Acceptance of AI by hospitality professionals

Bachelor Thesis for Obtaining the Degree

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Tourism, Hotel Management and Operations

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Affidavit

I hereby affirm that this Bachelor's Thesis represents my own written work and that I have used no sources and aids other than those indicated. All passages quoted from publications or paraphrased from these sources are properly cited and attributed.

The thesis was not submitted in the same or in a substantially similar version, not even partially, to another examination board and was not published elsewhere.

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Abstract

This bachelor thesis investigates the underlying relationships of the acceptance of AI tools by professionals in the hospitality industry. The aim of this paper is to find the nexuses between the concepts of training and communication by management to the perceived usefulness of AI tools by employees. Furthermore, the moderation of the mandated use by decision makers towards the aforementioned nexuses is examined before the relationship between the perceived usefulness and the intended duration and frequency of usage of AI tools in a professional setting is studied. The findings of this study support the strong positive relationship between the provision of training and positive communication towards the perceived usefulness of AI technology while not displaying a moderating effect by making usage of AI tools mandatory. The intended frequency of usage is found to be positively related with perceived usefulness while the intended duration of usage is found to be not related. Implications made to management suggest an emphasis as a supporting role by supplying adequate levels of training and a continuous high level of positive communication should the implication of AI be made into the respective hospitality company. Limitation of the study are being acknowledged and implication for future research on how to overcome those as well as how to expand in this study are given.

Table of Contents

Affidavit 2

Abstract 3

Table of Contents 4

List of Figures 6

List of tables 6

1 Introduction 7

1.1 Research Questions: 9

2 Literature review 9

2.1 AI 9

2.1.1 Definition of AI 9

2.1.2 Subfields of AI 11

2.2 Hospitality industry 14

2.2.1 History 14

2.2.2 Acceptance in Hospitality 15

2.2.3 Specialized Technology applications tailored to the hospitality industry 15

2.3 Technology acceptance – planned behaviour/technology acceptance theory 20

2.3.1 Voluntariness and mandated use by management 22

2.3.2 Perceived usefulness 23

2.3.3 Intention of Use 23

2.4 Research Model and Hypotheses 24

3 Methodology 25

3.1 Study design 26

3.2 Data Collection & Measures 26

3.3 Limitations ... 31

3.3.1 Limitation in sample size ... 32

3.3.2 Motivation bias ... 32

3.3.3 Lack of language selection ... 32

3.4 Research ethics ... 32

4 Data Processing and Results ... 33

4.1 Data processing ... 33

4.1.1 Data cleansing ... 33

4.1.2 Concept consisting of multiple items ... 34

4.1.3 Shapiro-Wilk Normality Test ... 34

4.2 Descriptive Analysis ... 35

4.3 Hypothesis testing ... 36

4.3.1 Hypothesis H1 ... 37

4.3.2 Hypothesis H2 ... 37

4.3.3 Hypothesis H3 ... 38

4.3.4 Hypothesis H4 ... 39

4.3.5 Hypothesis H5 ... 40

4.3.6 Hypothesis H6 ... 40

5 Discussion ... 41

5.1 Theoretical implications ... 41

5.2 Managerial implications ... 43

5.3 Limitations ... 43

5.4 Further research ... 44

6 Bibliography ... 44

Appendices ... 58

Survey Questionnaire ... 58

List of Figures

Figure 1: Research model 24

List of tables

Table 1: Constructs and Questionnaire items 30
Table 2: Descriptives 35
Table 3: Spearman's rho correlation matrix for H1 and H2 38
Table 4: Moderation of mandated use on training and communication 39
Table 5: Spearman's rho correlation matrix for H5 and H6 41

1 Introduction

The hotel and resort industry with a global market size of over 1.5 trillion USD pre-COVID in 2019 and a forecasted 1.21 trillion USD in 2023 with a tendency towards long term-growth is an industry with significant importance (statista, 2023). The hospitality industry has only slowly been reshaped by technology. It started in 1988 by adopting the first revenue management systems, heavily based upon SABRE which rose to great success within the airline industry only ten years prior in administration (Stuart-Hill, 2021). The operational part of the hospitality industry did not take all too long to catch up as the first automated bartending machines were tested and introduced in the early 1990s to save on liquor and labour costs in casinos based in Atlantic City, USA (waiting for full paper to be shared). Artificial intelligence and its possible application within managerial roles have been discussed in the 20th century with it given a mere supporting character(Jakubczyc & Owoc, 1998) With time technologies became more advanced and in recent times the application of artificial intelligence (AI) within different sectors of the hospitality industry has become more prevalent (Citak et al., 2021). Research in this field thus far has mostly covered customer-facing applications as AI enables the user to more easily deliver personalized services (Citak et al., 2021) and the usage of AI in smart hotels, a new style of hotels focused on making the greatest use of technology which has seen great investments from major corporations in the likes of Marriott International, Hilton and the Shangri-La Group who cooperated with tech-companies to spearhead the innovation (Yang et al., 2021). When changing the perspective from corporate decisions to decisions being made by individuals a difference in likelihood can be seen as individual managers, as suggested by the Unified Theory of Acceptance and Use of Technology (Marikyan & Papagiannidis, 2023). Individuals often act based on personal attributes, something corporations, due to the fact of them being a legal structure, lack. Therefore, a difference in adoption can be hypothesized while bringing up the question of the exact reason for the slower adoption of new technologies, which itself would benefit businesses who want to adopt and integrate new technologies as AI into their daily procedures to enhance efficiency and profitability. This furthermore may be hypothesized to be linked to key factors of successful integration of digital transformation being in place or their absence (de la Boutetière et al., 2018). De la Boutetière et al. 2018 further conducted that less than 30 per cent of digital transformations in companies were successfully leading to enhanced profitability and a positive return on investment. Those key success factors having a correlation with the successful integration of technology bear resemblance with the theory of planned behaviour by Ajzen, 1985, 1987, 1991, suggesting that the success of the integration of AI technology has a significant correlation with the intention of each individual employee which itself is formed by: 1) the attitude towards the behaviour, 2) the subjective norm, and 3) the perceived behavioural control.

With most research being conducted on the operational aspects of hotels the administrative part is often left without any further mention. This might be due to the fact that positions in the hospitality sector are among the positions most unlikely to be replaced by AI due to the unpredictable nature of the work environment (Chui et al., 2016). While AI tools with general applicability like automated meeting transcription tools (Alter, 2022) and algorithmic management technologies, which apply simple artificial intelligence,(Spektor et al., 2023) are being discussed within and outside of the hospitality industry, the overall active usage of AI technology, the individuals reasoning behind the usage or non-usage as well as the possible increased perceived productivity is yet to be discussed in academics.

This thesis aims to explore to what extent AI technology has been adapted into everyday practices of young industry professionals in the hospitality industry and how this affects overall work productivity by taking over repetitive tasks and therefore freeing up time. This furthermore gives decision-makers in the hospitality industry an overview of where on the Rogers Innovation Adoption Curve they and their company currently are located and if immediate action would be suggested. Taking into consideration the theory of planned behaviour and the key success factors of digital transformation, preliminary managerial suggestions regarding communication for companies wanting to include AI into their daily business towards how this can be achieved with the highest chance of success (Ajzen, 1991; de la Boutetière et al., 2018). Furthermore, it displays how reasonable a digital transformation might be regarding the return on investment as suggested by De la Boutetière et al. 2018

1.1 Research Questions:

RSQ1: To what extent has AI technology been made use of by young industry professionals in the hotel industry?

RSQ2: How much do social influences initiated by corporations affect the acceptance of AI?

RSQ3: How does the non-voluntariness of usage of AI tools affect the acceptance and perceived productivity compared to voluntary use?

RSQ3: How has the adoption of AI technology by young industry professionals in the hotel industry affected perceived productivity?

RSQ4:

2 Literature review

2.1 AI

2.1.1 Definition of AI

John McCarthy was the first person to use the word Artificial Intelligence (AI) to describe computer software with the same complexity and characteristics found in a human brain during the Dartmouth Conference in 1956(Tussyadiah, 2020). Over the years and decades since a multitude of definitions have emerged, often connected to recent technological accomplishments. Ranging from computers displaying human intelligence (Rich & Knight, 1991) and providing intelligent complexity to computers (Nilsson, 2014) to stating that it is neither pure psychology nor computer science as it emphazises perception, action, reasoning and computation(Pannu, 2015). A common consensus can be formed, that of AI being a complex combination of the fields of Mathematics, psychology, philosophy, linguistics, computer science and information engineering that is capable of surpassing human abilities shown in AI playing chess and GO(Chen, 2019; Pannu, 2015).

