NOVA IMS Information Management School

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Extending Pre-Adoptive Appraisal Model for ChatGPT

The Role of Task-Technology Fit, AI Empowerment, and Career Advancement Intentions

Seni Kamara

Dissertation
presented as a partial requirement for obtaining the Master's degree in Data-Driven Marketing

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Dissertation presented as a partial requirement to obtain the Master's degree in Data-Driven Marketing, with specialization in Data-Science for Marketing

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DECLARATION OF INTEGRITY

I declare that I have carried out this academic work with integrity. I confirm that I did not resort to plagiarism or any other form of misuse of information or falsification of results during the process of preparing this work. I further declare that I am aware of the Rules of Conduct and Code of Honor of NOVA Information Management School.

Seni Kamara
Lisbon, June 22nd, 2024

ABSTRACT

The rapid integration of Generative Artificial Intelligence (Gen AI) technologies, particularly ChatGPT, in organizational settings has necessitated a reevaluation of existing models of AI adoption. This study extends the Pre-Adoptive Appraisal Model towards AI (PAMAI) by incorporating concepts of Task-Technology Fit (TTF), AI Empowerment, and Career Advancement Intentions, to provide a more comprehensive understanding of employee attitudes and behaviors towards ChatGPT (AI) adoption. Using a sample of 133 professionals, this research employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the proposed model. The findings reveal that Task-Technology Fit significantly influences both Affective and Cognitive Attitudes towards ChatGPT (AI). These attitudes, in turn, positively impact AI Empowerment, which strongly predicts Intention to Use ChatGPT (AI) and Intention to Advance Career. Notably, AI Empowerment also shows a positive relationship with Intention to Leave Organization, highlighting the complex implications of ChatGPT (AI) adoption for talent retention. The study makes several theoretical contributions, including the validation of AI Empowerment as a crucial construct in the pre-adoptive appraisal process, and the integration of Career Construction Theory into ChatGPT (AI) adoption research. Practically, the findings emphasize the importance of aligning ChatGPT capabilities with job requirements, addressing employee concerns, and developing strategies to retain AI-empowered talent. This research provides valuable insights for organizations implementing Gen AI technologies, highlighting the need for a holistic approach that balances technological integration with employee empowerment and career development.

KEYWORDS

Generative AI, ChatGPT, Pre-adoptive Appraisal, Task-Technology Fit, AI Empowerment, Career Advancement, Cognitive Appraisal Theory, Career Construction Theory, Employee Attitudes, Individual Adoption, Workplace AI, Human-AI Collaboration, Technology Acceptance, Career Development, AI Implementation

Sustainable Development Goals (SDG):

INDEX

FIGURE INDEX

TABLE INDEX

LIST OF ACRONYMS AND ABBREVIATIONS

ACRONYM 1 CAT – Cognitive Appraisal Theory
ACRONYM 2 CCT – Career Construction Theory
ACRONYM 3 ChatGPT - Chat Generative Pre-Trained Transformer
ACRONYM 4 ITM - Initial Trust Model
ACRONYM 5 LLM – Large Language Model
ACRONYM 6 PAMAI – Pre-Adoptive Appraisal Model towards AI
ACRONYM 7 TTF – Task Technology Fit
ACRONYM 8 UTAUT - Theory of Acceptance and Use of Technology

1. INTRODUCTION

The rapid advancement and integration of Generative Artificial Intelligence (Gen AI) technologies in the workplace have necessitated a reevaluation of existing theories, models, and assumptions related to AI introduction and adoption in organizations (McKinsey & Company, 2024). AI agents like ChatGPT have emerged as powerful tools for employees to reshape various aspects of their work, improve productivity, enhance creativity, and facilitate decision-making processes (Dell' et al., 2023). As organizations increasingly adopt such technologies, understanding the factors that influence employee attitudes and behaviors towards ChatGPT (AI) becomes crucial for successful implementation and long-term organizational success.

Previous research has laid the groundwork for understanding the framework for pre-adoptive appraisal of employees towards AI technologies. The proposed Pre-Adoptive Appraisal Model towards AI (PAMAI) offers valuable insights into how employees evaluate AI technologies before their implementation in organizations (Chiu et al., 2021). However, most prior appraisal studies focused on enterprise forms of AI (Abdullah & Fakieh, 2020; Ardon & Schmidt, 2020; Brougham & Haar, 2018; Chiu et al., 2021) and have not accounted for the new perceptions, attitudes, and behavioral responses that Generative AI has the potential to elicit in users due to its advanced cognitive and anthropomorphic characteristics (Dell' et al., 2023). There is a need to refine and extend existing models to capture the new dimensions of ChatGPT (AI) adoption in contemporary organizational settings.

This study aims to extend the existing PAMAI model through the integration of new concepts: Task-Technology Fit (TTF) (Oliveira et al., 2014), AI Empowerment (Brynjolfsson & McAfee, 2014), and Career Advancement Intentions (Savickas & Porfeli, 2012). By doing so, this research seeks to provide a more comprehensive understanding of how employees appraise and respond to ChatGPT in a professional context. Through TTF theory (Goodhue & Thompson, 1995), we introduce practical knowledge (Oliveira et al., 2014) of ChatGPT (AI) to examine how the alignment between ChatGPT (AI) capabilities and job requirements influences employees' attitudes. Furthermore, this research seeks empirical evidence that AI Empowerment is one of the cognitive outcomes associated with ChatGPT (AI) and explores how it influences employee career trajectories and organizational retention.

Our research is provides considerable contributions to both theoretical understanding and practical application in the domain of ChatGPT (AI) adoption. It offers valuable insights for organizations seeking to implement Generative AI technologies effectively while fostering employee growth and satisfaction. Moreover, it provides beacons for future research into cognitive and behavioral dimensions of AI Empowerment and human-AI collaboration.

The Thesis is structured as follows. Chapter 2 presents the theoretical foundations underpinning this research, including Cognitive Appraisal Theory, Task-Technology Fit Theory, AI Empowerment, and Career Construction Theory. Chapter 3 introduces the research model and hypotheses, detailing the conceptual model, new constructs, and proposed relationships. Chapter 4 outlines the methodology employed, including data collection methods, measurement of constructs, and control variables. Chapter 5 presents the analyses and results, covering sample size determination, measurement model testing, and structural model testing. Chapter 6 discusses the interpretation of findings, contributions to research, and implications for practice. Chapter 7 addresses the limitations of the study and suggests directions for future research. Finally, Chapter 8 concludes the thesis with final thoughts about the research.

2. THEORETICAL FOUNDATIONS – LITERATURE REVIEW

This study draws on four key theoretical frameworks to understand employees' pre-adoptive appraisal of ChatGPT in organizations: Cognitive Appraisal Theory, Task-Technology Fit Theory, AI Empowerment theoretical assumptions and Career Construction Theory. These theories provide complementary perspectives on how individuals evaluate and respond to rapid Generative AI (ChatGPT) adoption.

2.1. Cognitive Appraisal Theory

Cognitive Appraisal Theory (CAT) is instrumental in understanding the cognitive processes that influence individuals' emotional and behavioral reactions to events (Lazarus & Folkman, 1984). CAT asserts that these reactions are shaped by how individuals appraise the significance of events for their well-being, particularly in stressful or challenging contexts. CAT distinguishes between two types of appraisals: primary and secondary. Primary appraisal involves assessing whether an event is perceived as beneficial, threatening, or irrelevant to one's well-being. Secondary appraisal involves evaluating one's ability to cope with or manage the implications of the event (Lazarus & Folkman, 1984). These cognitive appraisals concepts are pivotal in determining the resultant emotional and behavioral responses in people. That is why they beacame pivotal in appraisal research of employees' perceptions, attitudes and intentions towards adoption of AI technlogies within organizations (Chiu et al., 2021). Prior PAMAI research used CAT to validate the importance of dissecting employees' cognitive processes towards AI, into affective (feeling) and cognitive (thinking) attitudes, and successfully demonstrated how these attitudes influence behavioural intentions associated with AI technology (Chiu et al., 2021). Our research also leverages CAT and attempts to extend PAMAI with deeper insights into the cognitive and emotional mechanisms that drive employees' attitudes and intentions towards Generative AI (ChatGPT) technologies.

2.2. Task-Technology Fit (TTF) Theory

Task-Technology Fit (TTF) Theory provides a foundational framework for understanding how the alignment between technology capabilities and task requirements influences individual performance and technology utilization (Goodhue & Thompson, 1995). Integrated TTF with the Technology Acceptance Model (TAM), underscores the importance of perceived fit in shaping users' attitudes and intentions to use technology (Dishaw & Strong, 1999). Combination of TTF with the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Initial Trust Model (ITM) in mobile banking adoption research (Oliveira et al., 2014) also supports our introduction of TTF into PAMAI to investigate how task-technology fit shapes shape employees' attitudes and intentions towards ChatGPT.

ChatGPT capability has an opaque and "jagged technological frontier" that can improve as well as hinder employees' performance. Some tasks are easily performed by ChatGPT while others, seemingly similar in difficulty, are beyond its current abilities (Dell' et al., 2023). This ambuguity underscores the importance of using TTF dimensions in our research for the appraisal of employee practical knowledge (Oliveira et al., 2014). It enables us to discover how do the technologcial characteristics of ChatGPT align with various job tasks, and how does the resulting task-technology fit (TTF construct) influences their attitudes and intentions of employees' towards this emerging technology.

2.3. AI EMPOWERMENT

AI Empowerment, while not formally established as a singular theoretical framework, represents a convergence of scholarly perspectives on how AI technologies enhance employee capabilities and autonomy. Brynjolfsson and McAfee argue that digital technologies, including AI, augment employee skills and productivity, thereby fostering innovation (Brynjolfsson & McAfee, 2014). Davenport and Kirby highlight the symbiotic relationship between humans and AI, where AI handles routine tasks, allowing employees to focus on higher-value activities (Davenport & Kirby, 2016). Daugherty and Wilson introduced the concept of "Collaborative Intelligence," emphasizing the complementary strengths of humans and AI, leading to improved decision-making and innovation (Daugherty & Wilson, 2018). Central to this concept is empowerment itself, which involves granting employees greater control over their work, enhancing decision-making capabilities, and fostering a sense of autonomy and innovation (Thomas & Velthouse, 1990). Empowerment through AI aims to improve access to information, provide robust decision support, automate routine tasks, and enable employees to focus on complex and creative activities (Wilson et al., 2017). This research argues that these AI Empowerment postulates impact employee perceptions, attitudes and intentions towards ChatGPT (AI) and should be considered for appraisal within PAMAI.

