen (2023) investigated how perceived utility and technological readiness affected the adoption of AI among accounting students in Lebanon. According to 330 students' survey findings, perceived utility and technological preparedness had a positive impact on AI adoption, while perceived ease of use had no significant effect. Male students exhibited a higher tendency to adopt AI and moderated the relationship between these factors. The study underscores the need for AI integration in accounting curricula and efforts to close gender gaps in technology adoption. However, its findings are limited to a single cultural and academic context.

Meyer (2008) investigated the relationship between workforce age structure and the adoption of new technologies in ICT-intensive service sectors, using data from 362 German firms. The study found that firms with a higher proportion of younger employees were significantly more likely to adopt new technologies, while those with an older workforce exhibited lower adoption rates. However, the study also highlighted that workplace organization plays a crucial role in technology adoption. Firms that enhanced teamwork or flattened hierarchies were more likely to adopt new technologies when they had a higher proportion of employees aged 40–55, whereas those with a predominantly younger workforce showed a lower likelihood of adoption. The findings suggest that the integration of innovative workplace practices can relieve some of the challenges associated with an aging workforce. Despite the study’s contributions, it focused on a specific sector in Germany, limiting its generalizability, and called for further research across diverse industries and cultural contexts to increase generalization.

The literature on demographic factors in AI adoption suggests important variations in how different groups experience technological change. However, there is a notable gap in research specifically examining how demographic factors moderate the relationship between organizational AI adoption and employee psychological well-being across Ryff's (1989) six dimensions. While studies have explored demographic differences in adoption attitudes and general well-being impacts, few have examined how age and gender specifically influence the psychological experience of organizational AI implementation across multiple well-being dimensions. The present study addresses this gap by examining age and gender as potential moderators of the relationship between AI adoption and each dimension of psychological well-being.

In the aggregate, reviewed studies provide beneficial insights into the role of demographic factors in AI adoption and employee well-being, emphasizing the influence of culture, education, gender and other variables. However, limitations such as regional specificity, sample size constraints, and sectoral focus restrict broader generalizability, highlighting the need for further cross-cultural and industry-wide research that will address the gaps in the previous studies.

2.3 Rationale of the Study

The comprehensive literature review revealed several significant gaps in current research that this study aims to address:

1. Conceptual Integration Gap: While numerous studies have examined AI adoption or psychological well-being separately, there is limited research that specifically probes the relationship between organizational AI adoption and employee psychological well-being using Ryff's (1989) multidimensional framework especially from an African context. Most existing studies focus on general well-being measures rather than examining the specific dimensions of psychological functioning that might be differently affected by AI adoption.

2. Theoretical Framework Gap: Not many studies have incorporated robust theoretical foundation that integrates technology adoption models with well-being theories. This study addresses this gap by combining the Technology Acceptance Model (Davis, 1989) with the Job Demands-Resources Model (Bakker & Demerouti, 2007) to provide a robust theoretical framework for comprehending how and why AI adoption affects psychological well-being.

3. Contextual Research Gap: The majority of AI adoption and well-being studies have been conducted in Western contexts or developed economies. There is limited research examining these relationships in developing economies like Ghana, where cultural, economic, and technological contexts differ significantly. This study contributes to addressing this contextual gap by focusing on technology-driven organizations in Ghana.

4. Demographic Moderation Gap: While demographic factors have been studied in relation to technology adoption, few studies have examined how age and gender specifically moderate the relationship between organizational AI adoption and each dimension of psychological well-being. This study explicitly investigates these moderating relationships to provide a more subtle difference in understanding of diverse employee experiences.

Also, the study setting/ the study was conducted in Ghana which provides a different cultural context other than the west; and the sample will allow for generalization and replication in different parts of Ghana and other African countries. Moreover, the present study upon completion is a pioneer in the AI adoption and PWB literature and sets the pace for future studies as nothing was found per the researcher's search. In the Ghanaian context, researchers have studied the introduction of AI technologies to combat cybercrimes (Wiafe et al., 2020), studies have also been done to propel the implementation of AI technologies in the education system of Ghana (Gyamfi, Dayie & Asiedu, 2022), etc. By investigating the relationship between AI adoption and

PWB, this research bestows to the growing body of knowledge on the human side of AI implementation. It will shed light on the potential psychological challenges that employees may face during AI adoption and provide insights for organizations to proactively address well-being issues based on research findings.

Lastly, the pervasive integration of AI technologies into the workplace raises critical questions about how these advancements influence the psychosocial aspects of the workforce. As organizations embark on this transformative journey, it becomes essential to comprehensively investigate the factors that shape AI adoption, the varying views, perceptions and attitudes among employees, and the resulting impact on their PWB. The existing literature provides a foundation by acknowledging the potential benefits and challenges associated with AI adoption. However, a refined understanding of the dynamics influencing technology integration and the subsequent psychological outcomes for employees is still in its nascent stages in Ghana- individuals are just beginning to adopt AI technologies.

2.4 Purpose and Design for a Two-Part Study

The purpose of this research is to investigate the relationship between organizational AI adoption and employees' psychological well-being (PWB) within technology-driven organizations. While prior studies have investigated various organizational and technological factors influencing employee experiences, there is still a knowledge gap regarding how AI adoption affects specific dimensions of PWB, including self-acceptance, autonomy, personal growth, environmental mastery, purpose in life, and positive relations with others. Additionally, the role of demographic factors such as age and gender in moderating this relationship has not been sufficiently explored. Given the complexity of AI adoption and its psychological implications, a mixed-methods approach provides an extensive means of examining both the quantitative associations and the qualitative meaning of employees lived experiences.

First, this study quantitatively investigates the relationship between AI adoption and employees' psychological well-being by assessing key dimensions of PWB in a survey-based research design. This phase allows for statistical analysis of the extent to which AI adoption influences employees' well-being and how demographic factors moderate this relationship.

Second, the study qualitatively explores employees' views of AI adoption in technology driven organizations, as well as effects of AI adoption on the employees through interviews. This approach aims to uncover the deeper meanings and contextual factors that shape employees' responses to AI integration, including their concerns and perspectives on how AI adoption can be implemented in ways that support mental health and overall well-being. By integrating qualitative insights, the study seeks to provide managers and organizational leaders with practical recommendations for sustainable AI integration that prioritizes employee well-being.

The mixed-method approach is crucial in addressing the limitations of a purely using only quantitative study or qualitative method. While quantitative methods help establish statistical relationships, they may not adequately convey the complexity of employees' psychological experiences with AI adoption. For example, employees who report higher levels of well-being in AI-integrated workplaces may do so due to external factors not accounted for in the survey, such as workplace culture, leadership support, or their own adaptive strategies. **A qualitative follow-up** allows for an in-depth understanding of these dynamics. The combination of quantitative and qualitative methods ensures both breadth and depth in investigating the impact of AI adoption on employee PWB, providing a holistic structure for understanding and supporting employee well-being in the era of technological transformation.

Based on previous studies, research problems and study objectives listed in chapter 1 and 2, the following hypotheses and research questions are proposed for the quantitative study, and the qualitative study respectively.

2.5 Research Hypotheses of Study 1 (Quantitative)

The following hypotheses were proposed to be tested;

H_1: Organizational AI adoption will significantly predict employee' psychological well-being.

H_2: Organizational AI adoption will strongly relate with personal growth than the other dimensions of PWB.

H_3: Age moderates the relationship between organizational AI adoption and PWB such that younger adults will experience better PWB than older adults.

H_4: Gender moderates the relationship between organizational AI adoption and PWB such that males will experience better PWB than females.

2.6 Research Questions of Study Two (Qualitative)

The following research questions were asked:

RQ1: What are employees' views on AI adoption in Ghana?

RQ2: What are the likely challenges/ effects of AI adoption on employees?

2.7 Key Variables

The key variables in this study are:

1. Independent variable (IV)- Organizational AI Adoption

2. Dependent variable (DV)- Psychological Well-being (PWB)

3. Moderating variables: Age and gender serve as moderating variables that potentially influence the relationship between organizational AI adoption and psychological well-being.

2.8 Operational Definitions

Artificial Intelligence (AI) - For this study, AI refers to technologies that perform tasks requiring human-like intelligence, including:

- Intelligent software systems with embedded AI algorithms (e.g., ChatGPT, Microsoft Copilot)
- Automated systems that perform tasks with minimal human intervention (e.g., automated customer service platforms)
- Machine learning applications that analyze data and make predictions
- Robotic systems and intelligent agents (e.g., driverless cars, smart assistants)
- AI-powered analytical and decision support tools used in organizational contexts

Organizational AI Adoption (AI adoption) - The intentional implementation and integration of AI technologies by organizations into their operations, processes, and systems. This includes the acquisition of AI-enabled tools, training employees to use these tools, and adapting organizational processes to incorporate AI capabilities.

Technology-driven organizations- organizations that are abreast with AI and use AI algorithm for their day-to-day activities or in their organization, also refers to organizations that are technologically equipped with AI tools and technologically advanced.

Older adults- refers to participants from the age bracket of 41 years and above

Younger adults- In the present study, participants between the ages of 18 to 39 years were considered younger adults.

CHAPTER 3

METHODOLOGY

3.0 Introduction

The choice of research methodology to adopt is very important for every research. Research methodology refers to the particular procedures or techniques that were utilized to locate, gather, organize, process, and evaluate data (information) pertaining to a research issue. The methodological part of a research paper enables the reader to critically understand the steps used to conduct the research, it also allows people to replicate the study as well as accept or critique the outcomes of a study.

The Explanatory Sequential mixed-method design was utilized in the present study. According to Creswell (2011), the explanatory sequential design prioritizes the quantitative phase, which is followed by the qualitative phase. Explanation of the findings from the first quantitative phase and occasionally the explanation of outliers that are not totally consistent with the data gathered are the goals of the second qualitative phase (Toyon, 2021). Because the results of the quantitative phase are used before the analysis of qualitative data, the term "explanatory" is used. The chapter 3 therefore presents the methodology of study 1 (Quantitative), followed by methodology of Study 2 (Qualitative).

3.1 Study One (Quantitative)

3.1.1 Research Design

A framework of procedures and techniques selected by a researcher to integrate different study components in a reasonably logical manner so that the research is efficient is known as research design (Khanday & Khanam, 2019). Study 1 employed a cross-sectional survey design within the quantitative research tradition. A cross-sectional survey design involves gathering information at one particular moment from a sample taken from a given population (Creswell, 2014). This design is particularly suitable for examining relationships between variables and testing hypotheses without manipulating the independent variables. The quantitative approach facilitated the objective measurement and statistical analysis of the relationship between organizational AI adoption and employee psychological well-being dimensions.

This design was selected for several reasons:

1. Appropriateness for relationship testing: The study aims to examine the relationship between organizational AI adoption and employee psychological well-being, aligning with quantitative research's analytical capabilities.

2. Measurement precision: Quantitative methods allow for precise measurement of the key variables using validated scales (Kurup & Gupta, 2022; Ryff, 1989).

3. Hypothesis testing: The research questions involve specific hypotheses about the relationships between variables and how demographic factors might moderate these relationships, which can be rigorously tested through statistical analysis (Boncz, 2015).

4. Generalizability: The findings from a well-executed quantitative study can be generalized to the broader population of employees in technology-driven organizations in Ghana (Creswell & Creswell, 2018).

3.1.2 Population of the Study

Typically, a research population is explained as a sizable group of people or things that are the subject of a scientific inquiry (Mobbing, 2009). According to Fraenkel and Warren cited in Jilcha Sileyew (2020), a study population includes persons or objects having at least one common characteristic. The study population encompasses a diverse range of individuals working in various roles and departments within technology-driven organizations. Employees in technology-driven organizations from Ghana constitute people working in various sectors including the financial, educational, health, consultancy and service sectors across the country. This population was used in order to be able to draw a relevant target sample to ensure representativeness and have a basis for applying the research results.

3.1.3 Sample

The study sample consisted of employees in the Greater Accra region of Ghana. Employees in technology-driven organizations based in Accra were recruited for the study. Participants were from the Greater Region of Ghana, because of the researcher's current location, which provides easy access to participants. The study engaged 189 participants including males and females aged between 18 and 65. This sample size was adequate based on statistical power considerations for detecting moderate effect sizes in correlation and regression analyses (Cohen, 1988). A power analysis using GPower software with an alpha of .05, power of .80, and a moderate effect size ($f^2 = .15$) for regression analysis with up to three predictors (AI adoption and two demographic moderators) indicated a minimum required sample size of 77 participants. The sample of 189 participants exceeds this requirement, providing sufficient statistical power for the planned analyses.

3.1.4 Sampling Technique

The study employed a non-probability sampling technique for obtaining its data. Obilor (2023) states that non-probability sampling techniques include methods where the probability of selection cannot be precisely ascertained or where certain population units have no possibility of being selected. Usually, units are selected using non-random standards. The current study used a purposive non-probability sampling technique. Purposive sampling is a non-probability sampling strategy where the researcher selects only people who, in their opinion, fit the study's goals. The researcher selects participants from the study community using this selection strategy at their own discretion (Obilor, 2023). Sample members are selected from well-defined criteria, and per the criteria of the present study, employees in technology-driven organizations were recruited.

This sampling approach was chosen because it is a low-cost sample selection method. Purposive sampling also saves much time that would have been spent on selecting everyone in the population. Furthermore, this approach allowed the researcher to gather data from the most appropriate participants, reducing the sampling error margin and producing findings that are extremely pertinent to the study setting (technology-driven organizations).

3.1.5 Inclusion/Exclusion Criteria

In order to conduct research, a specific group of people from a relatively homogeneous population must be chosen. The inclusion/exclusion criteria establish who is eligible to join in your study (Hornberger & Rangu, 2020). The inclusion criteria reliably, consistently, uniformly, and objectively identify the study population. According to Hornberger et al. (2020), the inclusion criteria will outline the different prerequisites that must be fulfilled in order for someone to take part in your study. On the other side, exclusion criteria are traits or circumstances that make it impossible for the recruited group to participate in the study.

The following inclusion criteria were applied in selecting participants:

1. Employment status: Participants must be employed in an organization that has implemented AI technologies in at least one business function or process.
2. Employment duration: Participants must have worked in their current organization for at least three months to ensure adequate exposure to organizational AI systems.
3. Job role: To capture diverse perspectives on AI adoption, participants could be from any department or role within the organization, including both technical and non-technical positions.
4. Age: Participants had to be at least 18 years old, in compliance with the University of Ghana's ethical guidelines for research with adult participants.

5. Employment type: Both permanent and temporary employees were eligible to participate, as the study attempted to understand the experiences of all types of workers affected by organizational AI adoption.

Exclusion criteria included:

1. Employees from organizations that had not implemented any form of AI technology
2. Individuals who had worked at their current organization for less than three months
3. Individuals under 18 years of age
4. Employees who were on extended leave during the data collection period

These criteria were established to ensure that participants had sufficient exposure to organizational AI systems to provide meaningful responses while maintaining a diverse sample that represented various roles, departments, and employment types within technology-driven organizations.

Potential biases such as including individuals who, while working in technology-driven organizations, may not have in-depth knowledge about AI and related concepts, setting a benchmark of 20 years may exclude experienced staff below that age, etc were recognized. Potential biases were identified and transparently addressed to ensure the findings accurately represent the varied perspectives within the selected participant pool.

3.1.6 Instruments/Materials

The study utilized validated instruments to measure the key variables. Two standardized scales were employed, along with a demographic questionnaire, resulting in a total of 41 items divided into three sections:

1. Demographic Information Questionnaire
2. Organizational AI Adoption Scale (adapted from Kurup & Gupta, 2022)
3. Psychological Well-being Scale (Ryff, 1989)

The questionnaire has three (3) sections. The first part/section captures the demographic information of participants, which includes sex (male/female), age (20-39, 40-59, 60+), education level (degree, masters, PhD), and occupation.

