AI & hierarchy: Navigating adoption challenges and opportunities in the hotel industry

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Abstract

This study examines the challenges and opportunities of adopting AI within the hotel industry, focusing on how adoption perceptions vary by hierarchical level. Using consensus mapping with interviews from 21 participants across roles, including top managers, first-line managers, and non-managerial employees, the study identifies unique perspectives on AI's benefits and obstacles. Top managers view AI primarily as a means to gain a competitive advantage, while non-managerial employees focus on its potential for cost savings. Despite these advantages, AI adoption faces hesitance due to limited awareness, understanding, and resistance to change.

Keywords *Artificial Intelligence (AI), hospitality, drivers, barriers, stakeholders, consensus mapping*

1. Introduction

Technological advancements have become integral to human life and, notably, the integration of artificial intelligence (AI) has emerged as a prevalent trend in this technological era (Özen and Özgül Katlav, 2023).
The hospitality industry stands as the most rapidly expanding sector globally, yielding an estimated $8 trillion in revenue and facilitating the creation of 292 million jobs on a global scale (Ruel and Njoku, 2020). The advent of AI applications is reshaping prevailing business paradigms, digging novel opportunities and challenges for the hospitality domain. Hence, in the contemporary landscape of the hospitality industry, the integration of Artificial Intelligence (AI) technologies has emerged as a pivotal strategy to enhance operational efficiency, elevate guest experiences, and drive competitive advantage. However, the adoption of AI within the hotel sector is not devoid of challenges, as it necessitates navigating multifaceted barriers to achieve user acceptance (Morosan and Dursun-Cengizci, 2024).
Scholarly attention has predominantly focused on evaluating the costs and benefits associated with AI implementation in the hospitality sector. Notably, AI streamlines

tasks such as self-check-in/out, room services, housekeeping, concierge services, and chatbot interactions, enhancing efficiency while reducing human costs (Ersoy and Ehtiyar, 2023; Zhu et al., 2023). A distinct research avenue examines costumer acceptance or rejection of AI technology, with findings indicating varying levels of convenience and efficiency perception among costumers due to technological complexity and lack of knowledge (Rasheet et al., 2023; Vorobeva et al., 2023).

Although current studies primarily analyze the impacts of AI from the standpoint of customers, there is a justified need for additional exploration into its effects on employees (Rasheed et al., 2024; Li et al., 2022). Thus, it becomes imperative to explore the implications of AI technologies on hospitality employees, thus shedding light on emerging opportunities and threats in order to guide competency development aligned with evolving technology.

This paper delves into the intricate dynamics of AI adoption across different hierarchical levels within the hotel industry, elucidating the challenges and opportunities that characterize this transformative process. Specifically, this research engages with n. 21 information-rich participants spanning across varying roles within the hotel industry, including top managers, first-line managers, and non-managerial employees. Through semi-structured interviews and employing the consensus mapping approach (Taracki et al., 2014), this study endeavors to determine the individual perceptions of these distinct groups regarding the barriers and drivers influencing AI adoption.

2. Theoretical background

2.1 Drivers to AI adoption in hospitality

Following Rasheed et al. (2024), drivers to the adoption of AI in hospitality can be categorized in three distinct groups: functional, emotional and situational.

Functional drivers refer to the tangible advantages derived from the fundamental capabilities of AI technologies. Scholarly investigations have consistently emphasized the pivotal roles of perceived usefulness (PU) in shaping consumers' attitudes towards AI adoption (Park et al., 2021). For instance, AI facilitates humans in efficiently accomplishing various tasks, including self-check-in or out, housekeeping, concierge services, and chatbot interactions for information retrieval (Wong et al., 2023; Zhu et al., 2023; Law er al., 2023; Li et al., 2021). Hence, *operational efficiency* pertains to the tangible benefits stemming from the core features of AI technologies, specifically in terms of optimizing processes. Furthermore, AI adoption correlates with reduced workloads and heightened productivity among employees (Ersoy and Ehtiyar, 2023; Buhalis and Moldavska, 2022). Tasks such as data analysis, customer service, and administrative duties are streamlined, allowing staff to focus on higher-value activities. Indeed, prior studies underscore AI technologies' ability to optimize inventory management and streamline processes, leading to *cost savings* for businesses. In addition, factors such as perceived interactivity and innovativeness of AI technologies positively contribute to intentions to adopt and repurchase these technologies (Go et al., 2020; Pillai and Sivathanu, 2020). More specifically, AI technologies' ability to deliver *personalized experiences* based on individual preferences and behaviors fosters positive attitudes towards AI adoption, as users perceive the technology as valuable and relevant to their customization needs. Indeed, service customization triggers greater customers' knowledge, emotional attachment and behavioral commitment (Buehring & O'Mahony, 2019).