A more detailed definition is given by (Russell & Norvig, 2021) who discuss different definitions of AI and built their definition using those. Especially as prior research has shown differences in defining the term intelligence either in terms of human performance or adopting a more abstract idea called rationality. The dual perspectives of human vs. rational and thought vs. behaviour have led to four combinations of 1 Thinking humanly, 2 Thinking rationally, 3 Acting humanly and 4 Acting rationally, each supported by diverse adherents and research programs. The pursuit of human-like intelligence involves empirical science related to psychology, while a rationalist approach relies on mathematics and engineering. Despite differences, these approaches have both criticized and supported each other (Russell et al., 2010; Russell & Norvig, 2021)

Acting humanly is a parameter which can be tested with the Turing test, proposed by (Turing, 1950) by testing the computer's ability to make a human interrogator, through the form of written answers to questions asked, believe that he is communicating with a person instead of a computer. This would require specialized capabilities in the fields of natural language processing, knowledge representation, machine learning and automated reasoning (Russell & Norvig, 2021). Further implementation of the factors of interaction with objects and different humans are being made by researchers but seen as not necessary by Turing to demonstrate intelligence.

To define the quality of thinking humanly we must know how humans think, which itself is a current field of research for cognitive scientists with a consensus on a clear definition of what makes thinking human not being universally found yet (Wilson & Keil, 1999).

Rationality, as defined by (*Cambridge Dictionary*, 2023) is “the quality of being based on clear thought and reason, or of making decisions based on clear thought and reason”. This quality of thinking rationally could be attributed to computers from 1965 as they were already capable of solving any solvable problem as long as they were supplied with the correct data as well as the correct coding.

The one thing lacking in those solutions was the understanding of the surroundings and the rules which sometimes are not defined like in the case of politics or human behaviour, this can be supplemented by the theory of probability resulting in logical and rations decisions, but not intelligent behaviour as this demands rational behaviour (Minsky & Papert, 1987) as cited in (Russell & Norvig, 2021). Complete rational behaviour, or rational acting, according to (Russell & Norvig, 2021) can seldomly be achieved due to the lack of a perfect rational environment with human decisions often being influenced by factors other than rationality as well as the enormous computational demands leading to limited rationality, a more resource appropriate approach to AI.

2.1.2 Subfields of AI

AI nowadays is being used in countless applications with different features and functions being enabled by AI. It has evolved from "computations that make it possible to perceive, reason and act"(Winston, 1992) into a highly complex construct having its foundation built upon deep learning and machine learning with four concentrated subfields of natural language procession (NLP), computer vision, robotic processing automation (RPA) and specialized expert systems (Huang et al., 2022).

2.1.2.1 Machine learning

Machine learning, one of the foundations of AI, is referring to the ability of a computer to precisely predict outcomes by using pre-selected algorithms to process input data. This input data can be divided into two groups, structured and unstructured data, with data in tabular form being referred to as structured data and data in forms such as images, text files audio files, or a combination of those being referred to as unstructured data. The aforementioned algorithms being made use of in machine learning can also be divided into three subcategories unsupervised learning, semi-supervised learning, and supervised learning. The difference between those categories lies in the amount of input data being labelled and linked to output data with supervised learning having all input data labelled, semi-supervised having a small amount of data labelled and unsupervised learning having no data labelled at all.(Huang et al., 2022; Neapolitan & Jiang, 2018)

2.1.2.2 Deep learning

The approach to machine learning mimicking the functioning of the human brain by making use of artificial neural networks is called deep learning. This approach is capable of handling extensive datasets featuring numerous attributes or varying formats. The aforementioned artificial neural networks contain numerous neural units that react to each other via stimuli being sent and received by single units with the counterparts responding accordingly. The architecture of a neural network may be single-layered or multi-layered, with multi-layered structures consisting of input, output, and intermediate layers, commonly referred to as hidden layers. The communication of stimuli from the input layer to the output layer occurs through these hidden layers. Deep learning serves as a foundation for two specialized domains within AI: computer vision and natural language processing (NLP). This is made possible due to the ability of deep learning to process multiple layers of data simultaneously and effectively during the learning process, a critical capability when dealing with unstructured data such as images and natural language (Neapolitan & Jiang, 2018; Taulli, 2019).

2.1.2.3 Natural Language Processing

Natural Language Processing's (NLP) focus is on the comprehension and generation of text and speech in natural languages by machines. This can be achieved by its focus on the reverse-engineering of the human language acquisition process. A thorough preparatory phase involves the collection, archiving, and comprehension of existing linguistic rules. Initially, the composition of a given text is examined to establish a linguistic structure, which is subsequently employed for semantic analysis to discern its literal meaning which itself is used in a pragmatic interpretation to identify contextual nuances within. NLP has found various applications including speech recognition, automated translations, message-understanding systems, text critiquing, synthesis-generated speech, and information retrieval, catering to multiple languages with a famous example being ChatGPT (Chowdhury, 2003; Zharovskikh, 2023)

2.1.2.4 Computer vision

Analysing and describing objects from strictly visual data is made possible due to a specific AI technique called computer vision. This technique requires a substantial foundational understanding of the deconstruction of objects' properties including shape, colour, transparency, size, illumination and layers, followed by the reconstruction of these attributes into complex packages defining distinct objects. In the context of the hospitality and tourism industry, computer vision finds applicability in managing vast quantities of images through processes such as naming, filtering, and categorization. Instances of use include patrolling robots capable of scanning license plates and search/booking engines that can automatically identify room types (Huang et al., 2022; *Knightscope*, 2023; Yao, 2018)

2.1.2.5 Robotic Process Automation

Robotic Process Automation (RPA), in contrast to physical robots, describes software that facilitates the operation of virtual bots. It acts as a visual drag-and-drop system designed to automate various duties, including but not limited to invoicing, refunding customers, and the provision of standardized responses to clients. It is essential to note that RPA, on its own, does not fall within the domain of AI. However, when integrated with AI tools, RPA assumes a distinct technical domain known as cognitive robotic process automation. This integrated approach is commonly employed in commercial chatbots. This combination enables the execution of various functions such as human-like communication and issuing of real-time alerts.(Huang et al., 2022; Taulli, 2019)

2.1.2.6 Expert systems

Expert systems, the fourth subfield of AI is a collection of systems that are designed and programmed to handle highly specialized knowledge and data. Those systems require three components distinguishing them from others: domain knowledge of an expert as input data, the inference engine, and an end-user capable of using the output data. They furthermore do have special characteristics of being capable of using qualitative data and not being restricted to quantitative input data, being able to be enhanced and expanded based on the level of input data by an expert as well as its capability of using even uncertain and unreliable information or missing data when being adjusted correctly. Currently, there are only restricted applications for those systems as they have shown to be challenging during testing phases and unlike other systems are not capable of applying machine- and deep learning to the same extent as to improve themselves over time but rather need to be supported with new data to facilitate improvement (Bahrammirzaee, 2010; Taulli, 2019).

2.2 Hospitality industry

2.2.1 History

The hospitality industry has roots dating back to 1800 B.C. with it first being mentioned in the Code of Hammurabi. During the Roman Empire the expansion of road systems made travelling easier which led to taverns and Inns offering overnight accommodation being a more common sight along those routes. Centuries later, during the middle ages when taverns were housing pilgrims on their journeys through foreign terrain and countries, lodging quickly developed into its own industry with The Olde Bell, an Inn near Slough in the United Kingdoms being opened in 1135, still being operated today being a contemporary witness (Barrows, 2008; 'History', n.d.). In the early 19th century, with the evolution of railroads and stagecoach travel, early hotels like the City Hotel and the Tremont House opened their doors in Colonial America in 1826 and 1829 respectively, the bedrock was laid for the international success of the hospitality industry (Barrows, 2008).

