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AI-Driven Operational Intelligence and Workforce Reskilling in U.S. Hotels

Salami Abdul Mohammed

College of Business, Westcliff University, Irvine, California, USA, ORCID: 0009-0004-4729-1658

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ABSTRACT: This paper examines the relationship between AI-driven operational intelligence adoption as the independent variable and workforce reskilling outcomes as the dependent variable in U.S. hotel operations. AI-driven operational intelligence systems are being deployed across hotel operations at a pace that is structurally transforming what hotel managers are required to know and do. Conducting a systematic narrative literature review of peer-reviewed research and verified industry evidence, the paper identifies five AI deployment domains generating the most consequential reskilling demands: revenue management analytics, workforce scheduling analytics, procurement and inventory analytics, guest data and personalization systems, and business intelligence dashboards. Drawing on Human Capital Theory (Becker, 1964; Schultz, 1961) and the Technology-Organization-Environment framework (Tornatzky and Fleischer, 1990), the review documents that the reskilling response to AI adoption in U.S. hotels is constrained primarily by organizational and environmental barriers rather than by the unavailability of reskilling tools or programs. The paper proposes a three-level reskilling framework calibrated to the operational realities of U.S. hotel properties at different scales, identifies five barriers that currently limit reskilling effectiveness, and argues that the workforce consequences of failing to close the analytical skills gap extend beyond individual property performance to national workforce development outcomes across an industry employing 2.17 million workers (AHLA, 2025a).

KEYWORDS: Algorithmic oversight, Analytical capability development, Human Capital Theory, Labor productivity, Technology-Organization-Environment framework.

1. INTRODUCTION

The deployment of artificial intelligence across U.S. hotel operations has created a workforce reskilling problem that the industry has not yet solved. AI systems now set room prices, generate staff schedules, trigger purchase orders, and personalize guest interactions at thousands of hotel properties across the United States. The managers responsible for overseeing these systems were trained for an operational environment in which those decisions were made manually. The result is a growing mismatch between what AI-driven hotel operations require of frontline managers and supervisors and what those workers currently know how to do.

The independent variable is AI-driven operational intelligence adoption: the deployment of automated and algorithmically driven systems across hotel operations. The dependent variable is workforce reskilling outcomes: the degree to which hotel workers develop the analytical and oversight skills that AI-enabled operations require. The relationship between these two variables matters for individual property performance, for the competitive position of the U.S. hotel industry, and for the 2.17 million workers the industry employs (AHLA, 2025a).

Shin, Ryu, and Jo (2025), in a qualitative study of 22 accommodation managers published in the International Journal of Hospitality Management, identified five essential skills that frontline hospitality employees require as AI adoption accelerates: operational AI knowledge, human-AI collaboration ability, creative problem solving, emotional intelligence, and ethical reasoning. Kumawat, Datta, Prentice, and Leung (2025), in a systematic review of employee-centric AI studies published in the International Journal of Hospitality Management, found that sustainable and cohesive AI adoption by hospitality employees requires actionable reskilling approaches that most hotel organizations have not yet systematically implemented.

The workforce challenge is compounded by the industry's existing crisis. The U.S. hotel industry reports that 64.9% of properties still face staffing shortages as of December 2024, wages have risen 25.6% above 2019 levels without resolving the structural employment gap, and the industry remains approximately 200,000 jobs below pre-pandemic employment levels (AHLA, 2025a, 2025b). Bowen and Morosan (2018) predicted that AI and robotics would account for approximately 25% of the hotel sector's workforce equivalent by 2030, a structural shift whose reskilling implications the industry has yet to address systematically. This paper is organized as follows. Section 2 documents the current state of AI deployment in U.S. hotel operations and the workforce context. Section 3 presents the theoretical framework. Section 4 reviews the literature on AI adoption and reskilling demands across five operational domains. Section 5 proposes a three-level reskilling framework and identifies the barriers constraining its implementation. Section 6 presents the proposed empirical validation methodology. Section 7 discusses findings and implications. Section 8 concludes.

