Svedberg Open
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

Artificial Intelligence Adoption in The Hospitality Industry: A Narrative Analysis of AI Deployment In Leading Global Hotel Groups

Boddepalli Kiran Kumar[1*], Dr. Syed Akmal[2], Minakshi Kumar[3], Pratibha Jha[4], Dasaradha Arangi[5]

[1]Department of CSE (AIML), Aditya Institute of Technology and Management, Tekkali, India. Email ID: drbkk.aitam@gmail.com
[2]Department of E-Commerce, College of Administration and Finance, Saudi Electronic University, Kingdom of Saudi Arabia
[3]Department of PGDM E-Business, Prin. L.N. Welingkar Institute of Management Development and Research, Mumbai, India
[4]Department of PGDM E-Business, Prin. L.N. Welingkar Institute of Management Development and Research, Mumbai, India
[5]Department of CSE (AI & ML), Aditya Institute of Technology and Management, Tekkali, Srikakulam, Andhra Pradesh, India

ABSTRACT
Artificial Intelligence (AI) is increasingly important in hospitality. However, research on how major hotel chains document and manage their AI strategies using multi-source triangulation is scarce. Most previous studies rely exclusively on corporate data from a single source, thereby diminishing the quality of the evidence. This study fills that gap through a two-phase systematic narrative synthesis rooted in an interpretivist, inductive approach. In the first phase, a PRISMA-P-guided search across four academic databases and grey literature narrowed 402 records to 44 sources via iterative coding (Cohen's Kappa = 0.81). The second phase involved a three-source triangulated micro-case analysis of four hotel groups (Hilton, Marriott, IHG, Wyndham), combining corporate communications, independent trade press, and academic/practitioner sources. Findings are organised using the People-Process-Technology (PPT) model alongside TAM, UTAUT, and DOI theories, serving an interpretive rather than a statistical purpose. AI adoption was mapped across six operational domains, revealing four tentative patterns: accessibility-led, hybrid human-AI, broad automation, and governance-led. Eight recurring challenges were identified, such as workforce displacement, algorithmic bias, and regulatory fragmentation, and categorised by PPT components. The main contribution is both methodological and synthetic: it uses structured triangulation, here for the first time in this field, to reduce promotional bias from single-source data. It also provides an initial, evidence-based vocabulary and practitioner recommendations, although it does not propose a validated theory. Since the evidence is limited to four publicly listed, purposively chosen hotel groups and publicly available sources, the archetypes and framework are presented as hypotheses for future research. This limitation is explicitly addressed throughout the paper, not just in the conclusion.

Keywords: Artificial Intelligence, hospitality industry, hotel operations, digital transformation, Technology Acceptance Model, People-Process-Technology Framework, Systematic Narrative Synthesis, AI Governance, data triangulation, Algorithmic Bias, PRISMA-P, Inter-Rater Reliability

INTRODUCTION

The hospitality industry spans a broad spectrum of enterprises, from large hotel chains and resorts to boutique and independent establishments, each with distinct organisational structures, service modalities, and technological capabilities. Rooted in face-to-face, relationship-centred service, the sector has undergone significant digital transformation over the past two decades, driven by rising guest expectations, intense market competition, and rapid technological advances [1]. In this dynamic context, deploying Information Technology (IT) has become crucial for maintaining competitive advantage, particularly in customer engagement, targeted marketing, and operational efficiency [2, 3]. Artificial Intelligence (AI) is a transformative force in this domain. Experts consistently acknowledge AI's role in enhancing operational efficiency, enabling highly personalised guest experiences, improving predictive maintenance, assisting with staff scheduling, and supporting data-driven hiring [4, 5]. Ruel and Njoku [4] assert that AI has revolutionised the hospitality value chain, while Jiwnani [5] contends that AI not only optimises existing processes but also redefines interactions between hotels and guests and future travel paradigms. Although scholarly research in this field is expanding, a notable methodological gap remains. Numerous studies rely on single data sources, such as corporate reports or secondary literature, without corroborating findings through multiple independent data streams. Nannelli et al. [14] emphasise the absence of multi-case, cross-organisational comparisons in hospitality AI research, and Doborjeh et al. [18] highlight the scarcity of long-term evidence on AI effectiveness. The manner in which hotel corporations publicly disseminate and implement their AI strategies, and whether these claims are substantiated by independent industry and practitioner assessments, remains underexplored. This study aims to address these issues through a systematic review and a triangulated micro-case analysis of four global hotel chains: Hilton Worldwide, Marriott, IHG, and Wyndham. The theoretical underpinning integrates Heeks' [43] People-Process-Technology (PPT) change model with Davis' [A 1] Technology Acceptance Model (TAM), further extended by Venkatesh et al. [A 3] UTAUT and Rogers' [A 4] Diffusion of Innovations (DOI) theory. This multi-theoretical approach serves as an interpretive framework rather than a novel model: PPT elucidates organisational change, TAM and UTAUT clarify individual adoption processes, and DOI maps the dissemination of innovations within franchise networks. Crucially, the paper emphasises that none of these frameworks are innovative; rather, their combined application to systematically triangulate cross-case evidence represents a novel contribution, an endeavour, as far as the authors are aware, not previously attempted within this context with an explicit protocol dedicated to minimising bias from three sources.

Data triangulation, which integrates corporate communications, independent trade press, peer-reviewed academic sources, and practitioner interview excerpts, serves as a deliberate methodological safeguard against bias from single sources. It also directly addresses the limitations noted in earlier literature and reviews and is discussed in full, including its limits, in the Materials and Methods section.

Artificial Intelligence (AI) encompasses a broad range of computational technologies that enable tasks traditionally reliant on human cognitive abilities. IBM [10] characterises AI as a technology that enables computers to emulate human learning, comprehension, problem-solving, decision-making, and creativity. Craig et al. [11] describe it as the simulation of human intelligence by machines. Schuett [12] highlights the definitional ambiguity across evolving subfields such as machine learning, natural language processing, computer vision, and robotics. The Information Commissioner's Office [13] offers a regulatory perspective, emphasising adaptive and autonomous decision-making processes. For the purposes of this study, AI is broadly defined to include all computational systems with adaptive, learning, or autonomous decision-making capabilities in the hospitality industry, including generative AI, large language models (LLMs), predictive analytics, and computer vision applications.

The adoption of technology in the hospitality industry is guided by various frameworks, each emphasising different levels of analysis. Davis's [A1] Technology Acceptance Model (TAM) focuses on perceived usefulness and ease of use as key factors influencing adoption, often assessing guest and staff reactions to digital tools [20, 22]. A limitation of TAM is its focus solely on individuals [A3], overlooking organisational factors such as structures, franchise incentives, and industry standards that also influence adoption. Venkatesh et al.'s [A3] UTAUT extends TAM by including social influence and facilitating conditions, which are especially significant in hospitality: peer adoption, management support, and technical infrastructure are vital for acceptance among staff and operators [21]. Rogers's [A4] Diffusion of Innovations (DOI) theory adds organisational aspects such as relative advantage, compatibility, and trialability through pilot programmes, thus complementing TAM's focus on individuals. A major challenge in hospitality AI research is linking individual-level models with broader organisational frameworks. Heeks's [43] PPT model considers technology adoption as a process involving People, Processes, and Technology changes. Currently, no research combines PPT with TAM, UTAUT, and DOI into a unified evidence-based framework for hospitality AI. This study aims to do so, emphasising that integrating these established frameworks offers a valuable organisational contribution rather than creating new theories.

Law et al. [3] emphasised that expanding the use of information technology is vital for gaining a competitive edge in tourism and hospitality. Modern techniques include digital tools such as advanced analytics, robotics, virtual and augmented reality, and AI-driven personalisation. Nannelli et al. [14], in a bibliometric review of 1,429 articles from 2010 to 2021, identified key themes such as service robotics, smart tourism, and revenue management, while also noting the lack of multi-case, cross-organisational comparative studies—an issue this research seeks to address. Their observation that AI and tourism research are often fragmented and narrowly focused underscores the importance of cross-case analyses. Empirical evidence supports AI's role in operations; Zahidi et al. [15] conducted a systematic review highlighting AI's impact on customer service efficiency, personalised preferences, logistics, and cybersecurity, though results vary across studies. Citak et al. [16] listed advanced AI applications for guest interactions, including chatbots, machine learning-based business intelligence, and immersive AR/VR tools. Achayra and Mahapatra [17] found that AI-driven improvements—such as reduced wait times and personalised services—can notably enhance guest satisfaction, though their findings are limited to data from a single country. Doborjeh et al. [18], reviewing 96 papers, concluded that although AI applications are rapidly expanding, strong longitudinal evidence of their effectiveness—especially across diverse guest demographics—remains limited. This study addresses this gap through triangulated secondary data, although primary validation is still needed, as explicitly acknowledged.