2.4. CAREER CONSTRUCTION THEORY

Career Construction Theory (CCT), developed by Mark Savickas, explains how individuals shape their careers through personal narratives and proactive behaviors (Savickas, 2005). Core Constructs in CCT: (1) Career Adaptability, which includes concern, control, curiosity, and confidence—traits that help individuals manage career changes (Savickas & Porfeli, 2012); (2) Vocational Personality, which encompasses an individual's career-related abilities, needs, values, and interests, that guide career choices (Savickas, 2013); (3) Life Themes - these are overarching narratives that give meaning to career decisions, explaining why individuals make certain career choices (Savickas, 2005). These constructs drive proactive career behaviors, such as seeking new skills and exploring opportunities, which are essential for navigating career paths (Seibert et al., 2001). Proficiency with AI tools like ChatGPT facilitates role expansion, continuous learning, and professional growth, reflecting CCT's emphasis on proactive adaptation (Savickas & Porfeli, 2012; Savickas, 2005). By leveraging CCT, this research aims to examine how employees' perceptions of AI technologies like ChatGPT shape their career aspirations and behaviors, emphasizing the theory's relevance in an AI-driven work environment.

3. RESEARCH MODEL AND HYPOTHESES

3.1. Conceptual Model

The conceptual model proposed in this study (Figure 1) extends the pre-adoptive appraisal model (PAMAI) (Chiu et al., 2021) (Figure 2), and comprises four main stages: (1) Appraisal - factors influencing employees' initial evaluation of ChatGPT, (2) Attitudes - affective and cognitive attitudes of employees towards ChatGPT, (3) AI Empowerment - outcomes related to the empowerment provided by ChatGPT, and (4) Behavioral Responses - employees' behavioral responses to ChatGPT. This study introduces three core changes to the original PAMAI through new constructs: (1) Task-Technology Fit (TTF) (Oliveira et al., 2014) at the Appraisal stage, (2) AI Empowerment at the AI Empowerment stage, and (3) Intention to Advance Career at the Behavioral Response stage. The significance of this model lies in its effort to advance the theoretical domain of cognitive appraisal towards AI and to provide a more holistic framework for understanding employees' responses to emergent technologies like ChatGPT. It aims to demonstrate the relevance of TTF Theory (practical knowledge) alongside the concepts of AI Empowerment and career aspirations (Intention to Advance Career) in the pre-adoptive appraisal process by organizations. This conceptual model also lays the groundwork for future research to integrate additional theories, such as UTAUT2 (Venkatesh et al., 2012) and DOI (Rogers et al., 2014), enriching the theoretical landscape of AI adoption studies. Practically, organizations can leverage this model to gain deeper insights into employees' attitudes towards AI, enabling more targeted interventions and support strategies that facilitate smoother integration of AI technologies while enhancing employee satisfaction.

3.2. New Constructs

3.2.1. Task-Technology Fit (TTF):

Reinventing Employee Knowledge Construct: Prior PAMAI research (Chiu et al., 2021) emphasized the importance of employee knowledge in shaping attitudes towards AI adoption (E. M. Rogers, 2003; Klerck & Sweeney, 2007), their results revealed challenges in measuring this construct, particularly for complex technologies like AI. They noted that subjective knowledge measures might be unstable or distorted when the subject matter is difficult to grasp (Carlson et al., 2009; Klerck & Sweeney, 2007). To addresses the limitations identified in prior PAMAI research, where the expected relationship between *subjective employee knowledge* and attitudes was not confirmed (Chiu et al., 2021), we are repleacing it with *practical knowledge,* represented by Task-Technology Fit (TTF) constructs (Oliveira et al., 2014). By employing TTF, we aim to explore *practical dimension of employee knowledge* - how well AI technology aligns with and supports specific job tasks. This approach addresses the call for exploring alternative measures of employee understanding of AI applications and capabilities (Chiu et al., 2021; Dell' et al., 2023).

Our operationalization of TTF focuses on three key dimensions:

1. Task Characteristics (TaskC): Measures the nature and requirements of work tasks, including the need for quick information access, synthesis of information, rapid responses to inquiries, and handling of specialized language.

2. Technology Characteristics (TC): Assesses ChatGPT's capabilities in providing quick access to information, improving efficiency in documentation, automating routine tasks, and handling specialized knowledge.
3. Task-Technology Fit (TTF): Evaluates the alignment between task requirements and ChatGPT's capabilities, including its support for informed decision-making, efficiency in documentation, workload management, and handling of specialized information.

Proof of Concept (PoC) for Adoption Theories: Successful integration of TTF with relevant constructs within the pre-adoptive appraisal model aims to demonstrate the applicability of TTF in organisational appraisal of employees towards AI technologies like ChatGPT. Furthermore, it will serve as a proof of concept for future research to incorporate other contemporary adoption theories, Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012), Diffusion of Innovations (DOI) theory (E. M. Rogers, 2003) and others into PAMAI (Pre-adoptive Appraisal Model towards AI) (Table 1.).

Table 1 - Summary of Adoption Models at Individual Level

Theory/Model	Constructs	Citation
Diffusion Innovation Theory (IDT)	Relative Advantage, Compatibility, Complexity, Trialability, Observability	Rogers (1962)
Theory of Reasoned Action (TRA)	Attitude, Subjective Norms, Behavioral Intention	Fishbein and Ajzen (1975)
Theory of Interpersonal Behavior (TIB)	Affective Response, Social Factors, Habitual Behavior	Triandis (1977)
Social Cognitive Theory (SCT)	Behavioral, Personal, and Environmental Factors	Bandura (1986)
Technology Acceptance Model (TAM)	Perceived Usefulness, Perceived Ease of Use, Attitude, Behavioral Intention	Davis (1989)
Theory of Planned Behavior (TPB)	Attitude, Subjective Norms, Perceived Behavioral Control, Behavioral Intention	Ajzen (1991)
Task-Technology Fit (TTF)	Task Characteristics, Technology Characteristics, Task-Technology Fit	Goodhue and Thompson (1995)
Unified Theory of Acceptance and Use of Technology (UTAUT)	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions	Venkatesh et al. (2003)
Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit	Venkatesh et al. (2012)

3.2.2. AI Empowerment:

Result of Task-Technology Fit: The introduction of AI Empowerment as a construct in our model extends the concept of coping resources in Cognitive Appraisal Theory (CAT) beyond mere knowledge. It captures the transformative potential of AI technologies in enhancing employee capabilities and autonomy, as highlighted by recent research on Large Language Models (LLMs) and conversational AI systems like ChatGPT (Dell' et al., 2023; Gkinko & Elbanna, 2023). AI Empowerment construct is proposed as a potential outcome of attitudes that are shaped by Task-Technology Fit (TTF) and can create symbiotic relationships between humans and AI (GhatGPT) (Daugherty & Wilson, 2018). It aims to capture how ChatGPT, when well-aligned with job tasks (TTF), might enhance employees' perceived control, decision-making capabilities, and innovative potential in an AI-enhanced work environment (Wilson et al., 2017; Brynjolfsson & McAfee, 2014; Davenport & Kirby, 2016; Dell' et al., 2023). And how the later augmentation with ChatGPT’s capabilities influences employees' behavioral responses. This construct aims to explain the technical aspects of AI adoption (represented by TTF) and the consequent psychological and behavioral outcomes.

Our operationalization of AI Empowerment focuses on: (1) *Enhanced Problem-Solving Abilities*: Assessing employees' perceptions of how ChatGPT improves their capacity to tackle complex issues; (2) *Elevated Professional Status*: Measuring the extent to which employees feel ChatGPT enhances their professional standing and expertise; (3) *Accelerated Skill Development*: Evaluating employees' views on how ChatGPT facilitates rapid acquisition of new skills and knowledge; (4) *Increased Adaptability*: Gauging employees' sense of improved flexibility and responsiveness in their work due to ChatGPT. This approach aligns with the vision of AI as a technology that augments human capabilities (Brynjolfsson & McAfee, 2014) and reimagines work processes (Davenport & Kirby, 2016).

3.2.3. Intention to Advance Career:

New Behavioral Response Construct: Intention to Advance Career construct aims to capture the proactive efforts of individuals to progress in their professional lives during rapid individual AI adoption. This construct reflects employees' desires and plans to enhance their career trajectories within their current organization or elsewhere (Kraimer et al., 2011). AI technologies like ChatGPT could significantly impact career development by reshaping job roles, skill requirements, and future career prospects (Sgaramella et al., 2023). AI (ChatGPT) could act as a career catalyst, enabling employees to leverage AI proficiency for career advancement and proactive career management (Wang & Li, 2024). By introducing Career Construction Theory (CCT) (Savickas, 2005) through the Intention to Advance Career construct, we aim to gain insights into how AI technologies like ChatGPT shape employees' career aspirations and proactive career behaviors in an increasingly AI-driven work environment.

Our operationalization of Career Advancement Intentions focuses on: (1) *Role Expansion*: Assessing employees' perceptions of how their proficiency with ChatGPT enables them to seek new roles and responsibilities; (2) *Career Reimagination*: Measuring the extent to which employees believe ChatGPT is reshaping their career plans and opportunities; (3) *Professional Growth*: Evaluating employees' views on the importance of ChatGPT for their professional development and career growth; (4) *Organizational Recognition*: Gauging employees' expectations that their ability to effectively use ChatGPT will be valued and recognized within their organization.

The operationalization of this construct draws upon established career development literature on proactive career behaviors, emphasizing continuous learning and skill development for career success (Seibert et al., 2001; Sgaramella et al., 2023).

