MASTERS IN MANAGEMENT INFORMATION SYSTEMS

MASTER'S FINAL WORK

DISSERTATION

THE INFLUENCE OF GENERATIVE AI ON WORKFORCE DYNAMICS IN TOURISM AND HOSPITALITY.

AMAKIRI PROMISE GOODLUCK

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Abstract

Rapid advancements in recent years in computer science, particularly in generative artificial intelligence (AI) have enabled the development of intelligent systems increasingly sophisticatedly capable of performing tasks traditionally associated with human cognition. Within the tourism and hospitality sector, new technologies are reshaping operational processes, service delivery models, and the fundamental nature of workforce interactions. Although existing literature highlights AI's potential to enhance productivity and optimize workflows, the psychosocial dimensions of AI integration remain insufficiently examined. Specifically, limited research explores how individual perceptions of performance shape emotional adaptation and expectations regarding broader industry transformation. Addressing this gap, the present study investigates the mediating role of emotional responses in the relationship between perceived individual impact and perceived sector-wide change associated with generative AI adoption.

A quantitative research design was employed using a cross-sectional survey administered to 66 stakeholders, including managers, front-line employees, and students, within the Portuguese tourism and hospitality context. The survey instrument assessed three core constructs: Perceived Impact on Workforce Performance (PEWP), Emotional Responses (ER), and Perceived Impact on Tourism and Hospitality (PETH). Data was analyzed using IBM SPSS Statistics, incorporating descriptive statistics, correlation analysis, and mediation modeling via the process macro.

The findings reveal a significant positive relationship between the perceived impact of AI on workforce performance and employees' emotional responses ($p < .001$). This suggests that individuals who perceive AI as beneficial to their daily tasks exhibit heightened emotional engagement, characterized by both enthusiasm regarding improved efficiency and apprehension related to adaptation demands. However, no statistically significant relationship emerged between emotional responses and perceived industry-level transformation, nor did emotional responses mediate the relationship between individual perceptions and sector-wide assessments.

These results indicate that employees tend to cognitively separate their personal emotional reactions to AI from their strategic evaluations of the tourism and hospitality industry's future. While generative AI introduces substantial pressures for individual adaptation, these emotional dynamics do not appear to distort perceptions of industry-wide competitiveness or technological transformation. This distinction underscores a nuanced workforce perspective in which emotional adaptation and strategic judgment operate independently.

Overall, this study contributes to the growing body of literature on AI adoption in service-oriented industries by demonstrating the importance of treating emotional adaptation and strategic assessments as distinct yet parallel processes. For organizational leaders, these findings highlight the need to develop management strategies that support emotional well-being alongside clear, transparent communication to ensure the responsible and effective integration of generative AI technologies.

Keywords: Tourism and Hospitality, Workforce Dynamics, Emotional Response, Mediation Analysis, Generative AI, Technology Acceptance

ABBREVIATIONS

AI - Artificial Intelligence

CRM – Customer Relationship Management

ER – Emotional Response

ERP – Enterprise Resource Planning

GDS – Global Distribution Systems

GDPR – General Data Protection Regulation

JD-R – Job Demands Resources

LLM – Large Language Model

OTA – Online Travel Agency

PEWP – Perceived Impact of ChatGPT on Workforce

PETH – Perceived Impact of ChatGPT on Tourism and Hospitality

PMS – Property Management System

POS – Point of Sale

RMS – Revenue Management System

TAM – Technology Acceptance Model

UTAUT – Unified Theory of Acceptance and Use of Technology

SPSS – Statistical Package for the Social Sciences

SEM – Structural Equation Modelling

TABLE OF CONTENT

CHAPTER 1 - INTRODUCTION 1
1.1 Background and Context 1
1.2 Problem Statement 2
1.3 Research Questions 2
1.4 Research Objectives and Aims 3
1.5 Theoretical Framework 3
1.6 Significance and Contributions 5
1.7 Hypothesis Development 6
CHAPTER 2 – LITERATURE REVIEW 7
2.1 Theoretical Foundations of Technology Adoption and Workforce Transformation 7
2.2 Technological Evolution in Hospitality: From Legacy Systems to the Generative AI Paradigm 8
2.3 Organizational Change Management in the Context of AI Integration 11
2.4 The Macro-Level Impact of AI and Automation on Workforce Performance 12
2.5 Sector-Specific Dynamics: Generative AI in Tourism and Hospitality 13
2.6 Potential Benefits and Challenges of ChatGPT Integration 13
2.7 Role of ChatGPT in Enhancing Customer Experience and Operational Efficiency 14
2.8 Ethical Considerations and Concerns in AI Deployment 15
2.9 The Emerging Paradigm of Human-AI Collaboration 16
2.10 Gaps in the Current Literature 16
2.11 Conclusion of Literature Review 17
CHAPTER 3 – CONCEPTUAL FRAMEWORK 18
3.1 Defining the Core Constructs 18
3.2 The Central Mediational Model 19
3.3 Direct Effect Hypotheses 19
3.4 Visual Representation of the Full Research Model 20
3.5 Role of Control Variables 20
CHAPTER 4 – RESEARCH METHODOLOGY AND DATA ANALYSIS 21
4.1 Research Design 21
4.4 Data Collection Procedures 24
4.5 Data Analysis 24
4.5.1 Data Preparation 24
4.5.2 Methodological Pivot: Addressing Scale Reliability Issues 25
4.5.3 Reliability Analysis and Justification of Analytical Strategy 26
4.5.4 Hypothesis Testing and Comparative Analysis 27
CHAPTER 5 - DATA ANALYSIS AND RESULTS 27
5.1.2 Item-Level Descriptive Statistics 29

5.2 Correlation Analysis 30
5.3 Hypothesis Testing 31
5.4 Analysis of Demographic Group Differences 33
5.5 Summary of Results 33
5.4 Deeper Analysis of Mediational Pathways 34
CHAPTER 6 – CONCLUSIONS, LIMITATIONS AND SUGGESTIONS FOR FURTHER RESEARCH 36
6.1 Summary of Key Findings 36
6.2 Implications and Contributions of the Study 39
6.3 Limitations of the Study 41
6.4 Suggestions for Future Research 42

TABLE INDEX

Table 1: Sample Distribution by Participant Group and Organization 22
Table 2: Cronbach's Alpha Reliability Test Result 26
Table 3: Frequency Distribution of Demographic Characteristics 28
Table 4: Frequency Distribution of Responses for Each Survey Item (N=66) 29
Table 5: Pearson Correlation Matrix of Composite Variables and Age 31
Table 6: Summary of Mediation Analysis Results (PROCESS Model 4) 32
Table 7: Summary of Linear Regression Models for Direct Effects 32
Table 8: Summary of ANOVA Results 33
Table 9: Summary of Hypothesis Testing Results 34
Table 10: Pearson Correlation Matrix of Core Constructs 34
Table 11: Comparison of Total and Direct Effects of PEWP on PETH 35

IMAGES INDEX

Figure 1: Comprehensive Research Model 20
Figure 2: Frequency Distribution of Demographic Characteristics 28
Figure 3: Frequency Distribution of Responses for Each Survey Item 30

CHAPTER 1 – INTRODUCTION

1.1 Background and Context

The contemporary business landscape is undergoing a profound transformation driven by the rapid evolution of artificial intelligence (AI). A particularly potent catalyst in this shift is the emergence of generative AI, exemplified by sophisticated large language models (LLMs). These systems demonstrate a remarkable capacity for tasks involving natural language processing, content generation, and process automation, often achieving a level of performance that matches or exceeds human capabilities in specific domains (Teubner et al., 2023). Consequently, organizations across all sectors are compelled to explore the integration of these powerful tools, seeking to enhance operational efficiency, gain competitive advantages, and innovate their service offerings. This technological integration has placed the implications for workforce dynamics, including the nature of job roles, requisite employee skills, and overall performance at the forefront of academic and practical inquiry (Bankins et al., 2024).

Within this broad context, the tourism and hospitality sector present a uniquely compelling case for study. Characterized by its high degree of customer interaction and complex operational demands, the industry is a prime environment for AI integration. Industry players are progressively leveraging AI-powered solutions, from chatbots and personalized recommendation engines to advanced systems for revenue management and operational optimization (Dwivedi et al., 2023). Generative AI, with its advanced conversational and content-creation abilities, introduces novel possibilities for crafting personalized guest experiences, automating communication, and streamlining administrative processes (Carvalho & Ivanov, 2024).

As organizations within this people-centric industry adopt these technologies, critical questions arise regarding the subsequent effects on their employees and the fundamental nature of hospitality work. A significant potential exists for the alteration of service delivery models, operational management strategies, and the essential interaction between human employees, technology, and customers (Dogru et al., 2023). A systematic examination of these emergent workforce dynamics within the context of generative AI adoption is therefore both timely and necessary.

1.2 Problem Statement

The central research problem this dissertation addresses is the multifaceted influence of generative AI on workforce performance within the tourism and hospitality industry. While the potential benefits of AI adoption, such as increased efficiency and enhanced customer engagement, are frequently highlighted, the corresponding effects on job roles, skill demands, and employee perceptions require rigorous empirical investigation. The tourism and hospitality industry's foundational reliance on human interaction and service quality makes it a particularly critical context for examining the integration of advanced AI. A significant knowledge gap exists in understanding the complex interplay between perceived productivity gains and the associated challenges, emotional responses, and adaptation requirements faced by the workforce as these technologies become more prevalent (Wirtz et al., 2023). This study seeks to address this gap by empirically examining employee perceptions regarding generative AI's impact on their work and the broader industry implications within the Portuguese context.

1.3 Research Questions

To guide this investigation, the study addresses the following primary research questions:

1. How do employees in the Portuguese tourism and hospitality sector perceive the impact of generative AI on their individual job performance and work efficiency?
2. What is the relationship between employees' perceptions of generative AI's impact and their emotional responses, including feelings about efficiency, concerns about job displacement, and the recognized need for training?
3. What is the relationship between the perceived impact of generative AI and the perceived need for workforce reskilling?
4. How do employees' individual emotional responses to generative AI relate to their perceptions of its broader impact on the tourism and hospitality industry?