Shifting the focus away from the functional benefits for businesses, emotional drivers explore the complex domain of consumer sentiments and motivations towards AI adoption. Prior studies underscore the relevance of perceived human likeness and intrinsic motivations, moderated by socio-demographic aspects such as age, gender, and income in shaping consumers' propensity towards AI adoption in the hospitality sector (Belanche et al., 2020). AI technologies streamline processes (Rasheed et al., 2024), provide personalized experiences (Go et al., 2020), and offer real-time support (Li et al., 2021), enhancing overall service quality. Hence, studies suggest a positive correlation between AI adoption and *heightened customer satisfaction levels*, underscoring the importance of AI-driven innovations in meeting evolving consumer demand (Alam et al., 2023).

Focusing on the macro level, situational drivers are facilitating conditions that are key contextual drivers in AI adoption intentions. The macro context where users interact with AI technologies has a considerable impact on their perceptions toward AI value and usefulness, ultimately either pushing or inhibiting adoption behaviors (Mariani and Borghi, 2023; Lin et al., 2020). Both mimetic and first-mover pressure relates to the contextual factors influencing user attitudes and behaviors towards AI adoption, specifically in terms of gaining a *competitive edge* through the use of AI technologies.

2.2 Barriers to AI adoption

Barriers towards AI adoption in hospitality are mainly grouped into value, risk and usage barriers (Rasheed et al, 2024).

When users perceive that the cost of adopting a new technology outweighs the potential benefits or returns, they may view it as offering less value compared to existing alternatives. Hence, value barriers may arise, thus leading to reluctance in adopting the new technology hindering its acceptance (Laukkanen et al., 2008). Scholarly, *high implementation costs* (i.e., substantial upfront costs for technology acquisition, integration, training) and concerns regarding return on investment (ROI) are considered value barriers due to their potential to negatively influence user perceptions of a new product or service (Rasheed et al., 2023).

Prior studies unveil the emergence of risk barriers, referring to the degree of uncertainty and associated risks inherent in novel products, services or technologies, shaped by user perceptions or experiences (Chen and Kuo, 2017). *Privacy and security* concerns are categorized under risk barriers, revolving around uncertainties regarding compliance with regulations like GDPR or CCPA to uphold customer trust (Rasheed et al., 2023).

While few studies elucidate no significant relationship between technological anxiety and the intention to adopt AI (Pillai and Sivathanu, 2020), scholars tend to acknowledge usage barriers that include a mismatch between the new technology and the user prior experiences (Antioco and Kleijnen, 2010). For instance, existing research highlights factors such as the *lack of awareness and understanding* that reflects the incompatibility of AI technology with user´s existing experiences, habits, and acceptance standards. Businesses may not fully comprehend the potential of AI and its applications, indicating a lack of awareness as a barrier to adoption (Alam et al., 2023; Huang et al., 2022). Furthermore, Li et al. (2019) show a significant positive correlation between awareness of AI and robotics and employees' intention to turnover. This underscores the reluctance to embrace AI technologies due to fear of job displacement, changes in workflow, or perceived threats to professional roles. Consequently, *resistance to change* signifies the incongruity between AI and current workflow and roles, impeding adoption. Additionally, Rasheed et al. (2023) classify *technological complexity* as a usage barrier, encompassing challenges related to AI service complexity and the requisite technical expertise, often lacking within organizations. Technical complexity represents a usage barrier to AI adoption due to difficulties in implementing and integrating AI solutions into existing systems and workflows.