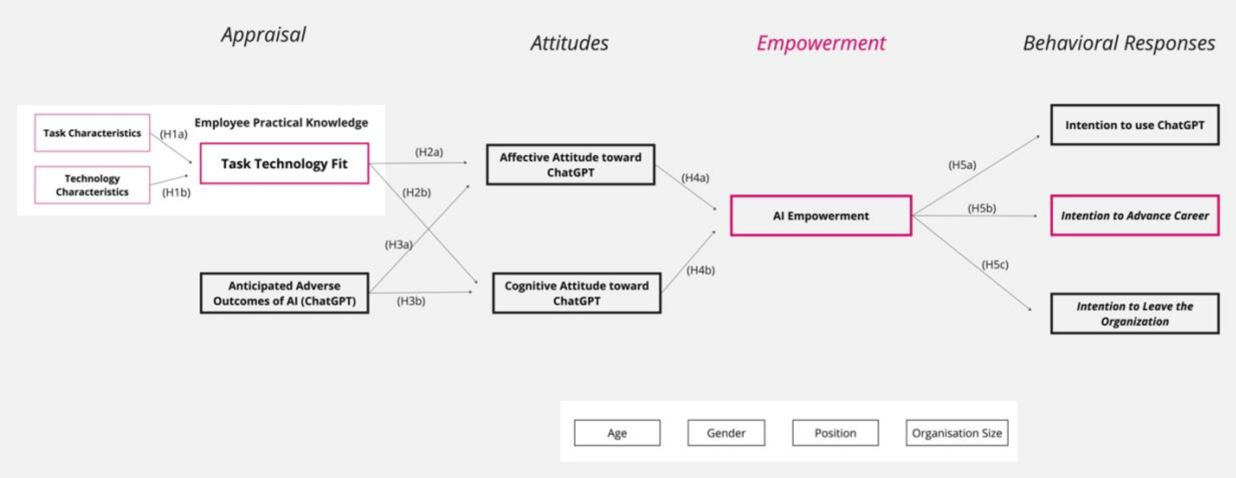

Figure 1: Pre-adoptive Appraisal of ChatGPT Research Model

3.3. HYPOTHESES

Hypothesis 1: Task Characteristics (TaskC) and Technology Characteristics (TC) positively influence Task-Technology Fit (TTF).

Drawing from Task-Technology Fit Theory and research (Goodhue & Thompson, 1995; Oliveira et al., 2014) we posit that the alignment between task requirements and ChatGPT's capabilities is crucial for employee appraisal. When job tasks (TaskC) align well with ChatGPT's features (TC), employees are more likely to perceive a good fit. Therefore, we hypothesize that both Task Characteristics **(H1a)** and Technology Characteristics **(H1b)** will positively influence Task-Technology Fit.

Hypothesis 2: Task-Technology Fit (TTF) positively influences Affective Attitude (AA) and Cognitive Attitude (CA) towards ChatGPT.

Building on Cognitive Appraisal Theory (Lazarus & Folkman, 1984) and the integration of TTF with technology acceptance models (Dishaw & Strong, 1999), we propose that a strong perceived fit between ChatGPT and job tasks will foster positive attitudes. This influence is expected to impact both affective (feelings) and cognitive (thoughts) components of employees' attitudes. Thus, we hypothesize that Task-Technology Fit will positively influence Affective Attitude **(H2a)** and Cognitive Attitude **(H2b)** towards ChatGPT.

Hypothesis 3: Anticipated Adverse Outcomes (AAO) negatively influence Affective Attitude (AA) and Cognitive Attitude (CA) towards ChatGPT.

Consistent with Cognitive Appraisal Theory's concept of primary appraisal (Folkman et al., 1986) and the results of the latest research, employees' concerns about potential negative consequences of ChatGPT adoption can lead to less favorable attitudes. These concerns are likely to impact both affective and cognitive components of employees' attitudes (Chiu et al., 2021). Therefore, we hypothesize that Anticipated Adverse Outcomes will negatively influence Affective Attitude **(H3a)** and Cognitive Attitude **(H3b)** towards ChatGPT.

Hypothesis 4: Affective Attitude (AA) and Cognitive Attitude (CA) positively influence AI Empowerment (AIE).

Drawing from AI Empowerment perspectives (Brynjolfsson & McAfee, 2014; Davenport & Kirby, 2016; Daugherty & Wilson, 2018) we propose that positive attitudes towards ChatGPT will enhance employees' sense of empowerment. When employees have favorable emotional responses and rational evaluations of ChatGPT, they are more likely to perceive enhanced capabilities and opportunities for growth. Thus, we hypothesize that Affective Attitude **(H4a)** and Cognitive Attitude **(H4b)** will positively influence AI Empowerment.

Hypothesis 5: AI Empowerment (AIE) positively influences Intention to Use ChatGPT (ITU), Intention to Advance Career (IAC), and Intention to Leave the Organization (ILO).

Building on AI Empowerment concepts and Career Construction Theory (Savickas, 2005), we anticipate that when employees feel empowered by ChatGPT, they are more likely to intend to use the technology **(H5a)**. Additionally, AI Empowerment may inspire employees to proactively plan for career advancement **(H5b)**, aligning with CCT's emphasis on career adaptability and proactive behaviors (Savickas & Porfeli, 2012). However, highly empowered employees might also consider exploring opportunities outside their current organization **(H5c)**, particularly if they perceive a mismatch between their enhanced capabilities and organizational recognition (Tambe et al., 2019).

4. METHODOLOGY

4.1. DATA COLLECTION

An online survey was conducted to collect data from employees across various industries in different countries, mostly the EU. The survey was distributed primarily through LinkedIn, targeting professionals with diverse backgrounds and experiences with AI Agents like ChatGPT. Participants were invited to take part in the study through direct messages and posts on relevant LinkedIn groups. The survey was hosted on Qualtrics, and responses were collected over a period of 3 weeks in May in 2024.

A pilot of 30 responses was initially conducted to test the model and constructs. No issues were discovered. Then a total of 175 responses were received, out of which 133 complete and valid responses were retained after data cleaning. The cleaning process involved removing incomplete responses, duplicates, and responses with inconsistent or illogical data patterns. The final sample size of 133 was statistically validated to be sufficient for the purposes of this study, considering the complexity of the research model and the use of PLS-SEM for data analysis (Hair et al., 2011).

4.2. MEASURE OF CONSTRUCTS

The survey questionnaire was structured to reflect the stages of the Research Model (Appraisal, Attitudes, AI Empowerment, Behavioral Intentions). All constructs were measured using multiple items on a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). Survey Instrument (Table 2) was developed using validated scales from previous research, adapted to the context of AI adoption and ChatGPT use. The sections and their corresponding constructs are as follows:

Appraisal:

1. Task Characteristics (TaskC) - adapted (Oliveira et al., 2014)
2. Technology Characteristics (TC) - adapted (Oliveira et al., 2014)
3. Task-Technology Fit (TTF) - adapted (Oliveira et al., 2014)
4. Anticipated Adverse Outcomes (AAO) - adapted (Chiu et al., 2021)

Attitudes:

5. Affective Attitude (AA) - adapted (Chiu et al., 2021)
6. Cognitive Attitude (CA) - adapted (Chiu et al., 2021)

AI Empowerment:

7. AI Empowerment (AIE) - (self-developed)

Behavioral Intentions:

8. Intention to Use ChatGPT (ITU) - adapted (Chiu et al., 2021)
9. Career Advancement Intentions (CAI) - adapted (Sgaramella et al., 2023)
10. Intention to Leave Organization (ILO) - adapted (Tambe et al., 2019).

The reliability and validity of these measures were assessed using established procedures in PLS-SEM, including composite reliability, convergent validity, and discriminant validity tests (Hair et al., 2017). The results of these tests are presented in the Analysis and Results section.

4.3. CONTROL VARIABLES

The survey collected data on several control variables to contextualize the analysis (Table 3).
Most of the control variables were not significant in statistical analysis, however they provided important insights into the diverse backgrounds and contexts of the respondents, ensuring a comprehensive analysis of the data.

Table 2 - Instrument Table

<table>
<tr><th>Constructs</th><th>Dimension</th><th>Item</th><th>Source</th></tr>
<tr><td rowspan="12">Employee Knowledge of AI</td><td rowspan="4">Task Characteristics</td><td>TaskC1. I need to quickly access and analyze information to make informed decisions at work.</td><td rowspan="12">Adapted (Oliveira et al., 2014)</td></tr>
<tr><td>TaskC2. I regularly synthesize information from various sources to produce reports or presentations.</td></tr>
<tr><td>TaskC3. I need quick and accurate responses to work-related inquiries.</td></tr>
<tr><td>TaskC4. I need to perform tasks that involve interpreting or using technical or specialized language.</td></tr>
<tr><td rowspan="4">Technology Characteristics</td><td>TC1. ChatGPT provides quick access to information for decision-making process.</td></tr>
<tr><td>TC2.ChatGPT improves efficiency when preparing comprehensive work-related documentation.</td></tr>
<tr><td>TC3. ChatGPT reduces workload by automating routine tasks.</td></tr>
<tr><td>TC4. ChatGPT is good at translating languages and information that requires specialized knowledge.</td></tr>
<tr><td rowspan="4">Task-Technology Fit</td><td>TTF1. The information retrieval capabilities of ChatGPT align well with my needs for making informed decisions.</td></tr>
<tr><td>TTF2. ChatGPT improves my efficiency in preparing comprehensive work-related documentation.</td></tr>
<tr><td>TTF3. ChatGPT supports me in managing my workload by automating routine tasks.</td></tr>
<tr><td>TTF4. ChatGPT helps me with language translation, and understanding information that requires specialized knowledge.</td></tr>
<tr><td colspan="2" rowspan="4">Anticipated Adverse Outcomes</td><td>AAO 1. I am concerned that the skills required for my job might change.</td><td rowspan="4">Adapted (Chiu et al., 2021)</td></tr>
<tr><td>AAO 2. I am concerned my job will become less secure.</td></tr>
<tr><td>AAO 3. I am concerned there will be fewer jobs for humans.</td></tr>
<tr><td>AAO 4. I’m concerned there will be less human to human interaction.</td></tr>
<tr><td colspan="2" rowspan="4">AI Empowerment:</td><td>AIE 1. ChatGPT has enhanced my ability to solve problems creatively and to innovate beyond my usual capabilities.</td><td rowspan="4">Self-developed</td></tr>
<tr><td>AIE 2. The skills I’ve developed with ChatGPT have raised my professional status on the job market.</td></tr>
<tr><td>AIE 3. Thanks to ChatGPT, I feel more skilled and capable in my professional role.</td></tr>
<tr><td>AIE 4. My experience with ChatGPT has made me more adaptable to technological changes in my field.</td></tr>
<tr><td colspan="2" rowspan="3">Affective Attitude</td><td>AA 1. I feel towards ChatGPT (Annoyed - Happy).</td><td rowspan="3">(Chiu et al., 2021)</td></tr>
<tr><td>AA 2. My sentiment towards ChatGPT (Negative - Positive).</td></tr>
<tr><td>AA 3. My overall emotions about ChatGPT (Bad - Good).</td></tr>
<tr><td colspan="2">Cognitive Attitude</td><td>CA 1. I think ChatGPT is (Foolish - Wise).</td><td>(Chiu et al., 2021)</td></tr>
</table>

	CA 2. I think ChatGPT is (Harmful - Beneficial).	
	CA 3. I think ChatGPT is (Worthless - Valuable).	
Intention to use ChatGPT	**ITU 1.** For professional education and knowledge building.	Adapted (Chiu et al., 2021)
	ITU 2. Integrate into my workflow to improve the quality of my work outputs.	
	ITU 3. To streamline administrative tasks and free up time for more strategic work.	
	ITU 4. To enhance my understanding of complex topics in my field.	
	ITU 5. Share positive experiences and best practices of using ChatGPT with my peers.	
Intention to Advance Career	**CAI 1**. My proficiency with ChatGPT enables me to seek new roles and responsibilities.	Adapted (Sgaramella et al., 2023)
	CAI 2. ChatGPT is reinventing my career plans and opportunities.	
	CAI 3. ChatGPT is vital for professional development and career growth.	
	CAI 4. My ability to leverage ChatGPT effectively will be recognized and valued by my organization.	
Intention to Leave Organization	**ILO 1.** If ChatGPT directly threatens my job security, I might consider searching for other opportunities.	Adapted (Chiu et al., 2021)
	ILO 2. The way the company implements ChatGPT and its effect on job security will influence whether I decide to stay or leave.	
	ILO 3. If ChatGPT alters aspects of my job in ways that reduce my job satisfaction, I'll likely explore other opportunities.	
	ILO 4. If AI like ChatGPT diminishes the meaningful parts of my job, I might consider leaving.	