1.4 Research Objectives and Aims

Aligned with the research questions, the main objectives of this dissertation are:

1. To assess the perceived impact of generative AI technologies on individual job performance among a sample of employees and students in the Portuguese tourism and hospitality sector.
2. To examine the statistical relationship between the perceived impact of generative AI and the emotional responses of the workforce.
3. To investigate the statistical relationship between the perceived impact of generative AI and the perceived need for workforce training and reskilling.
4. To test a mediational model where emotional responses may explain the relationship between perceived AI impact and perceived broader industry impact.
5. To provide empirically grounded insights into the workforce dynamics associated with generative AI adoption, informing both academic understanding and practical industry considerations.

1.5 Theoretical Framework

This study is grounded in established theoretical perspectives from the fields of technology adoption, organizational behavior, and organizational change, which provide a robust framework for investigating the influence of generative AI on the workforce. The primary theories informing this research are the Technology Acceptance Model (TAM), its successor the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Job Demands-Resources (JD-R) theory.

The Technology Acceptance Model (TAM) provides a foundational explanation for user adoption of new technologies. TAM posits a clear causal chain: external variables influence an individual's core beliefs about a technology, which in turn shape their attitudes and behavioral intentions, ultimately leading to actual use (Davis, 1989). The two central beliefs are Perceived Usefulness, defined as the degree to which an individual believes that using a particular system will enhance their job performance, and Perceived Ease of Use, the degree to which an individual believes that using the system will be free of effort. In the context of this study, "perceived usefulness" is directly reflected in constructs measuring generative AI's perceived impact on job performance and work efficiency. TAM provides a basis for hypothesizing that as employees perceive generative AI to be more useful, their emotional responses and behavioral intentions toward the technology will be significantly and positively influenced (Toros et al., 2024).

Building upon TAM, the Unified Theory of Acceptance and Use of Technology (UTAUT) offer a more comprehensive model by integrating elements from eight prominent technology acceptance theories (Venkatesh et al., 2003). UTAUT identifies four key direct determinants of usage intention and behavior: Performance Expectancy (similar to perceived usefulness), Effort Expectancy (similar to perceived ease of use), Social Influence (the degree to which an individual perceives that important others believe they should use the new system), and Facilitating Conditions (the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system). While this study does not measure all UTAUT constructs, the theory's emphasis on social and organizational factors reinforces the importance of examining AI adoption within a broader organizational context.

The Job Demands-Resources (JD-R) theory offers a complementary perspective focused on employee well-being and performance (Demerouti & Bakker, 2011). It suggests that these outcomes are a function of the balance between job demands and job resources. Job Demands are aspects of a job that require sustained physical, psychological, or emotional effort and are therefore associated with certain costs. Job Resources are aspects that are functional in achieving work goals, reducing job demands, and stimulating personal growth and development. The integration of generative AI can be viewed through this lens. Technology acts as a new job resource when it automates tedious administrative tasks (e.g., summarizing guest feedback), provides instant access to information (e.g., generating a list of local attractions), or enhances problem-solving, thereby reducing cognitive load. Simultaneously, it introduces new job demands, such as the requirement to learn prompt engineering skills, the cognitive load of verifying AI-generated information for accuracy, and the emotional labor of managing guest interactions that have been partially automated. This study conceptualizes employees' emotional responses as a reflection of this perceived balance between the resources AI provides and the new demands it creates.

Together, these frameworks suggest a clear line of inquiry: employee perceptions of AI's usefulness (TAM/UTAUT) and its role as a resource or demand (JD-R) are likely to shape their emotional reactions and their views on necessary adaptations, such as the need for training. The conceptual model of this study, therefore, examines these specific pathways.

1.6 Significance and Contributions

This dissertation aims to provide significant contributions to both academic knowledge and practical understanding regarding the integration of generative AI in the tourism and hospitality sector.

Academically, it contributes empirical data to the nascent field studying the specific workforce implications of advanced LLMs, moving beyond speculation toward observed employee perceptions within a particular industry and national context (Dwivedi et al., 2023). It empirically tests relationships suggested by established theories like TAM and JD-R in this novel technological setting.

Practically, the findings offer valuable insights for managers, human resource professionals, and educators within the tourism and hospitality industry, particularly in Portugal. Understanding the strong link between perceived AI impact and both perceived productivity gains and the recognized need for training can inform strategic decisions about AI implementation and workforce development (Valle-Cruz et al., 2024). Recognizing the prevalence of employee concerns about job displacement alongside positive views on efficiency highlights the need for balanced and transparent management approaches (Wirtz et al., 2023). The results can help organizations anticipate employee reactions and proactively design support systems and training programs to facilitate a smoother adaptation to generative AI.

1.7 Hypothesis Development

Based on the theoretical frameworks and a review of the relevant literature, the following hypotheses were formulated for empirical testing in this study:

- H1: The perceived impact of generative AI on workforce performance (PEWP) is positively associated with employees' emotional responses (ER). This hypothesis posits that as employees perceive AI to have a greater effect on their work, their overall emotional reaction—encompassing views on efficiency, displacement concerns, and training needs—will be stronger, consistent with models suggesting system characteristics influence user affect (Toros et al., 2024).
- H2: Employees' emotional responses (ER) mediate the relationship between the perceived impact of generative AI on workforce performance (PEWP) and the perceived impact of AI on the broader tourism and hospitality industry (PETH). This hypothesis proposes a causal chain were perceptions of individual impact influence emotional responses, which in turn shape broader industry outlooks.
- H3: The perceived impact of generative AI on workforce performance (PEWP) is positively associated with workforce productivity. This hypothesis predicts that employees who perceive AI as more impactful will also report higher levels of related productivity outcomes, consistent with literature on AI's potential efficiency benefits (Bansal et al., 2024; Sandelin, 2024).
- H4: The perceived impact of generative AI on workforce performance (PEWP) is positively associated with perceptions of enhanced industry competitiveness. This suggests that employees who see AI positively affecting their own work will also tend to believe it enhances the overall competitiveness of the industry.
- H5: The perceived impact of generative AI on workforce performance (PEWP) is positively associated with the perceived need for workforce reskilling. This hypothesis proposes that as employees perceive AI having a greater impact, they will more strongly recognize the need for training and skill development to adapt effectively (Dogru et al., 2023; Mohanty & Munir, 2024).

These hypotheses form the basis of the quantitative analysis detailed in the subsequent chapters, aimed at understanding the complex interplay between perceptions, emotions, and adaptation needs related to generative AI in the studied context.

CHAPTER 2 – LITERATURE REVIEW

This chapter provides a comprehensive and critical review of the academic literature relevant to the study's central focus: the influence of generative AI on workforce dynamics within the tourism and hospitality industry. The review is structured to build a clear theoretical and contextual foundation for the research. It begins by establishing the theoretical frameworks that govern technology adoption and workforce transformation. It then proceeds to a broad overview of the impacts of AI and automation on workforce performance, before narrowing its focus to the specific benefits and challenges posed by generative AI. The chapter subsequently examines the role of these technologies in enhancing customer experience and operational efficiency, addresses the critical ethical considerations, explores the emerging paradigm of human-AI collaboration, identifies existing gaps in the literature, and concludes by discussing the key factors that enable successful integration.

2.1 Theoretical Foundations of Technology and Workforce Transformation

To properly analyze the impact of generative AI, we must ground our inquiry in established theories of technology adoption and organizational change. The Technology Acceptance Model (TAM) provides a foundational perspective, positing that an individual's adoption of a new technology is primarily driven by two core beliefs: perceived usefulness (the degree to which a person believes using a system will enhance their job performance) and perceived ease of use (the degree to which a person believes using a system will be free of effort) (Davis, 1989). An extension of this, the Unified Theory of Acceptance and Use of Technology (UTAUT), incorporates additional determinants such as social influence and facilitating conditions, offering a more comprehensive view of the adoption process in organizational settings (Venkatesh et al., 2003).

Complementing these adoption models, the Job Demands-Resources (JD-R) theory offers a powerful lens for understanding the effects of technology on employee well-being and performance (Demerouti & Bakker, 2011). From a JD-R perspective, generative AI acts as both a job resource and a job demand. It is a resource when it automates tedious tasks, provides rapid access to information, and enhances problem-solving capabilities, thereby boosting efficiency and reducing cognitive load. Simultaneously, it introduces new demands by requiring employees to learn new skills, adapt to altered workflows, and manage the cognitive and emotional load of collaborating with a non-human agent (Sawang et al., 2023). The balance between these new resources and demands is critical in shaping employee outcomes like engagement, stress, and overall performance.

2.2 Technological Evolution in Hospitality: From Legacy Systems to the Generative AI Paradigm

To understand the transformative impact of generative AI, one must first analyze the technological foundation upon which the tourism and hospitality industry was built. For decades, this infrastructure has been characterized by a collection of specialized, often siloed, transactional systems designed to manage discrete operational processes. The emergence of Large Language Models (LLMs) represents a fundamental paradigm shift, introducing a layer of generative intelligence that redefines the capabilities of this legacy stack and the human workflows associated with it.

The traditional technology stack in hospitality was an ecosystem of systems focused on data management and process execution. Key components included:

Global Distribution Systems (GDS): Originating in the airline industry, GDSs like Amadeus, Sabre, and Galileo became the primary B2B marketplace for travel inventory (Law, Leung, & Buhalis, 2009). The workflow for a travel agent using a GDS was highly specialized, requiring mastery of a cryptic, command-line interface to perform complex searches for flights, hotels, and car rentals. The process was efficient for trained experts but entirely inaccessible to untrained users and lacked any capacity for interpreting natural language or nuanced requests.

Property Management Systems (PMS): The PMS is the operational core of any hotel, managing reservations, room assignments, guest folios, billing, and housekeeping status (Inversini & Masiero, 2014). A typical front-desk workflow involved manually navigating multiple screens within the PMS to check a guest in, process payment, and assign a room. Retrieving guest history or specific preferences required manually searching through past records within the system's structured database.

Central Reservation Systems (CRS) and Channel Managers: The CRS served as a central repository for a hotel's room inventory, while channel managers automated the distribution of that inventory to a multitude of online travel agencies (OTAs) and other booking channels (O'Connor & Frew, 2002). The primary workflow for a revenue or reservations manager involved manually setting and adjusting rates and availability rules within the CRS or channel manager interface. This process was often reactive, based on simple rules and periodic reviews of competitor pricing.