2. INDUSTRY CONTEXT: AI DEPLOYMENT AND THE WORKFORCE REALITY

2.1 The Scale of AI Deployment

The deployment of AI-driven operational intelligence in U.S. hotel operations has accelerated since the COVID-19 pandemic recovery period. AHLA's 2025 State of the Industry report documents that Oracle's analysis projects AI systems will move from experimental pilots to concrete operational deployments across hotel functions in 2025 (AHLA, 2025a). Automated revenue management systems are now standard at branded chain properties, predictive scheduling platforms have expanded significantly among mid-scale and upscale operators, and property management systems increasingly embed analytics modules that generate data-driven recommendations rather than simply recording transactions. Table 1 presents the verified industry statistics that establish the operational and workforce context for this analysis.

Table 1. U.S. Hotel Industry and Workforce: Key Statistics (2024 to 2025)

Metric	Data Point	Source
U.S. hotel employment (2025 projection)	2.17 million direct employees	AHLA (2025a)
Hotel jobs still below pre-pandemic levels	Approximately 200,000 fewer than 2019	AHLA (2025a)
Hotels reporting staffing shortages (December 2024)	64.9%	AHLA (2025b)
Hotels severely understaffed (December 2024)	9%	AHLA (2025b)
Primary retention strategy: higher wages	47.5% of hotels	AHLA (2025b)
U.S. hotel total compensation (2025 projection)	$128.47 billion: record level	AHLA (2025a)
Wage increase since 2019	25.6% above 2019 levels	AHLA (2025a)
AI and robotics projected share of hotel sector by 2030	Approximately 25%	Bowen and Morosan (2018)
Global travel and tourism GDP contribution (2024)	$10.9 trillion: 10% of global GDP	WTTC (2025)
Global travel and tourism employment (2024)	357 million jobs worldwide	WTTC (2025)

Sources: AHLA (2025a); AHLA (2025b); Bowen and Morosan (2018); WTTC (2025).

The figures in Table 1 reveal a structural contradiction. The industry is spending record amounts on compensation, with total projected compensation of $128.47 billion in 2025, yet 64.9% of hotels still report staffing shortages (AHLA, 2025b). The manager hired and retained at a higher wage but lacking the analytical skills to interpret AI system outputs is both more expensive and less operationally effective than their predecessor who managed those functions manually.

2.2 The Reskilling Gap as the Core Problem

The reskilling gap in U.S. hotel operations is not the result of insufficient technology access or unavailable training programs. Shin et al. (2025) found that facilitating factors for successful AI adoption, including manager confidence in interpreting AI outputs, organizational cultures supporting data-driven decision making, and clear channels for managers to challenge algorithmic recommendations, were systematically absent in most of the properties studied. Kumawat et al. (2025), in their systematic review, found that employees who receive structured AI literacy training demonstrate measurably better adoption outcomes than those who are simply exposed to AI systems without corresponding development support. Mariani and Baggio (2022), in a systematic literature review of big data and analytics in hospitality and tourism, identified that the human capability gap rather than the technology gap is the primary constraint on analytics value realization across hospitality operations.

3. THEORETICAL FRAMEWORK

Two theoretical frameworks organize this analysis. Human Capital Theory, introduced by Schultz (1961) and formalized by Becker (1964), holds that investments in worker capabilities generate returns to both the individual worker and the employing organization. Applied to hotel workforce reskilling, the theory generates a clear prediction: when AI systems change the capability requirements of hotel management roles, operators and workers who invest in developing the new capabilities will outperform those who do not. The theory also predicts why reskilling is systematically underprovided in competitive labor markets: when employees are mobile, employers bear the risk that reskilling investment will benefit a future employer. This mobility problem is particularly acute in hospitality, where employee turnover rates have historically exceeded 70% annually in some segments (AHLA, 2025b).

The Technology-Organization-Environment framework (Tornatzky and Fleischer, 1990), applied to hospitality technology adoption by Nikopoulou et al. (2023), explains the variation in reskilling responses across different hotel operating contexts. The technological dimension identifies the availability and characteristics of reskilling tools: CHIA certification, analytics simulation platforms, and AI literacy modules from HSMAI Academy (2024) are technically available and accessible. The organizational dimension identifies internal capacity constraints: most hotels outside the major branded chains lack dedicated learning and development functions, analytics specialists who can deliver internal training, and stable enough workforces to make structured reskilling programs viable. The environmental dimension identifies the external pressures and incentives shaping reskilling investment decisions: competitive pressure from analytically sophisticated branded chain operators, the absence of regulatory or accreditation mandates for AI literacy, and the current staffing shortage environment that prioritizes operational coverage over workforce development.