The second section measured organizational AI adoption using a scale adapted from Kurup and Gupta (2022). From their original instrument, which included multiple dimensions (AI readiness, change capability, leadership, trading partner, and AI adoption), only the five items measuring AI adoption were retained for this study. These five items focus specifically on organizational implementation and use of AI technologies, which aligns with the study's conceptualization of organizational AI adoption. Example items include:

- "My organization has implemented AI technologies in core business processes"
- "My organization actively uses AI for decision-making support"
- "AI technologies have been integrated into my daily work tasks"

Each item was scored on a 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree). Higher scores indicate higher levels of organizational AI adoption. The internal consistency reliability (Cronbach's alpha) for this scale in previous research was reported as .84 (Kurup & Gupta, 2022), indicating good reliability.

The third section measured psychological well-being using Ryff's (1989) Psychological Well-being Scale. This 18-item version of the scale (the medium form) includes three items for each of the six dimensions of psychological well-being:

1. Autonomy (e.g., "I have confidence in my opinions, even if they are contrary to the general consensus")
2. Environmental Mastery (e.g., "In general, I feel I am in charge of the situation in which I live")

3. Personal Growth (e.g., "I think it is important to have new experiences that challenge how you think about yourself and the world")

4. Positive Relations with Others (e.g., "People would describe me as a giving person, willing to share my time with others")

5. Purpose in Life (e.g., "Some people wander aimlessly through life, but I am not one of them")

6. Self-Acceptance (e.g., "When I look at the story of my life, I am pleased with how things have turned out")

Each item was rated on a 7-point scale (1 = Strongly Agree, 2 = Somewhat Agree, 3 = A Little Agree, 4 = Neither Agree nor Disagree, 5 = A Little Disagree, 6 = Somewhat Disagree, 7 = Strongly Disagree). Appropriate items were reverse-scored so that higher scores indicate higher levels of psychological well-being. Previous research has demonstrated good internal consistency for the six subscales, with Cronbach's alpha coefficients ranging from .86 to .93 (Ryff, 1989; Ryff & Keyes, 1995).

3.1.7 Procedure for Data Collection

For the quantitative part, the study was conducted by giving participants the questionnaires in their offices and homes. An online link/version was created and sent to employees who agreed to participate. The link was shared via emails, and some social media apps like WhatsApp, Facebook, and Telegram to the targeted sample with the established inclusion and exclusion criteria. The researcher administered the questionnaires, which took about 10 to 20 minutes to complete.

Data collection occurred from March to April 2023. Participants were initially contacted through organizational gatekeepers (HR managers and department heads) who distributed information about the study to employees. Those interested in participating were provided with either a hard copy of the questionnaire or a link to the online version.

Both data collection methods (paper and online) used identical questionnaires. For the paper-based collection, the researcher visited organizational premises and distributed questionnaires during pre-arranged times. Completed questionnaires were collected in sealed envelopes to ensure confidentiality. A secure survey platform (Google Forms) was used for online data collection, with data being automatically recorded in a password-protected spreadsheet available only to the researcher.

Each questionnaire included a cover page explaining the purpose of the study, confidentiality provisions, the voluntary nature of participation, and contact information for the researcher. Participants were assured that their responses would not be shared with their employers and that all data would only be reported in aggregate form.

3.1.8 Ethical Consideration and Institutional Review Board Certification

Research involving human participants must follow institutional and national guidelines. The present study thus solicited approval from the Department of Psychology Research Committee. Due to potential ethical issues that may arise, Ethical clearance was sort from the Departmental Research and Ethics Committee (DREC), before the study was conducted. The DREC forms were filled stating the relevance of the study, how the research will be conducted and was signed by 2 distinguished lecturers/supervisors and submitted online to the committee.

The research was conducted upon receiving full approval from the committee with **Protocol number**: **DREC/014/22-23**. The researcher ensured that the study did not harm participants and that confidentiality and privacy were assured. The data provided by the participants was securely stored.

The following ethical considerations were specifically addressed:

Informed consent: Prior to taking part in the study, each subject gave written informed consent. The objective, methods, dangers, rewards, and voluntary nature of participation in the study were all elucidated in detail in the consent form.

Confidentiality and privacy: All data collected was anonymized, with no personally identifying information retained in the dataset. Participants were assigned unique identification codes, and the key linking these codes to identities was stored separately from the data in a password-protected file.

Data security: All electronic data was stored on encrypted, password-protected devices. Paper questionnaires were stored in a locked cabinet and were accessible only to the researcher. After data entry, paper questionnaires were securely destroyed.

Right to withdraw: Participants were informed of their right to withdraw from the study without penalty or explanation, and their data would be removed from the analysis if requested.

Debriefing: After responding to the questionnaire, participants received a debriefing statement explaining the study's aims in more detail and providing contact information for the researcher should they have any questions or concerns.

Minimal risk: The study was designed to pose minimal risk to participants, focusing on non-sensitive topics related to their work experiences with AI and psychological well-being.

3.1.9 Data Analysis Plan

Statistical analyses were conducted using IBM SPSS Statistics version 26. The following analytical procedures were employed to address the research objectives and test the hypotheses:

1. Preliminary analyses:

- Data cleaning and screening for missing values and outliers

- Tests of statistical assumptions (normality, linearity, homoscedasticity)

- Descriptive statistics (means, standard deviations, frequencies) for all variables

- Reliability analyses (Cronbach's alpha) for all scales and subscales

2. Correlation analyses:

- Pearson's correlation coefficients to examine the relationships between organizational AI adoption and the six dimensions of psychological well-being

- Correlation matrix to identify patterns of relationships among all study variables

3. Regression analyses:

- Simple linear regression models to probe the relationship between organizational AI adoption and each dimension of psychological well-being.

- Hierarchical regression models to test the moderating effects of age and gender on the relationship between organizational AI adoption and psychological well-being dimensions

For hypothesis testing, a significance level of $p < .05$ was established. Effect sizes were reported using standardized regression coefficients (β) and changes in R^2 to indicate the practical significance of findings.

3.2 Study Two (Qualitative)

3.2.1 Rationale/Justification for the Qualitative Study

Some questions popped up during the study that needed to be addressed qualitatively. There was a need for an in-depth understanding of what Ghanaian workers thought about AI adoption and whether they felt AI adoption would affect them in any way, and this was not addressed in the quantitative study. The purpose of this study's qualitative component was to address the questions that surfaced during the quantitative investigation.

A qualitative study was deemed suitable because it would provide the opportunity for employees or workers to tell their views of AI adoption in technology-driven organizations, as well as the effects of AI adoption on employees through interviews. This approach aims to uncover the deeper meanings and contextual factors that shape employees' responses to AI integration, including their concerns and perspectives on how AI adoption can be implemented in ways that support mental health and overall well-being.

3.2.2 Design (Approach)

The study adopted a descriptive research design, which is well-suited to inquiries that aim to provide a straightforward and comprehensive summary of participants' views, without extensive theoretical interpretation. Qualitative description is especially appropriate in mixed-method studies where the intent is to clarify, expand upon, or contextualize findings from the initial quantitative phase. As Sandelowski (2000) notes, descriptive qualitative research stays close to the surface of the data and aims to present participants' experiences in their own terms.

This design was chosen because the study was not aimed at generating new theory (as in grounded theory), exploring deeply personal or existential experiences (as in phenomenology), or studying a cultural group in depth (as in ethnography). Instead, the goal was to answer two follow-up questions from the quantitative phase:

1. What are employees' views of AI adoption in Ghana?
2. What are the potential challenges/ effects of AI adoption on employees?

Focusing on these practical questions, the qualitative descriptive approach allowed for a more applied understanding of AI-related workplace experiences. The insights from this phase were intended to complement and enrich the quantitative results, ultimately contributing to actionable recommendations for organizational leaders and managers.

3.2.3 Sample and Sampling Technique

A sample size of 13 was used for the study. This was made of employees in technology-driven organization in 3 organizations in Accra, Ghana (COLDSiS Ghana Limited-CGL; Zelus Technologies, and the University of Ghana). Braun and Clarke (2006) recommend a sample size of 12 to 20 for qualitative research involving thematic analysis. In spite of this, choosing to use the present sample size was heavily influenced by saturation. At the point of data saturation, no new information is being gathered and the information that participants are providing becomes similar. After the thirteenth participant, the researcher decided to stop. Thirteen participants were chosen for the qualitative study using purposive sampling. In Table 3.1, the participants' demographic details are displayed.

Table 3.1: Demographic Information of Participants

Participant Number	Age of Participant	Occupation	Gender
P1	23	Software Engineer	Male
P2	22	Front End Engineer	Male
P3	21	User Interface Designer	Male
P4	24	Software Developer	Female
P5	27	Software Developer	Male
P6	30	Lead Software Developer	Male
P7	27	Marketing Executive	Male
P8	21	Software Developer	Male
P9	27	Social Media Manager	Female
P10	27	CEO- Software Developer	Male
P11	29	Visual Artist	Male
P12	25	Computer Technician	Female
P13	43	Computer Scientist/Lecturer	Male

3.2.4 Data Collection Material

A semi-structured interview guide was prepared for the qualitative study. The interview guide consisted of semi-structured questions on AI adoption and PWB, which the researcher used in the field to gather qualitative data. The researcher visited selected technology-driven organizations on the agreed date with the semi-structured interview guide. The most common questions in this type of questionnaire were open-ended questions that required a qualitative response. Questions on the interview guide included; “When you hear of Artificial Intelligence (AI), what comes to your mind? Can you give examples of AI?”, “How do you think the adoption of Artificial Intelligence affects wellbeing?”, among other questions.

The researcher developed an interview guide, which was examined for appropriateness by two separate experts before it was use. The interview guide is attached to the study’s appendices (appendix 3) for reference or adoption in future studies.

3.2.5 Data Collection Procedure

The Department of Psychology provided the researcher with a letter of introduction. This was to introduce the researcher to the study’s participants and to obtain consent for the qualitative interviews from the management of the organization where the research was to be conducted. The researcher personally did interviews (physical), and it took about 10 to 30 minutes. The objective of the study was explained to the participants. Before the interview, participants were made aware that it would be recorded and those who consented to take part in the study gave their verbal agreement. Confidentiality of information was promised to participants, and data was gathered.

3.2.6 Data Processing and Analysis

Data attained in the interviews were all tape recorded and backed up with a phone recorder. Each of the recording were named distinctively to avoid confusion and overlapping information. The recordings were transcribed verbatim by the researcher. Interviews were mainly held in English.

Transcribed documents/scripts were reviewed for spelling, punctuation and correctness of the information along the audio tape by the researcher to clarify the information they contained.

The data collected for this study were analyzed using thematic analysis. Braun and Clarke's (2006) six-step theme analysis method were applied in this process. An inductive coding procedure was used for the analysis. The researcher took notes, reviewed the interviews several times to become familiar with the facts, and then transcribed them. Nvivo software was used to produce the codes. After that, the researcher searched for themes within the data, the themes were reviewed. Themes were defined and named appropriately. Two separate researchers with significant expertise in qualitative analysis (one holding a master's degree and the other a doctorate in psychology) reviewed these themes and their accompanying codes. The codes were used to review the themes. Sub-themes were created to correspond with the codes' relationships. Ultimately, each theme and sub-theme was given a name. To demonstrate each subtheme, excerpts were extracted from the transcripts.

3.2.7 Methodological Rigor

3.2.7.1 Credibility and Trustworthiness of Data

To ensure credibility, the researcher employed member checking by sharing preliminary interpretations with selected participants to confirm that the findings accurately reflected their views, thereby enhancing the trustworthiness of the data. Using the purposive sampling technique also helped identify the right participants for the study. Additionally, the researcher met with a second coder to discuss the scope of the research and plan timelines for each stage of analysis. This offered the two independent coders the opportunity to acquire detailed data through the use of quality memos and comprehensive interview transcripts.

To maintain the study's credibility, all interviews were conducted using a semi-structured interview guide to ensure uniformity in the researcher's questions. The study design, sampling technique, data collection and analysis were all thoroughly discussed once again.

3.2.7.2 Transferability and Confirmability of Data

The study procedure was detailed to achieve transferability so that others may assess the data's application to different contexts and settings. Records of the transcribed interviews and analysis, as well as the study's findings were saved for the audit trail.

During interviews, the context of data collection was documented in a field notebook to ensure confirmability. This increased data interpretation during processing, allowing the participants' precise replies to be represented. The researcher carefully bracketed their own experiences and assumptions to avoid bias in data interpretation and analysis.

CHAPTER 4

RESULTS

4.0 Introduction

The broad objective of this study was to determine the relationship between organisational AI adoption and employee PWB. The findings and insights from a few technology-driven Ghanaian firms were examined and presented in this chapter. The same chapter contains both the qualitative and quantitative analyses. The results of the quantitative investigation (study 1) are presented in the first section, while the results of the qualitative inquiry (Study 2) are presented in the second.

4.1 Study 1 (Quantitative Findings)

4.1.1 Preliminary Analysis

Demographic Characteristics of Research Participants

Table 4.1 presents the demographic characteristics of the sample. It shows the age, gender, and educational background of the participants sampled for the study, as well as the frequencies and percentages.

Table 4.1: Demographic characteristics (*n* = 189)

Demographic variable	Frequency	Percentage
Age		
18 to 29	66	34.9
30 to 39	68	36.0
40 to 49	36	19.0
Above 50	19	10.1
Gender		
Male	97	51.3
Female	92	48.7
Educational background		
SHS	16	8.5
Degree	127	67.2
Masters	45	23.8
PhD	1	.5

The sample comprised 189 participants. Regarding age distribution, the majority fell within the 30 to 39-year age bracket (36.0%), followed by those aged 18 to 29 years (34.9%). Respondents aged 40 to 49 constituted 19.0%, while those above 50 accounted for 10.1%. The age distribution shows a predominantly young to middle-aged workforce, with 70.9% of respondents falling between 20 and 39 years. This age trend is typical for technology-driven sectors, particularly in emerging economies like Ghana, where digital and IT industries tend to employ younger professionals. Gender distribution was nearly balanced, with males representing 51.3% and females comprising 48.7% of the sample. This reflects positively on the inclusiveness between the number of males and females of the organizations sampled. Regarding educational background, a significant proportion of respondents held a bachelor's degree (67.2%), followed by those with a master's degree (23.8%). Participants with only senior high school (SHS) education comprised 8.5% of the sample, while just 0.5% possessed a PhD. This aligns well with expectations in technology-driven environments, where tertiary education is often a baseline requirement. It also suggests that respondents are likely to have baseline digital literacy, which is important.

Descriptive Analysis: Mean, Normality and Reliability

The data collected underwent thorough quality checks and was entered into Microsoft Excel 365, then exported to IBM SPSS for analysis. To determine the means and standard deviation of the various study measures, a descriptive analysis was carried out. The skewness, kurtosis, and reliability (Cronbach's alphas) of the various measurements were also examined in the analysis.

Table 4.2: Descriptive Statistics

Variable	Min	Max	Mean	SD	Skewness	Kurtosis	Cronbach's Alpha
AI Adoption	1.00	7.00	5.72	1.09	-1.34	2.27	.82
Psyc.Wellbeing	2.06	7.00	4.66	.89	-.17	.06	.75

The examination indicated a normal distribution, meeting the requirements for parametric analyses. Skewness and kurtosis values for key variables fell within the acceptable range of -3 to 3, meeting standard criteria for normality (Mishra et al., 2019). Cronbach's Alpha coefficients, ranging from .75 to .82, affirmed the strong psychometric properties of the study instruments.

Correlation Matrix

The correlation matrix is presented in Table 4.3 below. A Pearson correlation analysis examined the relationships among psychological well-being and AI adoption.

Table 4.3: Correlation Matrix

Variable	1	2	3	4	5	6	7	8
1. Psyc Wellbeing	-	.13	.17*	.13	.16*	.21**	.11	.27**
2. Autonomy		-	.28**	.16*	.13	.29**	.25**	.09
3. Env't Mastery			-	.03	.25*	.33**	.20**	.21**
4. Personal Growth				-	.15*	.07	.17*	.22**
5. Personal Relationship with Others					-	.50**	.37**	.22**
6. Purpose in Life						-	.51**	.2**
7. Self-Acceptance							-	.21**
8. AI Adoption								-

Note * = $p < .05$; ** = $p < .01$

As shown in the correlation matrix, psychological well-being was positively and significantly correlated with AI adoption ($r = .27$, $p < .001$), suggesting that more positive attitudes toward AI adoption are associated with higher psychological well-being.