Table 3 - Control Variables

Variable	Description	Scale
Q15	Age of the respondent in years.	Numeric
Q16	Gender of the respondent.	1: Male 2: Female 3: Non-binary/Third gender 4: Prefer not to say
Q17	Size of the organization.	1: Micro enterprise (1-10 employees) 2: Small enterprise (11-50 employees) 3: Medium enterprise (51-250 employees) 4: Medium to large enterprise (251-500 employees) 5: Large enterprise (501-1000 employees) 6: Very large enterprise (More than 1000 employees)
Q18	Status of ChatGPT in the organization.	1: Not allowed or discussed yet 2: Under discussion or consideration but not yet approved 3: Officially approved for certain tasks or departments 4: Widely adopted and encouraged for use in various tasks
Q19	Position level within the organization.	1: Entry-level 2: Mid-level 3: Senior-level 4: Executive-level 5: Other
Q0	Frequency of engagement with ChatGPT.	1: Always 2: Often 3: Sometimes 4: Rarely
Q20	Training received in ChatGPT.	1: Yes 2: No 3: Currently undergoing training
Q21_1	Familiarity with ChatGPT.	1: Very Limited 7: Very Good
Q21_2	Familiarity with NOVA IMS.	1: Very Limited 7: Very Good

5. ANALYSES AND RESULTS

5.1. SAMPLE SIZE DETERMINATION

An a priori power analysis using G*Power 3.1.9.7 was conducted to determine the required sample size for the study (Erdfelder et al., 2009). The research model includes 8 predictors: Task Characteristics, Technology Characteristics, Task-Technology Fit, Anticipated Adverse Outcomes, Affective Attitude, Cognitive Attitude and AI Empowerment. The power analysis parameters were set as follows (Figure 3., in the Appendix):

- Effect size (f^2): 0.15 (medium effect size)
- Alpha level (α): 0.05 (5% risk of Type I error)
- Power (1-β): 0.80 (80% probability of correctly rejecting the null hypothesis)
- Number of predictors: 8

The analysis indicated that a minimum sample size of 109 participants was required to achieve the desired statistical power. The survey collected a total of 133 valid responses, exceeding the minimum requirement, ensuring sufficient power to detect medium effect sizes with an 80% probability while maintaining the risk of Type I error at 5% (Figure 2 in the Appendix).

5.2. MEASUREMENT MODEL TESTING

We assessed the measurement model using SmartPLS 4, a widely used software for partial least squares structural equation modelling (PLS-SEM) (Ringle, C.M., et al., 2015). This evaluation is crucial in ensuring the reliability, validity, and distinctiveness of the constructs within the research model. The assessment encompassed several key analyses: reliability and validity testing, discriminant validity evaluation, and multicollinearity analysis.

Construct Reliability and Validity

To assess the reliability and validity of our constructs, we performed confirmatory factor analysis. Table 4 summarizes the reliability and validity metrics for each construct.

Table 4 - Construct reliability and validity

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AA	0,914	0,917	0,946	0,853
AAO	0,691	0,705	0,865	0,763
AIE	0,856	0,861	0,903	0,699
CA	0,807	0,831	0,886	0,724
CAI	0,896	0,899	0,928	0,763
ILO	0,665	0,795	0,848	0,738
ITU	0,787	0,806	0,862	0,611
TC	0,707	0,716	0,835	0,628
TTF	0,706	0,732	0,871	0,771
TaskC	0,695	0,695	0,831	0,622

Cronbach's Alpha: Measures the internal consistency of the items within each construct. Values above 0.7 are generally considered acceptable (Nunnally, J. C. et al., 1994) As shown in Table 4, most constructs exhibit Cronbach's alpha values above this threshold, indicating good internal consistency.

However, AAO, ILO, and TaskC have slightly lower values, which suggests a need for cautious interpretation for these constructs.

Composite Reliability (rho_A and rho_C): Provides an alternative assessment of internal consistency. Values above 0.7 indicate adequate reliability (Hair et al., 2017). While most constructs meet or exceed this criterion, TaskC falls short with a composite reliability (rho_C) of 0.695, indicating a potential reliability issue for this construct.

Average Variance Extracted (AVE): Assesses the amount of variance captured by the construct relative to the variance due to measurement error. An AVE value above 0.5 indicates that the construct explains more than half of the variance of its indicators (Fornell & Larcker, 1981). All constructs in our model exhibit AVE values above 0.5, indicating satisfactory convergent validity.

Discriminant Validity - Fornell-Lacker criterion

To evaluate discriminant validity, we employed the Fornell-Larcker criterion. For adequate discriminant validity, the square root of the AVE for each construct should be greater than the inter-construct correlations (Fornell & Larcker, 1981). Table 5 presents the results of this analysis.

Table 5 - Discriminant validity - Fornell-Lacker criterion

	AA	AAO	AIE	CA	CAI	ILO	ITU	TC	TTF	TaskC
AA	0,924									
AAO	-0,278	0,873								
AIE	0,53	0,118	0,836							
CA	0,776	-0,261	0,535	0,851						
CAI	0,307	0,206	0,668	0,302	0,873					
ILO	0,033	0,29	0,314	0,055	0,49	0,859				
ITU	0,527	0,056	0,674	0,517	0,601	0,397	0,782			
TC	0,38	0,07	0,317	0,316	0,326	0,327	0,482	0,793		
TTF	0,426	0,129	0,386	0,421	0,303	0,295	0,539	0,662	0,878	
TaskC	0,28	0,231	0,374	0,327	0,312	0,201	0,442	0,479	0,57	0,789

The diagonal values represent the square root of the AVE for each construct, while the off-diagonal values are the inter-construct correlations. The results indicate that the square root of the AVE for each construct is greater than its highest correlation with any other construct, confirming adequate discriminant validity.

Discriminant Validity - Cross Loadings Analysis

To further assess discriminant validity, we analyzed the cross loadings of the indicators. Discriminant validity is confirmed when each indicator loads higher on its designated construct than on any other construct (Hair et al., 2017).

Table 6 provides the cross loadings for our model, and it shows that all items have higher loadings on their corresponding constructs compared to other constructs. For instance, the item AA1 has a loading of 0.926 on the AA construct, which is significantly higher than its loadings on other constructs, such as 0.471 on AIE and 0.730 on CA. Similarly, other items exhibit higher loadings on their respective constructs, confirming discriminant validity and reinforcing the distinctiveness of each construct within the model.

Table 6 - Discriminant validity - Cross loadings

	AA	AAO	AIE	CA	CAI	ILO	ITU	TC	TTF	TaskC
AA1	0,926	-0,221	0,471	0,73	0,302	0,081	0,496	0,397	0,51	0,263
AA2	0,939	-0,233	0,537	0,712	0,303	-0,005	0,508	0,378	0,332	0,256
AA3	0,905	-0,32	0,462	0,706	0,243	0,011	0,453	0,273	0,325	0,258
AAO1	-0,227	0,85	0,151	-0,2	0,205	0,318	0,044	0,126	0,123	0,275
AAO2	-0,257	0,896	0,063	-0,252	0,16	0,199	0,053	0,007	0,104	0,141
AIE1	0,43	0,028	0,783	0,476	0,451	0,183	0,505	0,211	0,359	0,348
AIE2	0,444	0,129	0,872	0,466	0,633	0,319	0,58	0,291	0,261	0,317
AIE3	0,481	0,107	0,883	0,422	0,564	0,25	0,557	0,276	0,343	0,307
AIE4	0,419	0,12	0,801	0,429	0,569	0,285	0,607	0,275	0,338	0,284
CA1	0,525	-0,041	0,407	0,742	0,254	0,047	0,34	0,217	0,348	0,319
CA2	0,706	-0,315	0,48	0,897	0,263	0,042	0,458	0,254	0,36	0,244
CA3	0,729	-0,27	0,477	0,903	0,259	0,052	0,507	0,327	0,372	0,288
CAI1	0,305	0,162	0,629	0,297	0,899	0,392	0,539	0,284	0,221	0,338
CAI2	0,205	0,281	0,588	0,214	0,91	0,401	0,525	0,227	0,212	0,295
CAI3	0,252	0,183	0,524	0,272	0,871	0,486	0,518	0,295	0,269	0,171
CAI4	0,307	0,097	0,582	0,27	0,811	0,439	0,515	0,334	0,36	0,269
ILO2	0,081	0,266	0,324	0,072	0,513	0,93	0,387	0,279	0,311	0,155
ILO3	-0,06	0,232	0,19	0,008	0,285	0,781	0,281	0,297	0,168	0,212
ITU1	0,365	0,071	0,553	0,381	0,536	0,371	0,796	0,39	0,341	0,342
ITU2	0,526	0,015	0,623	0,519	0,478	0,249	0,849	0,412	0,568	0,397
ITU3	0,397	-0,031	0,413	0,359	0,353	0,273	0,722	0,387	0,508	0,293
ITU4	0,344	0,115	0,489	0,336	0,497	0,362	0,754	0,319	0,266	0,34
TC1	0,336	0,046	0,278	0,293	0,266	0,272	0,417	0,801	0,58	0,438
TC2	0,295	0,071	0,245	0,289	0,258	0,314	0,371	0,825	0,54	0,405
TC3	0,267	0,049	0,227	0,148	0,252	0,177	0,353	0,751	0,437	0,273
TTF1	0,291	0,096	0,232	0,342	0,194	0,14	0,395	0,52	0,848	0,446
TTF2	0,442	0,127	0,426	0,395	0,325	0,354	0,538	0,633	0,907	0,546
TaskC1	0,107	0,26	0,273	0,238	0,299	0,236	0,347	0,422	0,451	0,795
TaskC2	0,221	0,241	0,359	0,27	0,272	0,15	0,362	0,321	0,447	0,811
TaskC3	0,335	0,047	0,253	0,266	0,167	0,089	0,337	0,389	0,45	0,759

5.3. STRUCTURAL MODEL TESTING

Following the validation of the measurement model, the structural model was evaluated to assess the hypothesized relationships between constructs. This analysis was conducted using SmartPLS 4, employing Partial Least Squares Structural Equation Modeling (PLS-SEM), a method particularly suitable for exploratory research focusing on prediction and theory building (Hulland et al., 2010; Ringle et al., 2012). The structural model testing encompassed the examination of path coefficients, their statistical significance, the model's predictive power, and effect sizes (Table6, Table 7 and Table 8).