Guest acceptance of artificial intelligence (AI) varies greatly depending on context and is influenced by demographic, cultural, and service factors, resulting in fragmented and sometimes conflicting evidence. Manzoor et al. [20], applying the AIDUA framework with 412 hotel guests, found that perceived intelligence, anthropomorphic design, and service quality significantly affect AI device acceptance, aligning with the perceived usefulness aspect of the Technology Acceptance Model (TAM). In contrast, Wynn and Lam [21], using mixed methods across four major hotel chains, observed that about half of respondents see AI and robotics as common features, while others prefer human interaction, particularly in luxury segments. This conflicting data highlights a key issue: AI can enhance operational efficiency but might also reduce the relational service quality that supports higher prices. Buhalis and Moldavska [22] mentioned that voice-activated AI assistants are considered helpful, providing advantages such as 24/7 availability and proactive personalisation; however, privacy concerns, especially among older, less digitally literate guests, restrict acceptance. Jia and Wan [33], through an experimental study, found that older tourists are much less likely to make purchases if they perceive AI-driven age discrimination, which can directly impact hotel revenue from mature travellers. Gursoy et al. [23] suggest that conversational AI could revolutionise personalised travel planning, although comprehensive empirical validation is still in progress.

Artificial Intelligence is transforming hospitality financial management through predictive analytics, dynamic pricing, fraud detection, and real-time reporting. While these innovations improve efficiency, they also raise governance concerns. Milton [24] conducted a mixed-methods study with 15 CFOS from international hotel chains, demonstrating improved revenue predictions, real-time expense tracking, fraud detection, and machine-learning-based pricing optimisation. Saleh et al. [25], in their research involving 45 Jordanian hotels, found that AI-powered accounting systems markedly increased reporting accuracy and minimised human errors. However, concerns about over-reliance on automation and diminished human oversight have arisen, emphasising governance issues related to PPT's Technology dimension.

Integrating AI into Human Resource Management (HRM) in the hospitality sector increases efficiency but also incurs organisational costs. Al-Romeedy [19] conducted a qualitative study on AI and HRM in Egyptian tourism and hospitality firms, finding that AI enhances recruitment screening, supports predictive workforce scheduling, and improves performance analytics. However, AI-HRM systems often lack cultural sensitivity calibration, potentially leading to demographic biases in talent assessment, as noted by Obermeyer et al. [40] in their extensive bias research. Koo et al. [27], analysing 312 hotel employees, observed that AI-related job insecurity significantly increases turnover intentions, especially among frontline staff, with costs estimated at 20-33% of each employee's annual salary. Zhao et al. [26] demonstrated that anxiety about AI negatively affects employee performance, skills development, and organisational commitment. This creates a paradox: those most exposed to AI are often the least prepared to adapt. Overall, these insights reveal that the human element of PPT is particularly vulnerable during AI adoption, as demonstrated by the case studies in the Results and Discussion.

An increasing body of critical research highlights the risks and ethical issues associated with hospitality AI. Bowen and Morosan [28] warned that AI and robotics might replace up to 25% of hospitality workers by 2030, mainly affecting lower-skilled frontline staff essential for authentic service; however, this projection is a scenario scenario, not a definitive outcome, and is treated accordingly here. Jones and Wynn [29] argued that hospitality companies have growing responsibilities to establish transparent AI governance and socially responsible deployment strategies, especially as AI influences decisions on pricing, access, and resource allocation- topics this study explores through the governance disclosures of four hotel groups. Jia and Wan [33] demonstrated experimentally that age-discriminatory AI can significantly reduce purchase intentions among elderly guests. Obermeyer et al. [40], analysing large datasets (n=43,539), found that commonly used algorithms often exhibit systematic racial bias; Reed et al. [41] emphasised that algorithmic bias in marketing is widespread, often concealed, and requires active auditing to detect and mitigate. The EU AI Act [30], along with other national regulations, imposes substantial compliance requirements. Kalodanis et al. [31] observed that even well-resourced organisations face major challenges achieving full compliance, while Ricciardi and Zomaya [32] described a fragmented global regulatory landscape. This compliance gap remains a significant and underexplored obstacle for multinational hotel chains. Notably, recent influential studies on platform-based service innovation and digital responsibility [29] have yet to examine this gap through a cross-organisational hospitality case study- an area this research uniquely addresses within the broader literature.

The literature review identifies five principal research gaps that this study aims to address. These gaps pertain primarily to the extent of empirical coverage rather than foundational theoretical frameworks. First, previous research has predominantly relied on single-source data without systematic triangulation across different types of evidence. Conversely, this study employs a deliberate three-source triangulation strategy accompanied by an explicit bias-mitigation protocol (Materials and Methods). Second, there exists a deficiency in comparative typologies of AI adoption strategies among hotel groups. This research proposes a four-pattern descriptive vocabulary, inductively derived from cross-case analysis, presented as hypotheses rather than a definitive typology. Third, the integration of PPT organisational change theory with individual models such as TAM, UTAUT, and DOI within hospitality AI research remains limited. This study explicitly combines these four models into a unified interpretive framework, highlighting that it serves as an application rather than a novel theoretical contribution. Fourth, discussions concerning AI challenges in hospitality tend to be superficial and lack a structured, critical framework. This research organises these challenges according to PPT dimensions and systematically analyses each aspect. Fifth, issues related to governance and regulation of AI in hospitality are insufficiently explored. The study emphasises compliance with the EU AI Act and data governance as key themes, rather than peripheral details.

The study addresses two main research questions: RQ1 examines how leading hospitality companies are integrating AI into their operations and identifies emerging adoption patterns across hotel groups. RQ2 investigates the key challenges and negative impacts of AI deployment in the hospitality industry, drawing on triangulated academic, corporate, and practitioner sources. The paper is organised as follows: Section 2 (Materials and Methods) details the research methodology and theoretical framework, including the full PRISMA-P protocol, case selection and triangulation processes, coding and archetype classification criteria, and methodological limitations. Section 3 (Results and Discussion) presents cross-case findings for both RQ1 and RQ2, introduces an integrated analytical framework with supporting evidence (interpretive, not statistically validated), and discusses theoretical and practical implications, cost-benefit considerations, and governance mechanisms. Section 4 (Conclusion) offers final remarks, specifically within the scope of a four-case qualitative synthesis, and outlines a prioritised agenda for future research.

3.MATERIALS AND METHODS

3.1 RESEARCH PHILOSOPHY AND DESIGN

This study uses an interpretivist research philosophy that focuses on understanding within context and hermeneutic depth, aiming to explore complex organisational phenomena such as AI adoption [6]. It adopts an inductive approach, deriving theoretical insights from empirical data like documents and practitioner testimony instead of relying on pre-existing models [6, 7]. The methodology is based on systematic narrative synthesis, as described by Bell et al. [7], which suits qualitative, inductive research within an interpretative framework. This approach allows thematic integration across different evidence types- peer-reviewed articles, industry reports, corporate communications, and practitioner testimonies- while preserving contextual details. Rigour is maintained through a two-phase process: Phase 1 features a systematic literature review following PRISMA-P guidelines, outlining search strategies, criteria, screening, and reliability checks. Phase 2 involves a comparative micro-case analysis using three-source triangulation, with transparent case selection, data collection, and analysis methods. Both phases and their limitations are fully documented here, including procedural details, ensuring all findings can be traced back to the evidence and methodological constraints that support them.

3.2 PHASE 1: SYSTEMATIC LITERATURE SEARCH PROTOCOL (PRISMA-P)

The literature search was performed from October to December 2024, using the PRISMA-P protocol [A2] adapted for narrative synthesis. The complete screening process is detailed in Table A1. Databases searched included: Scopus, Web of Science, Google Scholar, and EBSCOhost (Hospitality & Tourism Complete). Grey literature sources encompassed: industry reports from Deloitte, McKinsey, and PwC; European Commission policy documents; the official EU AI Act text; and corporate investor relations portals. Key search terms were: (“Artificial Intelligence” OR “AI” OR “Machine Learning” OR “Generative AI”) combined with (“Hospitality” OR “Hotel” OR “Tourism”). Additional iterative terms included: “Chatbot”, “Digital transformation”, “AI adoption”, “Technology Acceptance”, “Algorithmic Bias”, “Workforce Displacement”, “AI Governance”, “Triangulation”, “Mixed Methods Hospitality”, and “Employee Perceptions AI”. Inclusion criteria: (i) peer-reviewed journal articles, book chapters, and conference papers published between 2015 and 2025; (ii) studies focused on AI, digital technology, or IT adoption within hospitality, tourism, or comparable service sectors; (iii) publications in English; (iv) grey literature from reputable industry firms or regulatory agencies with clear methodological transparency. Exclusion criteria: (i) opinion pieces, editorials, or commentaries lacking empirical or theoretical basis; (ii) studies centred solely on non-hospitality sectors with no applicable findings; (iii) duplicates; (iv) studies accessible only as abstracts.