4.1.2 Hypotheses Testing

Hypothesis 1: Organizational AI adoption will significantly predict psychological wellbeing

A simple linear regression was conducted to examine whether organizational AI adoption significantly predicts psychological well-being among employees. The results of the regression analysis are presented in Tables 4.4 and 4.5.

Table 4.4: Model Fit

Model	R	R^2	Adj R^2	F change	df 1	df 2	p
1	.27	.07	.07	14.60	1	187	.000

Table 4.5: Regression table for the relationship between AI adoption and psychological wellbeing

Model	Predictor	Estimate	SE	t	P
1	Intercept		2.45	28.85	.000
	AI	.27	.21	3.76	.000

From Table 4.4, a significant regression model was observed, (F=14.60, $p < .001$), accounting for 7.0% of the variance in psychological well-being ($R^2 = .07$, Adjusted $R^2 = .07$). The results in Table 4.5 further indicate that AI adoption significantly predicted psychological well-being, $\beta = .27$, $SE = .21$, $t = 3.76$, $p < .001$. Thus, the hypothesis that Organizational AI adoption will significantly predict psychological well-being was **supported**, with AI adoption explaining 7.0% of the variance in psychological well-being among employees in technology-driven organizations. The result suggests that AI adoption contributes meaningfully to employee well-being within technology-driven organizations.

Hypothesis 2: Organizational AI will be strongly related to personal growth than the other dimensions of PWB.

To test this hypothesis, a series of simple linear regressions were conducted with organizational AI adoption as the predictor and each dimension of psychological well-being (PWB) entered individually as the outcome variable. Autonomy was excluded from the analysis due to its non-significant correlation with AI adoption.

The regression results are presented in Table 4.6 and Table 4.7 below. Personal Growth emerged as a significant predictor of AI adoption, explaining **4.4% of the variance** (R^2 = .044), with a standardized beta of .222 (p = .002). This contribution was the highest among the PWB dimensions. Environmental Mastery (R^2 = .045, β = .212, p = .003), Positive Relations (R^2 = .048, β = .218, p = .003), Purpose in Life (R^2=.046, β = .215, p = .003), and Self-Acceptance (R^2 = .042, β =.242, p = .005) were also significant predictors of AI adoption, though with comparable variance contributions.

Although other PWB dimensions significantly predicted AI adoption, the findings indicate that **Personal Growth was the strongest predictor**, thereby providing support for the hypothesis, albeit modestly.

Table 4.6: *Model Fit Measures for Psychological Well-Being Dimensions Predicting Organizational AI Adoption (N = 189)*

Model	*R*	R^2	F change	Df1	Df 2	*p*
EM	.212	.045	8.83	1	187	.003
PG	.222	.044	9.67	1	187	.002
PRO	.218	.048	9.36	1	187	.003
PL	.215	.046	9.07	1	187	.003
SA	.205	.042	8.22	1	187	.005

Table 4.7: Regression table for the relationship between the dimensions of psychological wellbeing and AI adoption

Model	Predictor	β	SE	t	P
	Environ. Mastery	.21	.089	2.97	.003
	Personal Growth	.22	.078	3.11	.002
	PRO	.22	.097	3.06	.003
	PL	.22	.087	3.01	.003
	SA	.24	.084	2.87	.005

Hypothesis 3: Age moderates the relationship between organizational AI adoption and PWB such that younger adults will experience better PWB than older adults.

This hypothesis suggests a relationship between AI adoption and PWB, but Age acts as a moderator, that is, a variable that changes the strength (and possibly the direction) of the relationship between AI adoption and well-being

Hypothesis 4: Gender moderates the relationship between organizational AI adoption and PWB such that males will experience better PWB than females.

This hypothesis suggests a relationship between AI adoption and PWB, but gender acts as a moderator. This means Gender can possibly change the strength (or direction) of the relationship between AI adoption and well-being. The results of the hierarchical regression are presented for hypothesis 3 and 4 in Table 4.8

Table 4.8: Moderation Effects of Age and Gender in the Relationship between AI Adoption and Psychological Wellbeing

Relationship	**Beta**	**SE**	**P-value**
AI ->Psychological Wellbeing	.95	.29	.00
Gender_1 ->Psychological Wellbeing	1.30	7.20	.86
Moderating effect (AI*Gender_1) -> Psychological Wellbeing	-.34	.42	.42
AI ->Psychological Wellbeing	.64	.25	.01
Age_group 1 ->Psychological Wellbeing	-9.84	8.30	.24
Moderating effect (AI*Age_group1) -> Psychological Wellbeing	-.04	.05	.36

Gender: R =.34; R^2 = .12; F = 8.16; p < .00. Age: R = .28; R^2 = .08; F = 5.38; p < .000

Gender and age underwent dummy coding first. Males (Gender_1) and participants aged from 20 to 29 (Age_group1) were employed as the reference groups. The Process Macro model 1 of the SPSS was used in the moderation analysis. In the first model, the interaction effect (AI*Gender_1) was not statistically significant (β = -.34, SE = .42, p = .42), indicating that gender does not significantly influence the strength of the relationship between AI adoption and psychological wellbeing. Similarly, in the second model, the interaction effect (AI*Age_group1) was not statistically significant (β = -.04, SE = .05, p = .36), indicating that age does not significantly influence the strength of the relationship between AI adoption and psychological wellbeing. Thus hypotheses 3 and 4 were not supported.

4.1.3 Summary of Quantitative

Table 4.9: Summary of hypotheses and remarks

Number (#)	Hypotheses	Remarks
1	Organizational AI adoption will significantly predict psychological wellbeing	This hypothesis was supported
2	Organizational AI will be strongly related to personal growth than the other dimensions of PWB.	Hypothesis 2 was supported
3	Age moderates the relationship between organizational AI adoption and PWB such that younger adults will experience better PWB than older adults.	Hypothesis 3 was not supported
4	Gender moderates the relationship between organizational AI adoption and PWB such that males will experience better PWB than females.	This hypothesis was not supported

4.2 Study 2 (Qualitative Findings)

Thematic analysis was used to analyse the qualitative data obtained in this study. Thematic analysis was used because the researcher sought to find rich, useful insights in the data gathered. The themes that were obtained from analysing the interview are presented using participants' own verbal accounts.

In all, 2 themes were generated. The first theme answers the first research question, and the second theme answers the second research question. Each of these themes has subthemes, which are shown below along with quotes that go with them. The study's research questions were addressed and information provided by participants was reflected in the thoughtfully chosen themes.

4.2.1 Thematic Analysis

In trying to understand the employees' views on AI adoption, meanings made suggest a mix of reflections. One major theme that emerged from analysis of 13 transcripts was "mixed-feelings" toward AI.

Mixed Feelings

This theme captures the complex emotions and perspectives expressed by participants regarding the adoption of artificial intelligence (AI) within their workplaces. While others expressed positive sentiments, others expressed negative sentiments, some participants reported optimism and contentment while others raised concerns and fear, reflecting the dual impact of AI on their professional experiences and personal well-being.

This theme suggests that employees in technology-driven organizations were either happy, excited about the new technology or had negative views towards the technology. Consequently, within this theme, two subthemes surfaced, namely; *positive sentiments* and *negative sentiments.*

Positive: This subtheme describes the optimistic outlook and the favourable opinions that participants held about AI adoption. Participants who expressed positive views of AI adoption highlighted its potential to increase productivity, reduce manual workload, and create space for more strategic or creative tasks. They appreciated how AI tools helped streamline operations, automate repetitive duties, collaborate and improve accuracy. For example, one participant said;

> *"Honestly, I think it is a good initiative like to have AI in organizations and to help make things easier so actually I'm not against it I think it's actually a good initiative because it will make lives easier… you know when you are having problems although you can't always rely on it but there are some times …like me for example, when I am writing some codes and I have problems I just ask the AI… Oh how or what and it gives me the right answers. I can collaborate with the AI. I think it's actually a good initiative." (P2, Male, 22 years)*

From the above quote, the participant expressed an optimistic perspective on AI adoption, stating, *"I think it's actually a good initiative because it will make lives easier… I can collaborate with the AI"* (P2, Male, 22 years). This view reflects a sense of enthusiasm and adaptability, where AI is not seen as a threat but rather as a supportive tool that enhances productivity and problem-solving. The participant's mention of using AI for coding assistance highlights how younger, tech-savvy employees may view AI as a collaborative partner that complements their skills rather than replaces them.

Other participants who also shared positive sentiments with regards to making things easier and faster had this to say;

> *"Okay, so for me, it's a good thing. When we adopt AI, it actually makes the work easier. AI, is a good thing, it actually helps work to… because sometimes the work cannot be done very soon, but when we adopt AI, it actually makes the work easier." (Participant 12, Female, 25 years)*

> ***"****It makes our works easier and faster. Research, it has made research easier and faster. I am happy AI is here." (Participant 3, Male, 21 years)*

> *"Well, for me I think is positive. It's really helping us the way we work, the way we collaborate. Because now if I even want to send emails to our clients, I just copy and I paste it somewhere to verify to check if it's okay, you know, and then AI sometimes replies, it could be this, or it could be that then I select. So, it's positively affecting us". (Participant 10, Male, 27 years)*

These three participants shared consistent positive sentiments about AI adoption, emphasizing its role in enhancing efficiency, accuracy, and ease of work.

Participant 12 (Female, 25 years) expressed that *"AI… makes the work easier,"* highlighting how AI can accelerate tasks that would otherwise be time-consuming. Her repetition reinforces a strong belief in AI's practical value for productivity. Similarly, Participant 3 (Male, 21 years) noted, *"It* *has made research easier and faster. I am happy AI is here,"* reflecting a sense of appreciation for AI's role in improving both the speed and convenience of knowledge work. This enthusiasm suggests a readiness among younger employees to embrace digital tools that enhance their learning and workflow. Participant 10 (Male, 27 years) emphasized AI's supportive role in communication, saying, *"AI sometimes replies, it could be this, or it could be that then I select,"* illustrating how AI helps him refine professional tasks like email communication. His account shows not only practical use but also a degree of trust in AI as a collaborative assistant that enhances confidence and autonomy in daily operations.

Together, these quotes reinforce the sub-theme of **positive sentiments** and suggest that for many employees, AI is not just a tool, but a facilitator of smarter, smoother, and more efficient work.

Negative: This subtheme describes the fear and worry participants had about AI adoption. Despite the benefits, many participants also expressed worry, scepticism, or emotional discomfort about the growing use of AI. These negative views often revolved around themes such as job insecurity and unemployment. For example, some participants said;

> *"…in terms of work, hmm the little issue I have about it is hmm, I really do believe that it's killing some jobs, … cause, on the social media platform now you hear rest in peace developers, rest in peace UI designer, because the AI can now do stuff like that. People may be laid off." (Participant 6, Male, 30 years)*

> *"…it can also lay people off because working, …using AI, it can do the capacity or the work of humans. So, it can get to a time that we will not even need people where people will become unemployed because of AI." (Participant 12, Female, 25 years).*

From the quotes, the two participants conveyed clear negative sentiments about AI adoption, with a shared concern centred on job security and potential displacement.

Participant 6 (Male, 30 years) expressed apprehension, stating, *"…I really do believe that it's killing some jobs… rest in peace developers, rest in peace UI designer,"* reflecting a growing fear that AI's expanding capabilities in creative and technical fields could render certain roles obsolete. His tone suggests not only worry but a sense of inevitability, echoing widespread anxieties seen in global conversations about automation. Similarly, Participant 12 (Female, 25 years) noted that *"…it can get to a time that we will not even need people,"* highlighting the fear of redundancy as AI increasingly replicates human labor. Her concern reinforces the perception of AI as a potential threat to employment stability, particularly in roles that can be easily automated.

Other participants expressed fear or dread they had about the adoption of AI was due to a threat of danger. The "threat of danger" expressed by participants regarding the adoption of AI typically refers to the perceived risks or harm that AI poses to their job security. They panic, worry and feel emotionally unstable when they think about the adoption of AI. People's intention to adopt AI still brings unclear emotions like fear, and in psychology fear is a basic emotion which brings about fight or flight response. One participant stated:

> *"Hmmm, yeah for me I still have a little bit of fear in terms of hmm, hmm… just accepting it holistically. …I still recall the movies we watch before, where the AI turns against the human race and try attacking the humans and so I'm almost sceptical thinking that, what if this finally happens one day and then these AI, they have every information about us and know how we think, and all and that turn against us." (Participant 6, Male, 30 years).*

Another participant said;

> *"It will make people lazy, basically, it will make people feel like they have a lot of time, they procrastinate… yeah… as we progress, as technology advances, the human mind doubts, because we become over reliant on the technology." (Participant 11, Male, 29 years).*

From the above quotes cited above, two participants revealed psychological and behavioral concerns related to AI adoption, adding depth to the sub-theme of **negative sentiments**. Participant 6 (Male, 30 years) expressed a sense of fear and skepticism, rooted in broader cultural narratives and dystopian imagery. His reflection, *"what if this finally happens one day and then these AI… turn against us"* captures a fear of AI's potential control, driven by its capacity to access and manipulate human data. While speculative, this fear reflects a deeper anxiety about losing control over powerful technologies. Participant 11 (Male, 29 years) raised a different concern, pointing to the behavioral impact of overreliance on AI. He stated, *"It will make people lazy… we become over reliant on the technology,"* suggesting that AI could reduce human motivation, productivity, and critical thinking over time. His view implies that while AI might enhance efficiency, it could also undermine discipline and mental engagement, especially if used without limits. Together, these reflections illustrate that employees' reservations about AI are not only about job loss, but also about ethical, psychological, and cognitive implications.

The two subthemes highlight the complex views of employees about AI adoption captured under the theme of **mixed feelings**.

Psychosocial Impact

This theme answers the second research question. The researcher set out to find out what are the challenges/effects of AI adoption on employees. This theme captures the consequences or effects of AI adoption as experienced by employees in technology-driven organizations. While AI is primarily introduced to optimize productivity and automate tasks, its implementation also brings about unintended effects on how employees feel, interact, and relate to their work environment and one another.

Participants in this study expressed a range of internal and interpersonal challenges, which have been categorized into four key sub-themes: *Reduced Interactions*, *Unemployment*, *Feelings of Inadequacy*, and *Digital Stress*.

Reduced Interactions: This subtheme describes a decline in workplace communication and human connection and relation since the introduction of AI systems. Routine check-ins, informal mentorship, and face-to-face feedback have been replaced by automated systems. As a result, employees felt isolated and described a weakening of both mentorship relationships and leadership support. Participants had this to say;

> *"Well, to be honest, a lot has changed. Before, I used to interact with different departments every day; calls, emails, even walking down to their desks to sort things out. But now, most of those processes are automated. We use this AI system that routes requests and updates task statuses automatically, so I hardly talk to people anymore. It feels like I'm just communicating with a screen now." (Participant 4, Female, 24 years)*

Other participants reflected on how the adoption of AI had led to a noticeable decline in workplace interactions. They described a shift from collaborative, human-centered problem-solving to a more individualistic approach driven by technology. Tasks that once required consultation, teamwork, or mentorship could now be completed independently using AI tools.