Multi-collinearity Analysis

Multicollinearity was assessed using Tolerance and Variance Inflation Factor (VIF) values, as presented in Table 7. Tolerance values greater than 0.1 and VIF values less than 5 are considered acceptable, indicating no severe multicollinearity issues (Mansfield & Helms, 1982).

From Table 7, we observe that all constructs have Tolerance values well above 0.1 and VIF values below 5, confirming that multicollinearity is not a significant concern in our model. For instance, AA1 has a Tolerance of 0.310 and a VIF of 3.221, while TaskC1 has a Tolerance of 0.716 and a VIF of 1.397. This suggests that the independent variables do not exhibit problematic levels of multicollinearity, thereby ensuring the reliability of the regression coefficients and the stability of the model estimates.

In conclusion, the comprehensive assessment of the measurement model demonstrates high reliability, validity, and distinctiveness of the constructs, with some areas requiring further refinement. The analyses confirm that the constructs in the model accurately measure the intended concepts and are distinct from each other, enhancing the overall credibility of the research findings. However, constructs AAO, ILO, and TaskC warrant further investigation to address slight reliability concerns.

Table 7 – Multi-collinearity Analysis

Constructs	Tolerance	VIF
AA1	0.310	3,221
AA2	0.258	3,881
AA3	0.356	2,811
AAO1	0.721	1,387
AAO2	0.721	1,387
AIE1	0.587	1,703
AIE2	0.396	2,528
AIE3	0.364	2,745
AIE4	0.594	1,683
CA1	0.714	1,4
CA2	0.426	2,345
CA3	0.412	2,426
CAI1	0.301	3,326
CAI2	0.259	3,86
CAI3	0.379	2,636
CAI4	0.543	1,842
ILO2	0.752	1,33
ILO3	0.752	1,33
ITU1	0.529	1,891
ITU2	0.414	2,414
ITU3	0.486	2,059
ITU4	0.556	1,798
TC1	0.763	1,31
TC2	0.669	1,495
TC3	0.718	1,393
TTF1	0.702	1,425
TTF2	0.702	1,425
TaskC1	0.716	1,397
TaskC2	0.687	1,454
TaskC3	0.787	1,27

Path Coefficients Analysis

The path coefficients, representing the strength and direction of relationships between constructs, were estimated using the PLS-SEM algorithm. To assess the statistical significance of these coefficients, a bootstrapping procedure with 5,000 resamples was performed, as recommended (Hair et al., 2017). The results of this analysis are presented in Table 6.

Table 8 - Path Coefficients

Paths	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AA -> AIE	0,289	0,287	0,116	2,486	0,013
AAO -> AA	-0,338	-0,343	0,072	4,701	0
AAO -> CA	-0,32	-0,322	0,077	4,145	0
AIE -> CAI	0,668	0,67	0,054	12,326	0
AIE -> ILO	0,314	0,323	0,076	4,145	0
AIE -> ITU	0,674	0,679	0,045	14,863	0
CA -> AIE	0,311	0,316	0,106	2,927	0,003
TC -> TTF	0,505	0,511	0,091	5,528	0
TTF -> AA	0,469	0,473	0,076	6,181	0
TTF -> CA	0,463	0,465	0,07	6,632	0
TaskC -> TTF	0,328	0,328	0,086	3,825	0

The findings reveal that all hypothesized relationships in the model are statistically significant, with p-values below 0.05 and t-values exceeding 1.96. Notable significant paths include the positive relationship between Affective Attitude (AA) and AI Empowerment (AIE) ($\beta = 0.289$, $p = 0.013$), the negative relationship between Anticipated Adverse Outcomes (AAO) and Affective Attitude (AA) ($\beta = -0.338$, $p < 0.001$), and the strong positive relationship between AI Empowerment (AIE) and Career Advancement Intentions (CAI) ($\beta = 0.668$, $p < 0.001$).

Additionally, other important relationships were identified, such as the positive impact of Task-Technology Fit (TTF) on both Affective Attitude (AA) ($\beta = 0.469$, $p < 0.001$) and Cognitive Attitude (CA) ($\beta = 0.463$, $p < 0.001$), as well as the strong influence of AI Empowerment (AIE) on Intention to Use ChatGPT (ITU) ($\beta = 0.674$, $p < 0.001$). The model also revealed a significant relationship between AI Empowerment (AIE) and Intention to Leave Organization (ILO) ($\beta = 0.314$, $p < 0.001$), suggesting that AI empowerment might influence employee retention.

These statistically significant path coefficients validate the hypothesized relationships and confirm the theoretical framework underpinning the study, demonstrating the interconnectedness of various factors in the context of AI empowerment, technology adoption, and career-related intentions (Table 9).

Predictive Power Analysis: Coefficient of Determination (R^2)

The predictive power of the model was assessed using the coefficient of determination (R^2) for each endogenous construct. R^2 values indicate the proportion of variance in the endogenous constructs explained by the exogenous constructs (Hair et al., 2017). Table 7 presents the R^2 and adjusted R^2 values for each endogenous construct in the model.

Table 9 - R^2 values

Constructs	R-square	R-square adjusted
AA	0,294	0,283
AIE	0,32	0,309
CA	0,278	0,267
CAI	0,446	0,442
ILO	0,098	0,092

ITU	0,455	0,451
TTF	0,521	0,514

The results demonstrate that the model exhibits moderate to substantial explanatory power for several key constructs. Notably, Task-Technology Fit (TTF) and Intention to Use ChatGPT (ITU) show high R^2 values of 0.521 and 0.455, respectively. This indicates that the model explains 52.1% of the variance in TTF and 45.5% of the variance in ITU, suggesting strong predictive accuracy for these constructs. Additionally, the model explains a substantial portion of the variance in Career Advancement Intentions (CAI) with an R^2 value of 0.446. However, some constructs, such as Intention to Leave Organization (ILO), display lower R^2 values (0.098), pointing to areas where the model's explanatory power could be enhanced through further research and refinement.

Effect Size Analysis (f^2)

To assess the relative impact of each predictor variable on the endogenous constructs, f^2 effect sizes were calculated. These values indicate the magnitude of the contribution of each exogenous construct to the R^2 values of the endogenous constructs (Hair et al., 2011). Table 8 summarizes the f^2 values for each path in the model.

Table 10 - f^2 values

Paths	f-square
AA -> AIE	0,049
AAO -> AA	0,159
AAO -> CA	0,14
AIE -> CAI	0,805
AIE -> ILO	0,109
AIE -> ITU	0,834
CA -> AIE	0,057
TC -> TTF	0,41
TTF -> AA	0,307
TTF -> CA	0,292
TaskC -> TTF	0,174

The f^2 values indicate the magnitude of the impact of each exogenous construct. For example, AIE has a large effect on CAI (0.805) and ITU (0.834), while TC has a substantial effect on TTF (0.410). The analysis reveals varying effect sizes across the model. Notably, AI Empowerment (AIE) demonstrates large effect sizes on both Career Advancement Intentions (CAI) (f^2 = 0.805) and Intention to Use ChatGPT (ITU) (f^2 = 0.834), indicating substantial contributions to these constructs. Technology Characteristics (TC) also shows a considerable effect on Task-Technology Fit (TTF) (f^2 = 0.410).
Conversely, some paths exhibit more modest contributions, such as Affective Attitude (AA) to AI Empowerment (AIE) (f^2 = 0.049) and Cognitive Attitude (CA) to AI Empowerment (AIE) (f^2 = 0.057). Additionally, the effect of AI Empowerment (AIE) on Intention to Leave Organization (ILO) is relatively small (f^2 = 0.109). These smaller effect sizes suggest areas where the model could potentially be refined to strengthen these relationships.

Table 11 - Summary Hypotheses

Hypothesis	Path	Path Coefficient	t-Value	p-Value	Result
H1a	TaskC -> TTF	0.328	3.825	0.000	Supported
H1b	TC -> TTF	0.505	5.528	0.000	Supported
H2a	TTF -> AA	0.469	6.181	0.000	Supported
H2b	TTF -> CA	0.463	6.632	0.000	Supported
H3a	AAO -> AA	-0.338	4.701	0.000	Supported
H3b	AAO -> CA	-0.320	4.145	0.000	Supported
H4a	AA -> AIE	0.289	2.486	0.013	Supported
H4b	CA -> AIE	0.311	2.927	0.003	Supported
H5a	AIE -> ITU	0.674	14.863	0.000	Supported
H5b	AIE -> CAI	0.668	12.326	0.000	Supported
H5c	AIE -> ILO	0.314	4.145	0.000	Supported

6. DISCUSSION

6.1. INTERPRETATION OF FINDINGS

This study provides valuable insights into the factors influencing employees' attitudes and behavioral intentions towards ChatGPT adoption in organizations. The findings support the significance of Task-Technology Fit (TTF), Anticipated Adverse Outcomes (AAO), Affective and Cognitive Attitudes, and AI Empowerment in shaping employees' intentions to use ChatGPT, advance their careers, and potentially leave their organizations.