Figure 1 presents the integrated conceptual framework.

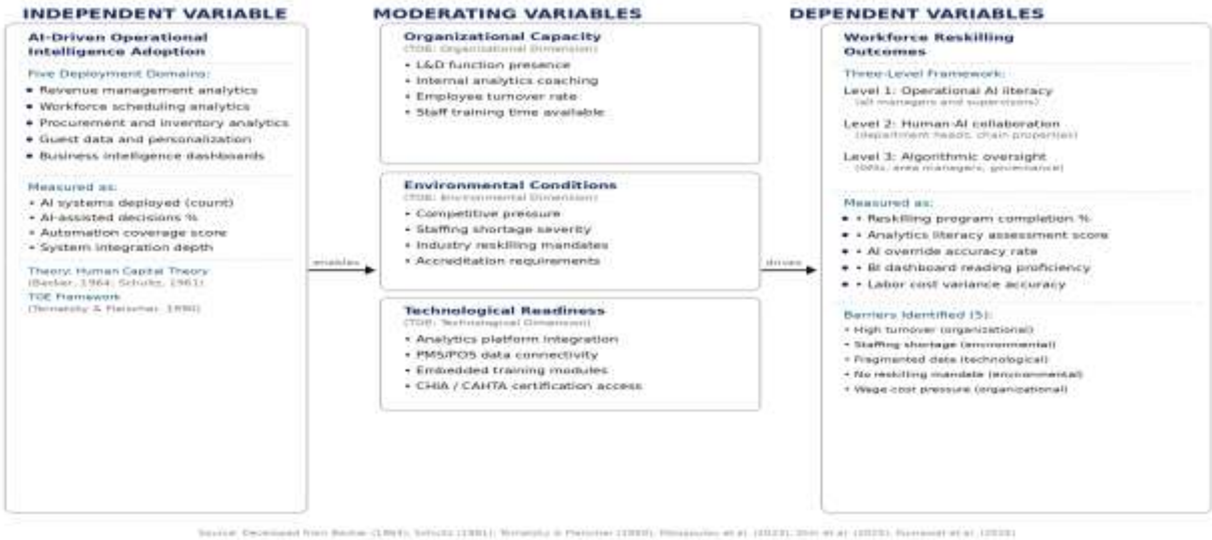

Figure 1. Conceptual Framework: AI-Driven Operational Intelligence Adoption and Workforce Reskilling Outcomes

Source: Framework developed from Becker (1964); Schultz (1961); Tornatzky and Fleischer (1990); Nikopoulou et al. (2023); Shin et al. (2025); Kumawat et al. (2025).

4. LITERATURE REVIEW: AI DEPLOYMENT DOMAINS AND RESKILLING DEMANDS

4.1 Overview of Reskilling Demands by Operational Domain

The reskilling demands generated by AI adoption are not uniform across hotel operational domains. They vary by the degree of AI automation in each domain, the operational consequence of manager disengagement from automated outputs, and the analytical skills required to maintain effective human oversight. Table 2 maps the five AI deployment domains generating the most consequential reskilling demands against the specific competencies each domain requires hotel workers to develop.

Table 2. AI Deployment Domains and Workforce Reskilling Demands in U.S. Hotel Operations