Revenue Management Systems (RMS): First-generation RMS tools brought analytical rigor to pricing, using historical booking data and competitor rate shopping to recommend optimal room prices (Kimes, 2003). The workflow involved a revenue analyst reviewing the system's recommendations, which were based on quantitative algorithms, and then manually implementing these price changes in the PMS or CRS. The system could identify patterns in structured data but could not incorporate unstructured external factors like public sentiment, local events, or weather forecasts into its analysis.

Customer Relationship Management (CRM) and Point of Sale (POS) Systems: CRM systems were designed to be the central database for guest information, while POS systems captured transactional data from restaurants, spas, and other outlets. In practice, these systems were often poorly integrated with the PMS (Sigala, 2008). A marketing manager's workflow to create a targeted campaign would involve manually exporting lists from the CRM, attempting to cross-reference them with spending data from the POS, and then using a separate email platform to send largely generic, templated communications.

The emergence of LLMs does not simply add another tool to this stack; it introduces a new layer of generative intelligence that can integrate with, analyze, and act upon the data within these legacy systems. LLMs function as a conversational, analytical, and generative fabric that breaks down data silos and fundamentally redesigns workflows, shifting the human role from process executor to strategic supervisor (Jackson et al., 2024).

This integration is actively changing established processes:

Redefining the Booking Process: The cryptic GDS workflow is being replaced by natural language interfaces. A corporate travel manager can now instruct an AI: "Find the most cost-effective travel option for a team of four from Lisbon to a conference in Berlin next month, including flights with minimal layovers, a hotel near the conference center with a meeting room, and ground transportation." The LLM can query multiple data sources, construct a complete itinerary, and present it for approval, a task that previously required hours of manual GDS navigation (Tredinnick, 2023).

Augmenting Hotel Operations: The front-desk agent's manual PMS navigation is augmented by an AI assistant. The agent can ask, "Summarize the last three stays for the guest checking in, note any complaints, and tell me their preferred newspaper." The LLM queries the PMS and CRM, synthesizes the information, and provides a concise summary, allowing the agent to focus on providing a personalized, empathetic welcome rather than on data retrieval (Pillai, Pandian, & Bapat, 2024).

Automating and Personalizing Marketing: The marketing manager's manual segmentation workflow becomes a strategic conversation with an AI. The instruction changes to: "Draft a promotional email campaign for past guests who have a high spa spend and have previously booked a suite. Generate three versions of the email: one emphasizing relaxation, one focusing on luxury, and one highlighting a new spa package. Personalize each with reference to their last stay" (Naslednikov, 2024). The manager's role shifts from writing copy to refining the AI's output and validating the strategic approach.

Evolving Revenue Management to Strategy: The revenue analyst's role is elevated from implementing system recommendations to validating AI-driven strategies. An advanced LLM can now analyze not only historical booking data from the RMS but also unstructured data from news sources, social media, and local event calendars. It can then generate a dynamic pricing recommendation complete with a written justification: "I recommend increasing rates of 15% for the weekend of October 12th due to a newly announced music festival and positive weather forecasts, which have historically increased last-minute booking demand by 22%" (Ivanov, 2023). The human expert validates this logic, adjusting based on their broader market knowledge.

This evolution represents a fundamental shift from a technology stack designed for data management to one capable of generative intelligence. The associated workflows are changing from manual, step-by-step processes to collaborative, goal-oriented conversations between humans and AI, repositioning employees as strategic decision-makers augmented by powerful analytical and generative tools.

2.3 Organizational Change Management in the Context of AI Integration

The integration of generative AI is not merely a technological upgrade; it is a significant organizational change event that affects processes, roles, and culture. Therefore, a review of established organizational change management theories is essential for understanding how to navigate this transition effectively.

Lewin's (1947) three-stage model of change provides a foundational framework. The Unfreeze stage involves preparing the organization for change by challenging existing beliefs and behaviors. For AI integration, this means communicating the strategic necessity for adoption and addressing initial resistance and anxiety about job displacement. The Change stage is the implementation phase, where new technologies are introduced, and employees are trained. This corresponds to the active process of workforce reskilling and workflow redesign. The Refreeze stage involves stabilizing the organization after the change has been made, embedding the new AI-driven processes into the organizational culture and standard operating procedures.

A more granular framework is offered by Kotter's (1996) 8-Step Process for Leading Change. This model provides a practical roadmap for managers. Key steps relevant to AI integration include:

1. Creating a Sense of Urgency: Articulating the competitive threats and opportunities that necessitate AI adoption.
2. Forming a Powerful Guiding Coalition: Assembling a team of leaders and key influencers to champion the change.
3. Developing a Vision and Strategy: Clearly defining how AI will be used to achieve organizational goals.
4. Communicating the Change Vision: Using multiple channels to consistently communicate the vision and address employee concerns.
5. Empowering Broad-Based Action: Removing obstacles to change, such as outdated IT infrastructure or rigid job descriptions, and encouraging risk-taking.

6. Generating Short-Term Wins: Highlighting early successes of AI implementation to build momentum and reinforce the value of the change.

Applying these models to the tourism and hospitality sector underscores that successful AI integration is as much a leadership and communication challenge as it is a technical one. The literature on change management suggests that failing to address the human side of this technological shift—by ignoring employee fears, failing to provide adequate training, or not communicating a clear vision—is a primary cause of implementation failure.

2.4 The Macro Impact of AI and Automation on Workforce Performance

The integration of AI and automation into the workplace is a subject of extensive scholarly investigation. A consistent finding across numerous sectors is that AI-driven solutions are fundamentally reshaping job roles, altering the allocation of tasks, and modifying the skill sets required of employees (Bankins et al., 2024). Much of this research focuses on how AI automates routine, repetitive, and data-intensive tasks, frequently leading to measurable gains in efficiency and productivity (Sandelin, 2024). Applications in data analysis, scheduling, and basic customer inquiries are consistently cited as primary sources of operational improvement (Valle-Cruz et al., 2024).

However, the literature also highlights the considerable workforce challenges that accompany AI adoption. Widespread concerns about job displacement due to automation are prevalent, creating a recognized and urgent need for substantial workforce reskilling and upskilling programs (Mohanty & Munir, 2024; Stahl, 2021). This research stream explores the changing nature of essential skills, with a growing emphasis on digital literacy, critical thinking, creativity, and the ability to collaborate effectively with AI systems (Wirtz et al., 2023).

Within the tourism and hospitality industry specifically, studies indicate that AI-powered solutions are being actively applied to enhance customer experiences through personalization, streamline operations via automated systems, and improve strategic decision-making (Dwivedi et al., 2023; Dogru et al., 2023). The potential of AI-driven chatbots and predictive analytics has been investigated as a means to transform service delivery (Carvalho & Ivanov, 2024). While the integration of these tools promises to alter the sector significantly, empirical research focused specifically on the workforce performance implications of generative AI within the unique, high-touch context of tourism and hospitality remains a developing area. This dissertation aims to contribute directly to this specific gap.

2.5 Sector-Specific Dynamics: Generative AI in Tourism and Hospitality

The tourism and hospitality industry provides a particularly salient context for studying the effects of generative AI due to several unique characteristics. First, it is an industry built upon the primacy of the service encounter. Unlike manufacturing or finance, the core product is often an intangible experience, co-created at the point of interaction between employee and guest (Grönroos, 2011). The quality of this interaction is a primary driver of customer satisfaction, loyalty, and brand reputation. The introduction of an AI intermediary like ChatGPT into this dynamic fundamentally alters the nature of the service encounter.

Second, industry has historically valued the "human touch"—the capacity for empathy, personalization, and genuine connection—as a key differentiator. The challenge for the sector is to integrate the efficiency of AI without eroding this essential human element, which is a core component of its value proposition (Farbod, 2024). Third, the industry's workforce is highly diverse, encompassing a wide range of roles from front-line service staff to strategic managers, each with different tasks and skill requirements. The impact of generative AI is unlikely to be uniform, affecting these roles in varied and complex ways. This heterogeneity makes the sector a rich environment for studying the differential effects of technological change.

2.6 Potential Benefits and Challenges of ChatGPT Integration

The emergence of powerful generative AI models like ChatGPT has catalyzed significant discussion about the potential for profound shifts in the tourism and hospitality sector (Dwivedi et al., 2023). Literature identifies several key benefits. A primary advantage lies in the enhancement of customer experience. The sophisticated natural language capabilities of generative AI enable the creation of intuitive and personalized interactions through advanced chatbots and virtual concierges (Carvalho & Ivanov, 2024). These systems can provide tailored recommendations and generate creative content, which can substantially increase guest satisfaction and loyalty (Bansal et al., 2024). Another key benefit is improved operational efficiency. Tools like ChatGPT can automate a wide array of routine administrative tasks, including answering frequently asked questions and drafting communications (Sandelin, 2024). This automation allows human employees to be redeployed to more complex or creative activities, thereby enhancing overall organizational productivity.

Conversely, the integration of ChatGPT also presents several formidable challenges that organizations must navigate. Foremost among these are pressing ethical concerns and data privacy issues. The use of generative AI trained on vast datasets raises critical questions about the secure handling of guest information, the potential for algorithmic bias, and the authenticity of AI-generated content (Al-Hasan et al., 2024; Stahl, 2021). A second major challenge involves workforce adaptation and potential job displacement. The automation capabilities of generative AI fuel legitimate concerns about job security, particularly for roles reliant on routine communication. This technological shift necessitates significant investment in comprehensive reskilling and upskilling programs to prepare the workforce for new, collaborative roles (Mohanty & Munir, 2024; Masera, 2024). Finally, the challenge of maintaining the human element is especially pertinent to this high-touch industry. An over-reliance on AI for customer interactions risks diminishing the personalized, empathetic service that is often a key differentiator for brands in the hospitality sector (Farbod, 2024).

2.7 Role of AI in Enhancing Customer Experience and Operational Efficiency

Generative AI tools offer specific, practical applications that can significantly improve both customer-facing services and internal operational workflows. In enhancing customer experience, ChatGPT can power highly sophisticated virtual assistants capable of engaging in natural, context-aware conversations. These assistants can deliver personalized recommendations, handle complex queries, and provide 24/7 support, thereby improving guest convenience and satisfaction (Carvalho & Ivanov, 2024; Bansal et al., 2024). Technology also allows for the generation of customized guest content, such as tailored travel itineraries and personalized welcome messages, which elevates the quality and relevance of guest communications (Dwivedi et al., 2023).