The strong positive influence of Task Characteristics and Technology Characteristics on TTF within the ChatGPT context demonstrates the alignment of ChatGPT's capabilities with employees' job requirements and expectations (Oliveira et al., 2014). This alignment fosters more positive emotional responses and rational evaluations of the technology. However, it's worth noting that the Task Characteristics construct showed lower reliability (Cronbach's alpha) than ideal, suggesting a need for refinement in future research to more accurately capture this aspect.

The significant impact of TTF on Affective and Cognitive Attitudes suggests that when employees perceive ChatGPT as enhancing their capabilities and supporting their work, they develop positive thoughts and feelings towards the technology. This finding is consistent with previous research on technology adoption (Dishaw & Strong, 1999), which asserts that task-technology alignment influences attitudes towards technology.

Anticipated Adverse Outcomes negatively influence both Affective and Cognitive Attitudes, highlighting the importance of addressing employees' concerns related to ChatGPT (AI) adoption. This finding extends the results of an earlier pre-adoptive appraisal study (Chiu et al., 2021), which showed a negative influence only on affective attitude, by demonstrating the pervasive impact on overall attitude formation. However, the lower reliability of the AAO construct indicates that further refinement of this measure may be necessary to fully capture the nuances of anticipated adverse outcomes in AI adoption.

The significant positive influence of Affective and Cognitive Attitudes on AI Empowerment underscores how employee attitudes towards ChatGPT shape their sense of empowerment (Thomas & Velthouse, 1990; Brynjolfsson & McAfee, 2014). This enhanced feeling of empowerment subsequently influences employees' intentions to use ChatGPT, pursue career advancement, and potentially seek opportunities outside their current organization (Daugherty & Wilson, 2018; Savickas & Porfeli, 2012).

These findings validate the crucial role of AI Empowerment in the pre-adoptive appraisal model towards ChatGPT (AI), highlighting its importance in connecting employee attitudes to their behavioral intentions (Chiu et al., 2021; Wilson et al., 2017). However, the effect size analysis revealed that the impact of Affective and Cognitive Attitudes on AI Empowerment was relatively small, suggesting that other factors not captured in this model may also contribute significantly to AI Empowerment (Hair et al., 2017; Davenport & Kirby, 2016).

The introduction of the Career Advancement Intentions construct provides insights into how ChatGPT adoption may influence employees' career trajectories. A very strong relationship between AI Empowerment and Career Advancement Intentions suggests that employees who feel empowered by ChatGPT are more likely to pursue career growth opportunities, aligning with the concept of AI as a catalyst for professional development (Brynjolfsson & McAfee, 2014).

While the model demonstrated substantial explanatory power for key outcomes like Task-Technology Fit (R^2 = 0.521) and Intention to Use ChatGPT (R^2 = 0.455), it showed lower explanatory power for Intention to Leave Organization (R^2 = 0.098). This indicates that additional factors beyond the scope of this model may play a significant role in explaining employee retention intentions in the context of AI adoption. The lower reliability of the ILO construct further emphasizes the need for a more comprehensive approach to understanding the complex dynamics of employee retention in the face of AI implementation. These findings provide a nuanced understanding of the factors influencing ChatGPT adoption in organizational settings, while also highlighting areas for future research and refinement of constructs to better capture the complexities of AI adoption in the workplace.

6.2. Theoretical Contributions

This study advances the theoretical understanding of ChatGPT (AI) adoption on individual level in organizational contexts by extending and integrating several key theoretical frameworks to address identified research gaps. Specifically, it introduces and validates new constructs within the Pre-Adoptive Appraisal Model towards AI (PAMAI), providing a comprehensive and nuanced understanding of how employees appraise and respond to ChatGPT (AI) in professional settings. The following theoretical contributions are noteworthy:

Extension of Cognitive Appraisal Theory (CAT)

Integration with Task-Technology Fit (TTF): This research extends the application of CAT by integrating TTF theory to explore how the alignment between technology capabilities and job tasks influences employees' cognitive and emotional appraisals. This integration addresses the limitation in previous appraisal research related to the lack of relationship between employee knowledge and affective attitudes towards AI (Chiu et al., 2021).

Comprehensive Appraisal Mechanisms: By focusing on practical knowledge through TTF, this study demonstrates how the perceived task-technology alignment (Dishaw & Strong, 1999; Oliveira et al., 2014) affects both affective and cognitive attitudes towards ChatGPT (AI). It validates the importance of including *practical knowledge* into ChatGPT (AI) appraisal studies for a deeper understanding how employees evaluate the alignment between ChatGPT (AI) capabilities and job requirements.

Introduction and Validation of AI Empowerment

Conceptualization and Empirical Evidence: This study introduces AI Empowerment as a novel construct within the PAMAI framework, drawing on prior research in the field The empirical validation of AI Empowerment concept as an outcome of positive attitudes towards ChatGPT (AI), and its significant influence on behavioral intentions towards the technology, support its inclusion into PAMAI.

Linking Attitudes to Empowerment: The significant positive influence of both affective and cognitive attitudes on AI Empowerment emphasizes the transformative potential of AI technologies in empowering employees by enhancing their capabilities. This finding bridges the gap between technical aspects of AI adoption and psychological outcomes, enriching the theoretical discourse on ChatGPT (AI)s' impact on workforce dynamics and contributes to the emerging body of literature on human-AI collaboration and augmentation (Wilson et al., 2017; Brynjolfsson & McAfee, 2014; Davenport & Kirby, 2016; Dell' et al., 2023).

Integration of Career Construction Theory (CCT)

Career Advancement Intentions: The incorporation of the Intention to Advance Career construct, grounded in Career Construction Theory (Savickas, 2005), extends the theoretical scope of AI adoption studies to include career-related outcomes. The strong relationship between AI Empowerment and career advancement intentions support ChatGPT (AI)'s role as a catalyst for professional growth (Wang & Li, 2024).

Impact of AI on Future Jobs: The study's findings provide empirical evidence on how ChatGPT (AI) adoption influences employees' career trajectories, emphasizing the importance of ChatGPT (A)I proficiency for role expansion, career reimagination, and professional growth. This integration extends CCT into the scope of ChatGPT (AI)-driven work environments that demand professional development and career adaptability (Savickas & Porfeli, 2012).

Refinement and Expansion of PAMAI

New Constructs and Relationships: Our research extends the PAMAI framework (Chiu et al., 2021) by integrating new constructs that capture the unique characteristics of Generative AI technologies like ChatGPT. This study redesigned the original PAMAI by replacing the employee knowledge construct with practical knowledge (TTF) and introducing AI Empowerment and Career Advancement Intentions. By validating the relationships between Task-Technology Fit, Attitudes, AI Empowerment, and various behavioral intentions (Intention to Use, Career Advancement Intentions, and Intention to Leave Organization), our work addresses the limitations identified in previous studies (Chiu et al., 2021) and contributes to literature on pre-adoptive appraisal and subsequent behavioral outcomes in ChatGPT (AI) adoption.

Proof of Concept for Adoption Theories: The successful integration of TTF with PAMAI serves as a proof of concept for future research to incorporate other contemporary adoption theories, such as UTAUT2 (Venkatesh et al., 2012) and Diffusion of Innovations (DOI) theory (Rogers, 2003) into PAMAI. This lays the groundwork for expanding theoretical landscape in ChatGPT (AI) adoption studies.

Refinement of Anticipated Adverse Outcomes' Impact: Our findings extend previous research by demonstrating that Anticipated Adverse Outcomes negatively influence both Affective and Cognitive Attitudes towards ChatGPT (AI). This understanding of how potential negative consequences shape overall attitudes contributes to a more comprehensive model of pre-adoptive appraisal (Chiu et al., 2021).

In summary, this study makes significant theoretical contributions by extending existing theories, introducing new constructs, and providing empirical evidence on the complex interplay between technology capabilities, employee attitudes, empowerment, and career behaviors. These contributions advance academic knowledge and offer valuable insights for organizations navigating the integration of AI technologies like ChatGPT.

6.3. Implications for Practice

The findings of this study offer several practical implications for organizations aiming to effectively implement ChatGPT and similar AI technologies:

Task-Technology Fit Assessment

The strong influence of Task-Technology Fit (TTF) (Oliveira et al., 2014) on employee attitudes emphasizes the necessity of aligning ChatGPT (AI) to employees' job requirements. Organisations should develop specialized assessments of task and technology characteristics, engage employees in the selection and implementation phases, provide sufficient training and leverage the findings of this research to ensure alignment of job requirements with ChatGPT's (AI) capabilities. This approach will help achieve optimal task-technology fit, foster positive employee attitudes, and enable companies to maximize the value of integrating ChatGPT (AI).

Proactive Management of Employee Concerns

The significant negative impact of Anticipated Adverse Outcomes on both Affective and Cognitive Attitudes underscores the need for organizations to proactively address employee concerns about ChatGPT (AI) adoption. Organizations should maintain clear communication with employees about the objectives and anticipated outcomes of ChatGPT (AI) implementation. They should engage in transparent discussions about potential job changes and reskilling opportunities, set clear policies on data privacy and job security and provide ongoing support to mitigate negative perceptions (Chiu et al., 2021).

Fostering AI Empowerment

The strong relationship between AI Empowerment and positive behavioral intentions suggests that organizations should focus on creating an environment where employees feel empowered by ChatGPT (AI) rather than threatened. This could involve training programs that emphasize how ChatGPT (AI) can enhance problem-solving abilities, elevate professional status, and accelerate skill development (Daugherty & Wilson, 2018).

Career Development and Retention Strategies

The significant link between AI Empowerment and Career Advancement Intentions suggests that organizations should integrate ChatGPT (AI) proficiency into their career development programs. This includes creating new roles that leverage ChatGPT literacy, offering training in ChatGPT-related skills, and recognizing employees who effectively use ChatGPT to drive innovation and productivity (Savickas & Porfeli, 2012; Wang & Li, 2024).

Additionally, the positive relationship between AI Empowerment and the Intention to Leave the Organization highlights the need for robust retention strategies for employees who become highly proficient with ChatGPT. Organizations should create supportive work environments that recognize and reward ChatGPT-related contributions. They can provide career paths aligned with ChatGPT initiatives, offer competitive compensation packages, and ensure that the organizational culture values and rewards ChatGPT-driven innovation (Tambe et al., 2019).

Continuous Evaluation and Adjustment

Given the rapid evolution of AI technologies like ChatGPT, the findings of this research underscore the necessity for organizations to implement mechanisms for ongoing evaluation of the technology's fit with evolving job tasks and employee needs. Regular assessments of employee attitudes, empowerment levels, and career intentions, as indicated by this study, can help organizations adapt their AI strategies to maintain positive employee attitudes and maximize the benefits of AI adoption. This continuous evaluation aligns with the research findings, ensuring successful long-term integration of ChatGPT (AI) by keeping strategies responsive to both technological advancements and employee dynamics.