3. Methodology

To explore the intriguing issues of challenges and opportunities toward AI adoption in the hotel industry, we conducted semi-structured face-to-face interviews with n. 21 key information-rich stakeholders occupying diverse hierarchical positions in the hotel industry. Following the managerial pyramid developed by Robbins et al. (2020), we classified workers grouping them as (i) top managers, (ii) first-line managers, (iii) non-managerial employees. The interviews lasted on average 18 minutes and were conducted in September 2023.

From the literature review, five main *themes* relative to drivers (i.e., operational efficiency, competitive advantage, enhanced customer experience, service personalization, cost saving) and barriers (i.e., lack of awareness and understanding, privacy and security concerns, resistance to change, technological complexity, cost concerns) emerge. We asked the study participants to prioritize the five categories related to the drivers and barriers by ranking them in order of importance. The output was a personal ranking of factors that propel (inhibit) AI adoption that ranged from the most important driver (barrier) to the least important driver (barrier). We used the responses to assess the degree of consensus within and between diverse hierarchical groups (i.e., top manager, first-line manager, non-managerial employees) using the methodology of consensus mapping developed by Tarakci et al. (2014).

We present a brief description of each informant in Table 1.

Table 1: Informants details

Interviewee category	Job Position / Initials of name	Age	Gender	Years of Professional Experience
Top manager	Hotel managing director, G. S.	48	Male	13
Top manager	Hotel managing director, P. I.	34	Male	15
Top manager	Hotel managing director, A. Z.	35	Male	10
Top manager	Hotel managing director, S. D.	45	Male	25
Top manager	Hotel managing director, E. R.	58	Male	33
Top manager	CEO, D. O.	38	Male	14
Top manager	CEO, H. P.	37	Male	13
First-line manager	Head of reception, K. N.	33	Female	14
First-line manager	Head of reception, M. S.	34	Male	10
First-line manager	Head of booking dept, M. N.	42	Female	18
First-line manager	Maître, L. S.	49	Male	30
First-line manager	Maître, T. L.	47	Male	29
First-line manager	Chef, G. D.	49	Male	29
First-line manager	Chef, S. M.	45	Male	26
Non-managerial employee	Waiter, M. D.	43	Male	23
Non-managerial employee	Waiter, R. S.	46	Female	26
Non-managerial employee	Receptionist, R. M.	37	Female	13
Non-managerial employee	Receptionist, L. R.	33	Female	11
Non-managerial employee	Housekeeper, G. M.	46	Female	28
Non-managerial employee	Commis chef, F. I.	34	Male	10
Non-managerial employee	Maintainer, A. N.	47	Male	29

4. Results and discussion

Top managers, first-line managers and non-managerial employees assigned priorities to five different categories of drivers and barriers. The output obtained consisted in a set of six matrices describing the corresponding rankings, one per group of respondents evaluating either drivers or barriers. Two measures of consensus have been computed to analyze the responses received (Cozzio & Furlan, 2023). The first one focuses on the degree of consensus within the members of each group and follows from principal component analysis (PCA). The second measure analyzes consensus between groups and is based on classic multidimensional scaling. All computations have been performed in MATLAB.

4.1 Assessing within-group consensus

The degree of consensus within a group is obtained by applying the vector model of unfolding (VMU) defined by Tarakci et al. (2014), which transposes the standard data matrix used in PCA (Borg and Groenen, 2005). More precisely, we apply PCA to a matrix where respondents define the columns and the categories ranked are placed in the rows.

Consider the standardized data matrix H that lists the m categories evaluated in its rows and the respondents along its n columns. The VMU method proposed by Tarakci et al. (2014) in p dimensions is based on the minimization of the sum of the squared errors derived from H and the low dimensional representation XA' and defined as follows

$$L_{VMU}(X,A) = \|H - XA'\|^2 = \sum_{ij} e_{ij}^2 \tag{1}$$

where X is an $m \times p$ matrix of object scores and A is an $n \times p$ matrix of component loadings for the first p components.

