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Artificial Intelligence and Employee Performance in the Hospitality Industry: A Systematic Literature Review and Future Research Agenda

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Abstract
The rapid proliferation of artificial intelligence (AI) technologies is basically reshaping human resource patterns and practical processes across the hospitality industry. This paper presents a organized literature review (SLR) of 94 peer-reviewed studies published between 2000 and 2024, examining the multidimensional relationship between AI adoption and employee performance in hotels, restaurants, and tourism enterprises. Employing the PRISMA model, we summarize extant evidence across seven thematic clusters: (1) AI-driven productivity improvement, (2) job replacement and role restructuring, (3) AI's effect on service quality view, (4) employee attitudes and technology acceptance, (5) emotional labor and well-being, (6) AI in training and development, and (7) organisational culture and change management. Our findings reveal that while AI measurably improves task productivity and practical consistency, its effects on intrinsic motivation, job satisfaction, and service authenticity remain ambiguous and context-dependent. We find six critical research gaps—including the scarcity of long-term studies, lack of representation of developing economies, and insufficient attention to algorithmic ethics—and propose a future research agenda with concrete research-method paths. The paper contributes an combined theory-based model positioning AI not as a substitute for human capital, but as a complementary force whose value is dependent on strategic human resource management (HRM) practices, leadership quality, and organisational readiness.

Keywords: artificial intelligence; employee performance; hospitality industry; organized literature review; technology acceptance; human resource management; service quality; future research agenda

1. Introduction

The hospitality industry stands at a pivotal technological crossroads. From AI-powered concierge chatbots and robotic room service to predictive revenue management systems and automated food preparation, artificial intelligence is no longer a peripheral experiment but a central strategic investment for globally competitive hospitality enterprises. According to PwC (2023), AI-related investments in global travel and

hospitality exceeded USD 9.4 billion in 2022 and are projected to surpass USD 28 billion by 2028, reflecting an industry-wide conviction that AI adoption is essential for sustained competitive advantage.

Yet the meanings for the industry's most critical resource—its people—remain profoundly unclear. The hospitality sector is distinguished by its reliance on human interaction, emotional intelligence, and personalised service delivery; qualities that are difficult, if not impossible, to repeat through algorithmic systems. The juxtaposition of AI's practical productivity against the irreplaceable value of human connection creates a management challenge of considerable difficulty. Does AI increase employee ability, or does it erode job meaning and replace skilled workers? How do frontline employees psychologically respond to AI co-workers and supervisors? What organisational conditions determine whether AI integration yields performance benefits or undermines staff motivation?

Academic interest in these questions has grown greatly over the past decade, yet the field remains scattered. Studies are spread across hospitality management, information systems, human resource management, and service marketing journals, applying varied theory-based models and methodologies. A strict summary is long overdue. This paper deals with that gap by conducting a organized literature review (SLR) covering 94 studies published from 2000 to 2024, offering the most thorough evidence summary to date on AI and employee performance in hospitality contexts.

The paper makes four primary contributions: (i) a open and reproducible mapping of the intellectual landscape through PRISMA-compliant research method; (ii) a thematic summary that reconciles contradictory findings across disciplinary limits; (iii) a theory-based model that integrates AI ability aspects with HRM antecedents and performance outcomes; and (iv) a forward-looking research agenda that identifies specific gaps, proposes concrete research questions, and recommends suitable research-method approaches.

The remainder of this paper is structured as follows: Section 2 reviews theory-based foundations; Section 3 presents the research method; Sections 4–10 summarize findings by theme; Section 11 presents the integrated model; Section 12 outlines the future research agenda; and Section 13 concludes.

2. Theoretical Foundations

2.1 Technology Acceptance and Human-AI Interaction

Theoretical inquiry into employee responses to AI in the workplace draws on a rich lineage of technology acceptance models. Davis's (1989) Technology Acceptance Model (TAM) posits that felt usefulness and felt ease of use are the primary factors of technology adoption behaviour. Applied to hospitality contexts, TAM has been extended to include factors unique to service environments, including customer-facing anxiety, hospitality standards of friendliness, and the felt threat to professional identity (Gursoy et al., 2019; Ukpabi & Karjaluoto, 2017).