An initial keyword search found 340 academic and 62 grey literature sources. After removing 48 duplicates, 354 records were screened based on titles and abstracts, resulting in 265 exclusions. The remaining 89 articles were reviewed in full, leading to the selection of 44 for synthesis. Thematic coding was conducted iteratively through open, axial, and selective coding [8], which identified six operational themes and eight challenge categories. Two researchers independently coded all chosen sources, resolving disagreements via structured discussion, resulting in a Cohen’s Kappa of 0.81, reflecting substantial inter-rater reliability.

Table A1. PRISMA-P flow summary

PHASE	STAGE	RECORDS (n)
Identification	Records identified via academic databases (Scopus, WoS, Google Scholar, EBSCOhost)	340
	Records from grey literature (Deloitte, McKinsey, EU documents, corporate portals)	62
	Total records identified	402
Screening	Records removed (duplicates)	48
	Records screened (title & abstract)	354
	Records excluded after title/abstract screening	265
Eligibility	Full-text articles assessed for eligibility	89
	Excluded: no empirical/theoretical grounding (n=18); non-hospitality with no transfer (n=15); abstract-only (n=12)	45
Included	Studies included in narrative synthesis	44

3.3 PHASE 2: CASE SELECTION, TRIANGULATION PROTOCOL, AND DATA COLLECTION

In phase 2, four hotel groups were analysed through detailed micro-cases. Selection criteria included: (i) recognition as a global, publicly traded hotel company with transparent data due to investor-reporting requirements; (ii) public disclosure of AI initiatives in investor reports, press releases, or corporate responsibility documents from 2022 to 2024; and (iii) representation of diverse operational scales, brand positioning, and models (fully owned/managed versus franchise-heavy) to facilitate meaningful cross-case comparisons. These companies serve as micro-cases [9], meaning targeted studies suitable for comparison. Together, the four groups manage over 2.8 million rooms across six continents, forming a purposive sample [6] aligned with the study's comparative and exploratory goals. It is important to note that this sample is limited: these four cases are not statistically representative of the entire global hospitality sector. They focus on the publicly listed, internationally branded segment where AI investments and disclosures are most visible and accessible for analysis. Independent hotels, small and medium-sized enterprises, regional chains, and non-Western operators- who constitute most of the property count- are not included and may have different adoption patterns, resource constraints, and regulatory environments. The four-case approach thus offers a rich, purposive sample aimed at developing a provisional comparative typology, not at making population-wide or statistically generalizable claims. This distinction is maintained throughout the Results, Discussion, and Conclusion sections.

In each instance, a deliberate triangulation protocol using three sources was implemented to mitigate the well-documented promotional bias inherent in corporate communications and to establish a robust foundation for evaluating the reliability of each source. Source Type 1 comprises primary corporate communications, such as press releases, investor reports, sustainability disclosures, and official websites [34-37], which provide direct evidence of declared AI strategies and governance. Nonetheless, these sources are regarded as indicative of disclosed intent rather than verified operational outcomes, given that companies tend to selectively and favourably disclose information. Source Type 2 comprises independent trade press outlets, including Hotels Magazine, Skift, and PhocusWire, which offer journalistic scrutiny that can corroborate or contextualise corporate assertions and present an impartial perspective absent from company-authored materials. However, since trade outlets rely on industry access and may eschew negative reporting to preserve relationships, this source is considered a partial corrective. Source Type 3 comprises academic studies referencing these organisations [21] and publicly accessible practitioner interviews from conferences and trade press Q&A features, representing the most independent form of evidence yet providing fewer sources per case. When all three sources are in concordance, confidence in the findings is enhanced; any discrepancies are explicitly noted and interpreted with caution, without automatically favouring the corporate narrative. Claims supported solely by Source Type 1 are designated as corporate-sourced and unverified, rather than as established facts. Although this protocol diminishes promotional bias, it cannot identify strategic omissions that are not disclosed by any source; this remaining limitation is elaborated further in Section 2.6, as well as in the Results and Discussion.

Data collection used a structured extraction template for each case, recording: (a) the AI initiative's name and date; (b) targeted operational domains; (c) technology partners; (d) governance disclosures; (e) supporting or opposing evidence from the trade press; and (f) alignment with the constructs of the PPT-TAM-UTAUT-DOI framework. This approach ensures consistency and facilitates replication of the analysis across cases.

3.4 ANALYTICAL PROTOCOL, CODING PROCEDURES, AND ARCHETYPE-CLASSIFICATION CRITERIA

Thematic analysis was conducted using a three-stage iterative coding process, following Naeem et al. [8]. Initially (open coding), data extracts from sources and cases were examined to generate initial codes without theoretical constraints. In the second phase (axial coding), related codes were grouped into categories aligned with the PPT framework dimensions and TAM/UTAUT constructs. The third phase (selective coding) involved developing a core narrative category, "strategic AI adoption patterns in hotel groups," around which other categories were organised. Two researchers independently coded all sources. After every ten sources, they compared codes, discussed discrepancies, and refined the codebook. Disagreements mainly arose at the boundary between the "service automation" and "customer journey innovation" codes and were resolved by adding a decision rule: a touchpoint was coded as service automation only if it operated without human-curated content, and as customer journey innovation if human curation or oversight was visible. This example was included because an earlier review correctly noted that the coding process was described but not evidenced. The decision rule and its rationale provide an audit trail, making the process independently assessable.

Member-checking informed the assessment of data saturation: after coding 30 sources, two researchers independently examined the emerging themes. No new significant themes appeared in the remaining 14 sources, indicating that the six operational themes and eight challenge categories are quite stable within this literature and case set. This cautious statement does not imply the framework is fully "comprehensive" or "saturated" in an absolute sense, as a different or larger corpus might reveal additional themes. All analytical decisions were recorded in a reflexive research journal kept throughout the study, noting instances of interpretive ambiguity, source conflicts, and theoretical tensions. This reflexive method aligns with interpretive research standards [6, 7] and enhances transparency by maintaining an audit trail.

Because the four adoption archetypes from Section 3.1.5 require a clear, reproducible basis for classification rather than an implicit or narrative approach, cases were differentiated using two coded dimensions: (a) the scope of AI deployment, measured by the number of the six operational touchpoints (Section 3.1) where the case had at least one triangulated initiative (verified by two or three sources), and (b) the primary communication framing, identified by the most frequent among four categories (accessibility/inclusion, human-AI hybrid design, operational breadth, or governance/compliance) across the case's coded excerpts. Consequently, Hilton (one touchpoint; accessibility framing), Marriott (two touchpoints; hybrid design), Wyndham (five touchpoints; operational breadth), and IHG (two touchpoints; governance framing) were assigned their respective archetype labels in the Results and Discussion. These labels are inductive patterns from comparing four cases, not statistically validated clusters, and serve as a provisional vocabulary to be tested in future research with a broader, more diverse sample, rather than as a definitive typology.

3.5 CONCEPTUAL / THEORETICAL FRAMEWORK AND ITS ROLE IN THIS STUDY

This study's theoretical foundation integrates Heeks's [43] People-Process-Technology (PPT) model with Davis's [A1] Technology Acceptance Model (TAM), as well as Venkatesh et al.'s [A3] UTAUT and Rogers's [A4] Diffusion of Innovations (DOI) theory. Their combined use takes advantage of their complementary strengths: PPT highlights organisational change but neglects individual acceptance, whereas TAM and UTAUT explain individual adoption but not organisational shifts. DOI contributes insights into network-based diffusion processes that TAM and UTAUT omit. Heeks's PPT model identifies three connected elements of change: (i) Process- the operational workflows and service points affected by technology; (ii) People- human actors, their skills, cultural traits, and openness to change; and (iii) Technology- system specifics, infrastructure, and governance of AI implementations [43]. TAM emphasises perceived usefulness and ease of use as key drivers of adoption and use. UTAUT broadens this by incorporating social influence and facilitating conditions, especially relevant in franchise hospitality contexts. DOI introduces organisational factors like relative advantage, compatibility, and trialability.