The component loadings in A are the correlations between the object scores for each category and the evaluations of each respondent. Tarakci et al. (2014) used this fact to define the consensus within each group as the length of the average component loading vectors in A across its first two components

$$\alpha = \sqrt{\sum_{p=1}^{2}\left(\sum_{i}\frac{a_{ip}}{n}\right)^2} \tag{2}$$

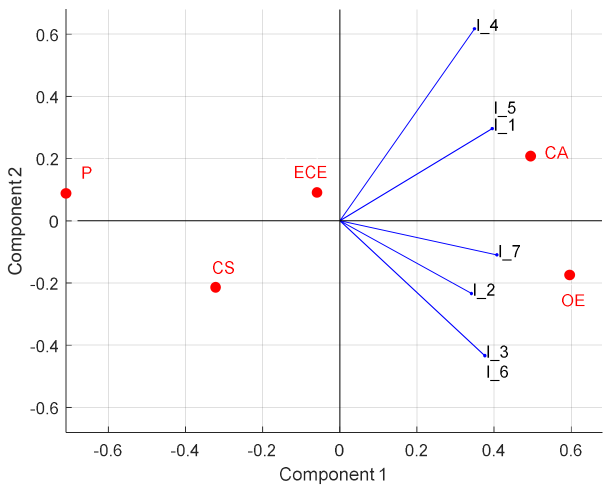
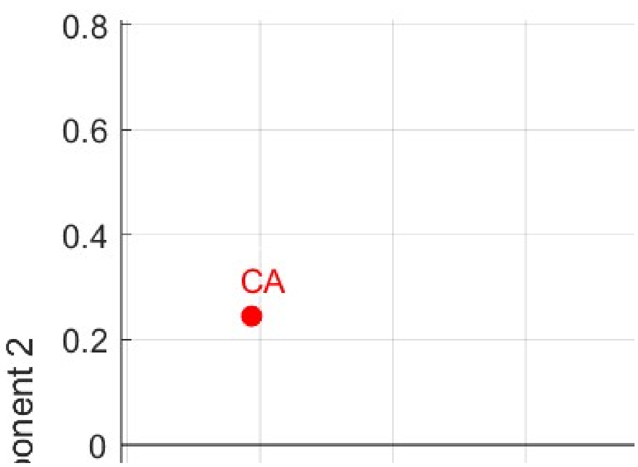
where a_{ip} denotes the p-th component loading for respondent i. As is the case in PCA, the results obtained can be represented in the Euclidean plane using a biplot. The categories are described in order of preference relative to the horizontal axis, while the respondents composing each group are depicted as vectors.

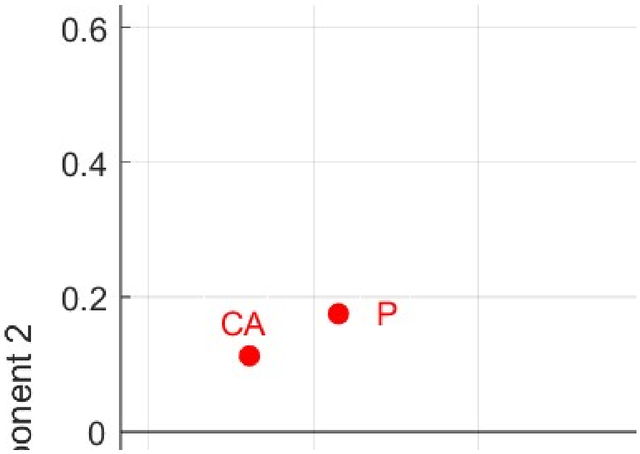
The correlation between respondents can be approximated via the cosine of the angle between their vectorial representations (Linting et al., 2007). Larger angles describe less similar evaluations, while the opposite is true for smaller angles. The same intuition applies to the consensus within the group, with tighter clusters of vectors demonstrating a higher degree of consensus.

The preferences of the different respondents are represented by the orthogonal projection of each category item of their corresponding vectors. The farther an item is projected into the vector the more preferred it is, while the items projected in the opposite direction are less preferred. In this regard, the horizontal axis corresponds to the prototypical member representing the opinion of the group. That is, the projection on the horizontal axis represents the overall ranking of the group.

Figures 1 and 2 illustrate the biplots defining the degree of within-group consensus for each group of respondents when considering drivers and barriers, respectively.