Nowadays tourism, in which the hospitality industry plays a critical role, has moved on from consisting of simple pilgrimages and travelling vendors to being a well-respected worldwide economic sector. While constantly growing year by year and only having temporary dips in demand following economic recessions, tourism has placed itself on the international landscape with a contribution of over 9.500 billion USD to the annual global GDP 2021 alone (statista, 2022)

2.2.2 Acceptance in Hospitality

To understand the difficulty of a uniform technology adoption within the hospitality industry as a whole, we must first understand its complex structure with a plentitude of combinations of diverse management contracts and franchise agreements and privately held components (Cobos et al., 2016; B. B. Stringam & Gerdes, 2017). Once characterized by a landscape of exclusively independent parties, the hotel industry has evolved to have diverse ownership and management structures combined with chain affiliations. Broadly, hotels and companies in the hospitality sector can be classified into distinct categories: 1) Independently owned and operated properties; 2) Independently owned and operated hotels with brand affiliations; 3) Independently owned properties managed by a management company, with or without brand affiliations; 4) hotels owned and managed by multi-property chains; and 5) properties affiliated with referral groups or consortia. To give an example, an independently owned hotel might possess both a management contract for brand affiliation with an international hotel chain while holding a management contract with a regional third party. Notably, most major international hotel chains engage in both management contracts and brand affiliations, thereby adding layers of complexity to the industry's structure. This complexity has also been shown to be impacting other factors like wages, job quality and labour standard violations(Batt & Nohara, 2009; Bernhardt et al., 2016; Dube & Kaplan, 2010; Ji & Weil, 2015) as cited in (Spektor et al., 2023). Examples of this are being displayed in the difference between smaller regional companies and international cooperations when it comes to overall budget and resources as well as flexibility in the adoption of new technologies. While larger companies may have the superior monetary means and manpower to research and test new technologies, their multi stage decision-making process involving a plentitude of stakeholders hinders them significantly in spearheading innovative technology adoption within a short period of time compared to their smaller counterparts (Cobos et al., 2016; B. Stringam & Gerdes, 2021).

2.2.3 Specialized Technology applications tailored to the hospitality industry

Applications and software making use of new technology available in the hospitality and tourism industry are plentiful and the market is growing exponentially with many more products entering the market every year. (Huang et al., 2022) identified different major types of software and tools made specifically for the hospitality sector using new technology with most of them making use of AI tools and categorized them into five categories as well provided examples with all of them being mentioned by at least two individual reputable sources. The categories are the following:: “(1) search/booking engines, (2) virtual agents/chatbots, (3) robots and autonomous vehicles, (4) kiosks/self-service screens and (5) AR/VR devices.”(Huang et al., 2022)

2.2.3.1 Booking and Search Engines:

AI-supported search and booking agents make use of NLP, machine learning and computer vision to enhance the guest experience and provide the company using them with valuable data and insights

Wayblazer search and booking engine:

Even though the company went bankrupt in 2018 it is listed as it spearheaded the intensive use of NLP during the process of searching and booking(Weissman, 2018). This was achieved by custom tailoring the appearance of search outcomes, especially the selection of pictures and reviews presented to the potential guest, based on phrases used during the process of searching. This showed the potential of AI in the context of individualizing each step of the customer journey even before the decision to book has been made (*About Way Blazer*, 2017; IBM, 2016) as cited in (Huang et al., 2022)

Allora.ai :

Allora.ai by SHR group functions as an underlying system which is already incorporated into the official websites of more than 2.000 hotels or resort groups globally. Through machine learning, Allora possesses the ability to understand users' booking patterns, identify the best scenario for the website owner, and dynamically adapt the website's configuration. Making use of deep learning, Allora uses data collected from all participating websites to make further improvements to its behaviour, thereby suggesting optimal website configurations to its clients (*Allora*, 2023)

2.2.3.2 Chatbots

Chatbots have transformed from simple response platforms to being capable of holding human-like turn-based-conversations in textual, as well as vocal form if connected to a smart device like Siri, Google, or Alexa. This enables them to be used for customer support, sales, and marketing purposes(Pillai & Sivathanu, 2020)

Chatbot Edward:

Making use of NLP this chatbot was released in 2016 for guests staying at one of the twelve Radisson Blu hotels in the United Kingdom owned by the name-inspiring company Edwardian Hotels. Being able to fulfil guest requests like informing them about hotel amenities, helping with directions inside as well as outside the hotels, giving tips, and even managing customer complaints without human intervention, takes a significant workload off front-line staff who can focus on guest interactions that need face to face communication. Chatbot Edward furthermore is programmed to automatically connect the guest with an employee to take over the chat should complaints or requests require a reply by a human.(Aspect, 2020)as cited in (Huang et al., 2022), (Burns, 2016)

Tacobot

Many companies in the service industry have also shown that Chatbots can be personalized to fit a brand image, a feature that can be especially applied and tailored to companies that have built a strong brand image over the years. Tacobot, the chatbot used by the American fast-food company Taco Bell is capable of taking requests in informal language and will, fitting to the brand image of Taco Bell, respond with snappy sentences like “How would you feel if I called you by Steve?” if a customer calls it Siri(Addady, 2016).

Subway order bot

Another chatbot utilized by a fast-food company displaying the versatility of personalization chatbots are capable of is the subway order bot. This chatbot imitates the conversation normally held between the customer and the employee during the ordering process which is very distinctive due to the wide range of ingredients that can be mixed when ordering a sandwich at Subway while giving the customer the option to order via text, voice or by tapping corresponding pictures of ingredients. Furthermore, it can be accessed directly via Meta's messenger service (formerly known as Facebook Messenger) and is connected to Meta's payment system and automatically uses the geolocation of the device being used for the conversation to suggest pick-up spots nearby(Calfas, 2017; Huang et al., 2022).

2.2.3.3 Physical robots

Physical robots employing AI tools to further enhance their capability of working without constant human supervision can take part as a physical replacement for a human in above-average dangerous situations as well as execute repetitive tasks.

Knightscope K5

Knightscope's K Series Robot and its successors are examples of surveillance robots. Their equipment of several high-definition cameras, thermal cameras, several lasers for orientation, GPS, and sound sensors give it the ability to navigate through environments and monitor its surroundings. It furthermore is capable of understanding vocals and is currently used to monitor indoor and outdoor areas and could replace most of the security staff due to its relatively low cost of operation and abilities like license plate registration when used in parking lots(Huang et al., 2022; *Knightscope*, 2023)

Connie

A more customer-oriented robot variant is Connie, a concierge robot used by Hilton since 20a6 where it was first introduced to the Hilton McLean hotel in Virginia and is a cooperation between the internationally acclaimed hotel chain Hilton and IBM whose AI software Watson is being used. The robot's role is to take over guest inquiries and function like a concierge which is achieved by using NLP to interact with its human guests. Watson, the AI program used, is connected to a cloud system connecting collected data and therefore improving itself over time. With the physical robot, in the case of Connie the French-made robot NAO was used, only costing around €10,000 it enables hotel chains to offer concierge services at hotels outside of the upper-upscale and luxury sector(generationrobots, 2023; Grandey & Morris, 2023; trejos, 2016; Volpicelli, 2016)

2.2.3.4 Self-service terminals

Using facial recognition by processing biometric data enables Self-service terminals to streamline certain tasks with enhanced efficiency compared to their human counterparts.

Self-service check-in terminals

Self-service check-ins, a feature already available at many airports through the help of specialized terminals, have been put into a trial run at several locations managed by Marriot International in China, more specifically the cities of Hangzhou and Sanya, in 2018. The implementation aims to cut the time needed for the check-in procedure by two-thirds should the customer wish to prefer the terminal over a face-to-face check-in procedure executed by a human. The significant time reduction during the procedure is achieved by using facial recognition AI facilitated by a joint venture between Marriot International and Alibaba Group(Marriott international, 2018; Wang, 2018).

2.2.3.5 Augmented reality /virtual reality

Augmented reality (AR) technology has been used by companies to the possibility of its usage via a smartphone or tablet, projecting virtual models into the environment when viewed from the screens of the device. Virtual reality (VR) technology on the other hand offers the user a more immersive experience by fully engaging him into a virtual space by using a head-mounted device and multiple sensors in a predetermined space.

In-room AR-map

Premier Inn, a London-based hotel chain started implementing AR technology into their hotel rooms in 2014 by enabling users of their App to scan the map of London, a feature in every of their hotel rooms, to find out more about the area in question and view information in the likes of restaurant and bar reviews(Edwards, 2015)as cited in (Huang et al., 2022)

Navitair by Amadeus

Enabled by VR technology the potential customer is fully immersed into the booking experience. Starting from seeing a geographical globe and choosing destinations to closely discover before deciding on the final booking choice enables the guest to tailor a bespoke vacation. Furthermore, additional services like car rentals can be chosen while immersed (Vallantin, 2017).