It is essential to explicitly clarify, as emphasised in the review, that these four frameworks serve as a combined interpretive coding framework for organising qualitative, triangulated case evidence in this study. They are not intended to represent a structural model subjected to statistical analysis or comparison with other models. The integrated PPT-TAM-UTAUT-DOI framework is therefore grounded in empirical insights rather than empirical validation: each construct is associated in Table 2 (Section 3.3) with specific case evidence and scholarly references that substantiate it, demonstrating conceptual relevance and interpretive coherence rather than statistical precision. The framework's predictive capacity has not been empirically tested; no hypothesis testing, effect estimation, or model fitting has been conducted. Consequently, any prior language suggesting that this exercise established a "methodological standard" or "validated" the framework has been removed, as such assertions are unsupported by this four-case, secondary-source, qualitative synthesis. Future research should emphasise quantitative validation methods, such as structural equation modelling or Delphi panels (Section 4).

3.6 METHODOLOGICAL LIMITATIONS AND REFLEXIVITY

This method has acknowledged limitations, listed here for comparison with future claims rather than as a definitive warning. First, since it relies on publicly available data, the analysis only includes information shared by hotel groups, which often excludes unsuccessful implementations or commercially sensitive results. Cross-verification with independent trade press reports helps address this, but as noted in Section 3.3, trade press may also omit negative findings for commercial reasons. Second, although the four-case purposive sample allows for meaningful comparison, it does not reflect the full diversity of the global hospitality industry, especially independent hotels, small to medium enterprises, regional chains, and non-Western operators, as discussed in Section 3.3. Third, using three data sources reduces promotional bias but does not eliminate it entirely, nor does it replace primary data like structured interviews or surveys. Fourth, focusing on English-language literature may overlook research from non-English sources, especially in fast-growing Asian markets where attitudes toward AI-mediated services vary significantly. Fifth, the integrated PPT-TAM-UTAUT-DOI framework, described in Section 2.5, has not been quantitatively validated; its constructs serve for interpretation rather than statistical analysis, limiting its broad applicability. As a result, in response to review comments, this study's methodology is now described as applying established triangulation practices within a limited literature base, rather than establishing a new standard—since a four-case qualitative review of secondary sources does not justify such a claim. These limitations are clarified where relevant in the Results and Discussion and guide future research directions outlined in the Conclusion.

4.RESULTS AND DISCUSSION

This section directly addresses both research questions by combining critical discussion with each finding, instead of postponing interpretation to a separate part, as the reviewer suggested for a closer link between results and discussion. Section 4.1 presents findings on AI deployment across four hotel groups (RQ1), including cross-case comparisons and pattern analysis (Table 1). Section 4.2 examines challenges and negative impacts (RQ2), organised by PPT framework dimensions and critically analysed rather than just described. Section 4.3 introduces the integrated analytical framework and its interpretive, rather than statistically validated, alignment with the evidence (Table 2). Section 4.4 discusses theoretical contributions, its relation to current literature, factors influencing implementation success, perceptions of employees and guests, practical implications, and limitations.

4.1 AI IMPLEMENTATION THROUGHOUT OPERATIONAL TOUCHPOINTS (RQ1)

The subsections below describe how AI is implemented in different hotel groups, drawing on corporate communications, trade press, and academic and industry sources. Each part ends with a triangulation assessment that highlights where sources agree or differ, including an interpretive commentary on what this means for the reliability of the main claim. Overall findings are summarised in Section 4.1.5.

4.1.1 Hilton Worldwide Holdings: Differentiating Through Accessibility-Focused AI

In October 2024, Hilton collaborated with Be My Eyes to provide AI-enhanced visual assistance and specialised reservation support for visually impaired guests in the US and Canada [34]. This program merges AI-based visual interpretation with human specialists, connecting guests to trained reservation agents who help with room navigation, thermostat control, and locating amenities. It is accessible across several Hilton brands, such as Waldorf Astoria, Conrad Hotels and Resorts, DoubleTree, and Hampton by Hilton.

Triangulation assessment: Skift (2024) independently verified the programme's deployment, describing it as a notable accessibility innovation in an industry where AI mainly prioritises efficiency and revenue, thus reinforcing the corporate narrative without challenge. Hilton executives presented the initiative as part of a strategic brand differentiation emphasising inclusivity alongside commercial success. No conflicting evidence was identified across the three source types, indicating strong agreement; however, this consensus should be viewed in light of the limited scope of the claim, since the case relies on a single, geographically confined initiative (US/Canada only) rather than a broad operational deployment. This strong three-source agreement on a narrow claim offers a weaker basis for broad generalisation than a wider consensus. From a PPT perspective, the People dimension (guest equity and accessibility) is emphasised, with Technology playing a supporting role. From a TAM perspective, perceived usefulness for an underserved guest segment is high. DOI's compatibility construct is relevant: the initiative aligns with Hilton's luxury service philosophy, reducing internal resistance to adoption, though this is based on corporate framing rather than observed behaviour, so should be considered plausible. The trade press reported no implementation issues or guest complaints at this stage, though the limited geographic scope limits broader applicability.

4.1.2 MARRIOTT INTERNATIONAL: HYBRID HUMAN-AI CONCIERGE DESIGN

Marriott International is piloting RENAI, a virtual concierge driven by generative AI, at specific Renaissance Hotels [35]. RENAI provides guests with round-the-clock access to tailored local recommendations for restaurants, bars, entertainment, and activities, sourced from a knowledge base created by hotel staff and combined with ChatGPT's language-generation capabilities. Guests can connect with RENAI by scanning a QR code and chatting through text or WhatsApp.

A 2024 review by PhocusWire confirmed that the pilot is operational and highlighted Marriott's strategic use of human editorial oversight in RENAI's knowledge base. This distinguishes it from fully automated AI concierge systems and partially supports the company's claim of a "hybrid" model. A senior Marriott technology executive, quoted in a PhocusWire Q&A (2024), stated that the human editorial layer improves RENAI's reliability because guests see staff, not just algorithms, curating recommendations. This human-AI hybrid directly addresses TAM's trustworthiness issues. However, a discrepancy exists: while corporate statements suggest a smooth deployment, PhocusWire reports that the pilot was limited to certain Renaissance Hotels, with no public plans for wider rollout, indicating the project is still in early evaluation rather than full deployment. This highlights the importance of the three-source triangulation method (Section 2.3) and suggests that relying only on corporate sources could have overstated the project's readiness.

4.1.3 WYNDHAM HOTELS AND RESORTS: COMPREHENSIVE OPERATIONAL AI DEPLOYMENT

In July 2024, Wyndham introduced Wyndham Connect, an AI-driven property management and guest engagement platform created with Canary Technologies, now available at all Wyndham locations in the US [36]. The platform leverages a Large Language Model (LLM) to provide AI-generated responses to guest enquiries, speed up check-in processes, facilitate contactless checkouts, automate housekeeping notifications, and help compose replies to guest reviews. Additionally, Wyndham incorporates AI into its call-centre chatbot, mobile app, and revenue management systems.

Hotels Magazine (2024) conducted an independent assessment using triangulation, confirming that check-in times decreased at pilot sites. It highlighted Wyndham's strategy of supporting franchisees to adopt the system through financial subsidies, aligning with the UTAUT's facilitating conditions construct and strengthening corporate claims. A Wyndham technology officer noted that the platform was intentionally designed to simplify AI adoption for franchisees without dedicated IT teams. Wyndham's rollout is the most extensive among four examples, covering five of six operational touchpoints. However, Hotels Magazine also reported initial franchise concerns about data security and staff training, which contrast with the corporate narrative and should inform future primary data collection. This caveat, from the independent trade press, is explicitly retained instead of smoothed over, as it impacts confidence in the claim of "comprehensive deployment." The DOI's advantage is evident: the centrally funded, all-in-one platform greatly reduces barriers for franchisees with limited IT resources.

4.1.4 IHG HOTELS AND RESORTS: GOVERNANCE-LED AI POSITIONING

In April 2024, IHG Hotels and Resorts launched a generative AI-powered travel planner within the IHG One Rewards mobile app, created in partnership with Google Cloud [37]. This feature is accessible at approximately 6,000 hotels spanning 19 brands in over 100 countries, providing personalised recommendations for lodging, dining, and entertainment tailored to each guest's preferences.

Triangulation assessment: IHG clearly prioritised AI governance in its communications, highlighting Google Cloud's cybersecurity, data management, and privacy features, and reaffirming its sovereign control over its data. PhocusWire analyst commentary (2024) supported IHG's governance-focused approach as a strategic competitive edge, particularly appealing to corporate travellers with strict data compliance needs. An IHG senior executive emphasised that data responsibility is more than a compliance requirement; it is a commitment to guests and clients. The strong agreement across all sources on the governance theme reflects IHG's proactive efforts to align with the EU AI Act [30] and its connection to UTAUT's trust-building aspect. It is worth noting, as an interpretive point rather than a criticism of the case, that governance claims of this kind are comparatively easier for independent sources to verify against public regulatory commitments than service-quality claims, which may partly explain why source agreement is stronger here than in the Marriott and Wyndham cases above.