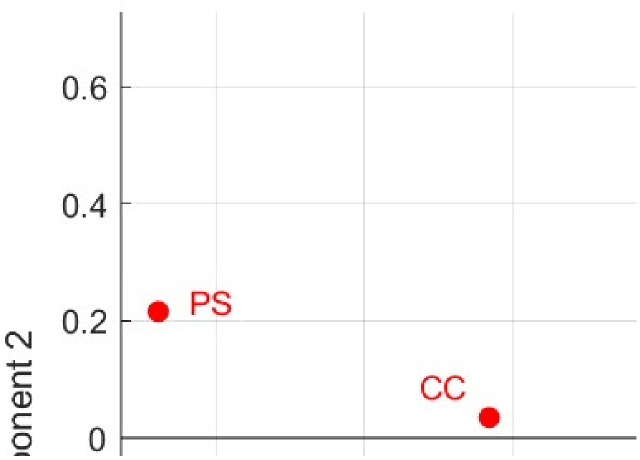
Figure 1: Within-group consensus (drivers)

 **Hotel Managers**	**Notation** **OE:** Operational efficiency **CA:** Competitive advantage **ECE:** Enhanced customer experience **P:** Personalization **CS:** Cost saving **Respondents** I_1 to I_7 each referring to the corresponding members from a given group
 **First-line Managers**	



Non-managerial Employees

Figure 2: Within-group consensus (barriers)

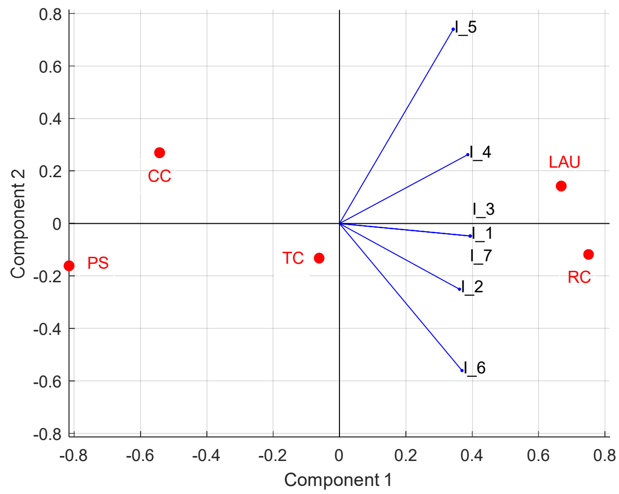


Hotel Managers

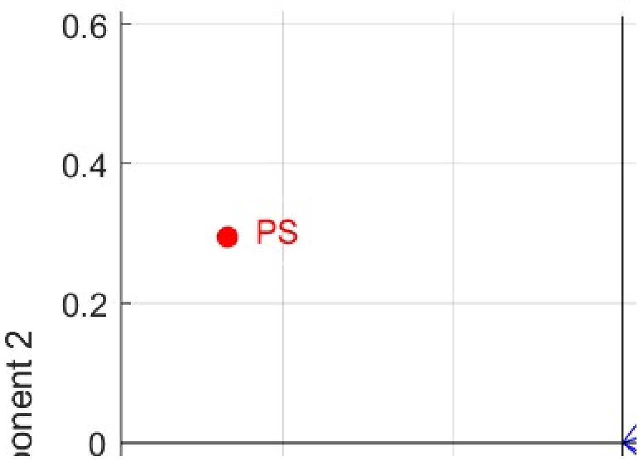
Notation
PS: Privacy & Security
CC: Cost concerns
LAU: Lack of awareness and understanding
TC: Technical complexity
RC: Resistance to change

Respondents
I_1 to I_7 each referring to the corresponding members from

a given group



First-line Managers



Non-managerial Employees

Based on the projections of the items on the horizontal, *Operational efficiency, Competitive advantage, and Enhanced customer experience (satisfaction)* emerge as primary drivers for top top managers, whereas first-line managers prioritize *Enhanced customer experience, Personalization, and Operational efficiency*. Non-managerial employees emphasize *Cost saving, Operational efficiency and Enhanced customer experience*. Overall, all groups recognize the benefits of AI adoption for operational efficiency and customer satisfaction. This highlights significant differences in their

orientations, with top managers focusing outward and non-managerial employees inward. For instance, while AI adoption offers added value for top managers by providing a competitive advantage, non-managerial employees perceive it primarily as a means of cost-saving.
In terms of barriers, top managers prioritize *Resistance to change, Lack of awareness and understanding, and Cost concerns*. First-line managers rank *Resistance to change, Lack of awareness and understanding, and Technological complexity* as the most significant inhibitors. Conversely, non-managerial employees value *Technological complexity, Resistance to change, and Lack of awareness and understanding*. *Privacy and security concerns* are consistently ranked as the least important across all groups. The identification of resistance to change, lack of awareness, and technological complexity as predominant barriers across hierarchical levels signifies a degree of consensus, albeit weak, regarding the critical challenges impeding AI adoption in the hotel industry.