2.3 Technology acceptance – planned behaviour/technology acceptance theory

New information technology is swiftly replacing outdated, old applications, delivering enhanced capabilities and better performance for end-users. The effectiveness of this transition hinges on the willing incorporation and proficient use of technology by personnel. Consequently, organizations must recognize the importance of the acceptance process in ensuring the efficiency of the transition. This currently applies especially to object-oriented technology, in which efforts are concentrated on optimizing effectiveness (Lee et al., 2006). The process of acceptance has been a well-discussed topic in academics and four leading theories have emerged over the years. Those theories are: [1] The theory of reasoned action (Martin Fishbein & Ajzen, 1975), [2] the theory of planned behaviour(Ajzen, 1991), [3]the technology acceptance model and [4] the innovation diffusion theory. (Ajzen, 1991; F. D. Davis, 1989; Martin Fishbein & Ajzen, 1975). The primary hypothesis of the Theory of Reasoned Action

(TRA) states that an individual's actions are predicated upon their behavioural intention, which, in turn, is shaped by both attitude and subjective norm. On the one hand, attitude is predominantly shaped by belief structures and evaluative considerations. On the other hand, the subjective norm is shown to be influenced by other factors, coming from norm beliefs and the will to fit into their social environment (Martin Fishbein & Ajzen, 1975) Based on the TRA, Ajzen, one of the two authors of the TRA, formed an extended model, further investigating the link between beliefs and behaviours, which now also included the component of perceived behavioural control. The product of his research, the Theory of planned behaviour (TPB) concludes that the actions of an individual not only are influenced by interior but also by exterior influences (Ajzen, 1991). The Technology acceptance model (TAM), another theory based upon the TRA, has found great application studies concerning the acceptance of technology and the behaviour of its usage (Kim et al., 2008). It uses the initial of the TRA while replacing its factors of belief with the concepts of perceived ease of use and the concept of perceived usefulness. Within the framework of a (TAM), the acceptance or utilization of technology is dependent upon behavioural intention. This intention itself is influenced by the attitude toward usage, incorporating both the direct and indirect effects of perceived ease of use and perceived usefulness. Notably, both perceived ease of use and perceived usefulness together shape the attitude toward usage, with the former having a direct influence on the latter (F. D. Davis, 1989). Through this change of factors of believe from the TRA to the TAM external factors stemming from different sources like the employer through the communication via top management, corporate organized pieces of training and support, personal features such as adoption behaviours in the past, computer knowledge and innovativeness, as well as features of the system to be adopted like its design or functionality now have influence on the attitude and behaviour of each individual (F. D. Davis et al., 1989).

A multitude of research conducted prior to this thesis has discovered a significant positive relation between conditions facilitating the use of new technology and the acceptance of technology. (Chong et al., 2009; Norzelan et al., 2024).Especially the support of upper management by facilitating enough resources towards the adoption of new technology is of paramount importance. This can be in various forms ranging from financial support, to providing additional material resources and the overall attitude of the top management towards the new technology(Chen, 2019) Additionally, this support of adoption needs to be continuous throughout the whole project execution as well as consistent to ensure the success of the process. Should this not be the case a negative impact towards adoption will be the case that can lead to the failure of the project(Elbanna, 2013). Perceived good support by an organization not only helps the adoption and minders the risk of failure but also helps to overcome temporary difficulties and obstacles that might occur during the process of implementing and adopting a new technology. Furthermore, it increases the speed of implementation as well as it forms the attitude towards the new technology by fostering knowledge and understanding of its usefulness and therefore eases the complexity of adoption(Chen, 2019).

We therefore hypothesize:

H1: there is a significant positive relationship between training and perceived usefulness

H2: There is a significant positive relationship between communication and perceived usefulness

2.3.1 Voluntariness and mandated use by management

Research conducted to identify the influences towards the effect of the subjective norm on the intention of usage found a significant difference between the subjects separated into groups with a voluntary and mandatory context of usage. While the respondents in the group of mandatory usage showed a significant influence of subjective norm on the intention of usage, the second group who were not forced to adapt showed no significant influence of their subjective norm on the concept of usage intention. This is argued to be the outcome of a causal mechanism underlying the effect made by a mandatory setting towards the significance of subjective norm, called compliance. This effect of compliance on the intention of usage by the concept of the subjective norm is theorized to activate as soon as an individual observes that an outside actor, with the ability to reward and punish behaviour and nonbehaviour, demands a specific behaviour (French & Raven, 1959; Hartwick & Barki, 1994;

Venkatesh & Davis, 2000) The outcome can be found in varying strengths of usage intention of a system, even when the system in question is being mandated to make use of, due to the human nature of some participants who are unwilling to comply mandates of such nature.

We therefore hypothesize:

H3: There is a significant negative moderation of mandated use on the relationship between training and perceived usefulness.

H4: There is a significant negative moderation of mandated use on the relationship between communication and perceived usefulness.

2.3.2 Perceived usefulness

Research has shown that positive perceived usefulness has a significant influence towards acceptance of new technology(F. D. Davis, 1989; Venkatesh & Davis, 2000). It furthermore has been seen as a consistent and strong determinant of usage intention in a multitude of empirical tests making use of the TAM, with a regression coefficient of approximately 0.6 and therefore has served as a driver of fundamental importance throughout the years especially considering its dominance in consistency when compared to the other direct determinant of the TAM, perceived ease of use(Venkatesh & Davis, 2000) This is further displayed in the failure of technology design failed in the past as ease of use was overemphasized and was given too much importance when compared perceived usefulness resulting in the ultimate failure of the product according to user acceptance (Branscomb & Thomas, 1984; Chin et al., 1988; Shneiderman, 1997). As attitude and acceptance of new technology in the TAM has displayed to be reliably and consistently driven by perceived usefulness the concept of perceived usefulness will be assumed to have a similar relationship with other concepts as the concept of acceptance.

2.3.3 Intention of Use

Usage of new technology has shown to be significantly positively related to the intention of use, which itself is correlated to perceived ease of use and perceived usefulness (F. D. Davis et al., 1989; Setiawan & Setyawati, 2020; Somasundaram et al., 2017). Multiple studies conducted prior to this research yielded similar results, especially when used in the context of the TAM. The order created by causality furthermore establishes the strong correlation formed between the attitude towards use and the intent of usage (A.Davis, 1985; BROWN, 1979; F. D. Davis, 1989) As established in the paragraph regarding the concept of perceived usefulness, the concept of acceptance will be assumed to have significantly similar properties to perceived usefulness. The concept of the intention of use has been displayed by the measurements of the intended duration and intended frequency of usage in prior studies(Compeau et al., 1999; F. Davis & Warshaw, 1992; Ha et al., 2020)

We therefore hypothesize:

H5: There is a significant positive relationship between the perceived usefulness and the intended duration of use.

H6: There is a significant positive relationship between perceived usefulness and the intended frequency of use.

2.4 Research Model and Hypotheses

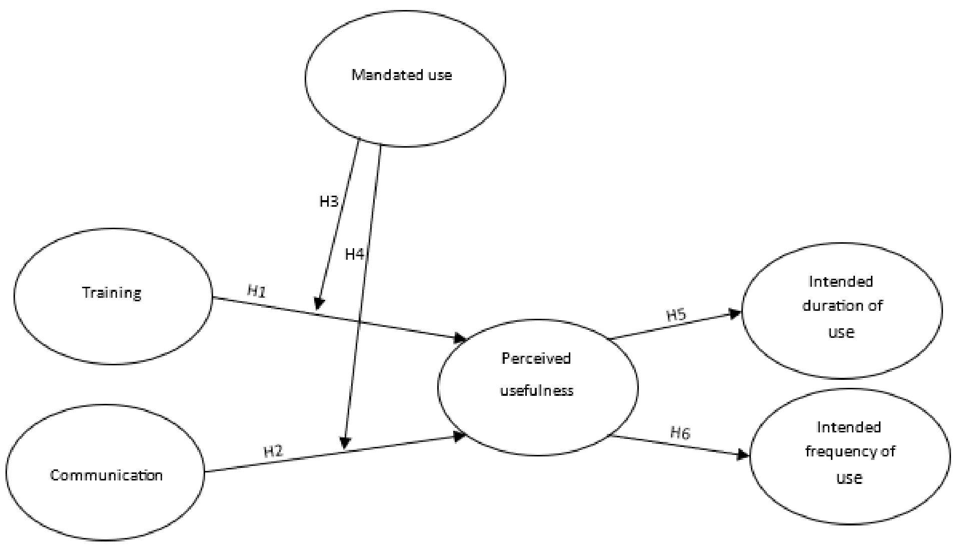

Figure 1: Research model

The hypotheses are the following:

H1: there is a significant positive relationship between training and perceived usefulness.