Regarding internal operational efficiency, generative AI excels at automating routine administrative tasks. This includes drafting standard operating procedures, summarizing reports, and generating internal communications, which frees up employee time for more strategic work (Sandelin, 2024). Technology also serves as a powerful tool for decision support. By rapidly processing and summarizing large quantities of unstructured text data—such as customer feedback or market trend reports, it can provide managers with synthesized, actionable insights to support critical decisions related to pricing, service adjustments, or operational improvements (Kumar, Gupta & Bapat, 2024). Finally, generative AI has promising applications in employee training and knowledge management. It can be used to create customized training materials or function as a virtual coach, supporting more effective employee development and continuous learning within the organization (Ooi et al., 2023). The successful implementation of these applications, however, depends on addressing challenges of accuracy, system integration, and ethics.

2.8 Ethical Considerations and Concerns in AI Deployment

The integration of sophisticated generative AI models into the tourism and hospitality sector brings a range of significant ethical considerations that demand careful and proactive attention (Stahl, 2021). A primary concern revolves around data privacy and security. These systems often process sensitive guest data, and ensure compliance with data protection regulations like GDPR and preventing misuse is paramount for maintaining guest trust (Al-Hasan et al., 2024). Another critical dimension is the potential for algorithmic bias and fairness. AI models can inherit and amplify societal biases present in their training data, which could lead to discriminatory outcomes in service delivery or recommendations. Organizations must implement proactive measures, such as fairness audits and bias mitigation techniques, to promote equity (Xia et al., 2024).

The profound impact on labor also raises substantial ethical questions. The automation capabilities of generative AI create widespread concerns about job displacement. Ethical considerations compel organizations to manage this transition responsibly by investing in reskilling opportunities and supporting employees whose roles are affected (Mohanty & Munir, 2024). Furthermore, concerns regarding the authenticity of AI-generated content and the potential for misinformation are prominent. The misuse of this technology to create false reviews or misleading descriptions could significantly damage brand reputation and erode customer trust (Shen et al., 2023). Establishing clear policies on transparency—disclosing when a customer is interacting with an AI—and verification processes is essential. Addressing this complex web of ethical issues requires a holistic approach involving robust governance structures and an unwavering organizational commitment to responsible innovation.

2.9 The Emerging Paradigm of Human-AI Collaboration

The discourse on AI in the workplace is evolving from a simple automation-versus-augmentation dichotomy to a more nuanced focus on human-AI collaboration. This paradigm views AI not merely as a tool to replace human tasks, but as a partner that can complement and extend human capabilities (Wilson & Daugherty, 2018). In this model, humans and AI systems work together, each leveraging their unique strengths. Humans provide critical thinking, emotional intelligence, ethical judgment, and complex problem-solving skills, while AI offers speed, data-processing power, and pattern recognition at scale.

In the tourism and hospitality context, this could manifest in several ways. A front-desk employee might use a generative AI assistant to instantly retrieve complex booking information or translate a guest's request, allowing the employee to focus on providing a warm, empathetic, and personalized welcome. A marketing manager might use AI to generate dozens of ad copy variations but then apply their own creativity and brand knowledge to select and refine the most compelling options. This collaborative approach suggests that the most significant value from generative AI may not come from full automation, but from creating hybrid workflows that produce outcomes superior to what either humans or AI could achieve alone. Understanding the factors that facilitate effective human-AI teaming is a critical area for future research and practice (Glikson & Woolley, 2020).

2.10 Gaps in Literature

Despite the rapidly growing interest in generative AI, a review of academic literature reveals several significant knowledge gaps that warrant further investigation. There is a notable lack of empirical evidence on workforce performance impacts specifically within the tourism and hospitality industry. Much of the current discourse remains speculative or is extrapolated from other sectors. Rigorous studies designed to quantify the measurable effects of tools like ChatGPT on productivity and job satisfaction in this unique service environment are needed (Dwivedi et al., 2023).

Furthermore, a deeper understanding of the nuanced impacts on customer experience is required. While potential benefits are frequently cited, empirical research that examines the actual effect of generative AI on outcomes like guest loyalty and perceived service quality remains limited (Carvalho & Ivanov, 2024). There is also a need for more thorough exploration of the organizational behavior and human resource management implications of this technology. Critical aspects such as employee perceptions, adaptation strategies, and the influence of organizational culture on successful integration have not yet been fully investigated (Bankins et al., 2024).

Finally, the concept of human-AI collaboration itself requires more empirical exploration. While theoretically appealing, research is needed to identify the specific competencies, training methods, and interface designs that best support effective teaming between employees and AI systems in real-world service contexts.

2.11 Conclusion of Literature Review

Summarily, the literature provides a clear picture of generative AI as a transformative technology with the potential to significantly reshape the tourism and hospitality industry. Grounded in theories of technology adoption and job design, the research indicates that these tools offer substantial benefits in operational efficiency and customer experience enhancement. However, these opportunities are accompanied by formidable challenges related to workforce adaptation, ethical deployment, and the preservation of the industry's essential human element. The emerging paradigm of human-AI collaboration offers a promising pathway forward, but much remains unknown about its practical implementation. Critically, established theories of organizational change management provide a necessary framework for navigating these challenges, emphasizing that the human and organizational dimensions of this transition are paramount. The existing scholarship reveals clear gaps, particularly in empirical, sector-specific research on workforce performance, customer experience outcomes, and the dynamics of human-AI teaming. This dissertation is designed to address a subset of these gaps by providing empirical data on employee perceptions and their emotional and adaptive responses to the integration of generative AI within the Portuguese tourism and hospitality context.

CHAPTER 3 – CONCEPTUAL FRAMEWORK

This chapter delineates the conceptual framework that provides theoretical scaffolding for this dissertation. Building upon the literature reviewed in the preceding chapter, this section synthesizes key concepts into a coherent and comprehensive research model. The purpose of this framework is to define the core constructs under investigation, articulate the full range of hypothesized relationships between them, and provide a visual representation of the model that will be empirically tested. This chapter serves as the crucial link between established literature and the research methodology that follows.

3.1 Defining the Core Constructs

The research model is built around three central constructs, derived from the literature on technology adoption and workforce dynamics.

- Perceived Impact of ChatGPT on Workforce Performance (PEWP): This is the primary independent variable of the study. It refers to an individual's subjective assessment of the extent to which generative AI influences their own work effectiveness and productivity. It encompasses an employee's familiarity with the technology, its perceived effect on their ability to perform their job, and their beliefs regarding its peripheral aspects, such as data security. In the context of the Technology Acceptance Model (TAM), this construct aligns closely with the concept of "perceived usefulness," a primary driver of technology adoption (Davis, 1989).
- Emotional Responses (ER): This construct serves as the key mediating variable in the primary model. It represents the affective and cognitive reactions of employees to the integration of generative AI. It is a multifaceted construct that includes feelings about efficiency gains, concerns regarding potential job displacement, and the recognized need for personal reskilling and training. Drawing from the Job Demands-Resources (JD-R) theory, ER can be seen as the net outcome of the balance between AI as a job resource (enhancing efficiency)

and a job demand (creating displacement anxiety and training needs) (Demerouti & Bakker, 2011).

- Perceived Impact of ChatGPT on Tourism and Hospitality (PETH): This is the final dependent variable in the mediational model. It captures an employee's broader perceptions of how generative AI will affect the tourism and hospitality industry. This includes views on its potential to alter service delivery models, create operational challenges or advantages, and influence the overall competitive landscape of the sector.

3.2 The Central Mediational Model

The conceptual framework's primary theoretical argument is a mediational model. This model suggests that the way employees perceive AI's impact on their own work influences their emotional state, which in turn colors their view of the technology's broader industry-level consequences. The core hypotheses embedded within this mediational model are:

- H1: The PEWP → ER Linkage. The model first posits a direct, positive relationship between the perceived impact on individual performance (PEWP) and the employee's emotional response (ER). This theoretical linkage suggests that as employees perceive AI to be more consequential to their daily tasks, the intensity of their emotional reaction—whether positive (excitement about efficiency) or negative (anxiety about displacement)—will increase.
- H2: The Mediating Role of Emotional Responses. The central hypothesis of the conceptual model is that Emotional Responses (ER) mediate the relationship between PEWP and PETH. This proposes a causal chain: the perceived impact of AI on an individual's job performance influences their emotional state, and it is this emotional state that subsequently shapes their perception of technology's overall impact on the industry.

3.3 Direct Effect Hypotheses

In addition to the central mediational model, this study tests several direct effect hypotheses. These hypotheses further explore the direct consequences of the primary independent variable (PEWP) on key outcomes related to productivity and workforce adaptation.

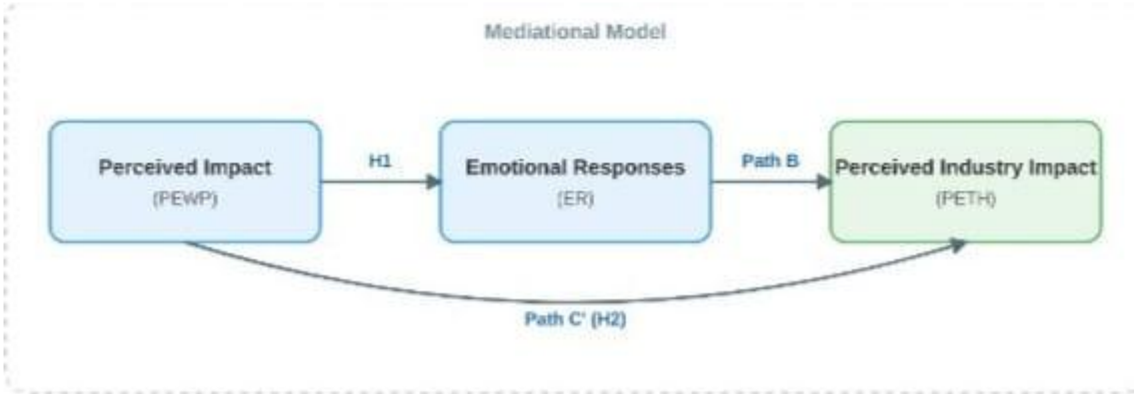
- H3: Impact on Workforce Productivity. This hypothesis posits a direct, positive relationship between the perceived impact of generative AI (PEWP) and self-reported workforce productivity. This is a foundational test based on technology adoption literature, which argues that technologies perceived as useful and impactful are expected to lead to performance gains (Bansal et al., 2024; Sandelin, 2024).
- H4: Impact on Industry Competitiveness. This hypothesis proposes a direct, positive relationship between the perceived impact of generative AI (PEWP) and perceptions of enhanced industry competitiveness. This linkage suggests that employees who view AI as a positive force in their own roles will extrapolate that benefit to the industry at large, seeing it as a tool for competitive advantage.
- H5: Impact on Reskilling Needs. This hypothesis posits a direct, positive relationship between the perceived impact of generative AI (PEWP) and the perceived need for workforce reskilling. This is grounded in JD-R theory, where the introduction of a new, impactful technology simultaneously creates a demand for new skills and competencies required to use it effectively (Dogru et al., 2023; Mohanty & Munir, 2024).