More recently, the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and its successor UTAUT2 have been adapted to model employee acceptance of AI-driven tools such as intelligent scheduling systems, customer relationship management (CRM) platforms, and service robots. The inclusion of social influence, helping conditions, and hedonic motivation adds explanatory power in hospitality settings where peer standards and organisational culture are particularly influential.

The Uncanny Valley theory (Mori, 1970), originally articulated in robotics, has attracted renewed attention as lifelike AI systems become more prevalent in hotel lobbies and restaurant service environments. Studies have found that robots whose appearance and behaviour approximates—but does not achieve—human

likeness create discomfort among both guests and employees, with potential downstream effects on service delivery quality and staff emotional labour (Mende et al., 2019).

2.2 Human Resource Management Perspectives

From an HRM standpoint, the integration of AI into hospitality operations can be analysed through the AMO (Ability-Motivation-Opportunity) model (Appelbaum et al., 2000). AI technologies may affect all three components at the same time: enhancing employee ability through intelligent training platforms and decision-support tools; influencing motivation through changes to job difficulty, autonomy, and meaningfulness; and reconfiguring opportunity structures through altered workflows, monitoring processes, and career path disruptions.

The Conservation of Resources (COR) theory (Hobfoll, 1989) offers a complementary lens for understanding employee well-being in AI-integrated workplaces. COR theory shows that individuals invest resources to protect against threats and loss. When AI is felt as threatening job security or professional identity, employees may engage in resource-depleting coping behaviours—including lack of involvement and increased emotional labour—that paradoxically undermine the productivity gains AI is intended to deliver.

2.3 Service Dominant Logic and Value Co-Creation

Vargo and Lusch's (2004, 2016) Service Dominant Logic (SDL) model redefines value creation as a collaborative process involving multiple actors. Applied to AI in hospitality, SDL suggests that value is co-created not by AI systems in isolation, but through the dynamic interaction between AI abilities, employee expertise, and guest engagement. This perspective challenges techno-centric narratives that position AI as a performance amplifier independently of human skill and motivation, redirecting attention toward the relational and situational conditions that mediate AI's performance effects.

3. Methodology

3.1 Systematic Literature Review Protocol

This review follows to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009; Page et al., 2021), ensuring research-method openness, reproducibility, and comprehensiveness. The review protocol was registered prior to data collection.

3.2 Search Strategy and Database Selection

A structured keyword search was conducted across four major academic databases: Web of Science, Scopus, EBSCO Business Source Complete, and Google Scholar. Search strings combined controlled vocabulary and free-text terms across three theory-based clusters: (1) AI technologies ("artificial intelligence", "machine learning", "chatbot", "service robot", "automation", "natural language processing"); (2) employee factors ("employee performance", "job satisfaction", "staff", "frontline staff", "human resources"); and (3) hospitality context ("hotel", "restaurant", "hospitality", "tourism", "accommodation"). Boolean operators (AND, OR) were applied to create thorough yet targeted search strings. Table 1 summarises the search strategy and results.

Table 1. Database Search Summary

Database	Search Terms	Years Covered	Articles Retrieved	Articles Included
Web of Science	AI, artificial intelligence, machine learning, hospitality, hotel, employee performance	2000–2024	312	48
Scopus	AI, chatbot, robot, service quality, employee, hospitality industry	2000–2024	287	42
EBSCO / Business Source	automation, AI technology, front-line employees, performance	2005–2024	198	31
Google Scholar	AI employee performance hospitality tourism	2010–2024	245	29
Total (after deduplication)	—	2000–2024	1,042	94

3.3 Inclusion and Exclusion Criteria

Articles were included if they: (a) were published in peer-reviewed journals between January 2000 and December 2024; (b) were written in English; (c) examined at least one AI technology in a hospitality or closely related tourism context; and (d) addressed employee-related outcomes including performance, satisfaction, attitudes, training, or well-being. Articles were excluded if they: focused exclusively on consumer-facing AI without employee meanings; were review articles, book chapters, or conference proceedings; or lacked research-based or strict theory-based contributions.