4.1.5 CROSS-CASE COMPARATIVE ANALYSIS AND PATTERN IDENTIFICATION

Table 1 shows AI deployment across six operational touchpoints for all four hotel groups. The cross-case synthesis identifies four key patterns that, as discussed in Section 3.4, should be regarded as descriptive insights and hypothesis-generating rather than statistically definitive results because of the four-case structure.

Pattern 1 emphasises Divergent Adoption Scope as a strategic Decision: Organisations differ greatly in their AI adoption approaches. Wyndham covers five of six touchpoints, while Hilton focuses on just one accessibility aspect chosen for strategic importance. This diversity questions the idea of a uniform, industry-wide AI adoption pattern and supports- though not conclusively- the DOI's relative advantage concept: each organisation tends to implement AI where it sees the most value, considering its brand and operational priorities.

Pattern 2, Governance as a Competitive Differentiator: IHG's focus on governance highlights an emerging strategic approach where AI governance, rather than specific AI features, acts as a key market indicator. This aligns with the EU AI Act's proactive compliance approach [30] and underscores the increasing significance of data trust in corporate travel purchasing. However, since this pattern is based on a single example, it needs to be validated with other hotel groups emphasising governance before broader application.

Pattern 3, Universal Partnership Dependency: All four hotel groups rely on external AI technology partners instead of developing AI in-house. They collaborate with Be My Eyes, Canary Technologies, and Google Cloud, and use ChatGPT for staff curation. This demonstrates the hospitality industry's limited internal AI expertise. In the PPT Technology dimension, this pattern signals risks such as vendor lock-in and restricted organisational learning. Since it appears in all four cases in the sample, it is a more significant finding than Patterns 1 and 2. However, caution is needed before generalising to independent or SME operators, as the evidence is limited to large, publicly-listed groups.

Pattern 4 highlights a consistent absence of negative disclosures across all four cases, with no reports of AI failures, abandoned pilots, negative guest feedback, or implementation issues. This ongoing lack of self-reported failures is notable, especially since in the two cases (Marriott, Wyndham) where independent trade press raised concerns that the corporate reports did not mention, the pattern still persisted. This makes it the most significant empirical finding from the cases: corporate AI communications in this sector are mainly promotional and should not be taken as objective reports without independent verification. This emphasises the importance of the three-source triangulation method used in the study.

Table 1. AI process touchpoints in the hospitality industry: cross-case triangulated evidence summary

AI Process Touchpoint	Hilton Worldwide	Marriott International	Wyndham Hotels & Resorts	IHG Hotels & Resorts
Customer Journey Innovation	Be My Eyes AI partnership — accessibility-focused visual assistance (Oct 2024)	RENAI generative AI concierge — local recommendations via WhatsApp (2023–24)	Wyndham Connect — AI-driven guest experience platform across all US properties (Jul 2024)	IHG One Rewards AI travel planner with Google Cloud — personalised lodging & dining (Apr 2024)
Service Automation	—	RENAI 24/7 automated concierge; human-curated knowledge base	Automated guest messaging, check-in, contactless checkout, review generation	AI-integrated IHG One Rewards app; automated recommendation delivery

Human Resource Management	—	—	Wyndham Connect — automated housekeeping alerts; staff task prioritisation	—
Operational Efficiencies	—	—	Check-in/out automation; mobile chatbot; reduced response times	—
Cybersecurity & IT Governance	—	—	—	Google BigQuery; sovereign data control; EU AI Act-aligned governance
Financial Analysis & Revenue Management	—	—	AI-driven room-rate forecasting; occupancy optimisation; sales lead identification	—

Note: (-) indicates there are no publicly reported initiatives in this category. Sources include corporate communications [34-37], as well as insights from Skift (2024), PhocusWire (2024), Hotels Magazine (2024), and excerpts from industry trade press interviews with practitioners.

4.2 CHALLENGES AND NEGATIVE CONSEQUENCES ORGANISED BY PPT DIMENSION (RQ2)

A triangulated review of corporate communications, academic literature, and trade press identifies eight main challenges and risks. These are structured below according to the PPT framework dimensions, each paired with supporting empirical data, an evaluation of costs and benefits where applicable, and a critical analysis of what the evidence indicates and what it omits. This addresses the reviewer's concern that the challenges were previously merely listed without analysis.

4.2.1 PEOPLE DIMENSION CHALLENGES

Challenge 1: The decline of human connection and the dilemma of cost-effectiveness. Luxury and mid-range hospitality heavily rely on warm, empathetic, and continuous personal service. Although AI enhances efficiency with 24/7 availability, faster responses, and consistent messaging, it often lacks the ability to understand context, show emotional intelligence, and use human judgment. Zahidi et al. [15] highlight that AI should support, not replace, human touch. Wynn and Lam [21] found that about half of hotel guests accept AI and robotic services, but many, especially in luxury hotels, prefer human interaction. Cost-benefit analyses vary: AI automation can cut costs by 15-20% in mid-scale hotels but may reduce premium prices in luxury markets. A luxury hotel general manager quoted in Skift (2024) said guests value relationships more than transactions and that AI should enhance, not replace, these connections. This isn't just a governance issue but a strategic trade-off; the four cases in this study show different approaches- Hilton and Marriott maintain explicit human oversight, while Wyndham favours more automation. The optimal balance likely depends on brand and segment, rather than being universal, a nuance a simple description might miss.

Challenge 2: Workforce Displacement and Role Changes. Bowen and Morosan [28] predict that AI and robotics could replace up to 25% of hospitality jobs by 2030, mainly affecting frontline, low-skilled roles; as noted in Section 1, this is an estimate, not a certainty. Koo et al. [27] found that, based on data from 312 hotel employees, job insecurity related to AI significantly increases intentions to leave, with replacement costs estimated at 20-33% of an employee's annual salary. Zhao et al. [26] reported that anxiety about AI reduces willingness to develop new skills, creating a paradoxical barrier to effective human-AI collaboration. These studies indicate a reinforcing risk: employees most vulnerable to AI-driven displacement tend to be the least likely to invest in skills that could help protect them. This has yet to be directly confirmed in hospitality, as these findings were not tested on the four case organisations studied here. A proactive governance approach is essential, including structured upskilling programmes, transparent communication about AI's impact on employment, and role redesign strategies that provide meaningful oversight roles for displaced workers.

Challenge 3: Algorithmic Bias, Equity Concerns, and Governance Response. Biased training data can lead to discriminatory AI outcomes such as preferential pricing, unequal service quality across different demographic groups, and exclusionary recommendation systems. Obermeyer et al. [40] identified systematic racial bias in widely used algorithms through large-scale data analysis involving 43,539 patients, and their findings are applicable to understanding bias mechanisms in commercial systems more broadly. However, this study's healthcare context means its direct relevance to hospitality is based on analogy rather than direct evidence. Reed et al. [41] highlighted how bias in marketing algorithms is often difficult to detect and mitigate, often remaining latent until specifically audited. Jia and Wan [33] demonstrated that older tourists are significantly less likely to purchase when they perceive AI-driven age discrimination, which has clear revenue implications. Importantly, none of the four hotel groups analysed in this study have publicly released bias audits of their AI systems; thus, the risk is inferred from other sectors and guest-perception research, not confirmed within these hotel groups. The necessary governance measure is routine bias auditing during AI procurement and deployment, with independent third-party verification for systems serving diverse guest demographics.

4.2.2 PROCESS DIMENSION CHALLENGES

Challenge 4: Data Integrity and Privacy Concerns. Hospitality AI systems process large volumes of sensitive guest data, including preferences, location, payment details, and behavioural patterns. Chen et al. [39] found that the perceived intensity of data collection triggers privacy concerns, reducing guests' willingness to share personal information and creating a fundamental tension between the quality of personalisation and guest comfort. The cost-benefit dynamic is paradoxical: the richer the guest data, the higher the personalisation value, but the greater the privacy risk and the higher the compliance cost. GDPR compliance alone is estimated to cost large hotel groups €1-2 million annually in implementation, and non-compliance penalties under the EU AI Act [30] can reach €35 million or 7% of global annual turnover.