H2: There is a significant positive relationship between communication and perceived usefulness.

H3: There is a significant negative moderation of mandated use on the relationship between training and perceived usefulness.

H4: There is a significant negative moderation of mandated use on the relationship between communication and perceived usefulness.

H5: There is a significant positive relationship between the perceived usefulness and the intended duration of use.

H6: There is a significant positive relationship between perceived usefulness and the intended frequency of use.

3 Methodology

To advance and further progress the understanding, of the impact of the concepts of training and communication has on perceived usefulness with the possibility of a moderating effect of mandated use, an empirical study is being carried out to put the hypotheses proposed during the literature review to a test and subsequently verify or refute those. It is imperative to establish the boundaries and parameters of the study containing the identification of the number of respondents, the design and methodology to be employed, limitations to research and ethical considerations to be addressed. Successively, the data will be assembled and assessed as part of the process.

3.1 Study design

The choice to conduct quantitative and explanatory research has been made as the objective of this research paper is to disclose the relationships between the dependent variables, perceived usefulness, intended frequency of use, intended duration of use, and the independent variables, received training and communication as well as the relationship between mandated usage and its moderating effect towards the significance of the nexuses between the concepts of received training and communication to perceived usefulness. This includes an empirical approach toward the collection of data and the testing of the hypotheses built during the literature review, allowing for conclusions to be drawn onto the broader population and for them to be generalized. The approach of using explanatory methods is crucial to uncovering and understanding nexuses between independent and dependent variables empowering the researcher to forecast and predict outcomes reflected by a shift of significance of a variable of dependent nature should a change in a connected independent variable be made(Creswell, 2014).To enable the comprehensive statistical analysis between factors and form quantifiable factors of relationship and correlation a quantitative approach is made use of(Gabor, 2010).

3.2 Data Collection & Measures

To reach and collect participants creating responses to the survey the method of convenience sampling commonly made use of in research studies was used. Convenience sampling refers to the approach of the collection of participants partaking in a survey dependent on the availability of the researcher in his direct environment and network. Therefore, the survey participants are acquired on the basis of convenience rather than on a systematic or random basis. The method of convenience sampling frequently is utilized when limitations in budget, restricted access to a target population or time constraints are limiting factors of a survey or research conducted (Etikan, 2016). A drawback and limitation of results achieved by conducting research by making use of convenience sampling is the difficulty of generalizability towards a wider population. As the findings are limited to be generalized to the respondents of the study, the drawing of conclusive statements about a broader population is challenged. Furthermore, due to the participants being selected on the basis of accessibility and availability, the resulting sample poses the risk of lacking representative accuracy. Convenience sampling additionally may also lead to a variety of different biases being introduced to the study and research. Motivation bias, one of the aforementioned biases, might lead to an impact on the rate of participation as individuals possessing particular viewpoints or interests may be overrepresented when being compared to individuals lacking such particular interests due to their increased tendency to participate (Stratton, 2021).

The target population and the sampling frame of this research are restricted to individuals currently working in the hospitality industry and students who are acquiring a hospitality degree, who are able to read and comprehend the English language in written form resulting in a sample size of n=94. Primary data has been acquired by making use of an online survey through the established online survey platform SoScisurvey.de. The online survey is initiated with an opening page stating the reason and aim of the survey to be the collection of informational data in the context of a bachelor thesis with a focus on attaining a deeper understanding of the attitude of hospitality professionals towards the usage of AI in a job setting. Furthermore, the possible participant is being informed that data acquired at the end of the survey is used solely for the academic purposes and is strictly anonymous. In the case of consenting to the collection of data, the participant is asked to proceed with the survey by pressing the button stating “proceed”. In case of this not being the case, the individual is asked to not further proceed. Throughout the whole process of the survey the contact information of the researcher is being provided should questions in the context of the questionnaire arise. Subsequent to giving his consent the participant will be presented with a filter question to establish if an individual is part of the target population. Should the participant answer the option of “No” to the screening question asking if the individual in question is a current student in the process of attaining a degree in the hospitality sector or is currently working in the hospitality industry the survey will end and they will be presented with the end page thanking the participant. In the case that the screening question is being answered positively by picking “Yes” as the answer, the participant will proceed with the questionnaire and will be presented with the items stated in Table 1. Each question needs to be answered to proceed to the next page to ensure the validity of the answers. Subsequently, to answer all items the individual will proceed to the end page thanking the participant for his time and participation in the survey.

The distribution of the questionnaire has been performed via the social media platforms LinkedIn, Instagram and Reddit on December 22nd, 2023, as well as being distributed to hospitality students via professors at the Polytechnical University of Hong Kong, School of Hospitality and Tourism Management (Polyu SHTM) from December 22nd 2023 until January 21st 2024. The distribution through the social media platform Reddit has been performed by sharing the weblink to the online survey with a short description of its content and purpose in the subreddits “r/SurveyExchange” and “r/takemysurvey”, subforums with the specific purpose of finding survey participants.

The items in the survey will be measured using multiple types of scales to ensure continued internal validity. A five-point Likert scale with the options to choose between "strongly agree", “somewhat agree”, “neutral”, “somewhat disagree” and “strongly disagree” as well as the additional option of “N/A”, which stands for not applicable, will be presented to the participants after each statement which is connected to the concepts of perceived productivity, received training, communication and mandated use. For the concept of intended frequency of use, the options to choose from will be “never”, “rarely”, “sometimes”, “often” and “always” with the supplementary option of “N/A” on a behavioural intention scale will be presented. Furthermore, the concept of intended duration of use will be measured on a behavioural intention scale with the possibilities of “less than 30min”, “30min to 1 hour”, “1 to 2 hours”, “2 to 4 hours” and “more than 4 hours” as well the additional option of “N/A” to choose from. These timeframes are constructed within the context of regulated working hours per day in Austria being eight per day (*Business-Service-Portal.Gv*, 2024). The options on all scales will be represented by a number ranging from 1 to 5. The number 1 will be representative of “strongly disagree” and 5 of “strongly agree” in the context of the five-point Likert scale, 1 embodying “never” and 5 “always” on the behavioural intention scale used for the concept of intended frequency of use and 1 representing the option of “less than 30min” and 5 of “more than 4 hours” for the measurement of intended duration of use measured on a behavioural intention scale. The option of “N/A” will be included to minimize bias should a respondent does not feel comfortable answering a question, think that the item in question lacks importance or relevance, or decide to not want to relate to a construct and therefore will not be represented by a number, but will be left as blank in the data collection, as to not influence the ultimate outcome of the data analysis. As presented in Table 1 the construct of Training will be measured using five items(Khan et al., 2023; Thompson et al., 1991; Venkatesh et al., 2003). The construct of Communication will be measured by three items (Murphy & Sashi, 2018; Venkatesh et al., 2003), and the construct of Mandated usage will be measured using three items(Venkatesh et al., 2003). The concepts of intended frequency and intended duration of usage will be presented with one item each(Compeau et al., 1999) while the concept of perceived usefulness will be composed of five items(Compeau et al., 1999; F. D. Davis et al., 1989).The questions used in the online survey were taken from peer-reviewed academic research and were adapted to fit the context of this research to ensure and verify their respective legitimacy. For the reason that Likert scales and behavioural intention scales will be made use of as the sole method of primary data collection, the assessment on an ordinal scale is facilitated. All questions with their detailed corresponding source are included in and can be found in Table 1.

The questionnaire used in the online survey can be found in its entirety and user-appearance can be found in the appendix.