3.4 Visual Representation of the Full Research Model

Figure 1: Comprehensive Research Model

3.5 Role of Control Variables

The model also acknowledges the potential influence of demographic variables, specifically Age, Gender, and Position. These variables are included as control variables, primarily acting on the mediator (ER) in the mediational analysis. It is plausible that an individual's life experience, role, or background could influence their emotional reactions to a new technology. While not the central focus of the hypotheses, their influence will be accounted for in the statistical analysis to ensure that the primary relationships of interest are not spurious.



CHAPTER 4 – RESEARCH METHODOLOGY AND DATA ANALYSIS

This chapter details the research methodology employed to investigate the influence of generative AI on workforce dynamics within the Portuguese tourism and hospitality sector. It provides a comprehensive account of the research design, the characteristics of the participants and the sampling strategy used, the instrument developed for data collection, the procedures followed for gathering data, and the specific statistical methods applied for data analysis. Critically, this chapter also provides detailed justification for the selection of the final analytical strategy based on preliminary testing of the data collected. The objective is to present a clear and replicable account of the study's execution, allowing for a thorough evaluation of its methodological rigor and the validity of its findings.

4.1 Research Design

The study employed quantitative research design, utilizing a cross-sectional survey methodology. This approach is well-suited for collecting standardized data from a sample of individuals at a single point in time, which allows for the statistical examination of relationships between variables and the testing of predefined hypotheses (Bryman, 2016). The primary data collection instrument was a structured online questionnaire designed to measure the core constructs of interest.

The quantitative survey method was chosen over qualitative alternatives because it facilitates data collection from a geographically dispersed sample within a defined timeframe. The structured nature of the questionnaire ensures consistency in measurement across all participants, which is a prerequisite for the statistical analysis of relationships between the key constructs: Perceived Impact on Workforce Performance (PEWP), Emotional Responses (ER), and Perceived Impact on Tourism and Hospitality (PETH) (De Vaus, 2014). This design focuses on identifying generalizable patterns and statistical associations within the sample, rather than the in-depth, idiosyncratic experiences that a qualitative approach would uncover.

4.2 Participants and Sampling

The target population for this research comprised individuals connected to the tourism and hospitality industry in Portugal. This included current employees across various functions as well as students enrolled in relevant academic programs who represent the near-future workforce. The inclusion of these diverse groups aimed to capture a broad spectrum of perspectives on the emerging role of AI in the sector.

A non-probability sampling strategy, combining both purposive and convenience sampling techniques, was utilized (Saunders et al., 2019). Purposive sampling was employed to intentionally target specific organizations and educational institutions known to be central to industry. Concurrently, convenience sampling was used to broaden participation by distributing the survey link through professional networks and accessible participant pools.

Table 1: Sample Distribution by Participant Group and Organization

Participant Group	Organization/Institution	Number of Questionnaires
Front Desk Staff	Marriott Hotels (Lisbon)	3
	Hilton Hotels (Porto)	3
	Sheraton Hotels (Algarve)	4
Managers	Marriott Hotels (Portugal)	4
	Hilton Hotels (Portugal)	4
	Pestana Hotel Group	2
	Accor Hotels	2
Employees	TUI Portugal	5
	Thomas Cook Portugal	5
	Mundicolor	5

IT & Digital Specialists	Capgemini Portugal	2
	Travelport Portugal	2
	Amadeus Portugal	2
	Salesforce Portugal	2
Students	University of Lisbon	7
	ESHTE (Estoril Higher Institute)	7
	ISCTE-IUL (University Institute of Lisbon)	6
Total		**66**

The final sample consisted of 66 individuals who provided complete questionnaire responses. While the non-probability sampling approach limits the statistical generalizability of the findings to the entire Portuguese tourism and hospitality industry, the diversity of roles and affiliations within the sample provides valuable exploratory insights.

4.3 Instrument Development

A structured questionnaire, developed specifically for this study, served as the primary instrument for data collection. The questionnaire was designed to be self-administered and comprised two main sections: demographic information and construct measurement. The core constructs - PEWP, ER, and PETH - were measured using a series of items rated on a 5-point Likert scale, ranging from 1 (Very Low) to 5 (Very High).

The development process followed established practices for survey design (Fowler, 2013). An initial pool of items was generated based on a detailed review of the academic literature presented in Chapter 2. Specifically, items for the Perceived Impact on Workforce Performance (PEWP) scale were informed by the "perceived usefulness" construct from the Technology Acceptance Model (Davis, 1989) and literature discussing AI's effect on productivity (Sandelin, 2024). Items for the Emotional Responses (ER) scale were derived from the Job Demands-Resources theory (Demerouti & Bakker, 2011), designed to capture both the resource aspect (efficiency gains) and the demand aspect (job displacement concerns, reskilling needs). Finally, items for the Perceived Impact on Tourism and Hospitality (PETH) scale were based on broader industry-level discussions concerning AI's transformative potential (Dwivedi et al., 2023; Carvalho & Ivanov, 2024).

This initial draft was subsequently reviewed for content validity and clarity by two academic professionals with expertise in information systems and one industry manager from the hospitality sector. A pilot test was then conducted with five individuals from the target population (two students, three employees). Feedback from the pilot test led to minor wording adjustments to improve comprehension and ensure the items were interpreted as intended.

4.4 Data Collection Procedures

The data collection phase was conducted over a period of three months. A mixed-mode approach was utilized, combining an online survey created with Google Forms and a limited number of paper-based questionnaires to maximize reach. Potential participants received an email invitation explaining the study's purpose and assuring confidentiality and anonymity. All participation was voluntary. Ethical protocols were strictly observed throughout the process, ensuring that collected data was treated confidentially, stored securely, and used solely for the purposes of this research project, in line with standard research ethics guidelines (Israel & Hay, 2012).

4.5 Data Analysis

The data were analyzed using IBM SPSS Statistics. The analysis proceeded in several stages, beginning with data preparation, followed by a critical reliability assessment of the measurement instrument, and concluding with inferential statistics to test the study's hypotheses. The reason for utilizing IBM SPSS Statistics for this research is because of the objective nature of the study, for a proper and in depth analysis of the variables, SPSS stands a great fit.

4.5.1 Data Preparation

The raw data was imported into SPSS, and preliminary data cleaning was performed. The dataset was anonymized, and variables were renamed for clarity. Demographic variables (Gender, Position, Age) were recoded into numerical formats suitable for use as factors in comparative analyses. Specifically, Age was converted into a categorical Age Group variable, and Position was converted into a numeric variable (Position_Num) to facilitate group comparisons.

4.5.2 Methodological Pivot: Addressing Scale Reliability Issues

A foundational step in any quantitative analysis that uses multi-item scales is the assessment of their internal consistency reliability. This procedure determines whether a set of items intended to measure a single latent construct do so in a consistent manner. The standard metric for this assessment is Cronbach's Alpha (α), which calculates the average correlation among items in a scale (Taber, 2018). An alpha coefficient ranges from 0 to 1, with higher values indicating greater reliability. According to established psychometric standards, a value of .70 is considered the minimum threshold for an acceptable, reliable scale in social science research.

The reliability analysis for this study's scales yielded a critical and determinative finding. While the Emotional Responses (ER) scale demonstrated good reliability, the scales for Perceived Impact on Workforce Performance (PEWP) and Perceived Impact on Tourism and Hospitality (PETH) fell well below the acceptable threshold. This result is not merely a statistical inconvenience; it is a methodologically significant finding that demands a principled change in the planned analytical strategy.

The low reliability of the PEWP and PETH scales suggests that the items within each scale did not consistently measure the same underlying concept for this sample. Several factors could explain this outcome. First, the constructs themselves may suffer from construct ambiguity. "Perceived impact," for example, may be too broad a concept, conflating distinct ideas such as impact on task efficiency, impact on job security, and impact on service quality. Respondents may have viewed these as separate, unrelated issues, leading to inconsistent responses across the items. Second, sample heterogeneity could be a contributing factor. The diverse sample, comprising students, front-line staff, and managers, may have interpreted the items through the lens of their unique experiences and roles, leading to a lack of shared understanding and, consequently, low internal consistency. This finding itself is a contribution of the study, highlighting the difficulty of measuring perceptions of a new, complex technology across a varied population.

4.5.3 Reliability Analysis and Justification of Analytical Strategy

The reliability scores for the three primary scales were as follows:

- Perceived Impact on Workforce Performance (PEWP): α = .504
- Emotional Responses (ER): α = .840
- Perceived Impact on Tourism and Hospitality (PETH): α = .257

Table 2: Cronbach's Alpha Reliability Test Result

Scale	Cronbach's Alpha (α)	N of Items	Reliability Assessment
Emotional Responses (ER)	**.840**	3	Good
Perceived Impact on Workforce Performance (PEWP)	**.504**	3	Not Reliable
Perceived Impact on Tourism & Hospitality (PETH)	**.257**	3	Not Reliable

This finding has a critical and non-negotiable implication for the analytical approach. The initial research plan had considered the use of Structural Equation Modeling (SEM), a powerful technique for testing complex theoretical models involving latent variables. However, the validity of SEM is predicated on the reliable measurement of its constituent latent constructs (Hair et al., 2021). Proceeding with an SEM analysis using scales with low reliability would constitute a severe methodological error. It would violate the fundamental assumptions of the technique and yield results that are statistically invalid and substantively uninterpretable.