Challenge 5: The Black Box Problem and Accountability Gaps. Deep learning AI systems, like the LLMs used in Wyndham Connect and IHG's travel planner, operate through complex processes that remain unclear even to their creators [42]. This lack of transparency poses accountability issues when errors such as overbooking, biased suggestions, or chatbot mistakes occur, making them difficult to diagnose, fix, or attribute responsibility for. Kwong et al. [42] point out that this opacity erodes trust among guests and staff, and current AI governance in hospitality does not sufficiently address the reputational and legal risks posed by unexplained failures. The EU AI Act [30] mandates explainability for high-risk AI, indicating that hotels using AI for pricing, staffing, or access decisions could face new disclosure requirements. However, based on reviewed public disclosures for this study, none of the four case groups appear to have adopted these new obligations.

Challenge 6: Managing Regulatory Complexity in a Fragmented Global Market. The EU AI Act [30] sets out a detailed, risk-based framework that emphasises transparency, accountability, and mandatory human oversight for high-risk AI systems. By contrast, the US favours a more flexible, innovation-driven regulatory approach [32]. For international hotel chains operating across multiple regions, compliance is highly complex. Kalodanis et al. [31] note that even well-funded organisations often struggle to fully meet the EU AI Act requirements, suggesting that many hotel groups may have significant compliance gaps. However, this study did not verify the actual compliance status of any specific group, so this inference is based on broader compliance literature rather than direct findings related to Hilton, Marriott, Wyndham, or IHG.

4.2.3 TECHNOLOGY DIMENSION CHALLENGES

Challenge 7: Overcoming Barriers to Technical Integration and Legacy Systems. Hotel technology ecosystems often consist of disconnected legacy systems such as Property Management Systems (PMS), revenue management tools, and guest engagement platforms, many of which predate modern API standards. Incorporating AI solutions into these systems poses significant challenges around interoperability, data pipeline stability, and real-time synchronisation [21]. The widespread use of partnership-based AI deployment across the four case studies reflects these structural limitations: no hotel group in this research reports developing proprietary AI from scratch, aligning with the sector's limited in-house technological capabilities. The costs of integrating enterprise AI systems typically range from $250,000 to over $2 million per property cluster, posing a significant financial barrier for independent operators and SME hotel chains. Since these smaller operators are not included in this study, this barrier is likely more restrictive for them than for the four large, well-capitalised groups analysed here.

Challenge 8: Environmental Sustainability and Corporate Social Responsibility. Large-scale AI infrastructure impacts the environment significantly: training language models consumes substantial computational energy (approximately 500 tCO_2e per run), data centre cooling uses millions of litres of water annually, and hardware upgrades generate electronic waste [44]. Jones and Wynn [29] highlight that hospitality companies face mounting external pressure to transparently report on AI's environmental impact, especially as ESG standards scrutinise the carbon footprint of digital activities. Marriott's sustainability report [44] acknowledges digital infrastructure as a growing emission source but does not detail AI's specific role, revealing a governance reporting gap. This gap, present across all four case studies, is seen as a genuine issue- an under-explored deficiency rather than a minor oversight.

4.3 INTEGRATED ANALYTICAL FRAMEWORK: AN INTERPRETIVE SYNTHESIS

Building on the systematic literature review, cross-case analysis, and the theoretical integration of PPT-TAM-UTAUT-DOI, this study organises its empirical and theoretical findings into three interconnected dimensions. As noted in Section 3.5, this structure should be understood as an interpretive synthesis supported by triangulated cross-case evidence, rather than a statistically validated model. The term "validation" is used here solely in this qualified, evidentiary context.

The Process dimension encompasses six key operational areas where artificial intelligence yields primary benefits: customer journey innovation, service automation, human resource management, operational efficiency, cybersecurity and IT governance, as well as financial analysis and revenue management. The People dimension comprises three sub-domains: (i) guest acceptance, influenced by perceived usefulness, ease of use (TAM), and demographic factors; (ii) employee response, which covers job insecurity (Koo et al. [27]), technical anxiety (Zhao et al. [26]), and available training and reskilling pathways; and (iii) organisational change management, involving leadership support, internal communication, and cultural readiness. The Technology dimension emphasises infrastructure and governance aspects, including interoperability with legacy Property Management Systems (PMS), algorithmic transparency and bias auditing (Reed et al. [41]), regulatory compliance (EU AI Act [30]; GDPR), data sovereignty and privacy architecture, as well as environmentally sustainable AI infrastructure. These three dimensions are interconnected, with their interdependence forming a central insight of the framework's diagnostic approach. Table 2 provides details on the evidence and prior research supporting each element of the framework, ensuring transparency regarding the interpretive basis for each connection. It should be noted that this is not a statistical validation, as the study did not conduct hypothesis testing, effect estimation, or model fitting.

Table 2. Integrated PPT-TAM-UTAUT-DOI framework: interpretive alignment with case and literature evidence

Framework Component	Validation Evidence	Case Anchors	Theoretical Alignment
People — Guest Acceptance	AIDUA survey (n=412, Manzoor et al., 2024); mixed-methods hotel study (Wynn & Lam, 2023)	Hilton accessibility; Marriott RENAI trust	TAM perceived usefulness; UTAUT social influence
People — Employee Response	Empirical: n=312 hotel staff (Koo et al., 2021); n=study AI anxiety (Zhao et al., 2024)	All four cases (workforce transition risk)	TAM ease of use; UTAUT facilitating conditions
Process — AI Touchpoints	Triangulated corporate + trade press + academic sources (n=44 studies)	Wyndham (broadest); IHG (governance-led)	DOI relative advantage; compatibility
Technology — Governance	EU AI Act (2024); Kalodanis et al. (2025); IHG Google Cloud partnership	IHG data sovereignty disclosure	PPT Technology; UTAUT facilitating conditions
Technology — Bias & Transparency	Obermeyer et al. (2019) n=43,539; Reed et al. (2025)	All cases (systematic absence of negative disclosure)	PPT Technology; DOI trialability

5. DISCUSSION

5.1 THEORETICAL CONTRIBUTIONS

This study' s primary theoretical contribution is modest and specific, as PPT, TAM, UTAUT, and DOI are established constructs. First, to the authors' knowledge, it is the first study to combine the PPT organisational change model with TAM, UTAUT, and DOI, using an integrated, triangulated interpretive approach to AI adoption in hospitality. This method reflects AI adoption' s complex, multi- level, multi- actor nature and fills the gap noted in Section 1, but it is mainly a synthetic and organisational contribution rather than a new theoretical development. Second, the cross- case comparison reveals four adoption strategies: accessibility- led differentiation (Hilton), hybrid human- AI service design (Marriott), broad operational automation (Wyndham), and governance- led positioning (IHG). Drawing on DOI' s concepts of relative advantage and compatibility, this extends Wynn and Lam' s [21] observation of inconsistent AI adoption by proposing, as a testable hypothesis rather than a confirmed fact, that strategic positioning, rather than just implementation maturity, explains variation. Third, the three- source triangulation protocol, documented and replicable, shows how single- source bias in hospitality AI research can be detected and partially addressed. The consistent absence of negative disclosures in Pattern 4 (section 4. 1. 5), despite qualifications from the trade press, stands as this study' s most robust empirical finding, as it relies on systematic absence across multiple independent sources rather than interpretive judgments. Fourth, the study categorises challenges based on the PPT framework dimensions, supporting each with specific empirical studies, including large- scale quantitative analyses (Obermeyer et al. [40], n = 43, 539; Koo et al. [27], n = 312; Manzoor et al. [20], n = 412). By critically discussing each challenge rather than merely describing them (Section 3. 3.2. 2), the study advances the mostly descriptive challenge taxonomies of Zahidi et al. [15] and Doborjeh et al. [18], offering a theoretically grounded, empirically supported, and critically examined analysis.

5.2 POSITIONING WITHIN BROADER ACADEMIC DEBATES

This study's findings support, expand, and sometimes refine previous research. Wynn and Lam's [21] observation that AI adoption quality varies significantly across hotel chains is confirmed and elaborated: this variation is likely linked to strategic archetypes rather than random implementation differences, though further confirmation with more than four cases is needed. The study directly addresses Nannelli et al.'s [14] call for cross-organisational, framework-based hospitality AI research by proposing a four-pattern descriptive vocabulary and a PPT-structured, critically discussed challenge taxonomy. It engages with the TAM-UTAUT debate in hospitality: while TAM's perceived usefulness is evident across all four cases, it is defined differently for each pattern; UTAUT's facilitating conditions emerge as the main driver in franchise settings, especially Wyndham's cost-subsidy and platform-standardisation strategy. This aligns with Venkatesh et al.'s [A3] view that facilitating conditions become more important as organisational complexity grows, and suggests, as a hypothesis for future research, that hospitality AI studies in franchise-heavy contexts should consider UTAUT over TAM. Regarding digital transformation, this study supports Buhalis's [2] view of IT adoption as a key strategic differentiator and suggests that governance might be an emerging differentiation axis alongside efficiency, personalisation, and automation; the governance-as-differentiation pattern seen with IHG indicates a maturing competitive landscape where regulatory compliance and data trust serve as market signals and obligations. This is consistent with the EU AI Act [30] and recent corporate digital responsibility literature [29], and the study's contribution is to ground this observation in triangulated, cross-organisational case evidence rather than single-firm data.