Table 1: Constructs and Questionnaire items

Construct	Question	Source
Training	Specialized instruction concerning AI is available to me	(Thompson et al., 1991)
	I have the training necessary to use the system.	(Venkatesh et al., 2003)
	I am satisfied with the length of the training course	(Khan et al., 2023)
	I am satisfied with the length of the training course	(Khan et al., 2023)
	I am satisfied with the relevance of the training I received	(Khan et al., 2023)
Communication	The senior management of the company I work at has been helpful in the use of AI.	(Venkatesh et al., 2003)
	In general, the organization has supported the use of AI.	(Venkatesh et al., 2003)
	The company has frequent two-way communication with us regarding the usage of AI	(Murphy & Sashi, 2018)
Mandated use	My use of AI is voluntary	(Venkatesh & Davis, 2000)

	My supervisor does not require me to AI	(Venkatesh & Davis, 2000)
	Although it might be helpful, using AI is certainly not compulsory in my job.	(Venkatesh & Davis, 2000)
Intended frequency of use	Frequency of use at work	(Compeau et al., 1999)
Intended duration of use	Duration of use at work	(Compeau et al., 1999)
Perceived usefulness	Using AI enhanced my effectiveness on the job	(F. D. Davis, 1989)
	Using AI in my job increased my productivity	(F. D. Davis, 1989)
	Using AI improved my job performance.	(F. D. Davis, 1989)
	Using AI I spend less time on routine job tasks	(Compeau et al., 1999)
	Using AI I increased the quantity of output for the same amount of effort	(Compeau et al., 1999)
Control question	I currently am a student in the hospitality sector or am working in the hospitality industry	

3.3 Limitations

This research is bound to limitations that need to be acknowledged and recognized.

3.3.1 Limitation in sample size

As a limited sample size may obstruct the possibility to detect patterns and correlations correctly as well as it minders the applicability of the findings to a broader population and increases the possibility of a sampling error, it is necessary to acknowledge the sample size of n=94. This sample size is significantly below the minimum sample size stated by the rule of thumb of 200 respondents. This lack of respondents weakens the representativeness of the findings, especially towards the total population.

3.3.2 Motivation bias

The usage of an online survey on a voluntary basis may result in a motivation bias, in which individuals participating in the survey with a strong personal investment and attitude towards a topic are more inclined to take part in it and answer the questionnaire when compared to someone lacking such strong personal interest towards a specific topic. This may constrain the generalizability of the findings and results due to the overrepresentation of individuals with a strong personal investment when compared to a broader population.

3.3.3 Lack of language selection

Constraining the availability of the survey's language selection to only feature English as the sole language the survey can be answered in results in the exclusion of possible participants of the survey that would be part of the population for the reason of their inability to comprehend English in written form. This bias may result in an overrepresentation of English-speaking individuals when compared to a broader population and may limit the possibility of generalizing the results and findings of this research to the population.

3.4 Research ethics

The possible participant, after following the weblink shared on social media, is presented with a statement of informed consent before being able to proceed with the questionnaire and therefore contribute to the data collection. This statement of informed consent ensures the awareness of the possible participants of the purpose of the study and the usage of the collected data to uncover the acceptance of AI by industry professionals in the context of an undergraduate bachelor thesis. The reader furthermore is being informed by the statement that all collected data is being handled confidentially and anonymously as well as that the participation in the survey is on a voluntary basis, can be opted out of at any time throughout the questionnaire and is not being rewarded in a monetary or any other form to insure internal validity. The name of the researcher and the supervisor of the thesis as well as the name of the university and contact information for the researcher is being provided should inquiries or difficulties arise before, during or after the participation. Proceeding from the statement of informed consent is only possible by pressing the button stating proceed which is being interpreted as the participant giving his consent to the collection and analysis of the data resulting from the questionnaire. The collected data has not tampered with the exception of the exclusion of unviable responses of individuals failing the filter question to ensure internal data and research quality and integrity.

4 Data Processing and Results

The section on data processing gives details on the process of the cleansing of data as well as to how the obtained responses were handled and analysed. Furthermore, it sheds light on the employed methods of data processing and the testing of the hypothesis formed during the literature review section of the research. The resulting data will subsequently be presented and analysed during the results section.

4.1 Data processing

Following the data collection by using the online survey platform SoSci.com, the data was managed and analysed by making use of the free and open statistical software Jamovi.

4.1.1 Data cleansing

The data has been cleansed by utilization of the filter question asked at the beginning of the questionnaire to determine if the participant is working in the hospitality industry or currently is in the process of obtaining a university degree in the hospitality sector. Data affiliated to participants choosing the negative answer and therefore failing the filter question have been excluded from the data analysis as participants need to be part of the target population for their data to be used in this study. The resulting pool of data yielded a final quantity of 94 valid responses.

4.1.2 Concept consisting of multiple items

Several concepts shown in Table 1 consist of multiple items being measured. The concept of Training consists of five measured items, the concepts of Communication and Mandated use both are measured by three separate items each and ultimately the concept of Perceived usefulness contains five items being measured during the questionnaire. Cronbach's Alpha, a statistical technique assessing the interrelation between indicators that are being used to collectively represent a latent variable, was made use of to warrant internal consistency between aforementioned variables. (Collins, 2007). The five items composing the concept of Training yielded a Cronbach's Alpha of 0.956 and therefore are reliable as they show a high inter-item consistency without dropping a variable. The Cronbach's alpha of the three indicators measuring the latent variable of Communication resulted in 0.950 showing a high correlation between each other and therefore can be used to reflect the construct of training reliably. The construct of Mandated use, reflected by three measured items yielded a Cronbach's alpha of 0.894, indicating a good internal consistency and subsequently are used to establish the construct. The ultimate latent variable, Perceived Usefulness, containing five measured items, displays a Cronbach's alpha of 0.887, this result is indicative of a good consistency and correlation between the items used. Subsequent to the computing of Cronbach's alpha for the indicators collectively representing a latent variable, compound variables were created, representative of every concept consisting of a collection of measured items as Cronbach's alpha, in all cases, was acceptable and all items were measured by using the same five-point Liker scale. These computed variables were created by calculating the mean of the respective items of measurement.

4.1.3 Shapiro-Wilk Normality Test

To determine the appropriate statistical test method of testing correlations between variables and therefore the examination of related hypotheses, a Shapiro Wilk normality test was made used. The resulting data shown in Table 2 revealed that none of the variables in question stood the assumption of normal distribution and therefore indicated that Spearman's was to be employed for the evaluation and measurement of nexuses between dependent variables at their respective predictors.

Table 2: Descriptives

	Mean	SD	Minimum	Maximum	Shapiro-Wilk p-value
Communication	2.64	1.335	1	5	<.001
Training	2.83	1.332	1	5	<.001
Perceived usefulness	3.84	0.876	2	5	<.001
Mandated use	4.21	4.33	1.67	5	<.001
Intended duration of use	2	0.839	1	4	<.001
Intended frequency of use	2.79	0.828	1	5	<.001

4.2 Descriptive Analysis

The data presented in Table 2 shows the descriptives of the variables made use in the study, both dependent and independent. The measured mean of the concept of mean is 2.64 suggesting a moderate level of communication with room for improvement from the employer to their employees as this latent variable has been measured on a five-point Likert scale with 1 indicating that there is no communication taking place, and 5 standing for frequent communication. The calculated standard deviation of 1.335 suggests a notable degree of dispersion between responses and therefore implies a significant variability in regard to levels of communication by the employer experienced by participants. The mean of the concepts of training was measured at 2.83. The data for this latent variable has been measured on a five-point Likert scale with 1 standing for an insignificant level of training has been facilitated, and 5 indicating received training surpassing a satisfactory level. This suggests that training is being facilitated but the amount and quality of it could be significantly improved upon. The measured standard deviation of 1.332 indicates a noticeable difference between answers given by individuals. Perceived usefulness was measured on a five-point Likert scale ranging from 1 indicating a negative perception towards the usefulness of AI and 5 a significant positive influence of AI in a job setting. The mean was measured at 3.84 indicating a positive perceived usefulness of AI in a professional job setting. The computed standard deviation of 0.876 is suggesting a moderate level of variation between perceived usefulness among the individuals participating in the survey. Mandated use was also measured on a five-point Likert scale implying strict mandated usage with 1 and usage on a true voluntary basis with 5. With the mean being measured at 4.21 significant trend of usage on a voluntary basis can be assumed. The calculated standard deviation of 4.33 indicates a severe difference in the answers given by participants. The variable of intended duration of use, is one of two constructs measured on a five-point behavioural intention scale. The scale used for this construct indicates usage of AI of less than 30min per day with 1 and heavy usage of AI tools with the option of 5 implying the usage to be more than 4 hours per day. The mean calculated is at 2 referring to an average intended usage of AI between 30min and 1 hour per day. The standard deviation computed lies at 0.839 and indicates the presence of variability between participants. The five-point behavioural intention scale used to collect data for the concept of intended frequency of usage indicated no intended usage of AI at 1 and ever-present intended usage at 5. With a mean calculated at 2.79, a moderate intended usage is implied. The standard deviation, computed at 0.828 indicated variability to be present between data collected from different individuals.