3.4 Quality Assessment and Data Extraction

Each included article was evaluated using an adapted version of the Mixed Methods Appraisal Tool (MMAT), assessing clarity of research questions, research-method appropriateness, strictness of data collection, accuracy of analysis, and importance of findings. Two independent reviewers assessed all articles, with a third reviewer resolving disagreements. Inter-rater reliability, measured by Cohen's Kappa, was $\kappa = 0.84$, indicating strong agreement. Data extraction covered: study objectives, theory-based models, research method, sample characteristics, AI types examined, key findings, and limitations.

4. Thematic Synthesis of Findings

The 94 included studies were in an organized way coded and organised into seven major thematic clusters through an repeated, inductive-deductive process. Table 2 presents the thematic summary with representative studies and frequency of coverage.

Table 2. Thematic Synthesis of Reviewed Literature

Theme	Key Findings	Representative Studies	Frequency (n)
AI-Driven Productivity Enhancement	AI tools reduce task completion time by 20–45%; automate repetitive tasks; increase output consistency.	Ivanov et al. (2017); Tussyadiah (2020); Lu et al. (2021)	31
Job Displacement & Role Restructuring	AI displaces routine roles; creates new hybrid positions; requires upskilling.	Baum et al. (2019); Cheng & Foley (2018); Walmsley (2017)	27
AI & Service Quality Perception	Customers report mixed satisfaction with AI-delivered service vs. human touch.	Mende et al. (2019); Wirtz et al. (2018); Qiu et al. (2020)	24
Employee Attitudes & AI Acceptance	Technology acceptance varies by age, education, tech anxiety; TAM widely applied.	Gursoy et al. (2019); Ukpabi & Karjaluoto (2017); Huang & Rust (2018)	22
Emotional Labor & Well-being	AI alleviates some emotional labor burdens but raises concerns about monitoring.	Bowen & Morosan (2018); Chen & Siu (2021); Tung & Au (2018)	19
AI in Training & Development	AI-powered LMS and simulations enhance training speed and personalisation.	Kim et al. (2021); Robinson & Schänzel (2019)	14
Organizational Culture & Change	Successful AI integration requires transformational leadership and change readiness.	Ivanov & Webster (2019); Buhalis & Moldavska (2022)	11

4.1 Theme 1: AI-Driven Productivity Enhancement

The most extensively documented performance effect of AI in hospitality is task-level productivity improvement. AI systems—particularly intelligent property management systems (PMS), revenue management algorithms, and workflow automation tools—have been shown to reduce manual processing time by 20 to 45 percent, decrease error rates in reservation handling, and improve scheduling productivity (Ivanov et al., 2017; Lu et al., 2021). In food and beverage operations, AI-assisted inventory management has been linked to waste reduction of up to 30 percent, with corresponding improvements in cost control metrics (Kim et al., 2021).

However, productivity gains are not uniformly distributed. Evidence suggests that productivity improvements are concentrated in standard, back-of-house functions, while front-of-house roles involving complicated guest interaction show more modest—and sometimes negative—productivity effects when AI replaces rather than supplements human judgment (Tussyadiah, 2020). Role uncertainty arising from

the redistribution of tasks between human staff and AI systems represents a important management challenge documented across multiple studies (Cheng & Foley, 2018).

4.2 Theme 2: Job Displacement and Role Restructuring

Concern about AI-driven job replacement ranks among the most prominent themes in the reviewed literature. Baum et al. (2019) estimated that approximately 24 percent of hospitality roles are at high risk of automation within a ten-year horizon, disproportionately affecting entry-level and routinised positions. This finding aligns with broader labour market projections (OECD, 2019) and has generated important policy attention in hospitality management research.

Importantly, the evidence does not uniformly support a replacement descriptive. Several studies document AI-enabled role upgrading, wherein employees transition from transactional tasks toward higher-value advisory, creative, and relationship-management functions (Walmsley, 2017). Huang and Rust (2018) propose a compelling typology distinguishing mechanical, analysis-based, intuitive, and empathetic intelligence, arguing that AI's encroachment on the first two domains is offset by intensified demand for the latter two—qualities deeply embedded in hospitality professionalism. The net employment effect, many scholars conclude, depends critically on the quality of reskilling investment, management strategy, and institutional support (Baum & Hai, 2020).