> *"…hmm five years ago, if you were assigned to task, you are very likely to collaborate with other people. But with AI, you don't actually need anyone, you don't even need to consult someone to like, read through for errors or spelling mistakes, you can just ask AI to search for errors or mistakes, and then it will give you the right answer. So, in a way, it affects the way we interact with each other." (Participant 10, Male, 27 years)*

> *"Yeah. One of the ways I think is with human relation …as in communication, it limits it because some of the things that we are supposed to ask or discuss in or in the workplace, we end up using AI to find our answer and it's with the communication." (Participant 8, Male, 21 years)*

"…things that my subordinate would come to me, now they wouldn't need me, things that I would go to my superior, I wouldn't go. Things that I would have to call Prof. about, Prof. is my boss, I do not. …Dr. Agyemang Badu is a psychologist. Things that sometimes I need to talk to him, I can sit here and get it for myself. That in a sense limits the interaction between myself and my peers, and my subordinates and my superiors. So, yes it certainly has an impact. Yes, it does. It has an effect on the social interaction." (Participant 13, Male, 43 years)

Another participant also shared their thought on reduced social interaction that was quite insightful. According to her, social interaction was impacted not just in her work but also when she felt bored. Participant 9's social interaction was impacted in a more personal and psychological way, extending beyond the workplace into her everyday social life. Her statement reveals that instead of reaching out to friends or engaging in face-to-face or even virtual conversations with real people when feeling bored, she often turned to her AI chatbot for interaction. Participant said:

"I mean, I've tried it… there are times I do that. I'm bored, I just… I don't have; I don't have to text anybody. I just pick my phone and then be texting with the AI, which I have on my phone, and …sometimes it makes me think I don't need to be around friends or whatever. Social interaction and human relation have been impacted greatly." (Participant 9, Female, 27 years)

These participants collectively highlight how AI adoption, while enhancing task efficiency, has introduced an unintended psychosocial challenge: the reduction of human interaction in the workplace and beyond. Participant 4 (Female, 24 years) described how automation has changed her daily work experience, stating, *"I hardly talk to people anymore. It feels like I'm just communicating with a screen now."* Her reflection expresses a sense of isolation, as AI systems increasingly replace interdepartmental communication with automated workflows. Similarly, Participant 10 (Male, 27 years) noted that *"with AI, you don't actually need anyone,"* pointing to how the ability to perform tasks independently using AI (such as editing, fact-checking, or task management) diminishes the need for collaboration. This shift signals a loss in team dynamics and peer support, which are often vital for workplace satisfaction and psychological well-being. Participant 13 (Male, 43 years) offered a deeper perspective, acknowledging that AI has reduced interaction *"between myself and my peers, and my subordinates and my superiors,"* suggesting that even hierarchical and mentoring relationships are affected. His experience points to a broader erosion of professional connection and mutual dependency in the workplace. Participant 9 (Female, 27 years) introduced a particularly insightful angle by linking reduced interaction not just to work, but to everyday social behavior. She shared, *"I don't have to text anybody... I just pick my phone and then be texting with the AI,"* revealing how AI might also be altering social habits and emotional reliance.

Together, these accounts highlight the subtheme of reduced interaction under the broader theme of **psychosocial impact**.

Unemployment: This sub-theme points to both actual job displacement and perceived job threat, which negatively affect employees' morale and sense of stability. AI adoption has also heightened fear of redundancy. Several participants shared that their roles had been partially or completely taken over by AI tools, or that they had seen colleagues laid off after automation was introduced. Even when layoffs had not yet occurred, the anticipation of it created a climate of job insecurity. Participants had this to say;

> *"It has affected how I feel about work. I'm more anxious than before, always wondering if the next meeting is about restructuring or downsizing. Some of my colleagues have already been let go. It feels like we're being replaced piece by piece." (Participant 9, Female, 27 years)*

"…the fear of … the excessive use of it is going to affect us the labour front …hmm, workers are going to be laid off, hmmm or people, businesses are not going to hire many people as they should because with AI you need a few people, human beings to use these tools to get things done quickly. There is …hmm, we are excited about it, it will get things done quickly, yet we are also afraid it is going to make people lazy and in the employment front to, it going to make fewer people are hired, and the effect will be enormous." (Participant 13, Male, 43 years)

"Generally, when they say AI, then some works will be done by AI, so there is going to be a lay off…and hmmm, you …and the little work that is left for human being to do ... you just …when it comes to the business or work settings, it wouldn't fit people. Yeah... So, I'll give an example. So, let's say in a work space, and AI does most of the work, let's say accounting and there's an AI that does all the accounting jobs there, after that…that means that the accountant is going to be laid off, which this will affect the well-being of the accountant." (Participant 1, Male, 23 years)

Other participants had this to share;

"…In a short time. So, you don't need a lot of people to get a result, all you need is a few people with a skill to use. So that's where the confusion comes in the work environments or in the working force because those who will be doing this job are now scared that … yeah…it will take their jobs, so the fear is there. But it can't take over everybody's job." (Participant 4, Female, 24 years)

"…we are still in the very early stages… of hmmm, what do you call it, the whole AI thing. So, it will take a while for us to measure how it is really affecting… but what I know is a lot of companies are actually laying people off …because… it is saving them money and generally it has more efficiency. So, hmm you can't really say… but I mean there are those who have, who have been seriously affected obviously lost their jobs." (Participant 11, Male, 29 years)

The quotes presented under the subtheme of unemployment reflect fears among employees that AI adoption may lead to job displacement, heightening anxiety and reducing workplace security. Participant 9 (Female, 27 years) captured this fear vividly, saying, *"I'm more anxious than before, always wondering if the next meeting is about restructuring or downsizing,"* highlighting how uncertainty about AI's role in layoffs is affecting her emotional connection to work and contributing to chronic workplace anxiety. Participant 13 echoed similar sentiments, acknowledging a paradox: while AI increases efficiency, it also contributes to shrinking labor demands, which may lead to fewer hires and mass layoffs. His statement – *"the effect will be enormous"* highlights the concern that AI might alter the very structure of employment, especially in labor-intensive sectors. Participant 1 expressed concern that AI could render entire professions obsolete, stating that if AI takes over tasks like accounting, *"the accountant is going to be laid off,"* directly linking AI adoption to threats to professional identity and livelihood. Participant 4 pointed out the emerging confusion and fear in work environments, noting that *"you don't need a lot of people to get a result,"* reinforcing the sense that fewer jobs are needed to achieve organizational goals, which creates fear among current employees. Participant 11 took a slightly more reflective stance, acknowledging that *"a lot of companies are actually laying people off … because it is saving them money,"* drawing attention to the economic incentive behind job cuts. He hints that even though Ghana is in the early stages of AI integration, the impact on employment is already being felt.

Together, these accounts paint a picture of how the introduction of AI; while beneficial for organizational efficiency, is also triggering psychological strain, fear of redundancy, and perceived job insecurity, thereby constituting a serious **psychosocial impact** of AI adoption.

Feelings of Inadequacy: AI systems often require employees to learn new digital tools or shift into new roles, which some found difficult or intimidating. This led to self-doubt and diminished confidence, especially among staff who were less technologically savvy. These feelings of inadequacy are closely tied to imposter syndrome, loss of professional identity, and reduced self-worth, all of which can affect performance and well-being.

"It's been a mixed bag. On one hand, it's exciting, the technology is powerful and impressive. But on a personal level, I often feel like I'm not smart enough or skilled enough to keep up. The AI performs certain tasks in seconds that would take me a whole hour. It makes me feel... inadequate, honestly." (Participant 11, Male, 29 years)

"There is some sort of fulfilment in getting things done as a human being, if you have a skill, if you are a trained professional, whatever it is that you do, hmmm, if it gets to some point that AI is being rated against you, you feel bad. ...I don't know how administrators feel nowadays, we go for meetings, and there is an AI which joins the meeting taking notes, whereby when we are done, it emails minutes and how do they feel? So I ...I feel like I am not adequate, somebody is doing my work for me. You will not believe it; I am not an excessive user of AI." (Participant 13, Male, 43 years)

"Another effect is that Sometimes I feel like the AI is smarter than me. It suggests better ideas faster than I can think them through. It's hard not to compare myself to it. I know it's just a tool, but when the system performs better than you, it definitely eats at your confidence." (Participant 12, Female, 25 years)

"Also, there is this silent pressure too; like if you are not immediately understanding the new AI tools, you are seen as outdated. It is frustrating because I have years of experience, but now I feel like all of that counts for less. It's a very humbling feeling and honestly, it is a disheartening experience." (Participant 4, Female, 24 years)

"I struggle with some of the new software they have introduced. It's not like I'm bad at technology, but the systems are complicated, and the younger staff seem to pick them up so easily. It makes me feel... less capable, like I'm not smart enough to keep up anymore." (Participant 9, Female, Age 27).

The quotes under the subtheme of feelings of inadequacy reveal how the adoption of AI in the workplace can negatively impact employees' self-confidence, professional identity, and emotional well-being. While AI is often praised for enhancing efficiency, these narratives highlight a deeper, more personal struggle; employees feeling outpaced, undervalued, or intellectually diminished by the very tools meant to support them.

Digital Stress: This subtheme provided insight into health, well-being and addiction. Participants described a constant pressure to keep up with AI tools, updates, and performance metrics. The increased screen time, automated feedback loops, and multitasking across digital platforms contributed to mental fatigue, anxiety, and burnout. Digital stress is not just a mental burden; it has direct implications for physical and psychological health. Respondents shared the following insights;

> *"I get mentally exhausted. There are days I leave work with a headache from just staring at screens and jumping between apps. It's not that the tools are bad; they are helpful, but the constant digital engagement and pressure to stay on top of everything is draining. Sometimes, I just wish for more human interaction or a moment to breathe." (P12, Female, 25 years).*

> *"…Definitely. Because everything is online and integrated with AI, it is like you are expected to be available all the time. Even after office hours, I'm checking emails and updates just to stay on top of things. I don't really disconnect anymore, and it's affecting my sleep and focus. …The thing is as a young lad, people in my office think I do not sleep early, but that is not the case, I cannot be online 24/7. Sometimes, I need to disconnect and rest, but I am unable to because I want to stay on top of things." (Participant 1, Male, 23 years)*

> *"…Since AI came in, the pressure has doubled. Everything is fast, everything is monitored. I feel anxious sometimes. I do not want a situation where my work will be compared with AI and it is doing better than me, so I try to always be prompt at my task. Also, I am someone that even small mistakes stay in my mind after work, and I find it hard to relax. I think it is starting to affect my health; I'm more tired, more stressed, and sometimes I even feel shortness of breath when deadlines pile up." (Participant 8, Male, 21 years)*

Other respondents shared this in relation to health and stress;

> *"I used to be someone who hardly ever got sick. But now, sitting for long hours tracking AI-generated reports makes my back hurt, and I also feel mentally drained. I have trouble*

concentrating outside of work because my mind is always racing with tasks and alerts. It feels like I am running a marathon that never ends. (Participant 2, Male, 22 years).

"…With AI, the mental load is heavier now. There are too many platforms to learn, too many updates happening all the time. I find myself staying up late just trying to understand new tools so I don't feel lost at work the next day. Yes, seminars and webinars are held to help us to become abreast with the technology, but sometimes it still feels mentally exhausting." (Participant 4, Female, 24 years)

The quotes under the subtheme of digital stress reveal how the increased presence of AI and digital systems in the workplace; though functionally helpful, has also contributed to mental exhaustion, pressure to be constantly connected, and declining physical and emotional health among employees. Participant 12 highlighted this tension, stating, *"the constant digital engagement and pressure to stay on top of everything is draining."* While she acknowledges that the tools are helpful, her experience reflects a deeper issue: the cognitive overload and screen fatigue associated with prolonged digital interaction, leading to mental exhaustion and a yearning for more human connection. Participant 1 reinforced this by pointing out the lack of digital boundaries, saying, *"I don't really disconnect anymore,"* which not only affects his sleep and focus but also reflects a blurring of work-life that is increasingly common in AI-integrated environments. The pressure to be perpetually available mirrors a culture of hyper-productivity and contributes to burnout. Participant 8, Participant 2, and Participant 4 also shared thoughts on digital stress.

Collectively, these reflections illustrate that digital stress is a significant psychosocial consequence of AI adoption. While AI is designed to optimize performance, the constant demands it places on employees' attention, time, and adaptability can lead to burnout, anxiety, and declining work-life quality, especially when not managed with clear boundaries and support structures.

4.2.2 Summary of Qualitative Findings

Table 4.10: Summary of Themes, Subthemes and Supporting quotes

Theme	Subtheme	Supporting Quote
Mixed Feelings	Positive	*"Honestly, I think it is a good initiative like to have AI in organizations and to help make things easier so actually I'm not against it I think it's actually a good initiative because it will make lives easier… you know when you are having problems although you can't always rely on it but there are some times …like me for example, when I am writing some codes and I have problems I just ask the AI… Oh how or what and it gives me the right answers. I can collaborate with the AI. I think it's actually a good initiative" (P2, Male, 22 years)*
	Negative	*"Hmmm, yeah for me I still have a little bit of fear in terms of hmm, hmm just accepting it holistically. …I still recall the movies we watch before, where the AI turns against the human race and try attacking the humans and so I'm almost sceptical thinking that, what if this finally happens one day and then these AI, they have every information about us and know how we think, and all and that turn against us." (P6, Male, 30 years)*
Psychosocial impact	Reduced interactions	*"Well, to be honest, a lot has changed. Before, I used to interact with different departments every day—calls, emails, even walking down to their desks to sort things out. But now, most of those processes are automated. We use this AI system that routes requests and updates task statuses automatically, so I hardly talk to people anymore. It feels like I'm just communicating with a screen now."* (P4, Female, 24 years)
	Unemployment	*"It's affected how I feel about work. I'm more anxious than before, always wondering if the next meeting is about restructuring or downsizing. Some of my colleagues have already been let go. It feels like we're being replaced piece by piece." (P9, Female, 27 years)*
	Feeling of inadequacy	*"It's been a mixed bag. On one hand, it's exciting — the technology is powerful and impressive. But on a personal level, I often feel like I'm not smart enough or skilled enough to keep up. The AI performs certain tasks in seconds that would take me a whole hour. It makes me feel... inadequate, honestly." (P11, Male, 29 years)*
	Digital stress	*"I get mentally exhausted. There are days I leave work with a headache from just staring at screens and jumping between apps. It's not that the tools are bad — they're helpful — but the constant digital engagement and pressure to stay on top of everything is draining. Sometimes, I just wish for more human interaction or a moment to breathe." (P12, Female, 25 years).*

CHAPTER 5

DISCUSSION

5.0 Introduction

This chapter laid out a discussion of what was found in relation to the study's objective and taking into account the current understanding in the field. The section gives an overview of the study's conclusions, presents recommendations for the subject area studied, and makes definitive conclusions based on the findings obtained. The purpose of the study was to determine the relationship between AI adoption and psychological well-being among employees in technology-driven organizations; to determine which dimension of PWB will predict AI adoption most; to determine if demographic factors (age and gender) moderate the relationship between AI adoption and PWB; and lastly employees views on AI adoption, as well as effects of adoption on employees. This chapter is a discussion on the research questions/ hypotheses and presents implications of the study, limitation of the study, recommendation for future researches and finally the conclusion.

5.1 Discussion of Hypotheses and Research Questions

In all, four hypotheses and two research questions were tested in this research. Out of the four hypotheses, two were supported with two being disconfirmed. These are discussed below. The research questions are also discussed right after.

5.1.1 Discussion of Study 1 Results

5.1.1.1 Organizational AI adoption and PWB

It was hypothesized that organizational AI adoption will significantly predict psychological well-being (PWB) among employees in technology-driven organizations. Based on data gathered and analysed, the hypothesis was confirmed by the results of the analysis, which showed a statistically significant positive predictive relationship between organizational AI adoption and employees' PWB.

This finding implies that as organizations increasingly adopt AI technologies, the psychological well-being of their employees also tends to improve. It suggests that employees may experience benefits such as increased efficiency, reduced workload, better work-life balance, or opportunities for skill development, all of which contribute positively to their well-being. This predictive relationship also positions AI not just as a technological asset but as a resource that can potentially enrich the work environment and employee experience.

The result aligns well with the Technology Acceptance Model (TAM), which posits that perceived usefulness and ease of use drive acceptance of technology. In this case, the predictive power of AI adoption on PWB suggests that employees likely perceive AI as a tool that enhances job performance and reduces strain, leading to improved psychological outcomes. Moreover, the result resonates with the Job Demands-Resources (JD-R) Model, which argues that job resources (like supportive technology) can buffer the effects of job demands and promote employee well-being. AI, when effectively implemented, can act as a resource that supports employees by automating routine tasks, improving decision-making, and providing new avenues for skill growth and autonomy; thus, reducing psychological strain and increasing well-being.