4.2 Assessing between-group consensus

Consensus between groups is measured in terms of the correlation exhibited by the ranking preferences of the prototypical group members. More precisely, the measure proposed by Tarakci et al. (2014), denoted by $r(A,B)$, is determined by the correlation of the object scores of the categories on the first principal component for respondent groups A and B. The higher this value, bounded between zero and one, the higher the consensus between both groups.
The distance between the groups of respondents defining the symmetric matrix of correlations is computed using classical multidimensional scaling (MDS). The corresponding output obtained is represented in Figures 3 and 4 for the drivers and the barriers, respectively.
Tarakci et al. (2014) suggested defining ten rings to describe the difference in correlations relative to the group placed at the center of the plot. In this regard, a higher level of consensus is observed as the distance between points decreases, representing a more aligned evaluation between groups. In our graphical representation, top managers are at the center of the MDS plots. The distance between the bubbles shows the degree of consensus between the groups. The sizes of the bubbles denote the degree of the within-group consensus in each group (α), and the rings that surround the bubbles depict the size of a bubble when there is perfect consensus within a group ($\alpha = 1$).
Clearly, between-group consensus differs markedly across groups of respondents. First-line managers and non-managerial employees display substantial differences with respect to top managers when considering the drivers. Consensus between groups increases when considering the barriers, though the correlations between groups remain quite low also in this case.
Figure 3: Between-group consensus (drivers)

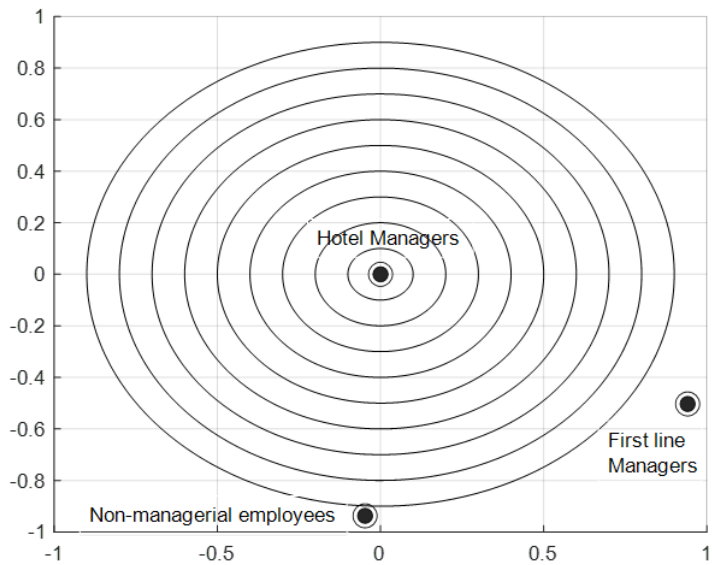
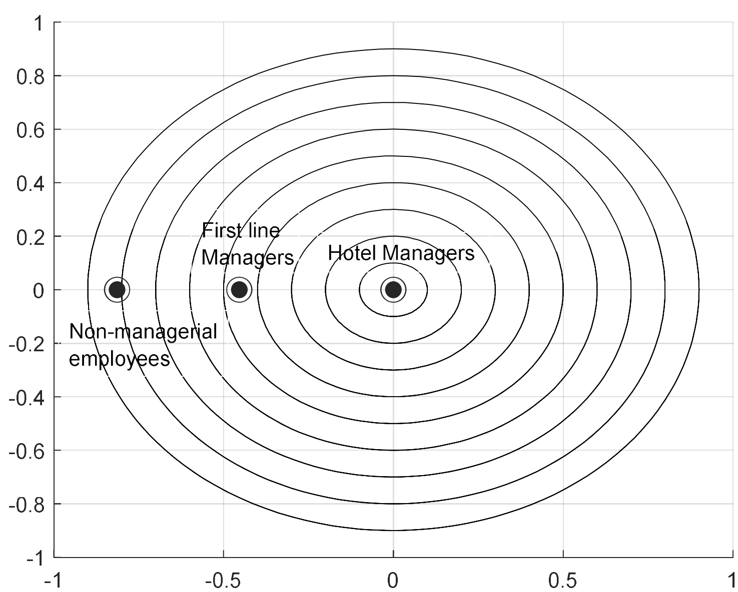