7. LIMITATIONS AND FUTURE RESEARCH

7.1. Limitations of the Study

While this study provides valuable insights into the adoption of ChatGPT in organizational settings, it is important to acknowledge several limitations that may affect the generalizability and interpretation of the results.

Firstly, the cross-sectional nature of the study limits our ability to capture the dynamic process of technology adoption over time. A longitudinal approach would provide a more comprehensive understanding of how attitudes and intentions towards ChatGPT evolve as users gain more experience with the technology (E. Rogers et al., 2014).

Secondly, the reliance on self-reported data may introduce common method bias, potentially inflating or deflating the relationships between constructs. Future studies could benefit from incorporating objective measures or multi-source data to mitigate this limitation (Carlson et al., 2009).

Thirdly, the sample size and composition present limitations. The relatively small sample size may have affected the statistical power of some analyses (Erdfelder et al., 2009). Additionally, the sample's geographic concentration in the European Union limits the generalizability of findings to other cultural contexts. Future research should aim for larger, more diverse samples to capture regional and cultural variations in AI adoption attitudes and behaviors.

Fourthly, the analyses revealed weaknesses in some constructs. Specifically, Anticipated Adverse Outcomes (AAO), Intention to Leave Organization (ILO), and Task Characteristics (TaskC) demonstrated lower reliability than ideal. This suggests a need for further refinement of these constructs in future research to more accurately capture these aspects of AI adoption (Hair et al., 2011).

Fifthly, the study's model, while comprehensive, did not include moderators or mediators. Some of the newly introduced constructs could potentially demonstrate significant moderating and mediating properties with respect to other constructs in the research model. Future studies could explore these potential interactions to provide a more nuanced understanding of the relationships between constructs (Venkatesh et al., 2012).

Sixthly, due to the limited scope of a master's thesis, several crucial constructs were not included in the model. Aspects such as AI ethics, data security, and AI anthropomorphism were not addressed, which could provide important insights into the adoption process. Future research could incorporate these constructs to provide a more holistic view of AI adoption in organizations (Duan et al., 2019; Dwivedi et al., 2021).

Seventhly, the study did not employ second-order constructs, which could have helped introduce and test more dimensions of both the newly introduced and existing constructs. For instance, the Cognitive and Affective Attitudes constructs, brought from the original model, test a limited scope of thoughts and feelings people have towards ChatGPT. Through second-order constructs, a wider range of attitudes could be represented and tested, providing a more comprehensive understanding of user perceptions (Chiu et al., 2021).

Lastly, the model showed lower explanatory power for Intention to Leave Organization (ILO), indicating that additional factors beyond the scope of this model may play a significant role in explaining employee retention intentions in the context of AI adoption. This suggests a need for a more comprehensive approach to understanding the complex dynamics of employee retention in the face of AI implementation (Tambe et al., 2019).

Despite these limitations, this study provides valuable insights into the adoption of ChatGPT in organizational settings and lays the groundwork for future research in this rapidly evolving field. Addressing these limitations in future studies will contribute to a more comprehensive understanding of AI adoption in the workplace and its implications for employees and organizations (Dell' et al., 2023; Singla Alex et al., 2024).

7.2. SUGGESTIONS FOR FUTURE RESEARCH DIRECTIONS

Based on the limitations identified in this study and drawing from additional insights, several avenues for future research emerge that could significantly enhance our understanding of ChatGPT and AI adoption in organizational settings:

Expanded Sample Diversity and Cross-Cultural Comparisons: Future research should aim for larger, more culturally diverse samples. This would enhance the generalizability of findings and allow for cross-cultural comparisons in AI adoption attitudes and behaviors. Investigating how cultural factors influence AI adoption could provide valuable insights for global organizations implementing AI technologies (Venkatesh et al., 2012; E. M. Rogers, 2003).

Refinement of Constructs: Further development and validation of constructs, particularly Anticipated Adverse Outcomes (AAO), Intention to Leave Organization (ILO), and Task Characteristics (TaskC), is needed. This refinement could involve scale development studies to improve the reliability and validity of these measures in the context of AI adoption (Hair et al., 2011).

Exploration of Moderators and Mediators: Future studies should investigate potential moderating and mediating effects within the model. This could include examining how individual characteristics (e.g., personality traits, cognitive styles, or technology readiness) or organizational factors (e.g., leadership support, organizational culture, change management practices) moderate the relationships between key constructs (Parasuraman, 2000; Duan et al., 2019).

Incorporation of Additional Constructs: Expanding the model to include constructs related to AI ethics, data security, and AI anthropomorphism could provide a more comprehensive understanding of AI adoption. Researchers could investigate how ethical considerations, such as data privacy, algorithmic bias, or job displacement, influence employees' attitudes and behavioral intentions towards AI (Duan et al., 2019; Dwivedi et al., 2021)

Development of Second-Order Constructs: Future research should consider developing and testing second-order constructs, particularly for complex concepts like attitudes towards AI. This approach could capture a wider range of dimensions and provide a more comprehensive representation of user perceptions and experiences with AI technologies (Hair et al., 2017; Chiu et al., 2021).

Investigation of Employee Retention: Given the lower explanatory power for Intention to Leave Organization, future studies should delve deeper into the factors influencing employee retention in the context of AI adoption. This could involve exploring additional organizational and individual factors that may impact employee turnover intentions in AI-enhanced work environments and developing effective retention strategies for AI-empowered employees (Tambe et al., 2019; Kraimer et al., 2011).

Integration with Existing Theories: Future research could benefit from integrating this model with other established theories in technology adoption, organizational behavior, and career development. This could include exploring the integration of theories such as the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) or Diffusion of Innovations (DOI) to further enrich our understanding of AI adoption in organizations (Venkatesh et al., 2012; E. M. Rogers, 2003).

Organizational-Level Outcomes: Future research could examine the relationship between employee-level variables (e.g., AI empowerment, career advancement intentions) and organizational-level outcomes (e.g., innovation, productivity) to provide a broader perspective on the impacts of AI adoption (Daugherty & Wilson, 2018; (Dell' et al., 2023).

Spillover Effects: Researchers could examine the potential spillover effects of AI empowerment on other work-related outcomes, such as job satisfaction, work engagement, or organizational citizenship behavior (Seibert et al., 2011).

Skill Development and AI: Studies focusing on the specific skills that contribute to AI empowerment could inform the development of targeted training programs for employees (Brynjolfsson & McAfee, 2014; Tambe et al., 2019).

8. CONCLUSION

As AI technologies like ChatGPT continue to transform the way people work, research of this nature becomes increasingly critical. It advances our theoretical understanding and provides practical insights for organizations striving to harness the potential of ChatGPT (AI) while supporting their workforce. By illuminating the factors that influence ChatGPT (AI) adoption and its implications for employee empowerment and career trajectories, this study contributes to the development of more effective, employee-centric strategies for ChatGPT (AI) implementation in organizational settings. Ultimately, this research highlights to organisations the importance of viewing ChatGPT (AI) adoption not just as a technological challenge, but as a multifaceted organizational and human resource management issue that will shape the future of work.

BIBLIOGRAPHY

Abdullah, R., & Fakieh, B. (2020). Health Care Employees' Perceptions of the Use of Artificial Intelligence Applications: Survey Study. *Journal of Medical Internet Research*, *22*. https://doi.org/10.2196/17620

Ardon, O., & Schmidt, R. L. (2020). Management & Administration Clinical Laboratory Employees' Attitudes Toward Artificial Intelligence. *Laboratory Medicine*, *51*, 649–654. https://doi.org/10.1093/labmed/lmaa023

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. https://doi.org/10.1017/jmo.2016.55

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* . W.W. Norton & Company. https://psycnet.apa.org/record/2014-07087-000

Carlson, J. P., Vincent, L. H., Hardesty, D. M., & Bearden, W. O. (2009). Objective and Subjective Knowledge Relationships: A Quantitative Analysis of Consumer Research Findings. *Journal of Consumer Research*, *35*(5), 864–876. https://www.researchgate.net/publication/23935626_Objective_and_Subjective_Knowledge_Relationships_A_Quantitative_Analysis_of_Consumer_Research_Findings

Chiu, Y. Te, Zhu, Y. Q., & Corbett, J. (2021). In the hearts and minds of employees: A model of pre-adoptive appraisal toward artificial intelligence in organizations. *International Journal of Information Management*, *60*. https://doi.org/10.1016/J.IJINFOMGT.2021.102379

Daugherty, P. R., & Wilson, H. J. (2018). *Human + Machine: Reimagining Work in the Age of AI*. Harvard Business Review Press. https://store.hbr.org/product/human-machine-reimagining-work-in-the-age-of-ai/10163

Davenport, T. H., & Kirby, J. (Business editor). (2016). *Only Humans Need Apply: Winners and Losers in the Age of Smart Machines*. Harper Business. https://books.google.com/books/about/Only_Humans_Need_Apply.html?hl=pt-PT&id=ZRp2CgAAQBAJ

Dell', F., Saran, A., Mcfowland, R. E., Krayer, L., Mollick, E., Candelon, F., Lifshitz-Assaf, H., Lakhani, K. R., & Kellogg, K. C. (2023). *Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality*.