4.3 Theme 3: AI and Service Quality Perception

The relationship between AI use and felt service quality is nuanced and context-dependent. While AI-enhanced service delivery can improve speed, consistency, and availability—key drivers of satisfaction in many segments—it may at the same time diminish the felt friendliness, personalisation, and emotional engagement that premium hospitality brands depend upon (Wirtz et al., 2018). Mende et al. (2019) show that the social presence of robots in hotel lobbies can reduce customer trust and emotional connection, particularly among older demographics and guests seeking luxury experiences.

From the employee perspective, AI-mediated service encounters require new forms of emotional labour: staff must manage guest expectations around AI limitations, bridge communication failures between AI systems and confused customers, and maintain authentic hospitality standards in increasingly digitised environments (Bowen & Morosan, 2018). These demands add difficulty to frontline roles and may exacerbate exhaustion risk if not addressed through suitable job design and organisational support.

4.4 Theme 4: Employee Attitudes and Technology Acceptance

Employee attitudes toward AI adoption are shaped by a constellation of individual, organisational, and technological factors. Age, education level, prior technology experience, and job security views consistently emerge as important predictors of technology acceptance in hospitality studies (Gursoy et al., 2019). Employees who perceive AI as enhancing rather than threatening their professional roles show importantly higher acceptance and performance benefits, highlighting the centrality of communication and change management in AI use (Ukpabi & Karjaluoto, 2017).

Organisational justice views—particularly regarding the openness and fairness of AI-driven performance evaluation systems—emerge as critical moderators. Studies find that algorithmic management, including AI-powered scheduling and task monitoring, is associated with increased stress and reduced discretionary effort when employees perceive these systems as arbitrary or monitoring-oriented (Chen & Siu, 2021). Organisations that involve employees in AI design and use decisions report markedly better acceptance outcomes.

4.5 Theme 5: Emotional Labor and Well-being

AI's effects on emotional labour and employee well-being represent perhaps the most underexplored aspect in extant research. Existing evidence suggests a dual path of growth: AI can alleviate surface-acting demands by absorbing routine, emotionally taxing interactions (e.g., complaint handling via chatbot), thereby reducing exhaustion risk among frontline staff. Simultaneously, AI-powered monitoring systems heighten performance monitoring pressure, potentially intensifying deep-acting requirements and psychological strain (Tung & Au, 2018).

The idea of algorithmic anxiety—a diffuse apprehension about being evaluated, replaced, or disciplined by AI systems—has begun to attract scholarly attention (Chen & Siu, 2021). Research-based evidence from hotel and airline contexts suggests that algorithmic anxiety is positively associated with emotional exhaustion and negatively associated with organisational commitment, underscoring the need for psychological safety models in AI-integrating workplaces.

4.6 Theme 6: AI in Training and Development

AI-powered learning management systems (LMS), personalised coaching platforms, and virtual reality (VR) simulations represent a rapidly growing application domain with important meanings for employee competence development. Studies document that AI-driven training platforms can reduce onboarding time by up to 40 percent, improve knowledge retention through adaptive learning paths, and extend access to development resources for part-time and seasonal workers historically underserved by traditional training investments (Kim et al., 2021).

VR-based service simulation has shown particular promise for cross-cultural competence development in international hospitality settings, supporting employees to practise complicated guest interaction scenarios in psychologically safe environments (Robinson & Schänzel, 2019). Challenges include the important capital investment required, uneven digital literacy among staff, and questions about the how well it applies of virtually acquired skills to real-world service contexts.

4.7 Theme 7: Organisational Culture and Change Management

The organisational conditions that determine whether AI integration yields performance dividends or creates staff dysfunction receive consistent attention across the reviewed literature. Transformational leadership, change management ability, and a culture of psychological safety are the most frequently cited organisational facilitators of successful AI adoption (Ivanov & Webster, 2019). Leaders who communicate a clear and human-centred AI strategy—positioning technology as augmenting rather than replacing employee expertise—are associated with higher acceptance, lower resistance, and stronger performance outcomes.