Figure 4: Between-group consensus (barriers)



5. Conclusion

5.1 Theoretical implications

This study constitutes a pioneering investigation into the implications of AI adoption from an employee-centric perspective, diverging from the prevalent customer-focused approach (Wong et al., 2023; Huang and Zheng, 2023). Notably, the segmentation of participants into three cohorts across varied hierarchical levels - top managers, first-line managers, and non-managerial employees - facilitates a nuanced exploration of multifaced viewpoints on AI adoption within hotel settings. Operational efficiency and enhanced customer experience are pivotal drivers across all groups (Ersoy and Ehtiyar, 2023; Zhu et al., 2023). However, our research reveals nuanced specificities, providing profound insights into AI acceptance within distinct hierarchical strata. Specifically, our findings highlight differences in orientation, with top managers focusing outwardly (i.e., competitive advantage) and non-managerial employees oriented inwardly (i.e., cost saving).

Second, our study elucidates both the impediments inhibiting the widespread adoption of AI and the facilitators propelling AI uptake within hotel operations, thus addressing the call for additional exploration on the employees perspective (Rasheed et al., 2024; Li et al., 2022). Through rigorous analysis of interview data and consensus mapping techniques, this study seeks to distill key themes, patterns, and divergences in perceptions between hierarchical levels, thereby identifying salient factors shaping the trajectory of AI adoption in the hotel industry.

Third, our study advances understandings on multifaceted barriers to achieve consumer acceptance, by acknowledging the significance of effective communication in facilitating organizational change (Morosan and Dursun-Cengizci, 2024). Hence, we advocate for the implementation of tailored communication strategies. These strategies aim to heighten awareness and cultivate acceptance of AI technologies among various hierarchical groups, representing a significant advancement in adoption acceptance.

5.2 Managerial implications

Tailored communication strategies should be designed to address the specific needs and concerns of different hierarchical groups within the organization. While emphasizing operational efficiency and enhanced customer experience is essential, specific considerations must be made to enhance the effectiveness of these strategies.

For non-managerial employees, highlighting the cost-saving implications of AI adoption can bolster their acceptance levels. Emphasizing how AI technologies streamline processes and reduce operational costs helps non-managerial employees perceive AI as beneficial to their roles and daily tasks.

Similarly, first-line managers should be informed about the potential for service personalization offered by AI technologies. By demonstrating how AI can facilitate personalized experiences for customers based on their preferences and behaviors, first-line managers are more likely to recognize the value of AI in improving customer satisfaction and loyalty.

5.3 Limitations and future research direction

While our study provides valuable insights into AI adoption within the hospitality sector, it is important to acknowledge its limitations. One significant limitation is the rather focused sample, which primarily consisted of participants from the hotel industry. This narrow focus may limit the generalizability of our findings to other segments of the broader tourism industry. Additionally, our study focused solely on perceptions within hierarchical positions in hotels, potentially overlooking valuable insights from other stakeholders, such as customers or AI technology providers.

To address these limitations and expand the scope of future research, several promising avenues emerge. Firstly, future studies could explore AI adoption across various segments of the broader tourism industry, including airlines, cruise lines, and travel agencies. This broader perspective would provide a more comprehensive understanding of the challenges and opportunities associated with AI adoption within different sectors of the tourism industry.

Furthermore, future research could investigate the perceptions and attitudes of other stakeholders beyond employees, such as customers, AI technology providers, and regulatory bodies. Understanding the perspectives of these diverse stakeholders could shed light on additional barriers and facilitators to AI adoption and inform more holistic strategies for AI implementation.

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