Dishaw, M. T., & Strong, D. M. (1999). Extending the technology acceptance model with task–technology fit constructs. *Information & Management*, *36*(1), 9–21. https://doi.org/10.1016/S0378-7206(98)00101-3

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71. https://doi.org/10.1016/J.IJINFOMGT.2019.01.021

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … 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. https://doi.org/10.1016/J.IJINFOMGT.2019.08.002

Erdfelder, E., FAul, F., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149/METRICS

Folkman, S., Lazarus, R. S., Dunkel-Schetter, C., DeLongis, A., & Gruen, R. J. (1986). Dynamics of a Stressful Encounter. Cognitive Appraisal, Coping, and Encounter Outcomes. *Journal of Personality and Social Psychology*, *50*(5), 992–1003. https://doi.org/10.1037/0022-3514.50.5.992

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

Gkinko, L., & Elbanna, A. (2023). The appropriation of conversational AI in the workplace: A taxonomy of AI chatbot users. *International Journal of Information Management*, *69*. https://doi.org/10.1016/J.IJINFOMGT.2022.102568

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly: Management Information Systems*, *19*(2), 213–233. https://doi.org/10.2307/249689

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., T, H. G., Ringle C. M., &, & M, S. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). *Research Gate*, 384. https://www.researchgate.net/publication/354331182_A_Primer_on_Partial_Least_Squares_Structural_Equation_Modeling_PLS-SEM

Hulland, J., Ryan, M. J., & Rayner, R. K. (2010). Modeling Customer Satisfaction: A Comparative Performance Evaluation of Covariance Structure Analysis Versus Partial Least Squares. *Handbook of Partial Least Squares*, 307–325. https://doi.org/10.1007/978-3-540-32827-8_15

Klerck, D., & Sweeney, J. C. (2007). The effect of knowledge types on consumer-perceived risk and adoption of genetically modified foods. *Psychology and Marketing*, *24*(2), 171–193. https://doi.org/10.1002/MAR.20157

Kornellis, N. (n.d.). *[Richard S. Lazarus PhD, Susan Folkman PhD] Stress(BookFi)*. Retrieved June 12, 2024, from https://www.academia.edu/37418588/_Richard_S_Lazarus_PhD_Susan_Folkman_PhD_Stress_BookFi_

Kraimer, M. L., Seibert, S. E., Wayne, S. J., Liden, R. C., & Bravo, J. (2011). Antecedents and outcomes of organizational support for development: The critical role of career opportunities. *Journal of Applied Psychology*, *96*(3), 485–500. https://doi.org/10.1037/A0021452

Lazarus, R., & Folkman, S. (1984). Stress, Appraisal, and Coping. In *Stress, appraisal and coping*. Springer Publishing Company. https://books.google.com/books/about/Stress_Appraisal_and_Coping.html?hl=pt-PT&id=i-ySQQuUpr8C

Mansfield, E. R., & Helms, B. P. (1982). Detecting Multicollinearity. *The American Statistician*, *36*(3), 158. https://doi.org/10.2307/2683167

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). New York McGraw-Hill. - References - Scientific Research Publishing. (n.d.). Retrieved June 14, 2024, from https://www.scirp.org/reference/ReferencesPapers?ReferenceID=1017362

Oliveira, T., Faria, M., Thomas, M. A., & Popovič, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management*, *34*(5), 689–703. https://doi.org/10.1016/J.IJINFOMGT.2014.06.004

Parasuraman, A. (2000). Technology Readiness Index (Tri): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies. *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Ringle, C.M., Wende, S. and Becker, J.M. (2015) SmartPLS 3. SmartPLS GmbH, Boenningstedt. - References - Scientific Research Publishing. (n.d.). Retrieved June 14, 2024, from https://www.scirp.org/reference/ReferencesPapers?ReferenceID=2376307

Ringle, Sarstedt, & Straub. (2012). Editor's Comments: A Critical Look at the Use of PLS-SEM in "MIS Quarterly." *MIS Quarterly*, *36*(1), iii. https://doi.org/10.2307/41410402

Rogers, E. M. (2003). *Diffusion of Innovations, 5th Edition* . Simon and Schuster. https://books.google.com/books/about/Diffusion_of_Innovations_5th_Edition.html?hl=pt-PT&id=9U1K5LjUOwEC

Rogers, E., Singhal, A., to, M. Q.-A. integrated approach, & 2014, undefined. (n.d.). Diffusion of innovations. *Taylorfrancis.ComEM Rogers, A Singhal, MM QuinlanAn Integrated Approach to*

Communication Theory and Research, 2014•taylorfrancis.Com. Retrieved June 14, 2024, from https://www.taylorfrancis.com/chapters/edit/10.4324/9780203887011-36/diffusion-innovations-everett-rogers-arvind-singhal-margaret-quinlan
Savickas, M. L. (2005). The Theory and Practice of Career Construction. In *Career development and counseling: Putting theory and research to work* (pp. 42–70). John Wiley & Sons, Inc.. https://psycnet.apa.org/record/2004-21312-003
Savickas, M. L. (2013). *Praise for Career Development and Counseling: Putting Theory and Research to Work, Second Edition* (Brown Steven D. & Lent Robert W., Eds.; 2nd ed.). John Wiley & Sons.
Savickas, M. L., & Porfeli, E. J. (2012). Career Adapt-Abilities Scale: Construction, reliability, and measurement equivalence across 13 countries. *Journal of Vocational Behavior*, *80*, 661–673. https://doi.org/10.1016/j.jvb.2012.01.011
Seibert, S. E., Kraimer, M. L., & Crant, J. M. (2001). What Do Proactive People Do? A Longitudinal Model Linking Proactive Personality and Career Success. *Personnel Psychology*, *54*(4), 845–874. https://doi.org/10.1111/J.1744-6570.2001.TB00234.X
Seibert, S. E., Wang, G., & Courtright, S. H. (2011). Antecedents and Consequences of Psychological and Team Empowerment in Organizations: A Meta-Analytic Review. *Journal of Applied Psychology*, *96*(5), 981–1003. https://doi.org/10.1037/A0022676
Sgaramella, M., Chang, P.-C., Guo, Y., Cai, Q., & Guo, H. (2023a). *Proactive Career Orientation and Subjective Career Success: A Perspective of Career Construction Theory*. https://doi.org/10.3390/bs13060503
Sgaramella, M., Chang, P.-C., Guo, Y., Cai, Q., & Guo, H. (2023b). *Proactive Career Orientation and Subjective Career Success: A Perspective of Career Construction Theory*. https://doi.org/10.3390/bs13060503
Singla Alex, Sukharevsky Alexander, Yee Lareina, Chui Michael, & Hall Bryce. (2024). *The state of AI in early 2024: Gen AI adoption spikes and starts to generate value | McKinsey*. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai#/
Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *California Management Review*, *61*(4), 15–42. https://doi.org/10.1177/0008125619867910
Thomas, K. W., & Velthouse, B. A. (1990). Cognitive Elements of Empowerment: An “Interpretive” Model of Intrinsic Task Motivation. *The Academy of Management Review*, *15*(4), 666. https://doi.org/10.2307/258687
Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly: Management Information Systems*, *36*(1), 157–178. https://doi.org/10.2307/41410412
Wang, D., & Li, Y. (2024). Career construction theory: tools, interventions, and future trends. *Frontiers in Psychology*, *15*. https://doi.org/10.3389/FPSYG.2024.1381233
Wilson, H. J., Daugherty, P. R., & Morini-Bianzino, N. (2017). The Jobs That Artificial Intelligence Will Create. *MIT Sloan Management Review*. https://sloanreview.mit.edu/article/will-ai-create-as-many-jobs-as-it-eliminates/

APPENDIX A

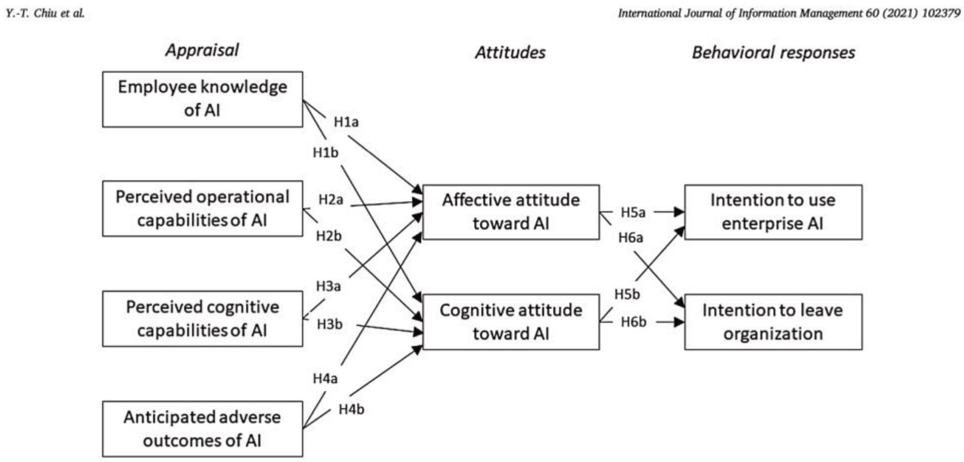

Figure 2: Research Model: Pre-adoptive Appraisal toward Artificial Intelligence.

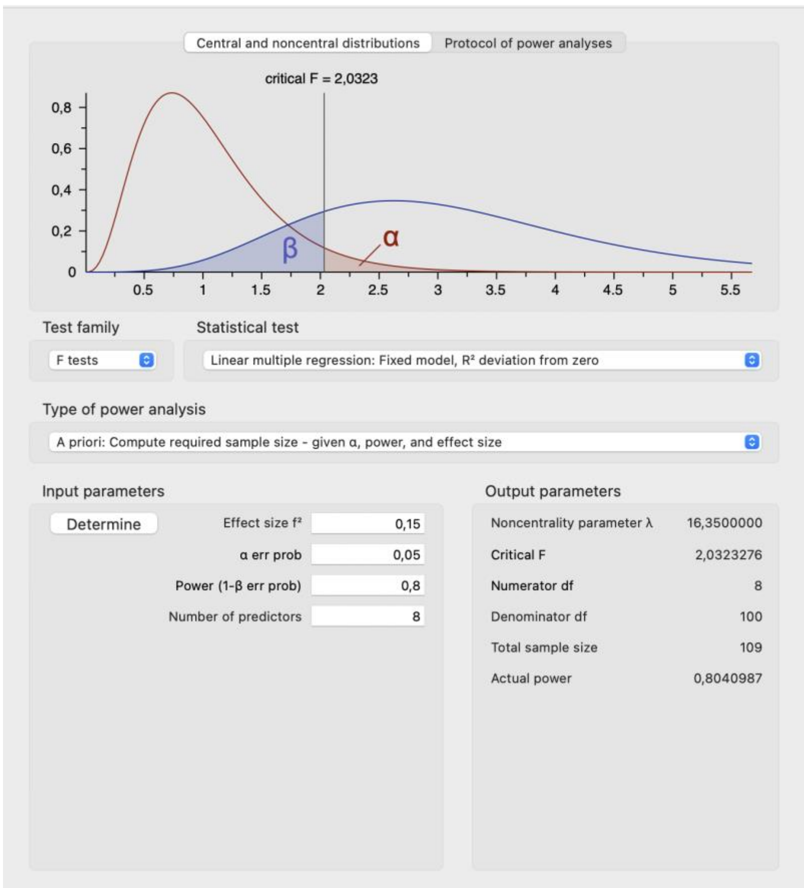

Figure 3: Sample size statistical G*Power Analysis