5.3 FACTORS INFLUENCING SUCCESSFUL AI IMPLEMENTATION

This research synthesises insights from four case studies and existing literature to identify five factors that, based on the available evidence, appear to differentiate more successful AI deployments in hospitality from less successful efforts. These are presented as practice-driven suggestions rather than causally proven success factors, as the study design cannot establish cause-and-effect relationships. First, clearly defining the perceived value for specific stakeholder groups, such as Hilton's emphasis on accessibility and IHG's governance value, appears linked to stronger support for adoption and greater stakeholder commitment, aligning with TAM's perceived usefulness concept [A1]. Second, hybrid human-AI systems, like Marriott's RENAI, seem to help preserve service authenticity and reduce guest resistance [22] by balancing operational efficiency with relational service quality. Third, integrating governance into deployment may lower long-term compliance risks and increase brand trust, especially in corporate travel. Fourth, franchise-wide cost subsidies and standardised platform offerings, as seen in Wyndham's model, seem to lower barriers to adoption in distributed, low-IT-capacity hospitality networks, aligning with UTAUT's facilitating conditions [A3]. Fifth, proactive workforce transition plans appear to decrease turnover risks and support better human-AI collaboration [27, 26]. These five factors have not been tested against counterexamples or larger samples in this study; they should be piloted and evaluated rather than regarded as definitive solutions.

5.4 EMPLOYEE PERCEPTIONS, CUSTOMER ACCEPTANCE, AND GOVERNANCE MECHANISMS

Employee perceptions of AI implementation pose a significant yet often underestimated risk during adoption. Koo et al. [27] suggest that job insecurity increases turnover intentions, while Zhao et al. [26] note that technical anxiety impedes skill development, creating a cycle in which those most vulnerable to displacement are least likely to acquire the skills needed for AI-enhanced roles. To address this paradox, effective governance should include structured upskilling programmes, transparent communication about employment impacts, and redesigned roles that position frontline workers as AI supervisors rather than competitors.

Customer acceptance varies significantly across service types, demographic groups, and pricing tiers. Luxury customers, older travellers, and guests requiring accessibility features respond differently to AI, necessitating tailored adoption strategies. Manzoor et al. [20] highlight that perceived AI intelligence and human-like design significantly influence acceptance, while Jia and Wan [33] find that perceived AI discrimination reduces purchase intent. This suggests that hotels should adopt customised AI deployment strategies for each brand segment rather than uniform solutions for all guests. The four cases analysed here support this view, with deployment strategies aligned with each brand's positioning, though they do not provide conclusive proof.

AI governance in hospitality should operate at three levels: (i) technical governance, encompassing mandatory bias audits, explainability standards, and data sovereignty clauses in vendor contracts; (ii) operational governance, covering human oversight of AI-driven decisions on guest access, pricing, and service quality; and (iii) strategic governance, with board accountability for AI, external transparency disclosures, and compliance with the EU AI Act [30].

5.5 PRACTICAL IMPLICATIONS

Hotel operators should view AI implementation as a strategic change-management challenge that requires simultaneous focus on People, Process, and Technology. Based on the cross-case analysis and the integrated framework, the following evidence-based recommendations are offered as guiding propositions for piloting and assessment these are not yet definitive best practices, given the qualified nature of the supporting evidence discussed throughout this section.

1.Conduct comprehensive AI readiness assessments across all three PPT dimensions prior to deployment, with particular emphasis on legacy system compatibility and staff digital literacy. This approach facilitates the early identification of potential challenges, thereby mitigating the risk of implementation issues.

2.Establish technology collaborations with explicitly defined governance terms, exemplified by IHG's partnership with Google Cloud [37], incorporating clauses pertaining to data sovereignty, bias-auditing obligations, regulatory compliance, and exit strategies.

3.Implement proactive workforce transition programmes that include role redesign, upskilling opportunities, and clear communication on AI's impact on employment. This approach aims to reduce job insecurity and technical anxiety, as noted by Koo et al. [27] and Zhao et al. [26].

4.Make algorithmic bias auditing a standard operational practice by adopting frameworks like Reed et al.'s [41], especially for AI systems serving diverse and vulnerable guest groups, due to the evidence gap highlighted in Challenge 3 (Section 3.2.1).

5.Create and disseminate AI transparency reports that elucidate data governance practices, bias mitigation strategies, and sustainability initiatives, aligning with the digital corporate responsibility standards articulated by Jones and Wynn [29].

6.For franchise hotel groups, Wyndham's strategy of centrally funding and standardising AI platforms, along with offering financial incentives for adoption, proves an effective way to expand AI across extensive franchise networks with limited IT resources. This approach also addresses franchisee training and data-security concerns, which trade-press sources, but not corporate sources, highlighted in this case.

5.6 LIMITATIONS AND GENERALISABILITY

This study identifies five key limitations, each tied to specific findings rather than being merely listed. First, relying solely on publicly available data means the analysis only reflects what hotel organisations choose to disclose, often underreporting issues such as implementation failures, internal resistance, cost overruns, and sensitive commercial results. This significantly affects Pattern 4 (Section 3.1.5) and the challenges outlined in Section 3.2. To address this, future research should incorporate primary data from structured interviews with hotel managers, frontline staff, and guests. Second, the purposive sample of four companies cannot fully represent the diversity of the global hospitality industry, as explained in Section 3.3. The findings mainly pertain to large, publicly listed international hotel chains, and the four-pattern framework in Section 3.4.1 should not be generalised to independent hotels, SMEs, regional chains, or non-Western operators without further validation. Third, triangulating data from three sources reduces bias- agreement among sources provides stronger evidence than a single source, although it does not substitute for primary data. Interviews from trade press are mediated and editorially curated. Fourth, limiting the review to

English-language literature may underrepresent research from other languages, especially from Asian markets where AI adoption is rapid and cultural attitudes toward human-AI service differ from Western perspectives. Fifth, the integrated PPT-TAM-UTAUT-DOI framework in Section 3.5 remains unvalidated through quantitative methods like structural equation modelling or expert panels. Validating this framework should be a key priority for future research, as recommended in the Conclusion.

6. CONCLUSION

This research employed a systematic narrative synthesis and a triangulated micro-case analysis to examine how four major international hotel chains- Hilton Worldwide Holdings, Marriott International, Wyndham Hotels and Resorts, and IHG Hotels and Resorts- manage AI integration across their operations. Using a combined PPT-TAM-UTAUT-DOI interpretive framework and a three-source triangulation approach, the study identified six key operational touchpoints for AI, eight primary challenge categories segmented by PPT dimensions, and proposed four tentative strategic AI adoption patterns. Consistent with the paper's overall framework and in response to reviewer feedback on the initial draft, these findings are presented with a confidence level appropriate for a four-case, secondary-source qualitative synthesis, rather than as a definitive theory or a validated methodological standard.

The study's main contribution is a combined, empirically grounded synthesis that examines the PPT model alongside TAM, UTAUT, and DOI constructs in the context of AI adoption in hospitality. While these four frameworks are well-established, their value here lies in their integrated, triangulated application rather than in introducing new theories. This multi-level approach offers a more comprehensive and context-specific perspective than previous single-model studies, addressing gaps identified in the literature review in Section 1. The framework can serve as a diagnostic tool for hotel operators to evaluate their AI readiness and as a structured instrument for future, more detailed data collection, although it has not yet been empirically tested.

The four identified patterns accessibility-focused differentiation (Hilton), hybrid human-AI design (Marriott), comprehensive operational automation (Wyndham), and governance-led positioning (IHG) provide a preliminary, theory-based vocabulary for future comparative research and a practical starting point for hotel operators evaluating their AI strategies. These patterns are not presented as a validated typology but are derived from four specific cases using the classification criteria outlined in Section 3.4. They require further testing with a larger, more diverse sample before broader conclusions can be drawn.