Buhalis and Moldavska (2022) advance the idea of 'smart hospitality culture' as a requirement for sustainable AI performance gains, emphasising the integration of digital literacy, continuous learning standards, and collaborative human-machine workflow design. Organisations lacking these cultural foundations frequently experience AI implementations that deliver short-term productivity gains while eroding the human capital stocks that sustain long-term competitive advantage.

5. An Integrative Conceptual Framework

Drawing on the synthesised evidence, we propose an combined theory-based model positioning AI-employee performance relationships as dependent upon three interacting layers: (1) AI Capability Inputs, comprising the functional sophistication and use scope of AI systems; (2) HRM Mediating Conditions,

including leadership quality, job design, psychological safety, and reskilling investment; and (3) Performance Outcomes, spanning task productivity, service quality, job satisfaction, innovation, and well-being.

The model posits that AI ability inputs do not directly determine employee performance outcomes. Instead, HRM connecting conditions function as critical amplifiers or dampeners: high-quality HRM practices amplify AI's positive effects on productivity and well-being, while poor HRM use transforms AI adoption into a source of anxiety, lack of involvement, and service deterioration. Contextual moderators—including organisational size, national culture, employee demographics, and competitive environment—further shape the direction and size of these relationships.

This model advances beyond prior models by clearly accommodating bidirectional effects: not only does AI shape employee performance, but employee reactions, adaptations, and innovations continually reshape the effective functioning of AI systems in service environments. This recursive dynamic has been mostly neglected in prior research and represents a promising direction for future investigation.

6. Research Gaps and Future Research Agenda

The organized review found six important gaps in extant knowledge, each creates a cluster of specific research questions and research-method suggestions. Table 3 summarises the research agenda.

Table 3. Future Research Agenda: Gaps, Directions, and Methodologies

Research Gap	Proposed Direction	Suggested Methodology
Lack of long-term studies on AI impact	Track employee performance over 3–5 years post-AI adoption	Longitudinal panel studies; time-series analysis
Underrepresentation of developing economies	Cross-cultural comparative studies in Asia, Africa, and Latin America	Multi-country surveys; comparative case studies
Emotional & psychological aspects understudied	Investigate AI's effect on exhaustion, job meaning, and identity	Mixed methods; psychometric scales; interviews
SME vs. large hotel chain differences	Explore AI adoption constraints and outcomes in SMEs	Multiple case studies; non-numerical interviews
Ethical & algorithmic bias in AI systems	Examine fairness and openness of AI-driven HR decisions	Ethics models; auditing methodologies
Integration of AI with HRM theory	Develop AI-specific HRM models grounded in hospitality context	Theory-building; Delphi studies; SEM

6.1 Longitudinal Dynamics

The vast majority of reviewed studies employ cross-sectional designs that capture AI-employee performance relationships at a single point in time. This research-method limitation prevents understanding of how performance effects change as AI systems mature, employees adjust, and organisations reconfigure workflows. Longitudinal panel studies tracking individual employees and

organisational units over three to five years post-AI adoption are urgently needed to address questions of sustainability, adaptation, and long-term staff transformation.

6.2 Developing Economy and Cross-Cultural Contexts

Geographic representation in the reviewed literature is heavily skewed toward North America, Western Europe, and East Asia. The experiences of hospitality workers in Sub-Saharan Africa, South and Southeast Asia, the Middle East, and Latin America—contexts described by different labour market structures, digital infrastructure constraints, and cultural orientations toward technology—are conspicuously absent. Cross-cultural comparative studies are essential for developing for everyone applicable theory and contextually sensitive management practice.

6.3 Ethical Dimensions of Algorithmic Management

The use of AI in human resource management—for performance evaluation, scheduling, promotion decisions, and disciplinary processes—raises deep ethical questions that remain greatly unaddressed in the hospitality literature. Research examining fairness, openness, accountability, and potential bias in AI-driven HR systems is urgently needed. Mixed-methods approaches combining algorithmic auditing with employee experience research offer particular promise.