While much of the literature presents a mixed picture, with some studies highlighting stress, job insecurity, or role ambiguity due to AI, others emphasize its potential for enhancing productivity and satisfaction. For instance, studies like those of Makridis (2020) support the positive outcomes of AI integration, consistent with your findings. However, studies such as Nazareno and Schiff (2021), which report negative psychological impacts, suggest that context and implementation strategies play a crucial role in determining outcomes with the adoption of artificial intelligence.

In the Ghanaian context, the positive predictive relationship between AI adoption and PWB may be influenced by several local dynamics. First, AI adoption in Ghana is still at a growth stage, and its novelty may contribute to enthusiasm and optimism among employees who associate it with modernization, skill advancement, collaboration, efficiency and career progression. Additionally, many technology-driven organizations in Ghana operate within tight-knit, collaborative cultures. The introduction of AI in such settings may enhance team efficiency and relieve workers of repetitive or cognitively taxing tasks, thereby supporting their psychological well-being. Moreover, the relatively low saturation of AI in routine operations means employees are not yet experiencing the full brunt of automation-related job displacement, which may explain the more positive perception of AI. Also, government policies and corporate training initiatives promoting digital literacy and upskilling may reinforce employee confidence, leading to a more favourable impact of AI on well-being.

5.1.1.2 Dimension of PWB (Personal Growth) and AI adoption

It was hypothesized that personal growth, as a dimension of psychological well-being (PWB), would significantly predict AI adoption more than the other dimensions of PWB among employees in technology-driven organizations. This hypothesis was confirmed. Among the various PWB dimensions, personal growth emerged as the strongest predictor of AI adoption, explaining 4.4% of the variance.

The confirmation of this hypothesis implies that employees who report a strong sense of personal growth are more likely to embrace AI technologies within their organizations. Personal growth- characterized by openness to new experiences, continual self-improvement, and striving to realize one's potential - appears to foster a mindset that is receptive to innovation and technological advancement. This finding suggests that employees who view themselves as evolving and developing are more inclined to adopt AI tools as part of that trajectory. In practical terms, fostering a work environment that supports learning and self-actualization may be key to successful AI integration.

However, it is important to note that other psychological well-being dimensions—environmental mastery, positive relations, purpose in life, and self-acceptance—also significantly predicted AI adoption, with variance contributions comparable to that of personal growth. This pattern implies that while personal growth is particularly relevant, employees' broader sense of well-being also shapes their openness to AI integration. For instance, those with greater environmental mastery may feel more capable of managing technological demands, whereas individuals with higher self-acceptance may approach AI adoption with less fear of inadequacy.

From a theoretical standpoint, this finding aligns with the Technology Acceptance Model (TAM). Employees with high levels of personal growth are likely to perceive AI as useful and manageable - two key components of TAM. Their orientation toward improvement and novelty likely enhances their perceived ease of use and perceived usefulness of AI technologies, thus promoting adoption. The Job Demands-Resources (JD-R) Model also supports this interpretation. Personal growth can be understood as a personal resource, which, according to the model, enables individuals to better cope with demands and take initiative in the workplace. Employees with higher levels of personal growth may view AI not as a threat but as a valuable resource that aligns with their goals for development and performance enhancement. AI thus turns as a tool for amplifying their capabilities, consistent with the JD-R's emphasis on resources facilitating engagement and positive outcomes.

In terms of literature, this finding resonates with research highlighting how intrinsic motivation and a growth mindset are associated with greater openness to technology (Deci & Ryan, 2000; Venkatesh et al., 2003). For example, recent studies have shown that employees with higher selfdirected learning and developmental orientation are more adaptive in digital transformations (Zhang & Venkatesh, 2018), in this case AI. Conversely, dimensions of PWB like environmental mastery or positive relations, while important, may not inherently drive the same level of proactive engagement with technological change.

In the Ghanaian context, this finding may reflect the growing value placed on personal and professional development in the face of rapid digital transformation. For many professionals, especially in urban and technology-focused sectors, personal growth is increasingly tied to digital fluency and adaptability. Given Ghana's strong youth population and growing access to digital education platforms, individuals who are growth-oriented may view AI adoption as an avenue for upward mobility, skill acquisition, and future readiness.

Furthermore, organizations in Ghana that promote learning cultures, sponsor tech-related training, or reward innovation may foster a link between personal growth and technology use. For such employees', adopting AI is not merely a job requirement; it becomes a pathway toward self-improvement and professional competitiveness in a globalizing labour market. Additionally, with the rise of entrepreneurship and digital start-ups in Ghana, growth-oriented individuals may view AI adoption as a strategic move to stay ahead in increasingly tech-driven industries.

5.1.1.3 Demographic Factors (Age, Gender) as moderators in the relationship between AI adoption and PWB

The third hypothesis hypothesized that age would moderate the relationship between AI adoption and psychological well-being (PWB) such that the relationship would be stronger for older employees. In essence, it was expected that age would amplify the positive impact of AI adoption on PWB. This hypothesis was not confirmed. The analysis showed that age did not significantly moderate the relationship between AI adoption and PWB. That is, the strength of the association between AI adoption and employees' psychological well-being did not differ significantly based on age.

The lack of support for this moderating effect suggests that the positive relationship between AI adoption and PWB is not significantly influenced by employees' age. This implies that, in the context of this study, both younger and older employees experienced similar psychological outcomes in response to AI adoption. This challenges assumptions that older employees necessarily benefit more from, or are more sensitive to, AI integration in terms of well-being. It may indicate a relatively uniform perception or experience of AI across age groups within the sampled participants/ organizations.

This result runs somewhat counter to prior expectations based on the Job Demands-Resources (JD-R) Model, which would suggest that older workers, possibly having greater job experience and coping resources, might derive more psychological benefit from AI if it eases workload or provides support. Similarly, prior applications of the Technology Acceptance Model (TAM) often suggest that younger employees adopt new technology more readily due to greater digital familiarity, but in terms of well-being outcomes, age effects can be inconsistent.

Some studies (e.g., Czaja et al., 2006; Mitzner et al., 2010) have shown that older workers may initially be less comfortable with new technologies but may benefit more once adoption is achieved, due to improved efficiency and support. Other studies have found no significant age-based differences in psychological outcomes of workplace technologies, particularly in environments where training and support are uniformly provided (Rana et al., 2022). The finding of this study aligns with Medeiros (2024), who found that generational differences had minimal influence on AI attitudes in both the U.S. and India. This supports the notion that modern employees (regardless of age) may share more convergent experiences with digital tools than previously assumed, especially in work environments where digital exposure is normalized. Similarly, Rojas-Méndez et al. (2017) found that age, though significant, was a weaker predictor of technology adoption compared to education, suggesting that other factors may override age effects.

In the Ghanaian setting, the absence of age-related moderation could stem from a relatively youthful labour market in technology-driven sectors, where digital fluency may not vary widely across age brackets. Additionally, ongoing national efforts to promote digital literacy among all citizens, regardless of age, may be narrowing traditional generational divides in tech comfort and usage. Moreover, many Ghanaian organizations in the tech space are actively investing in capacity building and inclusive digital training programs, enabling older employees to keep pace with technological advancements. A communal or team-oriented work culture which is common in Ghana; may also foster peer learning and mentorship that minimizes age-based disparities in technology adoption and its psychological effects.

The fourth hypothesis hypothesized that gender would moderate the relationship between AI adoption and psychological well-being (PWB) such that the relationship would be stronger for one gender (typically assumed to be males based on prior research). This hypothesis was not confirmed. The analysis revealed that gender did not significantly moderate the relationship between AI adoption and PWB. In other words, both male and female employees experienced similar psychological well-being outcomes from AI adoption.

This finding suggests that the psychological benefits of AI adoption in technology-driven organizations are not gender-dependent, at least within the context of this study. It implies a relatively equitable experience of AI's impact on well-being among male and female employees, countering prior assumptions that one gender may be more psychologically affected by technological shifts in the workplace (Nouraldeen, 2022).

The result challenges expectations rooted in the TAM theory and broader gender-related studies on digital technology. According to TAM, perceived ease of use and usefulness influence technology acceptance, and prior studies have found gender differences in how these perceptions translate into actual adoption behaviour. However, this study's findings indicate that, even if gender influences attitudes toward AI, it may not necessarily translate into differential well-being outcomes once adoption occurs.

The result aligns with Medeiros (2024), who found that while males exhibited greater enthusiasm for AI adoption than females, generational or gender-based differences in psychological outcomes were minimal. Similarly, Rojas-Méndez et al. (2017) acknowledged gender as a predictor of technology readiness but emphasized that such demographic variables often interact with broader cultural and organizational factors.

However, the finding diverges from Nouraldeen (2023), whose study showed that gender moderated the relationship between technology readiness and AI adoption among Lebanese accounting students, with males showing stronger tendencies. While Nouraldeen focused on adoption behavior rather than PWB, the contrast highlights that demographic moderation effects can vary based on context, domain, and outcome variables.

In the Ghanaian context, several cultural and organizational dynamics may explain the absence of a gender moderation effect. In many technology-driven organizations in Ghana, there is a growing emphasis on gender inclusivity, particularly in digital upskilling and professional development. Initiatives aimed at reducing gender disparities in technology; such as coding bootcamps for women, corporate diversity policies, and public-private partnerships may have contributed to a levelling effect in how both men and women experience AI at work. Additionally, collaborative work environments and strong communal values in many Ghanaian organizations may dilute potential gender differences in access to AI resources or training. If both male and female employees are equally supported in adapting to AI tools and systems, the psychological outcomes - such as purpose in life, autonomy, and growth- may naturally converge regardless of gender.

5.1.2 Discussion of Study 2 Results

5.1.2.1 Employees views about AI adoption

The present study also explored the question: *What are employees' views about AI adoption?* This qualitative question sought to understand employees' subjective experiences and perceptions regarding the integration of AI in their work environments. In the qualitative, the researcher sought to determine the views held my employees in technology-driven organizations with regards to AI adoption. This research question was answered. Thematic analysis revealed a central theme of "mixed feelings" toward AI adoption. Two major sub-themes emerged: positive sentiments, where employees highlighted benefits such as increased efficiency, reduced workload, and support or collaboration in tasks; and negative sentiments, including concerns about job security, dehumanization of work, and lack of clarity about AI's long-term implications. These perspectives were supported by direct quotations from participants, capturing both optimism and apprehension regarding AI's role in the workplace.

The findings highlight the complex nature of employee reactions to AI adoption. While many recognize its potential to enhance work processes, others fear displacement or a loss of human agency. This duality suggests that employee well-being and technology acceptance cannot be assumed to follow a uniform trajectory; rather, organizations must actively engage with these emotional and cognitive responses when implementing AI systems.

The TAM theory helps explain the positive responses - employees who view AI as useful and manageable are more likely to accept and embrace it, which is consistent with Ankamah et al. (2024). However, the negative sentiments reflect aspects beyond TAM, including perceived threats and emotional resistance, which TAM does not fully account for. Also, the JD-R Model provides a helpful complement: if AI is seen as a resource (e.g., enhancing efficiency), it supports employee well-being. But if it is perceived as a demand (e.g., posing job threats or requiring constant upskilling), it may increase strain. This dual framing supports the emergence of mixed feelings.

The findings are consistent with Medeiros (2024), who observed that employees globally exhibit varying degrees of trust and comfort with AI, influenced by demographic and cultural factors; employees in both the U.S. and India expressed both excitement and caution, paralleling the dual perspectives uncovered in the present study. Additionally, Rojas-Méndez et al. (2017) and Nouraldeen (2023) emphasized that while technology readiness and perceived usefulness drive adoption, factors like gender, education, and cultural expectations can moderate attitudes, contributing to complex, mixed responses.

In Ghana, the theme of "mixed feelings" likely reflects a combination of enthusiasm about technological progress and caution about its socioeconomic implications. This finding akin to the work of Acheampong et al. (2025). On the positive side, Ghana's increasing investment in digital infrastructure and skills development (such as government-backed digital initiatives and private sector innovation) has generated optimism about AI's potential to improve productivity and create new opportunities. However, negative sentiments may stem from concerns about unemployment, technological inequality, and insufficient stakeholder communication about AI's role. In a country where job security is a major concern and formal social protections are limited, the fear of job displacement by AI remains valid. Additionally, in workplaces where change management processes are weak or top-down, employees may feel alienated or unprepared for AI transitions. Thus, the mixed feelings expressed by employees are not only psychologically and theoretically coherent but also socially and contextually grounded.

5.1.2.2 Potential Challenges of AI Adoption

The present study also explored the question: What are the effects of AI adoption on employees? This research question aimed to uncover how AI adoption is experienced within the workplace.

This research question was fairly answered. The analysis revealed a major theme of psycho-social impact, with four key sub-themes emerging from employee responses: Reduced social interaction, Unemployment or fear of job loss, Feelings of inadequacy, and Digital stress. Participants' quotes illustrated how AI adoption, while offering some efficiency benefits, also introduced emotional strain, social disconnection, and job-related anxieties. These reflect the broader, often under-explored, human cost of rapid technological transformation in the workplace.

These findings suggest that AI adoption affects more than operational workflows; it penetrates the emotional and interpersonal fabric of employee experience. The psycho-social toll includes not just fear of job loss but also diminished opportunities for collegial bonding and increasing mental pressure to keep pace with new technologies. If unaddressed, these outcomes can undermine employee PWB and organizational morale, even in otherwise technologically progressive environments.

The JD-R Model offers a critical lens for interpreting these effects. While AI may function as a resource in some contexts (e.g., automation of routine tasks), it can also become a demand when it leads to job insecurity, the need for constant skill updates, or the erosion of social bonds; all of which drain psychological resources and increase stress. The TAM is less equipped to explain these negative psycho-social effects, as it focuses mainly on cognitive perceptions (usefulness and ease of use) and not emotional or social consequences. However, the emergence of digital stress and feelings of inadequacy suggest that emotional responses may act as hidden moderators in the technology adoption process—an area that newer extensions of TAM, like the Unified Theory of Acceptance and Use of Technology (UTAUT), are beginning to consider.

In terms of literature, the findings akin Nazareno and Schiff (2021), who found that AI adoption in healthcare and logistics was associated with heightened stress, role overload, and job insecurity. Similarly, Makridakis (2017) warned that while AI increases productivity, it can also exacerbate psychological strain and labour displacement. In addition, Susskind and Susskind (2015) argued that AI's encroachment into traditionally human roles leads not only to deskilling but to existential concerns about professional identity; an interpretation consistent with employees' expressed feelings of inadequacy in this study. Lastly, the sub-theme of reduced social interaction is consistent with findings by Brougham and Haar (2018), who noted that AI-mediated environments can erode interpersonal relationships at work, as tasks become more isolated and screen-mediated. This can be particularly detrimental in cultures or organizations where teamwork and collective engagement are highly valued.

In the Ghanaian context, the psycho-social effects may be intensified by certain structural and cultural realities. First, Ghana has a strong collectivist orientation, and social relationships in the workplace are vital to employee satisfaction and mental well-being. The shift toward AI-driven processes that reduce face-to-face collaboration may therefore have a more pronounced psychological impact in Ghana than in more individualistic cultures. Second, in a developing economy where formal employment is scarce and job security is fragile, fears of unemployment due to AI are especially salient. Employees may lack access to robust reskilling programs or digital literacy initiatives, exacerbating feelings of inadequacy and digital stress. Furthermore, the relatively uneven pace of technological development across sectors in Ghana means that employees may feel caught between traditional work expectations and emerging digital demands, compounding the emotional strain. Finally, limited access to mental health support in most Ghanaian workplaces may mean that employees experiencing AI-related stress are less likely to receive adequate support, allowing these effects to persist and potentially escalate.

5.2 Integration of Findings – Convergence and Divergence

According to Bronstein and Kovacs (2013), integration of findings in a mixed study is essential because it enables the researcher duly communicate and highlight the points of divergence and convergence in the study. Also, it aids in pulling together the findings of the research. The present study investigated the relationship between AI adoption and psychological well-being (PWB) among employees in technology-driven organizations in Ghana, drawing on both quantitative hypotheses and qualitative research questions. Across both methods, a complex, varied narrative emerged; firstly, one that stresses the promise of AI for enhancing employee well-being and secondly one that highlights significant psychological and social risks.