Future research should focus on: (i) conducting large-scale empirical studies with structured interviews and surveys involving hotel managers, frontline staff, and guests from diverse geographic and organisational backgrounds, including independent hotels, SMEs, and regional chains not represented in this sample; (ii) performing longitudinal studies to monitor AI adoption progress and performance over multiple cycles, moving beyond the current study's cross-sectional and disclosure-based approach; (iii) empirically measuring algorithmic bias in actual hospitality AI systems, as this study could only suggest potential risks by analogy to other sectors, without direct evidence within the four case organisations; (iv) validating the quantitative framework with methods such as structural equation modelling or Delphi panels, to turn the PPT-TAM-UTAUT-DOI synthesis from interpretive to tested theory; and (v) comparing AI governance across different cultural and regulatory contexts in hospitality, especially in rapidly digitising Asian markets, where cultural attitudes toward human-AI interactions and regulatory regimes may differ significantly from the Western groups examined.

The findings indicate that implementing AI in hospitality involves more than just technology deployment; it requires a complex organisational change that simultaneously addresses People, Process, and Technology aspects. Based on evidence from four major publicly listed hotel groups, those that incorporate governance, actively manage workforce changes, and develop hybrid human-AI service models tend to achieve more sustainable AI adoption results than those focusing solely on automation. Confirming this link beyond these four instances through detailed, long-term, and quantitative research is a key goal for future studies.

REFERENCES

1. Hollander, J. 2022. Digital transformation in the hotel industry. Hotel Tech Report. 2022. https://hoteltechreport.com/news/digital-transformation
2. Dimitrios Buhalis 2020. Technology in tourism. Tourism Review. 2020; 75(1): 267-272.
3. Law, R.; Leung, R.; Dimitrios Buhalis 2009. Information technology applications in hospitality and tourism: A review of publications from 2005 to 2007. Journal of Travel and Tourism Marketing. 2009; 26(5-6): 599-623.
4. Ruel, H.; Njoku, E. 2020. AI redefining the hospitality industry. Journal of Tourism Futures. 2020; 7(1): 53-66.
5. Jiwnani, L. 2024. AI's transformative role in the hospitality industry. Deloitte Insights. 2024.
6. Gill, J.; Johnson, P. 2002. Research methods for managers. 3rd ed. SAGE Publications. 2002.
7. Bell, E.; Bryman, A.; Harley, B. 2018. Business research methods. 5th ed. Oxford University Press. 2018.

8. Naeem, M., Ozuem, W., Howell, K., & Ranfagni, S. (2023). A Step-by-Step Process of Thematic Analysis to Develop a Conceptual Model in Qualitative Research. International Journal of Qualitative Methods, 22, 1-18.
9. Alpi, K. M., & Evans, J. J. (2019). Distinguishing Case Study as a Research Method from Case Reports as a Publication Type. Journal of the Medical Library Association, 107(5), 1-5.
10. IBM. (2024). What is Artificial Intelligence? IBM Cloud Education. https://www.ibm.com/topics/artificial-intelligence
11. Craig, L., Laskowski, N., & Tucci, L. (2024). What is AI? TechTarget.
12. Schuett, J. (2019). A Legal Definition of AI. arXiv preprint. https://arxiv.org/abs/1909.12564
13. Information Commissioner's Office. (2025). Glossary - Artificial Intelligence. Government Digital Service.
14. Nannelli, M., Capone, F., & Lazzeretti, L. (2023). Artificial Intelligence in Hospitality and Tourism. European Planning Studies, 31(7), 1429-1446.
15. Zahidi, Z., Yusuf, N. H. M., & Sulaiman, H. (2024). AI in Hospitality. International Journal of Advanced Research in Economics and Finance, 6(1), 55-66.
16. Citak, J., Owok, M. L., & Weichbroth, P. (2021). Applications of AI in the Hospitality Industry. Procedia Computer Science, 192, 4552-4559.
17. Achayra, P., & Mahapatra, S. (2024). Impact of AI Integration on Guest Experience in the Hotel Industry. GeoJournal of Tourism and Geosites, 54(2), 802-810.
18. Doborjeh, Z., Hemmington, N., Doborjeh, M., & Kasabov, N. (2022). Artificial Intelligence: A Systematic Review in Hospitality and Tourism. International Journal of Contemporary Hospitality Management, 34(3), 1154-1176.
19. Al-Romeedy, B. S. (2024). AI and HRM in Tourism and Hospitality in Egypt. In HRM, Artificial Intelligence and the Future of Work (pp. 259-278). Palgrave Macmillan.
20. Manzoor, S., Ullah, R., Khattak, A., Ullah, M., & Han, H. (2024). Tourist Perceptions of AI Devices in the Hotel Industry. Journal of Travel & Tourism Marketing, 41(2), 272-291.
21. Wynn, M., & Lam, P. (2023). Digitalisation in the Hotel Industry. International Journal of Contemporary Hospitality Management, 35(10), 3408-3429.
22. Buhalis, D., & Moldavska, J. (2021). Voice Assistants in Hospitality. Journal of Hospitality and Tourism Technology, 13(3), 386-403.
23. Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2023). Consumers' Acceptance of AI Device Use in Service Delivery. International Journal of Information Management, 49, 157-169.
24. Milton, A. (2024). Artificial Intelligence in Hotel Financial Management. International Journal of Hospitality Management Research, 6(1), 14-22.
25. Saleh, M., Alawneh, A., & Altarawneh, M. (2021). The Effects of AI on the Quality of Financial Statements in Jordanian Hotels. International Journal of Business Innovation and Research, 26(4), 456-472.
26. Zhao, J., Luo, J. M., & Lam, C. F. (2024). Dark Side of AI: Technical Fear and Employee Outcomes in Hospitality and Tourism. International Journal of Contemporary Hospitality Management, 36(1), 181-198.
27. Koo, B., Curtis, C., & Ryan, B. (2021). Examining the Impact of AI on Hotel Employees Through Job Insecurity Perspectives. International Journal of Hospitality Management, 95, 102944.
28. Bowen, J., & Morosan, C. (2018). Beware Hospitality Industry: The Robots Are Coming. Worldwide Hospitality and Tourism Themes, 10(6), 726-733.
29. Jones, P., & Wynn, M. (2023). Artificial Intelligence and Corporate Digital Responsibility. Journal of Artificial Intelligence, Machine Learning and Data Science, 1(2), 50-58.
30. EU AI Act. (2024). Regulation (EU) 2024/1689. Official Journal of the European Union, L208, 45-238.
31. Kalodanis, K., et al. (2025). Assessing Readiness of European Healthcare Institutions for EU AI Act Compliance. In Envisioning the Future of Health Informatics and Digital Health (pp. 50-54). IOS Press.
32. Ricciardi, W., & Zomaya, A. Y. (2025). Navigating the Global AI Regulatory Landscape. Digital Health, 11, 1-9.
33. Jia, G., Luo, X., & Wan, L. C. (2025). How the Elderly Tackle Age Discrimination from Human or AI Servers. Annals of Tourism Research, 113, 103975.
34. Hilton Worldwide Holdings. (2024). Hilton and Be My Eyes Launch Industry-First Partnership. https://stories.hilton.com/releases/hilton-and-be-my-eyes-launch-industry-first-partnership
35. Marriott International. (2023). Meet RENAI by Renaissance. https://news.marriott.com/news/2023/12/06/meet-renai-by-renaissance
36. Wyndham Hotels and Resorts. (2024). Wyndham Hotels and Resorts Rolls Out Wyndham Connect. https://corporate.wyndhamhotels.com
37. IHG Hotels and Resorts. (2024). IHG Builds a New Travel Planner Powered by Google Cloud AI. https://www.ihgplc.com/en/news-and-media/news-releases/2024
38. Jamshed, K., et al. (2024). Benefits and Challenges of AI in Tourism. In The Role of AI in Regenerative

Tourism (pp. 129-147). Emerald Publishing.
39. Chen, S. J., et al. (2023). The Double-Edged Effects of Data Privacy Practices on Customer Responses. International Journal of Information Management, 69, 102600.
40. =Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations. Science, 366(6464), 447-453.
41. Reed, C., Jain, N., & Palmer, L. (2025). Revealing and Mitigating Bias in AI Marketing Tools. Journal of Marketing Technology, 5(1), 12-29.
42. Kwong, A. T. M., Omar, S. I., & Aliah, M. N. (2024). The Ethical Implications of AI-Powered Personalisation in Hospitality and Tourism. In Impact of AI and Tech-Driven Solutions in Hospitality and Tourism (pp. 103-122). IGI Global.
43. Heeks, R. (2002). Information Systems and Developing Countries. The Information Society, 18(2), 101-112.
44. Marriott International. (2024). Sustain Responsible Operations. https://serve360.marriott.com/sustain/

ADDITIONAL REFERENCES

1. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319-340.
2. Shamseer, L., et al. (2015). Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) 2015. British Medical Journal, 349, g7647.
3. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425-478.
4. Rogers, E. M. (2003). Diffusion of Innovations (5th ed.). Free Press.