Therefore, a data-driven and methodologically necessary decision was made to abandon the SEM approach. Instead, this study employs a more robust and appropriate strategy given the data's psychometric properties: Multiple Linear Regression and the PROCESS macro for SPSS. This revised strategy utilizes observed composite scores (the average of the items in each scale) and does not rely on the strong, and in this case unmet, assumptions of latent variable modeling. While this approach acknowledges the measurement limitations of the instrument, it allows for a rigorous and valid test of the research hypotheses based on the data as it was collected. This pivot ensures the analytical integrity of the study.

4.5.4 Hypothesis Testing and Comparative Analysis

Based on the justified analytical strategy, the following statistical procedures were used:

- Descriptive Statistics and Correlation: Frequencies, means, standard deviations, and a Pearson correlation matrix were computed to describe the sample and examine the initial bivariate relationships between variables.
- Mediation Analysis (H1, H2): To test the proposed mediation model, the PROCESS macro for SPSS (Model 4) was used (Hayes, 2018). This method estimates the direct and indirect effects in a mediation model and uses bootstrapping to generate robust confidence intervals for the indirect effect, which is the statistical test of mediation.
- Regression Analysis (H3, H4, H5): The remaining hypotheses were tested using a series of Multiple Linear Regression models to assess the predictive relationship between the independent and dependent variables.
- Comparative Analysis: To explore differences between demographic groups, Independent Samples T-tests (for Gender) and One-Way Analysis of Variance (ANOVA) (for Position_Num and Age_Group) were conducted.

CHAPTER 5 - DATA ANALYSIS AND RESULTS

This chapter presents the empirical results derived from the statistical analysis of the survey data. The chapter begins by detailing the descriptive statistics of the sample presented to provide context. The main body of the chapter is dedicated to reporting the results of the inferential statistical tests used to examine the research hypotheses, including correlation, regression, and mediation analysis. Finally, the results of comparative analyses across demographic groups are discussed.

5.1 Descriptive Analysis of Sample and Variables

The analysis was conducted on a final sample of 66 participants from the Portuguese tourism and hospitality sector.

Figure 2: Frequency Distribution of Demographic Characteristics

Table 3: Frequency Distribution of Demographic Characteristics

Characteristic	Category	Frequency	Percent
Gender	Female	41	62.1%
	Male	25	37.9%
	Total	**66**	**100.0%**
Age Group	20-30 years	37	56.1%
	31-40 years	15	22.7%
	41+ years	14	21.2%
	Total	**66**	**100.0%**

Position	Customer Service	27	40.9%
	Manager	17	25.8%
	Student	16	24.2%
	IT	4	6.1%
	Other	2	3.0%
	Total	**66**	**100.0%**

A note on the Company/School variable is warranted here. This variable is conceptually very interesting. One could hypothesize that the culture, policies, or technology adoption rates at a large international chain like Marriott might lead to different employee perceptions of AI compared to a domestic group like Pestana, or a university like ISCTE-IUL. This is a valid research idea. However, to test this hypothesis statistically (e.g., using an ANOVA to compare mean scores across companies), enough participants are required within each group. The sample distribution for this study, which includes groups as small as two or three participants from a single organization, makes such statistical comparison invalid. The results would lack statistical power and would be highly unreliable. Therefore, while this variable provides important descriptive context about the sample, it was not used for inferential statistical comparisons. This is a recognized limitation of the study and an avenue for future research.

5.1.2 Item-Level Descriptive Statistics

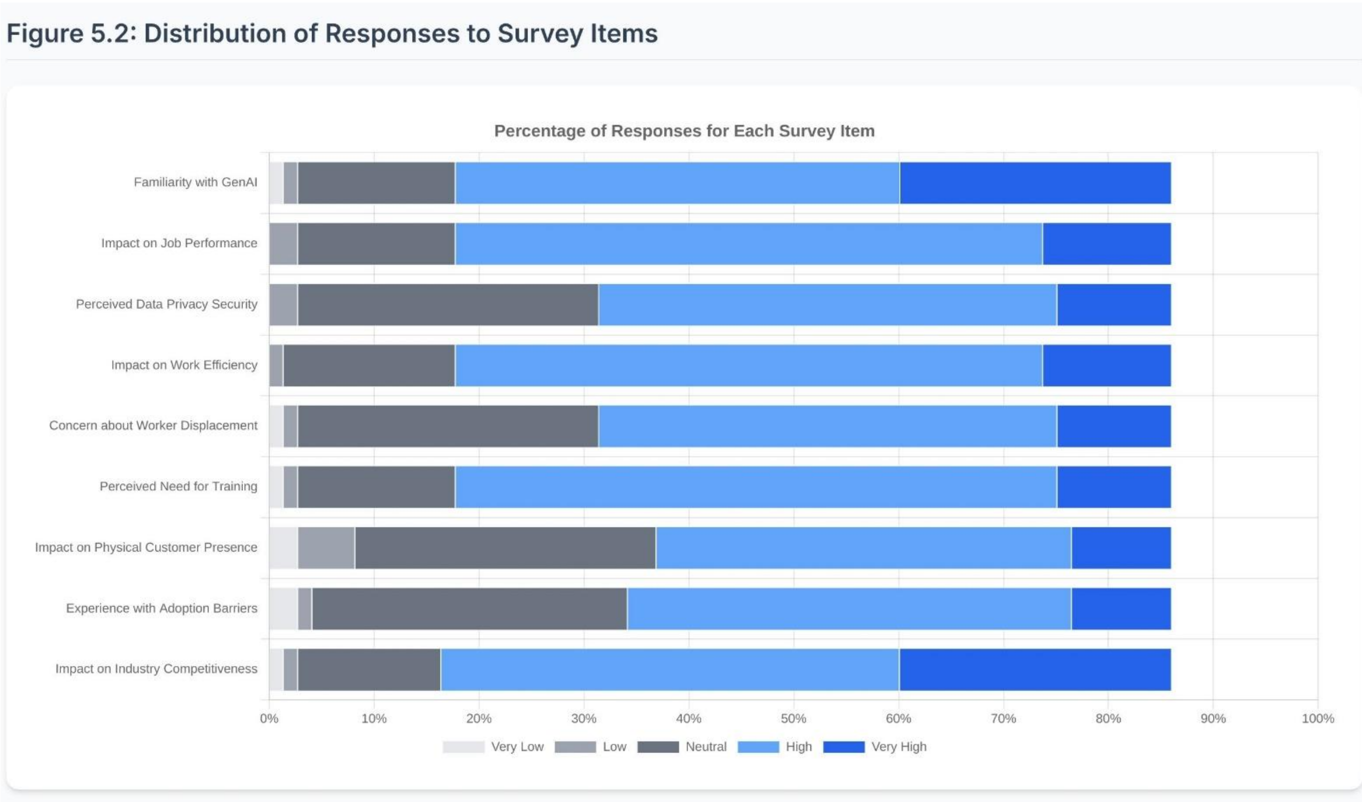
To provide a granular understanding of participant perceptions, the frequency distributions for each individual Likert-scale item are presented in Table 5.2. The responses show a strong consensus on several key issues. For instance, an overwhelming majority (92.4%) perceived AI's impact on industry competitiveness as "High" or "Very High" (PETH3). Similarly, large majorities perceived a positive impact on their work efficiency (ER1; 77.3% rated 4 or 5) and job performance (PEWP2; 75.8% rated 4 or 5), and saw a strong need for training (ER3; 70.0% rated 4 or 5). In contrast, responses regarding the impact on physical customer presence (PETH1) and experiences with adoption barriers (PETH2) were more varied, clustering around the "Neutral" point.

Table 4: Frequency Distribution of Responses for Each Survey Item (N=66)

Construct	**Item**	**1** (Very low)	**2** (Low)	**3** (Neutral)	**4** (High)	**5** (Very high)	**Mean (SD)**

PEWP	PEWP1	4 (6.1%)	4 (6.1%)	12 (18.2%)	22 (33.3%)	24 (36.4%)	3.88 (1.16)
	PEWP2	0 (0.0%)	4 (6.1%)	12 (18.2%)	29 (43.9%)	21 (31.8%)	4.02 (0.87)
	PEWP3	0 (0.0%)	5 (7.6%)	14 (21.2%)	23 (34.8%)	24 (36.4%)	4.00 (0.95)
ER	ER1	0 (0.0%)	4 (6.1%)	11 (16.7%)	30 (45.5%)	21 (31.8%)	4.03 (0.86)
	ER2	1 (1.5%)	7 (10.6%)	17 (25.8%)	24 (36.4%)	17 (25.8%)	3.74 (1.01)
	ER3	1 (1.5%)	4 (6.1%)	15 (22.7%)	25 (37.9%)	21 (31.8%)	3.92 (0.97)
PETH	PETH1	7 (10.6%)	14 (21.2%)	17 (25.8%)	22 (33.3%)	6 (9.1%)	3.09 (1.16)
	PETH2	8 (12.1%)	11 (16.7%)	15 (22.7%)	22 (33.3%)	10 (15.2%)	3.23 (1.25)
	PETH3	1 (1.5%)	1 (1.5%)	3 (4.5%)	22 (33.3%)	39 (59.1%)	4.47 (0.79)

Figure 3: Frequency Distribution of Responses for Each Survey Item



5.2 Correlation Analysis

A Pearson correlation analysis was conducted to examine the bivariate relationships between the three composite variables and age. The results, presented in Table 5.3, provide a preliminary test of the associations between the core constructs. A strong, statistically significant positive correlation was found between Perceived Impact on

Workforce Performance (PEWP) and Emotional Responses (ER) ($r = .604$, $p < .001$). A weaker, but still significant, positive correlation was found between PEWP and Perceived Impact on Tourism & Hospitality (PETH) ($r = .308$, $p = .012$). Age was not significantly correlated with any of the composite variables.