5.2.1 Point of Convergence

At a broad level, the findings support a positive link between AI adoption and PWB, particularly when AI is perceived as useful, manageable, and aligned with personal development goals. The confirmation of the first hypothesis (that organizational AI adoption significantly predicts PWB) aligns with the TAM theory and suggests that when technology is introduced thoughtfully, it can be psychologically empowering. Furthermore, the finding that personal growth was the strongest PWB predictor of AI adoption reinforces this positive view, suggesting that employees who view AI as an opportunity for self-development are more likely to embrace it. These results echo findings from Makridis (2020) and others, indicating that in environments where AI adoption is accompanied by growth opportunities, job satisfaction and well-being improve. Additionally, qualitative data reinforced this narrative: many employees acknowledged AI's role in improving efficiency, reducing workload, and supporting decision-making; hallmarks of a supportive job resource within the JD-R framework.

5.2.2 Point of Divergence

Optimistic trends coexist with more complex findings. Firstly, the moderation hypotheses (age and gender) were not confirmed, indicating that demographic variables did not significantly shape the relationship between AI adoption and PWB. This finding diverges from portions of prior literature (e.g., Meyer, 2008; Nouraldeen, 2023), suggesting that in the Ghanaian context, organizational and cultural factors may outweigh individual demographic characteristics in shaping technology outcomes. In contrast, the qualitative findings highlighted a more ambivalent and emotionally textured picture. While some employees embraced AI, others reported digital stress, feelings of inadequacy, reduced social interaction, and even fear of job loss. These psycho-social impacts complicate the assumption that technological progress uniformly enhances well-being. The ambivalence was most clearly captured in the theme of “mixed feelings” that emerged from employee views. AI was seen as both an enabler and a disruptor; offering efficiency but threatening relational, emotional, and existential aspects of work life. This duality highlights a critical gap in TAM, which emphasizes rational adoption drivers but overlooks emotional and social implications. Here, the JD-R model offers a more balanced theoretical lens, accounting for both resource-enhancing and demand-inducing aspects of AI.

5.3 Implications of the Study

5.3.1 Theoretical Implications

From a theoretical standpoint, this study contributes meaningfully to the discourse on technology adoption and employee well-being by bridging gaps between existing models and real-world employee experiences in an emerging economy context (Ghana). The study confirms the relevance of TAM in explaining AI adoption in the workplace, particularly the importance of perceived usefulness in promoting positive outcomes like PWB. However, findings, especially from qualitative data, suggest that TAM's focus on cognitive evaluations may be insufficient in capturing emotional and social dimensions of technology adoption. The results highlight the need to expand TAM to include affective and contextual factors such as digital stress, fear of obsolescence, and perceived threats to social interaction.

Also, the JD-R model has been validated in the present study Luguyare (2025) as a useful framework for understanding how AI adoption can function both as a job resource (enhancing efficiency and personal growth) and a job demand (inducing stress and emotional strain). The dual role of AI adoption uncovered in this study suggests that well-being outcomes depend on the interplay between how AI is implemented and the support systems available within the organization. Lastly, the study demonstrates that models developed in Western or high-tech contexts must be cautiously applied in African and emerging economies. Cultural, infrastructural, and organizational differences significantly shape how employees perceive and respond to AI, making it necessary to localize and adapt these theories. The insignificant moderating role of age and gender, for instance, challenges findings from more developed settings and calls for culturally sensitive models of technology adoption.

5.3.2 Practical Implications

The study's conclusions have significant ramifications for practitioners, policymakers, and organizational leaders looking to apply AI in ways that promote worker well-being. Firstly, in Strategic and Inclusive AI Implementation, organizations should know that while AI can enhance PWB when perceived as empowering, it can also generate fear, stress, and resistance. Organizations must therefore adopt AI in ways that prioritize employee inclusion. This includes engaging employees early in the implementation process, clarifying the purpose and benefits of AI tools, and addressing fears related to job security and redundancy. Secondly, the strong predictive power of personal growth in AI adoption highlights the need for continuous learning and upskilling programs. Organizations should offer tailored training that not only improves technical competence but also builds employees' confidence and sense of control, reducing feelings of inadequacy or digital overwhelm.

In Ghana, where communal values and interpersonal relationships are vital to workplace cohesion, AI systems should be designed and implemented in ways that preserve human connection. Managers must be culturally sensitive, acknowledging that perceived losses in social interaction may negatively impact morale and productivity. Hybrid work models or AI tools that enhance rather than replace teamwork should be prioritized. Lastly, given the documented psycho-social effects; such as digital stress and reduced social interaction organizations should integrate mental health monitoring and support into their digital transformation strategies. This may include employee assistance programs, counselling services, and promoting a healthy digital culture that balances automation with human interaction. Policymakers can use these findings to guide national strategies on AI integration. There is a need for regulations that promote equitable access to AI benefits, protect workers from displacement, and encourage businesses to implement AI in a psychologically safe and ethically sound manner.

5.4 Limitations of the Study

This study undoubtedly has shortcomings/ limitations. Firstly, the issue of generalizability and limited exploration of organizational diversity. The study's findings are limited in their generalizability due to the specific sample size of 189 and 13 participants respectively drawn from a particular sector or industry (technology-driven organizations). The study's focus on a specific sector may limit the exploration of organizational diversity. Different industries or organizational structures could present unique challenges and opportunities related to AI adoption and its effects on employee well-being, and these nuances may not be fully captured. The results may not be universally applicable to diverse organizational settings or sectors, and caution should be exercised when extending conclusions beyond the studied population.

Also, the reliance on self-report measures for data collection, especially in the survey component of the study, introduces the potential for response bias and social desirability. Participants may provide responses that they believe are socially acceptable, potentially influencing the accuracy of reported attitudes and perceptions. The voluntary nature of participation in the study might introduce biases, as individuals with strong opinions or experiences related to AI adoption and PWB may be more inclined to participate, potentially skewing the data gathered and subsequent findings.

Another limitation is that limited moderating variables were tested. Although demographic variables such as age and gender were tested as moderators, other potentially influential factors such as education level, job role, organizational culture, or technological infrastructure were not examined. Including a broader range of moderators may have provided more understanding of the conditions under which AI adoption affects employee well-being. Lastly, the rapidly changing nature of AI technologies means that employee perceptions and organizational impacts may shift quickly. The findings reflect a snapshot in time and may not fully capture long-term trends or reactions to newer AI applications that are yet to be implemented.

5.5 Recommendations for Future Studies

Building on the findings and constraints of this investigation, a number of directions for further study are suggested to further comprehension of the interaction between AI adoption and employee PWB; First and foremost, adopt longitudinal research designs. Future studies should utilize longitudinal designs to track changes in employee well-being over time as AI adoption progresses. This approach would help establish causal relationships and reveal potential delayed or cumulative effects of AI integration on psychological outcomes.

In addition, future studies can consider expanding the study by exploring additional moderating and mediating variables. Further research should explore additional moderators and mediators such as organizational culture, leadership style, digital literacy, education level, and perceived job security. These factors may influence how different employee groups experience the psychological effects of AI adoption.

To enhance generalizability, future studies should replicate this research across different cultural, national, and industry contexts. Comparative studies involving countries at different stages of technological development can illuminate how cultural norms and institutional environments shape AI-related outcomes. Also, while this study used both quantitative and qualitative approaches, future research can strengthen the qualitative component by involving larger and more diverse samples across job roles, departments, and hierarchical levels. This would provide richer, more inclusive perspectives on how employees experience AI.

Finally, explore ethical and policy dimensions. As AI becomes more embedded in organizational decision-making, future research should explore the ethical implications for employee well-being. Future research should delve deeper into the emotional, relational, and identity-related consequences of AI adoption, particularly in collectivist or community-oriented cultures.

5.6 Conclusion

The current study explored the relationship between organizational AI adoption and the PWB of employees in technology-driven organizations in Ghana. Drawing on the TAM and the JD-R Model, the research employed both quantitative and qualitative methods to examine how AI integration influences various dimensions of well-being, and how individual factors such as age, gender, and personal growth interact with this process. Key findings revealed that AI adoption positively predicts PWB, and that personal growth, among the dimensions of PWB, is the strongest predictor of willingness to adopt AI. However, the hypothesized moderating roles of age and gender were not supported. These findings suggest that while AI adoption can serve as a resource that enhances well-being, its psychological impact is shaped more by individual development and contextual readiness than by demographic factors alone. The qualitative findings further illuminated the experiences of employees, highlighting both optimism about AI's potential and concerns over digital stress, reduced social interaction, and job displacement.

The study contributes to theory by extending TAM and the JD-R model within a culturally specific, under-researched context, and by highlighting the dual nature of AI as both a tool for empowerment and a source of psychosocial tension. Practically, it offers organizations and policymakers valuable guidance on fostering AI acceptance while safeguarding employee well-being.

Overall, the findings emphasize the need for thoughtful, inclusive, and psychologically informed approaches to AI integration in the workplace. As AI continues to evolve, it is imperative that human-centered values remain at the core of technological advancement; especially in emerging economies like Ghana where digital transformation is rapidly accelerating.

References.

Ahumada-Tello, E., Evans, R. D., Romero-Gómez, D., López-García, J., & Castañón-Puga, M. (2023). Impact of AI on employee well-being and decision-making: Insights from OECD member countries. In *2023 IEEE Global Conference on Artificial Intelligence and Internet of Things (GCAIoT)* (pp. 121-126). IEEE.

Aiken, L. S., West, S. G., & Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions*. sage.

Ali, I., Warraich, N. F., & Butt, K. (2024). Acceptance and use of artificial intelligence and AI-based applications in education: A meta-analysis and future direction. *Information Development*, 02666669241257206.

Ampofo, J. W., Emery, C. V., & Ofori, I. N. (2023). Assessing the level of understanding (knowledge) and awareness of diagnostic imaging students in Ghana on artificial intelligence and its applications in medical imaging. *Radiology Research and Practice*, *2023*(1), 4704342.

Amponsah, W., & Kaur, P. (2021). Exploratory Data Analysis and Crime Prevention using Machine Learning: The case of Ghana. International Journal of Innovative Science and Research Technology, Vol 6, Issue 3. ISSN No:-2456-2165

Ankamah, S., Gyesi, K., & Amponsah, V. (2024). Awareness, knowledge, and attitude towards artificial intelligence: Perspective of medical students in Ghana. *Information Development*, 02666669241283790.

Arboh, F., Zhu, X., Atingabili, S., Yeboah, E., & Drokow, E. K. (2025). From fear to empowerment: the impact of employees AI awareness on workplace well-being–a new insight from the JD–R model. *Journal of Health Organization and Management*.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of economic perspectives*, *29*(3), 3-30.

Baabdullah, A. (2024). The precursors of AI adoption in business: Towards an efficient decision-making and functional performance. *Int. J. Inf. Manag.*, 75, 102745. https://doi.org/10.1016/j.ijinfomgt.2023.102745.

Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of managerial psychology*, *22*(3), 309-328.

Bakker, A. B., & Demerouti, E. (2014). Job demands–resources theory. *Wellbeing: A complete reference guide*, 1-28.

Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of occupational health psychology*, *22*(3), 273.

Banerjee, A., Kabadi, S., & Karimov, D. (2023). The transformative power of AI: projected impacts on the global economy by 2030. *Review of Artificial Intelligence in Education*, *4*, e20-e20.

Boncz, I. (2015). Introduction to research methodology. University of Pecs.

Braganza, A., Chen, W., Canhoto, A., & Sap, S. (2021). Productive employment and decent work: The impact of AI adoption on psychological contracts, job engagement and employee trust. *Journal of business research*, *131*, 485-494.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology*, *3*(2), 77-101.

Bronstein, L. R., & Kovacs, P. J. (2013). Writing a Mixed Methods Report in Social Work Research. Research on Social Work Practice, 23(3), 354–360. https://doi.org/10.1177/1049731512471564

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, *24*(2), 239-257.

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company.

Carroll, N., & Richardson, I. (2019). Mapping a careflow network to assess the connectedness of connected health. *Health informatics journal*, *25*(1), 106-125.

Chang, R. (2024). The Impact of Employees' Health and Well-being on Job Performance. *Journal of Education, Humanities and Social Sciences*. https://doi.org/10.54097/9ft7db35.

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change*, *170*, 120880.

Chinnaswamy, D. B. (2021). CHALLENGES OF E-LEARNING IN AN ERA OF SOCIAL DISTANCING IN HIGHER EDUCATION. *Available at SSRN 3863011*.

Christoforou, R., Lange, S., & Schweiker, M. (2024). Individual differences in the definitions of health and well-being and the underlying promotional effect of the built environment. *Journal of Building Engineering*, *84*, 108560.

Chuang, S., Shahhosseini, M., Javaid, M., & Wang, G. (2024). Machine learning and AI technology-induced skill gaps and opportunities for continuous development of middle-skilled employees. *Journal of Work-Applied Management*. https://doi.org/10.1108/jwam-08-2024-0111 .

Clifton, J., Glasmeier, A., & Gray, M. (2020). When machines think for us: the consequences for work and place. *Cambridge Journal of Regions, Economy and Society*, *13*(1), 3-23.

Clipper, B. (2020). The influence of the COVID-19 pandemic on technology: adoption in health care. *Nurse leader*, *18*(5), 500-503.

Creswell, J. (2011). Planning, Conducting, and Evaluating Quantitative and Qualitative Research. New York: Pearson.

Creswell, J. W. (2014). Research design: Qualitative, quantitative, and mixed methods approaches (4th ed.). SAGE.

Creswell, J. W. & Creswell, J. D. (2018). Research design: Qualitative, quantitative and mixed method approaches (5th ed). Thousand Oaks: SAGE.

Czaja, S. J., Charness, N., Fisk, A. D., Hertzog, C., Nair, S. N., Rogers, W. A., & Sharit, J. (2006). Factors predicting the use of technology: findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). *Psychology and aging*, *21*(2), 333.

Dalisaymo, L., & Patalay, M. (2024). Artificial Intelligence Impact on Digital Nomad Work Life Balance: The Role of Automation. *2024 2nd International Conference on Computing and Data Analytics (ICCDA)*, 1-6. https://doi.org/10.1109/ICCDA64887.2024.10867307

Danna, K., & Griffin, R. W. (1999). Health and well-being in the workplace: A review and synthesis of the literature. *Journal of management*, *25*(3), 357-384.

Danso, W. B., & Hanson, E. (2023). Artificial Intelligence Disruption and its Impacts on Future Employment in Africa- A Case of the Banking and Financial Sector in Ghana. *i-manager's Journal on Software Engineering*, *18*(1).

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

De Andrade, I. M., & Tumelero, C. (2022). Increasing customer service efficiency through artificial intelligence chatbot. *Revista de Gestão*, *29*(3), 238-251.

DeCanio, S. (2016). Robots and humans – Complements or substitutes? Journal of Macroeconomics, 49, 280–291. https://doi.org/10.1016/j.jmacro.2016.08.003

Deci, E. L., & Ryan, R. M. (2000). The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological inquiry*, *11*(4), 227-268.

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied psychology*, *86*(3), 499.

Demerouti, E., & Bakker, A. B. (2011). The job demands-resources model: Challenges for future research. *SA Journal of Industrial Psychology*, *37*(2), 01-09.

Demerouti, E., & Nachreiner, F. (2019). The job demands—job resources model of burnout and work engagement—state of the art. *Zeitschrift für Arbeitswissenschaft*, *73*, 119-130.

Dissanayake, J. (2024). Exploring the impact of remote work on the psychological well-being of software professionals in New Zealand.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994.

Dzisah, J. S. (2022). Digitalisation of Basic Services in Ghana: State of Policies in Action and Lesson for Progress.

Eke, D. O., Chintu, S. S., & Wakunuma, K. (2023). Towards shaping the future of responsible AI in africa. In *Responsible AI in Africa: Challenges and Opportunities* (pp. 169-193). Cham: Springer International Publishing.

Ford, M. (2015). Rise of the robots: Technology and the threat of a jobless future. Basic Books.