4.3 Hypothesis testing

Spearman's rho was made to test and determine the significance testing of the hypothesis as the assumption of normal distribution was violated by all variables shown in the results of the Shapiro Wilk test displayed in Table 2. The cutoff of significance lies as commonly applied at a p-value of 0.05 with results displaying a p-value of greater value than the cutoff point to be considered as not significant and results with an outcome of a p-value smaller than the cutoff point to be counted as showing a significant relationship between two variables. The outcomes of the testing of all hypotheses are being displayed in the tables providing an inclusive overview of the results yielded by the statistical testing conducted.

4.3.1 Hypothesis H1

H1: there is a significant positive relationship between training and perceived usefulness.

This hypothesis is intended to what importance the amount of training received by the employer in the field of AI tools used in the hospitality industry has on the perceived usefulness of AI and its application. This provides information to enhance the understanding of the importance of training provided by the company to their employees in the context of user acceptance and therefore allows an insight into the allocation of significant resources towards improved training is recommended.

Table 3 shows evidence that hypothesis H1 can be accepted. The computed p-value of <0.001 signifies a high statistical significance of the correlation between the independent variable of training and the dependent variable of perceived usefulness. The Spearman's rho correlation coefficient of 0.655, shown in Table 3, indicates a strong positive correlation between training and perceived usefulness. This implies that by improving the level of training the level of perceived usefulness, in the context of AI usage in the hospitality industry, will improve as well. Therefore, the alternative hypothesis H1 was accepted.

4.3.2 Hypothesis H2

H2: There is a significant positive relationship between communication and perceived usefulness.

The aim of this hypothesis is to indicate the relationship between the concepts of communication and perceived usefulness, with communication being the independent variable and perceived usefulness being the dependent variable. This determines whether resources allocated towards improving communication will have an influence on perceived usefulness.

As the evidence provided in Table 3 displays, hypothesis H2 can be accepted. The relationship between the two variables, based on Spearman's rho correlation coefficient of 0.622, is of a strong positive nature. This suggests that with an increase in the level of communication, an increase in the level of perceived usefulness is imminent. The p-value of <0.001 is substantially below the threshold of 0.05 and therefore indicates a significant statistical correlation. Therefore, we conclude that the observed relationship between the variables of communication and perceived usefulness is supportive of hypothesis H2 and indicates a strong positive and significant correlation between communication and support by the employer when adopting AI technology and the perceived usefulness of the technology in a workplace setting.

Table 3: Spearman's rho correlation matrix for H1 and H2

		Training	Communication
Perceived usefulness	Spearman's rho	0.655	0.620
	p-value	<0.001	<0.001

4.3.3 Hypothesis H3

H3: There is a significant negative moderation of mandated use on the relationship between training and perceived usefulness.

This hypothesis aims to identify the level of moderation on the relationship between the variables of training and perceived usefulness by making the usage of AI technology mandatory.

Table 4 displays the findings of hypothesis H3. As evident in the data of the statistical analysis supplied, hypothesis H3 is not accepted as the p-value, indicating significance, lies at 0.820 and therefore is considerably above the cutoff point of a p-value of <0.05. This indicator of non-significance implies that there is a substantially insufficient amount of evidence to support the assumption of significant moderation of the relationship between training and perceived usefulness by the variable of mandated use.

4.3.4 Hypothesis H4

H4: There is a significant negative moderation of mandated use on the relationship between communication and perceived usefulness.

This hypothesis is intended to reveal the intensity of moderation on the relationship between the independent variable of communication and the dependent variable of perceived usefulness by the concept of mandated use.

According to the findings displayed in Table 4 hypothesis H4 is not accepted. This is due to the lack of statistical significance in moderation displayed. Reflected in a p-value of 0.055, which lies above the level of acceptance, the level of evidence to the direct moderation by mandated use on the relationship between communication and perceived usefulness is inefficient in forming statistical assumptions. We therefore accept the null hypothesis.

Table 4: Moderation of mandated use of training and communication

Moderation Estimates of mandated use	**Estimate**	**SE**	**Z**	**p**
Training	0.4563	0.0614	7.430	< .001
Mandated use	0.0733	0.0881	0.832	0.406
Training ✻ Mandated use	-0.0193	0.0848	-0.227	0.820
Moderation Estimates of mandated use				
Communication	0.37837	0.0577	6.5611	< .001
Mandated use	-0.00832	0.0885	-0.0940	0.925

Communication ✻ Mandated use	0.12409	0.0645	1.9225	0.055

4.3.5 Hypothesis H5

H5: There is a significant positive relationship between the perceived usefulness and the intended duration of use.

This hypothesis is aimed at unravelling the relationship between the perceived and intended duration of use. Based on the results, assumptions towards the shift in intended usage duration of AI tools in a job setting can be made should the level of perceived usefulness change.

The results of Spearman's rho correlation coefficient on hypothesis H5, shown in Table 5, established a p-value of 0.271 and thus indicate to accept the null hypothesis as the evidence of a relationship between the two variables is not statistically significant enough to predict possible changes in the intended duration of use based on a correlation with perceived usefulness.

4.3.6 Hypothesis H6

H6: There is a significant positive relationship between perceived usefulness and the intended frequency of use.

The target of H6 was to determine whether perceived usefulness would impact the intended frequency of AI tool usage.

Based on the results displayed in Table 5, hypothesis H6 is accepted. The computed p-value of $p < 0.001$ is signalling a strong statistical significance. Spearman's rho correlation coefficient of 0.5737 demonstrates a moderate positive relationship between the variables of perceived usefulness and intended frequency of use thusly indicating a moderate positive shift in intended frequency of use correlated with an initial increase in the level of perceived usefulness AI tools used in the hospitality industry. As for the statistically significant result, the alternative hypothesis H6 has been accepted.

Table 5: Spearman's rho correlation matrix for H5 and H6

	Perceived usefulness	
	Spearman’s rho	p-value
Intended duration of use	0.117	0.271
Intended frequency of use	0.537	<0.001

5 Discussion

The section is dedicated to discussing theoretical as well as managerial implications emerging from this thesis, its accumulated data and the subsequent results. Additionally, an acknowledgement of the study's limitations is made to ensure clarity and transparency, as well as suggestions towards further research, are granted.

5.1 Theoretical implications

This bachelor thesis is aimed to assess the relationships between communication and training facilitated by the employer on the topic of AI tools being used in the hospitality industry and the subsequent perceived usefulness of those tools. Furthermore, it was tested if making the usage of those tools mandatory would influence the aforementioned relationships as well as the intention in frequency and duration of use can be predicted by the perceived usefulness.

The investigation of the relationship between the training facilitated and the perceived usefulness resulted in uncovering a strong and significant positive correlation between the two variables. Thus, the hypothesis H1 is supported by the study. Another strong and significant correlation was found between the variables of Communication and perceived usefulness. Hypothesis H2, stating a significant and positive relationship between the two concepts therefore is accepted by the findings. The moderation of mandated use on the effects of both, communication as well as training has yielded statistically insignificant results and led to the rejection of the hypotheses H3 and H4 and the subsequent acceptance of the corresponding null hypothesis in both cases. The results of the testing of hypothesis H5, hypothesising a significant relationship between the perceived usefulness of AI in the hospitality industry and the intended duration of use were found to be statistically not significant enough for hypothesis H5 to be accepted. The final assumption of the relationship investigated in this bachelor thesis of hypothesis H6, assuming a significant positive relationship between the perceived usefulness and the intended frequence of Ai usage was accepted as the statistical analysis came to the conclusion that a significant moderate and positive correlation dies exist between the two observed variables.

The acceptance of the hypotheses H1 and H2 aligned with prior research conducted on the acceptance of technology based on a positive relationship between support and resources facilitated and the ultimate acceptance of a newly introduced technology. The TAM has been loosely applied in this study as well as the studies predating this bachelor thesis(Chen, 2019; Chong et al., 2009; F. D. Davis et al., 1989; Norzelan et al., 2024) The results implicate a strong positive correlation between both, training and communication with perceived usefulness, supporting the claim of their position as facilitators of technology acceptance and emphasises their importance when the perceived usefulness of new technology is being introduced.