Table 5: Pearson Correlation Matrix of Composite Variables and Age

Variable	**1**	**2**	**3**	**4**
1. PEWP_Composite	--			
2. ER_Composite	.604**	--		
3. PETH_Composite	.308*	--		
4. Age	.197	.049	.133	--

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

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

5.3 Hypothesis Testing

The study's five hypotheses were tested using the justified analytical strategy of mediation and multiple regression analysis. A significant level of $p < .05$ was used for all tests.

5.3.1 H1 & H2: Mediation Analysis

The central mediational model was tested using the PROCESS macro for SPSS (Model 4), with 5,000 bootstrap samples. The model tested whether Emotional Responses (ER) mediated the relationship between Perceived Impact (PEWP) and Perceived Industry Impact (PETH), while controlling demographic variables. The results are summarized in Table 5.4.

- Hypothesis 1: The test for Path 'a' of the mediation model (PEWP → ER) provided strong support for H1. The effect of PEWP on ER was positive and highly significant ($\beta = .742$, $p < .001$).
- Hypothesis 2: The primary test for mediation is the significance of the indirect effect. The 95% bootstrapped confidence interval for the indirect effect ranged from -.180 to .244. As this interval contains zero, the indirect effect is not statistically significant. Therefore, H2 is not supported.

Table 6: Summary of Mediation Analysis Results (PROCESS Model 4)

Path	Dependent Var.	Predictor Var.	Coefficient (β)	Std. Error	t-value	p-value	95% CI
Path a	ER_Composite	PEWP_Composite	**.742**	.120	6.20	**<.001**	[.503, .981]
Path b	PETH_Composite	ER_Composite	.046	.130	0.35	.724	[-.214, .307]
Path c'	PETH_Composite	PEWP_Composite	.263	.155	1.70	.095	[-.047, .574]
Indirect Effect			**.034**	.107			**[-.180, .244]**

Note. β = unstandardized regression coefficient; SE = Standard Error; t = t-statistic; p = significance value; CI = Confidence Interval. Statistically significant results (p < .05) are shown in bold. The confidence interval for the indirect effect is a bootstrapped interval.

5.3.2 H3, H4, & H5: Direct Effects Analysis

The remaining hypotheses were tested using separate linear regression models. The results are summarized in Table 5.5.

- Hypothesis 3: The regression model predicting workforce productivity (proxied by ER1) from PEWP_Composite was statistically significant ($p < .001$). H3 is supported.
- Hypothesis 4: The regression model predicting industry competitiveness (proxied by PETH3) from PEWP_Composite was not statistically significant ($p = .166$). H4 is not supported.
- Hypothesis 5: The regression model predicting the need for reskilling (proxied by ER3) from PEWP_Composite was statistically significant ($p < .001$). H5 is supported.

Table 7: Summary of Linear Regression Models for Direct Effects

Hypothesis	Dependent Variable (Proxy)	Independent Variable	β	R²	F-statistic	p-value
H3	Work Efficiency (ER1)	PEWP_Composite	**.702**	.309	28.52	**<.001**
H4	Industry Competitiveness (PETH3)	PEWP_Composite	.186	.015	1.96	.166
H5	Reskilling Need (ER3)	PEWP_Composite	**.721**	.247	21.01	**<.001**

Note. β = Standardized Beta Coefficient; R^2 = R-squared (Coefficient of Determination); F = F-statistic from ANOVA test; p = significance value. Statistically significant results ($p < .05$) are shown in bold.

5.4 Analysis of Demographic Group Differences

A series of tests were conducted to explore whether perceptions of AI differed across key demographic groups. An independent samples t-test revealed no statistically significant differences between male and female participants on any of the three composite variables. Similarly, a one-way ANOVA found no statistically significant differences across the three age groups or the various job positions on any of the composite variables.

Table 8: Summary of ANOVA Results

Grouping Variable	Dependent Variable	F-statistic	df	p-value	Result
Age Group	PEWP_Composite	1.631	(2, 63)	.204	Not Significant
	ER_Composite	0.205	(2, 63)	.815	Not Significant
	PETH_Composite	1.839	(2, 63)	.167	Not Significant
Position	PEWP_Composite	0.650	(5, 60)	.662	Not Significant
	ER_Composite	0.669	(5, 60)	.649	Not Significant
	PETH_Composite	1.629	(5, 60)	.166	Not Significant

Note: Degrees of freedom (df) are presented as (df_between, df_within). A significance level of $p < .05$ was used.

A methodological note is warranted for the ANOVA by Position. SPSS issued a warning that post-hoc tests could not be performed. This is an expected outcome and a direct result of the study's sample composition. Post-hoc tests require a minimum of two cases in each group being compared. As some professional roles in the sample contained only one participant, these pairwise comparisons could not be validly executed. This reinforces the decision not to draw conclusions about differences between specific job roles. The modest overall sample size (N=66) also limits the statistical power to detect smaller effects or to conduct complex subgroup analyses.

5.5 Summary of Results

Table 5.7 provides a concise summary of the outcomes for each research hypothesis. The analysis confirms that while individual perceptions of AI's impact strongly relate to emotional reactions and adaptation needs, this does not appear to translate into a mediated effect on broader industry perceptions, nor does it directly predict perceptions of industry competitiveness within this dataset.

Table 9: Summary of Hypothesis Testing Results

Hypothesis	Relationship Tested	Statistical Test	Result	Conclusion
H1	PEWP → ER	Mediation (Path a)	p < .001	**Supported**
H2	PEWP → ER → PETH	Mediation (Indirect Effect)	CI contains 0	**Not Supported**
H3	PEWP → Productivity (ER1)	Linear Regression	p < .001	**Supported**
H4	PEWP → Competitiveness (PETH3)	Linear Regression	p = .166	**Not Supported**
H5	PEWP → Reskilling Need (ER3)	Linear Regression	p < .001	**Supported**

5.4 Deeper Analysis of Mediational Pathways

While the primary hypothesis tests provide clear outcomes, a more granular examination of statistical models offers a deeper understanding of the underlying relationships between constructs. This section explores two nuanced findings from the analysis that explain the failure of the mediation hypothesis (H2) and suggest a more complex relationship between individual perceptions and industry-level assessments.

5.4.1 The Non-Significant Link Between Emotional Response and Industry Perception

The conceptual model proposed that an employee's emotional response (ER) mediate the relationship between their perception of individual impact (PEWP) and their perception of the broader industry impact (PETH). A prerequisite for mediation is a statistically significant relationship between the mediator (ER) and the dependent variable (PETH). The correlation analysis, however, reveals that this foundational link is absent in the data.

Table 10: Pearson Correlation Matrix of Core Constructs

Variable	1	2	3
1. Perceived Impact (PEWP)	--		
2. Emotional Response (ER)	.604**	--	
3. Industry Impact (PETH)	.308*	.219	--

**. Correlation is significant at the 0.01 level (2-tailed).*
. Correlation is significant at the 0.05 level (2-tailed).

As shown in Table 5.6, the Pearson correlation coefficient between Emotional Response (ER) and Perceived Industry Impact (PETH) is $r = .219$, with a significance value of $p = .077$. As this p-value is greater than the .05 threshold, the relationship is not statistically significant.

This finding is methodologically critical as it explains the failure of the mediation hypothesis. The proposed causal chain is broken at the final step. Substantively, this result suggests a cognitive separation between how employees feel about generative AI and how they analyze its industry-wide implications. Their emotional reactions—encompassing both excitement about efficiency and anxiety about job security—appear to be a distinct psychological domain from their analytical assessment of the technology's impact on the industry's competitive structure. This challenges the assumption that personal feelings directly translate into broader strategic analysis and provides a key insight for managers: addressing employee sentiment and explaining industry strategy may be two separate, though related, communication challenges.

5.4.2 The Significance of the Total Effect and Evidence of Indirect Effects

The PROCESS macro facilitates a comparison between the "total effect" of an independent variable on a dependent variable and the "direct effect" when a mediator is included. This comparison provides compelling evidence that while the specific mediator tested (ER) was not significant, the relationship between individual and industry perceptions is indeed indirect.

Table 11: Comparison of Total and Direct Effects of PEWP on PETH

Model	**Predictor**	**Effect (β)**	**Std. Error**	**t-value**	**p-value**	**95% CI**
Total Effect Model	PEWP_Composite	.298	.121	2.46	.017	[.056, .539]
Direct Effect (in Mediation Model)	PEWP_Composite	.263	.155	1.70	.095	[-.047, .574]

Note: The Total Effect Model regresses PETH on PEWP and covariates. The Direct Effect is the effect of PEWP on PETH in the full mediation model that includes ER as a predictor.

The results in Table 5.7 reveal a methodologically significant pattern. The total effect of Perceived Impact on Workforce Performance (PEWP) on Perceived Industry Impact

(PETH) is statistically significant (β = .298, p = .017). This indicates that a direct relationship exists between these two constructs. However, when the mediator (Emotional Response) is introduced into the model, this relationship weakens, and the direct effect becomes non-significant (p = .095).

This pattern, where a significant total effect becomes non-significant after adding a mediator, is considered classic evidence of an indirect effect (Hayes, 2018). Although this study did not identify the correct mediating variable, the analysis strongly suggests that one exists. The relationship between how employees perceive AI's impact on their own job and how they view its impact on the industry is not direct; it is channeled through some other factor. This refutes a simplistic direct-effects model and provides a clear, data-driven mandate for future research to investigate other potential mediators, such as an employee's perception of their organization's innovative capacity or their confidence in leadership's strategic vision.

CHAPTER 6 – CONCLUSIONS, LIMITATIONS AND SUGGESTIONS FOR FURTHER RESEARCH

The integration of Artificial Intelligence (AI) into the tourism and hospitality industry is not merely an emerging trend but a reality that is fundamentally reshaping workforce dynamics. This study sought to bridge the gap in empirical literature by assessing the complex interplay between employees' perceived impact of Generative AI on their performance, their emotional responses, and their broader perceptions of industry transformation. Guided by the Technology Acceptance Model (TAM) and the Job Demands–Resources (JD-R) framework, the research has provided evidence-based insights into how the workforce is cognitively and emotionally processing this technological disruption.