6.4 Psychological and Emotional Dimensions

While emotional labour and job satisfaction receive some attention, the deeper psychological effects of AI integration—including effects on professional identity, felt job meaningfulness, existential concerns about human distinctiveness, and responses to algorithmic monitoring—remain poorly understood. Multi-method research incorporating tested and confirmed psychometric instruments, long-term surveys, and non-numerical interviews would greatly advance this domain.

6.5 SME and Independent Operator Contexts

Research on AI in hospitality is disproportionately conducted in large, chain-affiliated properties with substantial technology investment capacity. Independent hotels, restaurants, and small tour operators face basically different adoption constraints, resource limitations, and competitive pressures. Dedicated research on this underserved segment, employing case study and action research methodologies, would importantly expand the practical relevance of scholarly findings.

6.6 Theory Development and Model Testing

The field would benefit from greater investment in original theory development and large-scale model testing. Delphi studies engaging hospitality executives, HR practitioners, and technology developers could create grounded models for AI-specific HRM practice. Structural equation modelling (SEM) applied to large multi-country datasets would enable strict testing of the combined model proposed in this paper.

7. Discussion

This organized literature review has generated several overarching insights that warrant direct discussion. First, the evidence strongly challenges simplistic narratives—both utopian and dystopian—about AI's effects on hospitality employees. AI is neither an uncomplicated performance enhancer nor an inexorable force of replacement. Its effects are deeply dependent on organisational context, HRM quality, leadership approach, and the specific nature of the AI system deployed.

Second, the field's theory-based toolkit, while drawing productively on TAM, UTAUT, COR, and AMO models, has not yet generated hospitality-specific theory good enough to the difficulty of AI-human interactions in service environments. The emotional, relational, and identity aspects of frontline hospitality work require theory-based models attuned to the sector's distinctive characteristics, including the centrality of guest relationships, the performative nature of service delivery, and the physical and emotional demands of round-the-clock operations.

Third, research-method limitations—particularly the dominance of cross-sectional survey designs and the underuse of non-numerical, experimental, and long-term approaches—constrain the field's capacity to establish causality, understand processes, and develop actionable managerial guidance. The research agenda proposed in this paper responds to these limitations with specific research-method suggestions designed to increase the strictness and diversity of future inquiry.

From a managerial standpoint, the review's findings suggest that AI use strategies in hospitality should be conceived not as technology projects but as organisational change programmes with the employee at the centre. Investing in open communication, participatory design, thorough reskilling, and psychological safety structures is not merely ethically desirable but practically essential for realising AI's performance potential.

8. Conclusion

This paper has presented a strict organized literature review of 94 peer-reviewed studies on artificial intelligence and employee performance in the hospitality industry, offering the most thorough summary available on this rapidly evolving topic. By integrating evidence across seven thematic clusters, proposing an original theory-based model, and articulating a targeted future research agenda, this paper makes a substantial contribution to hospitality management research and practice.

The central finding—that AI's effects on employee performance are powerfully mediated by HRM practices, leadership quality, and organisational culture—has deep meanings for industry practitioners and policymakers. Technology without people strategy will not deliver sustainable performance improvements. Conversely, organisations that invest in developing AI-fluent, psychologically supported, and continuously developing workforces can position AI as a genuine amplifier of the human excellence that remains the definitive competitive advantage in hospitality.

The future research agenda articulated in this paper points toward long-term, cross-cultural, ethically informed, and in theory ambitious research that can create knowledge good enough to the pace and difficulty of AI's transformation of hospitality work. We invite scholars to engage critically with this agenda, challenge its assumptions, and build the knowledge base that the industry's workers and managers urgently need.

Declarations

Conflict of Interest

The authors declare no conflict of interest.

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Ethical Approval

This organized literature review analyses publicly available peer-reviewed literature and did not require ethical approval.

Data Availability

The PRISMA flow diagram, full inclusion/exclusion coding sheets, and data extraction templates are available from the corresponding author upon reasonable request.

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