Fussell, S. G., & Truong, D. (2022). Using virtual reality for dynamic learning: an extended technology acceptance model. *Virtual Reality*, *26*(1), 249-267.

Gikunda, K. & Kute D. (2023). Empowering Africa: An In-depth Exploration of the Adoption of Artificial Intelligence Across the Continent. *ArXiv*, abs/2401.09457. https://doi.org/10.48550/arXiv.2401.09457.

Gyamfi, N. K., Dayie, R., & Asiedu, E. K. (2022). Application of Artificial Intelligence Techniques in Educational Delivery; Ghana Perspective. *Webology*, *19*(1), 480-492.

Hornberger, B., & Rangu, S. (2020). Designing Inclusion and Exclusion Criteria. In N. Gooneratne, G. Yerrabolu, & K.-C. Chen (Eds.), Writing Biomedical Research Proposals: A concise guide (First Edit). Penn Libraries. https://repository.upenn.edu/crphttps://repository.upenn.edu/crp/1

Huang, I. C., Du, P. L., Lin, L. S., Lin, T. F., & Kuo, S. C. (2021). Factors beyond workplace matter: The effect of family support and religious attendance on sustaining well-being of high-technology employees. In *Healthcare* (Vol. 9, No. 5, p. 602). MDPI.

Hunkenschroer, A. L., & Kriebitz, A. (2023). Is AI recruiting (un) ethical? A human rights perspective on the use of AI for hiring. *AI and Ethics*, *3*(1), 199-213.

Jackman, P. C., & Sisson, K. (2022). Promoting psychological well-being in doctoral students: a qualitative study adopting a positive psychology perspective. *Studies in Graduate and Postdoctoral Education*, *13*(1), 19-35.

Jain, P. (2017). Impact of Demographic Factors: Technology Adoption in Agriculure. *SCMS Journal of Indian Management*, *14*(3).

Jilcha Sileyew, K. (2020). Research Design and Methodology. IntechOpen. doi: 10.5772/intechopen.85731

Jin, G., Jiang, J. & Liao, H. (2024). The work affective well-being under the impact of AI. *Sci Rep* **14**, 25483. https://doi.org/10.1038/s41598-024-75113-w

Johnson, A., Dey, S., Nguyen, H., Groth, M., Joyce, S., Tan, L., Glozier, N., & Harvey, S. (2020). A review and agenda for examining how technology-driven changes at work will impact workplace mental health and employee well-being. *Australian Journal of Management*, 45, 402 - 424. https://doi.org/10.1177/0312896220922292.

Khanday, S. A. & Khanam, D. (2019). The Research design. *Journal of Critical Reviews.* ISSN-2394-5125 VOL 06, ISSUE 03, 2019

Kim, B. J., & Lee, J. (2024). The mental health implications of artificial intelligence adoption: the crucial role of self-efficacy. *Humanities and Social Sciences Communications*, *11*(1), 1-15.

Kurup, S., & Gupta, V. (2022). Factors Influencing the AI Adoption in Organizations. Metamorphosis, 21(2), 129-139.

Kusuma, H., Muafi, M., AJI, H. M., & Pamungkas, S. (2020). Information and communication technology adoption in small-and medium-sized enterprises: Demographic characteristics. The Journal of Asian Finance, Economics and Business, 7(10), 969-980.

Lee, Y. (2019). JD-R model on psychological well-being and the moderating effect of job discrimination in the model: Findings from the MIDUS. *European Journal of Training and Development*, *43*(3/4), 232-249.

Leonardi, F. (2018). The definition of health: towards new perspectives. *International Journal of Health Services*, *48*(4), 735-748.

Løvik, T. (2024). *A quantitative study of factors affecting Norwegian employees' attitude to the introduction of artificial intelligence in the workplace* (Master's thesis, UIS).

Malatji, W. R., Eck, R. V., & Zuva, T. (2020). Understanding the usage, modifications, limitations and criticisms of technology acceptance model (TAM). *Advances in Science, Technology and Engineering Systems Journal*, *5*(6), 113-117

Malik, N., Tripathi, S. N., Kar, A. K., & Gupta, S. (2021). Impact of artificial intelligence on employees working in industry 4.0 led organizations. *International Journal of Manpower*, *43*(2), 334-354.

Marquis, Y., Oladoyinbo, T. O., Olabanji, S. O., Olaniyi, O. O., & Ajayi, S. A. (2024). Proliferation of AI tools: A multifaceted evaluation of user perceptions and emerging trend. *Asian Journal of Advanced Research and Reports*, *18*(1), 30-55.

Matud, M. P., López-Curbelo, M., & Fortes, D. (2019). Gender and psychological well-being. *International journal of environmental research and public health*, *16*(19), 3531.

McClure, P. K. (2018). "You're fired," says the robot: the rise of automation in the workplace, technophobes, and fears of unemployment. *Social Science Computer Review*, *36*(2), 139-156.

McPherson, S. S. (2018). *Artificial intelligence: building smarter machines.* Twenty-First Century Books™.

Medeiros, W. (2024). Understanding Global Attitudes Towards Artificial Intelligence in the Workplace.

Meyer, J. (2008). *Older workers and the adoption of new technologies* (No. 07-050 [rev.]). ZEW Discussion Papers.

Michaels, G., Natraj, A., & van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. The Review of Economics and Statistics, 96(1), 60–77. https://doi.org/10.1162/REST_a_00366

Mishra, P., Singh, U., Gupta, a., Sahu, C., & Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. *Annals of Cardiac Anaesthesia, 22*(1), 67–72. https://doi.org/10.4103/aca.aca_157_18.

Mitzner, T. L., Boron, J. B., Fausset, C. B., Adams, A. E., Charness, N., Czaja, S. J., ... & Sharit, J. (2010). Older adults talk technology: Technology usage and attitudes. *Computers in human behavior*, *26*(6), 1710-1721.

Mobbing, S. (2009). Research population. Retrieved from www.exploratory.com/researchpopulation

Modhoriye, P., Yadav, P., & Jadhav, D. (2023). AI transformation in business: Unveiling the dual effects of advancement and challenges. *International Journal of Scientific Research Engineering and Management*, *7*, 12.

Moghayedi, A., Michell, K., Awuzie, B., & Adama, U. J. (2024). A comprehensive analysis of the implications of artificial intelligence adoption on employee social well-being in South African facility management organizations. *Journal of Corporate Real Estate*, *26*(3), 237-261.

Morandini, S., Fraboni, F., Angelis, M., Puzzo, G., Giusino, D., & Pietrantoni. L. (2023). The impact of Artificial Intelligence on Workers' Skills: Upskilling and Reskilling in organizations. *Informing Sci. Int. J. an Emerg. Transdiscipl.,* 26, 39-68. https://doi.org/10.28945/5078

Muqodas, I., Kartadinata, S., Nurihsan, J., Dahlan, T., Yusuf, S., & Imaddudin, A. (2020). Psychological well-being: A preliminary study of guidance and counseling services development of preservice teachers in Indonesia. In *International Conference on Educational Psychology and Pedagogy-" Diversity in Education"(ICEPP 2019)* (pp. 56-60). Atlantis Press.

Musikanski, L., Rakova, B., Bradbury, J., Phillips, R., & Manson, M. (2020). Artificial intelligence and community well-being: A proposal for an emerging area of research. International Journal of Community Well-Being, 3(1), 39-55.

Nazareno, L., & Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. Technology in Society, 67, 101679.

Neumann, O., Guirguis, K., & Steiner, R. (2024). Exploring artificial intelligence adoption in public organizations: a comparative case study. *Public Management Review*, *26*(1), 114-141.

Nouraldeen, R. M. (2023). The impact of technology readiness and use perceptions on students' adoption of artificial intelligence: the moderating role of gender. *Development and Learning in Organizations: An International Journal*, *37*(3), 7-10.

Obilor, E. I. (2023). Convenience and purposive sampling techniques: Are they the same. *International Journal of Innovative Social & Science Education Research*, *11*(1), 1-7.

Ofori-Acquah, C., Avortri, C. & Preko, A. Taking Stock of Policies, Regulations, and Initiatives That Leverage Technology to Build Trust: Lessons from Ghana's Financial Sector. *Glob Soc Welf* **10**, 9–17 (2023). https://doi.org/10.1007/s40609-022-00260-9

Ofosu-Ampong, K. (2023). Gender differences in perception of artificial intelligence-based tools. *Journal of Digital Art & Humanities*, *4*(2), 52-56.

Othman, W. N. bt W., Zainudin, Z. N., Yusop, Y. M., Jaafar, W. M. W., & Mokhtar, M. Y. O. (2022). A Systematic Review of Marital Satisfaction and Psychological Well-Being Among Career Women. *Journal of Positive School Psychology*, *6*(4), 5831–5844. http://journalppw.com

Oyman, M., Bal, D., & Ozer, S. (2022). Extending the technology acceptance model to explain how perceived augmented reality affects consumers' perceptions. *Computers in Human Behavior*, *128*, 107127.

Page, K., & Vella-Brodrick, D. (2009). The 'What', 'Why' and 'How' of Employee Well-Being: A New Model. *Social Indicators Research*, 90, 441-458. https://doi.org/10.1007/S11205-008-9270-3.

Park, S., Jeong, S., & Chai, D. S. (2021). Remote e-workers' psychological well-being and career development in the era of COVID-19: Challenges, success factors, and the roles of HRD professionals. *Advances in Developing Human Resources*, *23*(3), 222-236.

PwC. (2018) Macroeconomic Impact of Artificial Intelligence. https://www.pwc.co.uk/ economic-services/assets/macroeconomic-impact-of-ai-technical-report-feb-18.pdf.

Raj, H. (2024). The Impact of AI on Job Roles, Workforce and Employment. *International Journal of Scientific Research in Engineering and Management.* https://doi.org/10.55041/ijsrem33782

Rojas-Mendez, J. I., Parasuraman, A., & Papadopoulos, N. (2017). Demographics, attitudes, and technology readiness: A cross-cultural analysis and model validation. *Marketing Intelligence & Planning*, *35*(1), 18-39.

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology, 57*(6), 1069–1081. https://doi.org/10.1037/0022-3514.57.6.1069

Sadeghi, S. (2024). Employee Well-being in the Age of AI: Perceptions, Concerns, Behaviors, and Outcomes. *arXiv preprint arXiv:2412.04796*.

Sangster Jokić, C. A., & Jokić-Begić, N. (2022). Occupational disruption during the COVID-19 pandemic: Exploring changes to daily routines and their potential impact on mental health. *Journal of Occupational Science*, *29*(3), 336–351.

Scholze, A., & Hecker, A. (2024). The job demands-resources model as a theoretical lens for the bright and dark side of digitization. *Computers in Human Behavior*, *155*, 108177.

Serdar, C. C., Cihan, M., Yucel, D., & Serdar, M. A. (2021). Sample size, power and effect size revisited: simplified and practical approaches in pre-clinical, clinical and laboratory studies. Biochemia medica, 31 (1), 010502. https://doi.org/10.11613/BM.2021.010502

Sharma, M., & Sehgal, M. L. (2023). The Revolutionary Computer Technology Artificial Intelligence that is Changing Our World & it's Impact on Different Jobs. *International Journal for Research in Applied Science and Engineering Technology*, *11*(4), 286-293.

Soomro, S., Fan, M., Sohu, J. M., Soomro, S., & Shaikh, S. N. (2024). AI adoption: a bridge or a barrier? The moderating role of organizational support in the path toward employee well-being. *Kybernetes*.

Soulami, M., Benchekroun, S., & Galiulina, A. (2024). Exploring how AI adoption in the workplace affects employees: a bibliometric and systematic review. *Frontiers in Artificial Intelligence*, *7*, 1473872.

Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., Hager, G., ... & Teller, A. (2022). Artificial intelligence and life in 2030: the one-hundred-year study on artificial intelligence. *arXiv preprint arXiv:2211.06318*.

Susskind, D., & Susskind, R. (2015). The Future of the Professions. Oxford: OUP

Syeda, S. H. (2018). An exploratory study to identify critical success factors of agile systems engineering (Doctoral dissertation). The George Washington University.

Tai, M. C. T. (2020). The impact of artificial intelligence on human society and bioethics. *Tzu-Chi Medical Journal*, *32*(4), 339.

Thakur, R. A., Talukdar, M., Iyer, S., Liu, L. C., Chen, C. L., & Singh, A. (2025). AI and Employee Well-Being: Assessing the Ethical Implications of AI-Driven Human Resource Practices in Indian Universities. *Journal of Ecohumanism*, *4*(1), 2338-2351.

Thomas, J. (2017). Scholarly views on theory: Its nature, practical application, and relation to world view in business research. *International Journal of Business Management*, *12*(9).

Toyon, M. A. S. (2021). Explanatory sequential design of mixed methods research: Phases and challenges. *International Journal of Research in Business and Social Science*, *10*(5), 253-260.

Uzir, M. U. H., Bukari, Z., Al Halbusi, H., Lim, R., Wahab, S. N., Rasul, T., ... & Eneizan, B. (2023). Applied artificial intelligence: Acceptance-intention-purchase and satisfaction on smartwatch usage in a Ghanaian context. Heliyon, 9(8).

Vocabulary.com. (n.d.). Adoption. In *Vocabulary.com Dictionary*. Retrieved January 24, 2025, from https://www.vocabulary.com/dictionary/adoption

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Vyas-Doorgapersad, S. (2023). A Critical Review of Employee Health, Wellbeing Programs, and Organizational Success: Navigating Post-COVID-19 Sustainable Development. *International Journal of Research in Business and Social Science (2147-4478)*, *12*(6), 91-100.

Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business Process Management Journal*, *26*(7), 1893- 1924.

Wiafe, I., Koranteng, F. N., Obeng, E. N., Assyne, N., Wiafe, A., & Gulliver, S. R. (2020). Artificial intelligence for cybersecurity: a systematic mapping of literature. *IEEE Access*, *8*, 146598-146612

Wijayati, D. T., Rahman, Z., Rahman, M. F. W., Arifah, I. D. C., & Kautsar, A. (2022). A study of artificial intelligence on employee performance and work engagement: the moderating role of change leadership. International Journal of Manpower, 43(2), 486-512.

World Economic Forum. (2023a). Future of Jobs 2023: These Are the Most In-Demand Skills Now – and beyond. Retrieved from https://www.weforum.org/agenda/2023/05/future-of-jobs-2023-skills

World Health Organization. (2022). *WHO European framework for action on mental health 2021–2025*. World Health Organization. Regional Office for Europe.

Yu, X., Xu, S. and Ashton, M. (2023), "Antecedents and outcomes of artificial intelligence adoption and application in the workplace: the socio-technical system theory perspective", *Information Technology & People*, Vol. 36 No. 1, pp. 454-474. https://doi.org/10.1108/ITP-04-2021-0254

Yigitcanlar, T., & Cugurullo, F. (2020). The Sustainability of Artificial Intelligence: An Urbanistic Viewpoint from the Lens of Smart and Sustainable Cities. Sustainability. https://doi.org/10.3390/su12208548.

Zahoor, N., Donbesuur, F., Christofi, M., & Miri, D. (2022). Technological innovation and employee psychological well-being: The moderating role of employee learning orientation and perceived organizational support. *Technological Forecasting and Social Change*, *179*, 121610.

Zhang, X., & Venkatesh, V. (2018). From Design Principles to Impacts: A Theoretical Framework and Research Agenda. AIS Transactions on Human-Computer Interaction, 10(2), 105-128. https://doi.org/ 10.17705/1thci.00106

Zhang, Z., & Chen, W. (2019). A systematic review of measures for psychological well-being in physical activity studies and identification of critical issues. *Journal of affective disorders*, *256*, 473-485.

Zhao, Y., Yin, D., Wang, L., & Yu, Y. (2022). The rise of artificial intelligence, the fall of human wellbeing? *International Journal of Social Welfare*.

Appendix 1- Questionnaire

Introduction

Hello, my name is Sheila Luguyare, a final year Industrial/Organizational Psychology MPhil student at the University of Ghana. I am conducting a survey on Artificial Intelligence and psychological well-being.

Your participation is completely voluntary, and you may decide to quit at any point during the survey. Your confidentiality and privacy is greatly assured by participating. Thank you.