Furthermore, the study revealed an insignificant level of moderation of mandatory usage of AI of the effect of communication as well as training. This contradicts prior research indicating a statistically significant moderation of mandated usage on acceptance (French & Raven, 1959; Hartwick & Barki, 1994; Venkatesh & Davis, 2000).

Regarding the positive correlation between the perceived usefulness of new technology and the intended duration of usage the hypothesis was not accepted due to statistical insignificance. This is of special interest as the hypothesis H6 regarding a significant positive relationship between perceived usefulness and intended frequency of use has been accepted. The acceptance of hypothesis H6 allies with research conducted earlier in this study while the same studies do not align with the rejection of hypothesis H5 (A.Davis, 1985; Compeau et al., 1999; F. Davis & Warshaw, 1992; Ha et al., 2020).

5.2 Managerial implications

Senior management and employers in the hospitality industry aiming to implement AI technology into their daily operations to further enhance the profitability of their business and the efficiency of their workforce should be aware of the driving factors of technology acceptance. The status quo of training and communication perceived by hospitality professionals is rather low indicating that the current overall level of AI being used in the hospitality industry by employees seems to be rather low. A strong emphasis on especially initial support is given. This support can take the form of resources assigned specifically to supply the workforce intended to use AI technology in their daily work with special training to prepare them professionally for the work and usage of the new technology. This existence of such training has a strong positive correlation with perceived usefulness, the driving factor of technology acceptance. Therefore, employees who have received adequate training are not only more versed in the usage of new technology but are more accepting of it. The communication of the usage and continuous support and two-way communication of top management also has to be given high importance by employers as prior research as well as this study conclude its strong positive relationship with technology acceptance in addition to providing the needed training. The continuous fostering of a positive attitude towards the acceptance of new technology communicated by decision-makers and leaders leads to an increase in the level of overall acceptance. The insignificant moderation of the mandated use of AI technology towards the aforementioned effects of communication and training may indicate that the mandatory usage of AI will not lead to a lower level of acceptance. Furthermore, the indications of the statistical insignificance of the relationship between perceived usefulness and the intended duration of use when compared to the statistical significance of a positive relationship concerning perceived usefulness and intended frequency of use may be interpreted that the interest of AI usage in a job setting is given in a variety of situations but not in significant amounts.

5.3 Limitations

Recognizing the limitations of this research is a mandatory aspect as to hold internal integrity and validity and must not be overlooked. Crucial limitations of this study included the low response rate of n=94, significantly below the rule of thumb of n=200. With possible participants located on a global scale in the number of millions a large-scale study, conducted in multiple languages would yield much more significant data, especially taking into consideration the studies focus on respondents from Austria and Hong Kong, two industrial countries not representative of the population of hospitality workers on a global scale. Including questions to determine demographics might be able to solve this problem. Furthermore, the study was distributed solely online via social media and in written English confining potential respondents to English-speaking individuals with access to social media. The low mean of the results of the concepts of communication and training may indicate an overall low use of AI tools in everyday operations. The sole usage of quantitative research methods may have led to results that offer a less deep insight compared to an approach applying both, quantitative and qualitative methods.

5.4 Further research

Further research, as implied in the section discussing the limitations of this study, might be able to mitigate limitations associated with this bachelor thesis by being conducted and a greater scale and include demographical questions to establish geographical trends. Furthermore, the difference between the concepts of intended frequency of use and intended duration of use in the context of AI acceptance in the hospitality industry may be explored in closer detail to establish their respective difference in relationship towards AI acceptance, something that was not accomplished by this study. The application of qualitative a research method may yield results as this study was confined to the sole usage of quantitative research.

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Appendices

Survey Questionnaire

0% completed

Invitation

You are invited to participate in a research project aimed at determining the attitude of young hospitality professionals toward the usage of AI in a job setting. This study is being conducted under the supervision of Professor Jason Stienmetz, Assistant Professor at Modul University Vienna, to complete the undergraduate program in Tourism, Hotel Management & Operations.

The primary objective of this study is to gain a deeper understanding on the attitude of young hospitality professionals toward the usage of AI in a job setting. The results will help hospitality companies and cooperations to successfully implement AI technology into their standard operating procedures and everyday business in general.
The term AI, in the context of this survey, will be defined as artificial intelligence with the purpose of supporting or taking over repetitive tasks or analysing complex databases or

After completion of the interview, the data will be securely saved and analyzed for this study.
If you are interested in participating in this study, please proceed through the interview/questionnaire process. If you have any questions, please do not hesitate to reach out. Participation is voluntary but greatly appreciated!

Thank you for your participation,
Mauritio Lux

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13% completed

Informed Consent

Informed consent is to verify the voluntary participant has been equipped with the necessary information about the study and their involvement. Both the researcher and participant will be respected and protected. Please, thoroughly read through the acknowledgment statements below.
I am fully willing to volunteer for this research project and fulfill the interview questionnaire process. I understand that the objective of this research is to collect data on the attitude of young hospitality professionals toward the usage of AI in a job setting. The information utilized will be used in the Bachelor Thesis Project and will contribute to the understanding of corporations on how to integrate AI technology successfully into their standard operating procedures.
- I affirm that I was given a copy of the cover letter sheet, read it, and fully understood the information it provided.
- I am aware that my involvement in this study is completely voluntary. No volunteer will be compensated for their participation. Every participant is free to leave the project at any moment and for any reason.
- I have read and understand that any information supplied will be kept confidential and that my name and personal data will not be used. Every participant's personal information will be stored securely and confidentially.
- I acknowledge that Modul University Vienna has authorized this research.
- I read and comprehended the overview of the research assignment that was presented to me. I could ask any questions I had, and they were all addressed satisfactorily.

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25% completed

1. I currently am a student in the hospitality sector or am working in the hospitality industry

[Please choose]

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38% completed

2. Training

The following questions are concerning training provided by your employer/ former employer to facilitate the proper usage of AI in a workspace environment

	strongly disagree	somewhat disagree	neutral	somewhat agree	strongly agree	N/A
Specialized instruction concerning AI is available to me	○	○	○	○	○	○
I have the training necessary to use AI	○	○	○	○	○	○
I am satisfied with the length of the training I have received	○	○	○	○	○	○
I am satisfied with the difficulty of the training I have received	○	○	○	○	○	○
I am satisfied with the relevance of the training I received	○	○	○	○	○	○

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PRIVATE UNIVERSITY VIENNA

50% completed

3. Communication

	strongly disagree	somewhat disagree	neutral	somewhat agree	strongly agree	N/A
The senior management of the company I work at/ worked at has been helpful in the use of AI.	○	○	○	○	○	○
In general, my employer/ former employer has supported the use of AI.	○	○	○	○	○	○
My employer/ former employer has/ had frequent two-way communication with us regarding the usage of AI	○	○	○	○	○	○

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63% completed

4. Mandatory use of AI

	strongly disagree	somewhat disagree	neutral	somewhat agree	strongly agree	N/A
My use of AI is voluntary	○	○	○	○	○	○
My supervisor does not require me to use AI	○	○	○	○	○	○
Although it might be helpful, using AI is certainly not compulsory in my job.	○	○	○	○	○	○

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75% completed

5. percieved enhanced productivity

	strongly disagree	somewhat disagree	neutral	somewhat agree	strongly agree	N/A
Using AI will enhance my effectiveness on the job	○	○	○	○	○	○
Using AI in my job will increase my productivity	○	○	○	○	○	○
Using AI will improve my job performance.	○	○	○	○	○	○
Using AI I will spend less time on routine job tasks	○	○	○	○	○	○
Using AI I will increase the quantity of output for the same amount of effort	○	○	○	○	○	○

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88% completed

6. Please indicate how often you intend to use AI at your workspace.

- ○ Never
- ○ Rarely
- ○ Sometimes
- ○ Often
- ○ Always

- ○ N/A

7. Please indicate your intended duration of usage of AI per day on a typical day.

- ○ Less than 30min
- ○ 30min to 1 hour
- ○ 1 to 2 hours
- ○ 2 to 4 hours
- ○ more than 4 hours

- ○ N/A

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Thank you for completing this questionnaire!