Based on empirical analysis, it is definite that the introduction of Generative AI elicits a significant emotional response from the workforce. The rejection of the first null hypothesis confirms that employees who perceive AI as highly impactful on their daily tasks do not remain passive; rather, they exhibit strong emotional reactions that include a mix of performance-related optimism and adaptation-related anxiety. This underscores that AI adoption is as much a psychological process as it is a technical one.

However, the findings regarding the mediational model offer a nuanced and critical insight. The failure to reject the null hypotheses regarding the link between emotional responses and industry perception implies a distinct cognitive separation among the workforces. It appears that employees possess the capacity to compartmentalize their personal emotional adaptation challenges from their objective assessment of AI’s strategic value to the industry. The perceived transformation of the tourism and hospitality sector is driven by direct assessments of utility and competitiveness, rather than being filtered through the lens of individual emotional sentiment. This outcome challenges the assumption that workforce anxiety will necessarily cloud strategic judgment or lead to resistance against industry-level innovation.

In summary, while the workforce acknowledges the profound personal and emotional adjustments required by Generative AI, this does not diminish their recognition of its transformative potential for the sector. The successful integration of AI education and practice in tourism and hospitality is, therefore, contingent upon acknowledging these distinct cognitive domains: supporting the individual emotionally while engaging the professional strategically.

Considering the findings, the following recommendations are offered for industry stakeholders, educators, and policymakers:

1. Dual-Track Change Management: Organizations should implement change management strategies that address emotional support (counseling, reassurance regarding job security) separately from strategic communication (industry competitiveness, market trends), as employees process these distinctively.
2. Targeted Reskilling Initiatives: Given the strong link between impact and emotional response, educational curricula must move beyond technical training to include "AI adaptability" and emotional resilience, preparing graduates for the psychological demands of human-AI collaboration.
3. Strategic Policy Formulation: Policymakers and industry leaders should leverage the workforce's objective view of industry impact to push for aggressive AI adoption policies, knowing that personal anxiety does not necessarily equate to strategic opposition.

This study contributes to the body of knowledge by empirically testing a mediational model of AI perception in the Portuguese context. It provides a theoretical refinement to technology acceptance literature by demonstrating the limits of effect (emotion) as a mediator in professional settings, highlighting the rationality of the hospitality workforce in evaluating technological change.

6.1 Summary of Key Findings

This study utilized a quantitative survey approach to gather data from 66 individuals within the Portuguese tourism and hospitality sector. A preliminary reliability analysis confirmed that while the scale for Emotional Responses (ER) was robust, the scales measuring Perceived Impact on Workforce Performance (PEWP) and Perceived Impact on Tourism and Hospitality (PETH) were not. This critical finding necessitated an adaptation of the analytical strategy, moving from a planned Structural Equation Model to a more appropriate series of multiple linear regression and mediation analyses. The main empirical findings are summarized below in direct relation to the research questions that guided the study.

The first research question sought to understand how employees perceive the impact of generative AI on their individual job performance and work efficiency. The findings indicate a generally positive perception. Descriptively, a large majority of participants rated the technology's impact on their work efficiency (77.3% rated 'High' or 'Very High') and overall job performance (75.8% rated 'High' or 'Very High') favorably. This was substantiated by the inferential analysis for Hypothesis 3, which found a strong, statistically significant positive relationship between the perceived impact of AI and self-reported work efficiency.

The second research question examined the relationship between employees' perceptions of AI's impact and their multifaceted emotional responses. The results for Hypothesis 1 demonstrated a strong, positive, and statistically significant association between Perceived Impact on Workforce Performance (PEWP) and the Emotional Responses (ER) construct. This confirms that as employees perceive technology to be more consequential to their work, the intensity of their cognitive and affective reactions - which encompasses positive feelings about efficiency as well as negative concerns about displacement and adaptation demands also increases.

The third research question focused specifically on the link between perceived AI impact and the need for adaptation. In line with this, the test for Hypothesis 5 revealed a significant positive relationship between Perceived Impact on Workforce Performance (PEWP) and the perceived need for workforce reskilling. This finding indicates that participants who see AI as more impactful are also more likely to recognize that training and skill development are essential for the workforce to adapt effectively.

Finally, the fourth research question explored the potential for emotional responses to mediate the relationship between individual perceptions and broader industry outlooks. The study's central mediation hypothesis (H2) was not supported by the data. The analysis found no significant indirect effect of perceived individual impact on perceived industry impact through the channel of emotional responses. This suggests that, for this sample, an employee's personal feelings about AI do not appear to be the mechanism that explains their broader views on the industry's transformation. Furthermore, the analyses revealed no statistically significant differences in perceptions or emotional responses based on participants' gender, age group, or professional position.

In essence, the empirical results paint a clear picture of a workforce that recognizes the individual-level productivity benefits of generative AI and understands the concurrent need for personal and collective adaptation, even if these individual perceptions do not directly translate into a mediated view of the industry's future.

6.2 Implications and Contributions of the Study

This research offers several distinct contributions to the academic and practical understanding of generative AI's integration into the service sector.

6.2.1 Theoretical Implications

From a theoretical perspective, the study's findings lend empirical support to established frameworks within the new context of generative AI. The significant relationships found for H1, H3, and H5 align well with the core tenets of the Technology Acceptance Model (TAM) and the Job Demands-Resources (JD-R) theory. The findings demonstrate that perceived usefulness (a core component of TAM) is a strong predictor of user reactions and adaptation needs. The dual finding of perceived efficiency gains (a job resource) and a strong need for training (a new job demand) fits squarely within the JD-R perspective.

Furthermore, the non-significant mediation result for H2 offers a nuanced contribution to theory. It suggests that the cognitive pathway from an individual's personal experience with technology to their broader, industry-level assessment is not straightforward. The lack of a mediating effect of emotional responses implies that personal feelings about AI (e.g., excitement, anxiety) and analytical assessments of its industry-wide impact may be separate cognitive domains. It is plausible that an individual's assessment of the industry's competitive landscape is driven more by rational analysis of market trends than by their personal emotional state. These finding challenges simplistic models of influence and suggests a more complex relationship between individual affect and macro-level perception.

6.2.2 Managerial Implications

From a practical and managerial perspective, the findings provide a clear, actionable agenda for organizations in the tourism and hospitality sector.

1. Adopt a Two-Pronged Implementation Strategy: The strong support for both H3 (impact on productivity) and H5 (need for reskilling) indicates that a successful AI implementation strategy must be dual-focused. Managers must actively promote and demonstrate the efficiency benefits of AI to secure employee buy-in. Concurrently, they must invest proactively and substantially in training programs to address the skills gap that employees themselves clearly perceive.
2. Manage the Socio-Technical Transition: The strong support for H1 (impact on emotional responses) highlights that AI adoption is a socio-technical issue, not a purely technical one. Organizations must manage the emotional component of this transition. This requires transparent communication about AI's intended role, clear articulation of how it will augment rather than replace human employees, and direct engagement with concerns about job security to foster a positive environment for adaptation.
3. Leverage Change Management Principles: The challenges identified by employees align with classic organizational change management theory. Leaders should apply structured models, such as Kotter's (1996) 8-Step Process, to guide

the transition. This includes creating a sense of urgency, forming a guiding coalition of AI champions, communicating the vision consistently, and celebrating short-term wins to build momentum.

6.2.3 Educational Implications

For educators and institutions preparing the next generation of hospitality professionals, the findings underscore an urgent mandate for curriculum reform. The strong perceived need for reskilling among current professionals signals a clear demand from the industry. Academic curricula must be updated to include:

- Digital and AI Literacy: Foundational knowledge of how AI systems, particularly LLMs, function.
- Human-AI Collaboration Skills: Training on how to work effectively with AI tools, including prompt engineering and the critical evaluation of AI-generated content.
- AI Ethics and Responsible Implementation: In-depth discussion of the ethical challenges related to data privacy, algorithmic bias, and transparency in AI-driven service encounters.

Failure to integrate these topics will leave graduates unprepared for the technological realities of the modern tourism and hospitality workplace.

6.3 Limitations of the Study

A rigorous and honest appraisal of this study's limitations is essential for contextualizing the findings and informing future research.

First, the most significant limitation of this research was the utilization of a single quantitative approach which limited the degree of resourcefulness to numerical data only, a qualitative approach also should have given in-depth analysis and captured detailed perceptions of employees based on their experiences and collaboration with AI/ChatGPT.

Second, the study utilized a non-probability sample of 66 participants. While adequate for the regression analyses performed, this modest sample size limits the statistical power to detect more subtle effects that might exist in the population. Furthersmore, the use of convenience and purposive sampling means the results cannot be statistically generalized to the entire population of tourism and hospitality professionals in Portugal. The findings are representative only of the sample studied.

Finally, the study relied on self-report measures for all variables including productivity, thereby limiting its focus on key industry indicators such as revenue and profitability.

6.4 Suggestions for Future Research

Based on the findings and limitations of this study, several clear and productive avenues for future research emerge.

The most critical need is for the development and rigorous validation of robust survey instruments designed to measure perceptions of generative AI in the workplace. The measurement issues encountered in this study highlight a significant gap. Future research must move beyond ad hoc item creation and undertake a formal, multi-phase scale development study. Such a study should include:

1. Phase 1 (Item Generation): Conduct in-depth qualitative interviews with a diverse group of hospitality professionals (e.g., hotel managers, event planners, front-desk staff) to generate a rich pool of items that capture the nuanced ways they perceive AI's impact.
2. Phase 2 (Exploratory Factor Analysis): Administer the initial item pool to a pilot sample and use Exploratory Factor Analysis (EFA) to identify the underlying factor structure of the "perceived impact" construct. This would reveal whether it is a single concept or composed of multiple distinct dimensions (e.g., impact on efficiency, impact on creativity, impact on guest interaction).
3. Phase 3 (Confirmatory Factor Analysis): Administer the refined scale to a new, larger sample and use Confirmatory Factor Analysis (CFA) to validate the factor structure identified in the EFA, confirming the scale's construct validity and reliability.

This study examined how generative AI, particularly ChatGPT, is influencing workforce dynamics in the tourism and hospitality sector. Findings show that employees generally view AI as a tool that enhances efficiency and productivity but also recognize the need for continuous reskilling to meet technological demands. While AI's role in boosting individual performance is clear, its broader impact on industry competitiveness requires further exploration.

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