I have agreed to participate in this study with the understanding that my responses to these questions will not affect me in any way and that my responses to these questions will not be exposed or traced to me.

Signature of Participant _______________ **Date** __________________

Section A: Demographic Information

Kindly tick which of the following applies to you.

Sex: Male [ ] Female [ ]

Age: 18-39 [ ] 40-59 [ ] 60+ [ ]

Education: Degree [ ] Masters [ ] PhD [ ] others [ ]

Occupation: ______________________

Organization: _____________________________

Section B: Artificial Intelligence Adoption scale

Instructions for participants: We are interested in Artificial Intelligence adoption. By Artificial Intelligence we mean devices that can perform tasks that would usually require human intelligence. Please note that these can be computers, robots or other hardware devices, possibly augmented with sensors or cameras, programmed software, etc. Please complete the following scale, indicating your response to each item. There are no right or wrong answers. We are interested in your personal views.

Response Key

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
SD = 1	D = 2	N = 3	A = 4	SA = 5

1	I would consider adopting AI in my project or line of business	1	2	3	4	5
2	I am aware of AI implementation in my industry	1	2	3	4	5
3	AI has created an impact on industry	1	2	3	4	5
4	My industry has a positive outlook towards AI	1	2	3	4	5
5	My organization has resources for building AI applications	1	2	3	4	5
6	My organization provides timely resources for AI deployment	1	2	3	4	5
7	My organization has consultants who understand AI and the industry	1	2	3	4	5
8	My organization has resources for model monitoring and feedback	1	2	3	4	5

9	My organization has centrally managed AI practice	1	2	3	4	5
10	My organization has business function where prior business process change done	1	2	3	4	5
11	My organization has business functions that successfully switched to using new technology products from old ones	1	2	3	4	5
12	My organization has successfully implemented process change	1	2	3	4	5
13	Leaders in my organization are ready to accept risks related to AI implementation	1	2	3	4	5
14	Leaders in my organization have vision of using IT capability as a strategic competence	1	2	3	4	5
15	Leaders in my organization have vision to use AI technology	1	2	3	4	5
16	Leaders believe that adopting AI makes our organization remain competitive in the industry	1	2	3	4	5
17	I am aware of the output generated by applications being used by trading partners	1	2	3	4	5
18	I am aware of applications using input from trading partners	1	2	3	4	5
19	I am aware of applications that connect our organization's IT systems to trading partners	1	2	3	4	5

Section C: Psychological Wellbeing

We are interested in studying the psychological well-being of respondents. **Instructions:** Circle one response below each statement to indicate how much you agree or disagree.

Answer Format: 1 = strongly agree; **2** = somewhat agree; **3** = a little agree; **4** = neither agree or disagree; **5** = a little disagree; **6** = somewhat disagree; **7** = strongly disagree.

Number	Item	Response						
1	I like most parts of my personality.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2	When I look at the story of my life, I am pleased with how things have turned out so far.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3	Some people wander aimlessly through life, but I am not one of them.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4	The demands of everyday life often get me down.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5	In many ways I feel disappointed about my achievements in life.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6	Maintaining close relationships has been difficult and frustrating for me.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7	I live life one day at a time and don't really think about the future.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
8	In general, I feel I am in charge of the situation in which I live.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9	I am good at managing the responsibilities of daily life.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
10	I sometimes feel as if I've done all there is to do in life.	**1**	**2**	**3**	**4**	**5**	**6**	**7**

11	For me, life has been a continuous process of learning, changing, and growth.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
12	I think it is important to have new experiences that challenge how I think about myself and the world.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
13	People would describe me as a giving person, willing to share my time with others.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
14	I gave up trying to make big improvements or changes in my life a long time ago.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
15	I tend to be influenced by people with strong opinions.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
16	I have not experienced many warm and trusting relationships with others.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
17	I have confidence in my own opinions, even if they are different from the way most other people think.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
18	I judge myself by what I think is important, not by the values of what others think is important.	**1**	**2**	**3**	**4**	**5**	**6**	**7**

Appendix 2- Project plan/ Time table

The study will commence upon approval from the proposal and clearance from the Ethical Committee of the Humanities. The second semester will be used to carry out the study where data will be collected, analyzed and reported upon approval.

Week/month	**Task/activity**
April- May (week 1-4)	Proposal defense, Corrections in proposal, and commencement of project.
May-June (week 5-6) (week 7-8)	Ethical Clearance approval received.
June-August (week 8-9)	Introduction, literature review, methodology writing.
September (week 10-13)	Data collection (Interviews and Questionnaire).
October (week 14)	Analysis
November	Report and discussion of results. Submission of 1st draft to Supervisors.
December	Thesis Defense
January-March	Submission of 2nd Draft Chapter 1 to 3
April- May	Amendments Submission

Appendix 3- Interview Guide

1. Can you please tell me a little about yourself?
    - Age
    - Occupation
    - Educational level
2. When you hear of AI, what comes into your mind?
    - Can you give examples?
3. In your view, will AI affect the way we think?
    - If yes, can you elaborate, if no can you elaborate?
4. Do you think AI can affect human relation at work?
5. What are your views on AI adoption?
6. Do you think AI adoption in your workplace?
    - In what ways?
7. What are some ways in which AI is being adopted in your daily life (outside of work)
8. What are the
9. How do you think the adoption of Artificial Intelligence affects people's wellbeing?
10. Have you noticed any changes in your psychological wellbeing (mood, behavior, social interaction, etc) since the adoption of Artificial Intelligence in your work/organization or daily life?
11. Is there anything you want to share concerning what we are discussing? Your final thoughts

Appendix 4- Budget

Printing	GHC 250.00
Airtime and bundles	GHC 100.00
Stationary	GHC 10.00
Meals	GHC 700.00
Transportation	GHC 200.00
TOTAL =	**GHC 1,260.00**

Appendix 5 - Outputs

Correlations

		AI	F_Well	Auto	EM	PG	PRO	PL	SA
AI	Pearson Correlation	1	.269**	.093	.212**	.222**	.218**	.215**	.205**
	Sig. (2-tailed)		.000	.201	.003	.002	.003	.003	.005
	N	189	189	189	189	189	189	189	189
F_Well	Pearson Correlation	.269**	1	.134	.165*	.130	.155*	.207**	.108
	Sig. (2-tailed)	.000		.065	.023	.075	.033	.004	.140
	N	189	189	189	189	189	189	189	189
Auto	Pearson Correlation	.093	.134	1	.281**	.159*	.126	.289**	.254**
	Sig. (2-tailed)	.201	.065		.000	.029	.084	.000	.000
	N	189	189	189	189	189	189	189	189
EM	Pearson Correlation	.212**	.165*	.281**	1	.033	.252**	.332**	.199**
	Sig. (2-tailed)	.003	.023	.000		.650	.000	.000	.006
	N	189	189	189	189	189	189	189	189
PG	Pearson Correlation	.222**	.130	.159*	.033	1	.148*	.072	.172*
	Sig. (2-tailed)	.002	.075	.029	.650		.042	.324	.018
	N	189	189	189	189	189	189	189	189
PRO	Pearson Correlation	.218**	.155*	.126	.252**	.148*	1	.497**	.373**
	Sig. (2-tailed)	.003	.033	.084	.000	.042		.000	.000
	N	189	189	189	189	189	189	189	189
PL	Pearson Correlation	.215**	.207**	.289**	.332**	.072	.497**	1	.509**
	Sig. (2-tailed)	.003	.004	.000	.000	.324	.000		.000
	N	189	189	189	189	189	189	189	189
SA	Pearson Correlation	.205**	.108	.254**	.199**	.172*	.373**	.509**	1
	Sig. (2-tailed)	.005	.140	.000	.006	.018	.000	.000	
	N	189	189	189	189	189	189	189	189

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

```
DATASET ACTIVATE DataSet1.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT EM
  /METHOD=ENTER AI.
```

Regression

Notes

Output Created		16-AUG-2025 11:45:07
Comments		
Input	Data	D:\Users\DELL\Downloads\Sheila_MPhil Questionnaire.csv\Sheila[16.04.25].sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	189
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.

Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA CHANGE /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT EM /METHOD=ENTER AI.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.01
	Memory Required	4528 bytes
	Additional Memory Required for Residual Plots	0 bytes

[DataSet1] D:\Users\DELL\Downloads\Sheila_MPhil Questionnaire.csv\Sheila[16.04.25].sav

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	AI[b]	.	Enter

a. Dependent Variable: EM

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics		
					R Square Change	F Change	df1
1	.212[a]	.045	.040	4.42889	.045	8.832	1

Model Summary

Model	Change Statistics	
	df2	Sig. F Change
1	187[a]	.003

a. Predictors: (Constant), AI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	173.236	1	173.236	8.832	.003[b]
	Residual	3668.012	187	19.615		
	Total	3841.249	188			

a. Dependent Variable: EM

b. Predictors: (Constant), AI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.041	1.535		5.888	.000
	AI	.263	.089	.212	2.972	.003

a. Dependent Variable: EM

REGRESSION

/MISSING LISTWISE

/STATISTICS COEFF OUTS R ANOVA CHANGE

/CRITERIA=PIN(.05) POUT(.10)

/NOORIGIN

/DEPENDENT PG

/METHOD=ENTER AI.

Regression

Notes

Output Created		16-AUG-2025 11:56:35
Comments		
Input	Data	D:\Users\DELL\Downloads\Sheila_MPhil Questionnaire.csv\Sheila[16.04.25].sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	189
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA CHANGE /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT PG /METHOD=ENTER AI.
Resources	Processor Time	00:00:00.03
	Elapsed Time	00:00:00.02
	Memory Required	4528 bytes

	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	AI[b]	.	Enter

a. Dependent Variable: PG

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics		
					R Square Change	F Change	df1
1	.222[a]	.049	.044	3.87478	.049	9.671	1

Model Summary

Model	Change Statistics	
	df2	Sig. F Change
1	187[a]	.002

a. Predictors: (Constant), AI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	145.201	1	145.201	9.671	.002[b]
	Residual	2807.603	187	15.014		

Total	2952.804	188			

a. Dependent Variable: PG

b. Predictors: (Constant), AI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	12.159	1.343		9.051	.000
	AI	.241	.078	.222	3.110	.002

a. Dependent Variable: PG

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT PRO
 /METHOD=ENTER AI.
```

Regression

Notes

Output Created		16-AUG-2025 11:59:03
Comments		
Input	Data	D:\Users\DELL\Downloads\Sheila_MPhil Questionnaire.csv\Sheila[16.04.25].sav
	Active Dataset	DataSet1

	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	189
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA CHANGE /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT PRO /METHOD=ENTER AI.
Resources	Processor Time	00:00:00.03
	Elapsed Time	00:00:00.02
	Memory Required	4528 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	AI[b]	.	Enter

a. Dependent Variable: PRO

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics		
					R Square Change	F Change	df1
1	.218[a]	.048	.043	4.84830	.048	9.356	1

Model Summary

Model	Change Statistics	
	df2	Sig. F Change
1	187[a]	.003

a. Predictors: (Constant), AI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	219.917	1	219.917	9.356	.003[b]
	Residual	4395.617	187	23.506		
	Total	4615.534	188			

a. Dependent Variable: PRO

b. Predictors: (Constant), AI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	7.613	1.681		4.529	.000
	AI	.297	.097	.218	3.059	.003

a. Dependent Variable: PRO

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT PL
 /METHOD=ENTER AI.
```

Regression

Notes

Output Created		16-AUG-2025 12:03:32
Comments		
Input	Data	D:\Users\DELL\Downloads\Sheila_MPhil Questionnaire.csv\Sheila[16.04.25].sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	189
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.

Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA CHANGE /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT PL /METHOD=ENTER AI.
Resources	Processor Time	00:00:00.05
	Elapsed Time	00:00:00.02
	Memory Required	4528 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	AI[b]	.	Enter

a. Dependent Variable: PL

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics		
					R Square Change	F Change	df1
1	.215[a]	.046	.041	4.35101	.046	9.073	1

Model Summary

Model	Change Statistics	
	df2	Sig. F Change
1	187[a]	.003

a. Predictors: (Constant), AI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	171.757	1	171.757	9.073	.003[b]
	Residual	3540.158	187	18.931		
	Total	3711.915	188			

a. Dependent Variable: PL

b. Predictors: (Constant), AI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.579	1.508		6.350	.000
	AI	.262	.087	.215	3.012	.003

a. Dependent Variable: PL

REGRESSION

/MISSING LISTWISE

/STATISTICS COEFF OUTS R ANOVA CHANGE

/CRITERIA=PIN(.05) POUT(.10)

/NOORIGIN

/DEPENDENT SA

/METHOD=ENTER AI.

Regression

Notes

Output Created		16-AUG-2025 12:12:46
Comments		
Input	Data	D:\Users\DELL\Downloads\Sheila_MPhil Questionnaire.csv\Sheila[16.04.25].sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	189
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA CHANGE /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT SA /METHOD=ENTER AI.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.02
	Memory Required	4528 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	AI[b]	.	Enter

a. Dependent Variable: SA

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics		
					R Square Change	F Change	df1
1	.205[a]	.042	.037	4.22076	.042	8.220	1

Model Summary

Model	Change Statistics	
	df2	Sig. F Change
1	187[a]	.005

a. Predictors: (Constant), AI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	146.433	1	146.433	8.220	.005[b]
	Residual	3331.376	187	17.815		
	Total	3477.810	188			

a. Dependent Variable: SA

b. Predictors: (Constant), AI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.596	1.463		6.558	.000
	AI	.242	.084	.205	2.867	.005

a. Dependent Variable: SA

```
Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 4.2 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

************************************************************************
Model  : 1
    Y  : F_Well
    X  : AI
    W  : Age_grou

Sample
Size:  189

************************************************************************
OUTCOME VARIABLE:
```

F_Well

Model Summary

R	R-sq	MSE	F	df1	df2	p
.28	.08	112.30	5.14	3.00	185.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	62.76	4.17	15.05	.00	54.53	70.98
AI	.88	.24	3.70	.00	.41	1.35
Age_grou	6.03	8.93	.68	.50	-11.58	23.64
Int_1	-.43	.53	-.81	.42	-1.48	.62

Product terms key:

Int_1 : AI x Age_grou

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.00	.65	1.00	185.00	.42

Focal predict: AI (X)

Mod var: Age_grou (W)

Data for visualizing the conditional effect of the focal predictor:

Paste text below into a SPSS syntax window and execute to produce plot.

```
DATA LIST FREE/
   AI          Age_grou    F_Well      .
BEGIN DATA.
     13.30         .00     74.50
     16.95         .00     77.72
     20.59         .00     80.94
     13.30        1.00     74.82
```

```
      16.95       1.00       76.48
      20.59       1.00       78.14
END DATA.
GRAPH/SCATTERPLOT=
 AI        WITH     F_Well    BY        Age_grou .

********************** ANALYSIS NOTES AND ERRORS ***********************

Level of confidence for all confidence intervals in output:
  95.0000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----

Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 4.2 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

************************************************************************
Model  : 1
    Y  : F_Well
    X  : AI
```

W : Gender_1

Sample
Size: 189

****

OUTCOME VARIABLE:
F_Well

Model Summary

R	R-sq	MSE	F	df1	df2	p
.34	.12	107.45	8.16	3.00	185.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	63.76	5.10	12.49	.00	53.69	73.83
AI	.95	.29	3.25	.00	.37	1.52
Gender_1	1.30	7.20	.18	.86	-12.90	15.50
Int_1	-.34	.42	-.82	.42	-1.16	.48

Product terms key:
Int_1 : AI x Gender_1

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.00	.66	1.00	185.00	.42

Focal predict: AI (X)
Mod var: Gender_1 (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

```
DATA LIST FREE/
   AI          Gender_1    F_Well     .
BEGIN DATA.
      13.30         .00      76.34
      16.95         .00      79.79
      20.59         .00      83.24
      13.30        1.00      73.14
      16.95        1.00      75.36
      20.59        1.00      77.57
END DATA.
GRAPH/SCATTERPLOT=
 AI       WITH     F_Well    BY       Gender_1 .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000
```