AI Deployment Domain	Current Operational Application	Reskilling Demand Generated	Evidence Base
Revenue management analytics	Algorithmic pricing systems set room rates continuously based on demand signals, competitor data, and booking pace, with minimal manual input at most branded properties	Managers need the ability to interpret demand forecast outputs, identify when algorithmic pricing recommendations are contextually incorrect, and override the system with justified rationale	Shin et al. (2025); Bowen and Morosan (2018); Mariani and Baggio (2022)
Workforce scheduling analytics	Predictive scheduling platforms generate staff rosters based on occupancy forecasts, historical labor patterns, and cost targets, replacing manual schedule-building at chain-level properties	Managers need to read labor cost variance reports, understand the data inputs driving schedule recommendations, and identify when platform outputs conflict with operational reality	Shin et al. (2025); AHLA (2025a, 2025b)
Procurement and inventory analytics	Automated reorder systems trigger purchase orders based on par level data and occupancy projections, reducing direct manager involvement in routine purchasing decisions	Managers need to understand how occupancy data connects to procurement recommendations, monitor cost-of-goods variance, and recognize when automated ordering reflects inaccurate baseline data	Kumawat et al. (2025); Mariani and Baggio (2022)
Guest data and personalization systems	CRM and loyalty analytics generate personalized guest recommendations, recognition triggers, and upsell prompts, creating automated guest intelligence that managers must interpret and act on	Managers need to understand how guest data is collected and used, apply personalization recommendations accurately, and navigate privacy obligations under GDPR and CCPA in daily operations	Kumawat et al. (2025); Shin et al. (2025); Nikopoulou et al. (2023)
Business intelligence dashboards	KPI dashboards providing real-time visibility into RevPAR, labor cost per occupied room, food cost percentage, and guest satisfaction scores are now standard at branded chain properties	Managers need to read and interpret multi-metric BI dashboards, identify anomalies requiring investigation, and connect dashboard signals across departments into coherent operational judgments	Mariani and Baggio (2022); AHLA (2025a); Shin et al. (2025)

Sources: Shin et al. (2025); Kumawat et al. (2025); Mariani and Baggio (2022); Nikopoulou et al. (2023); AHLA (2025a, 2025b); Bowen and Morosan (2018); CoStar Group (2024).

4.2 Revenue Management Analytics

Revenue management is the AI deployment domain where the gap between system capability and manager analytical literacy is most consequential and most extensively documented. Automated pricing systems at branded chain properties now set room rates continuously based on demand signals, competitive rate data, booking pace, and channel mix. The reskilling demand is specific: managers need to understand what inputs drive algorithmic pricing recommendations, recognize when the system is producing contextually inappropriate outputs, and exercise overrides with documented rationale. Mariani and Baggio (2022), in their systematic literature review of big data and analytics in hospitality and tourism, identified revenue management as the domain where hospitality analytics capability has advanced most rapidly, and correspondingly where the skills gap between AI system capability and manager literacy is most acute.

4.3 Workforce Scheduling Analytics and Procurement Analytics

Predictive scheduling platforms generate staff rosters based on occupancy forecasts, historical labor patterns, and cost targets. Shin et al. (2025) found that workforce scheduling was among the operational domains where the inhibiting factors for AI adoption were most pronounced. Managers who could not interpret labor cost variance reports were unable to evaluate whether scheduling platform recommendations were appropriate, and were therefore either accepting inappropriate recommendations or overriding them without analytical justification. In procurement, automated reorder systems and spend analytics platforms generate purchasing recommendations that require managers to understand the relationship between occupancy data, par level management, and food and beverage margin outcomes. Kumawat et al. (2025) identified procurement analytics as an emerging reskilling frontier as AI-driven procurement systems become more widely adopted.

4.4 Guest Data, Personalization Systems, and Business Intelligence Dashboards

CRM and loyalty analytics systems generate personalized guest recommendations, recognition triggers, and upsell prompts that front-of-house managers are expected to apply accurately. Nikopoulou et al. (2023), in their study of digital transformation determinants in hospitality, found that privacy regulation awareness and data governance capability were among the most significant organizational competencies required for effective technology adoption, competencies that most current hotel training programs do not systematically develop. Business intelligence dashboards presenting real-time KPI data across rooms, food and beverage, labor, and guest satisfaction are now standard at branded chain properties. Mariani and Baggio (2022) identified BI dashboard literacy as foundational: without it, the other reskilling investments documented in Table 2 cannot be applied effectively.

5. A RESKILLING FRAMEWORK FOR AI-ENABLED U.S. HOTEL OPERATIONS

5.1 The TOE Framework Applied to Reskilling Response

Table 3 applies the TOE framework to the reskilling response problem, mapping the enabling and constraining conditions across the three framework dimensions.

Table 3. TOE Framework Applied to Workforce Reskilling Response in U.S. Hotel Operations

TOE Dimension	Enabling Conditions for Reskilling	Constraining Conditions for Reskilling
Technological	AI platforms increasingly include embedded training modules and analytics interpretation guides; industry certification programs such as CHIA (CoStar Group, 2024) provide standardized analytics literacy credentials accessible to working hotel managers at low cost; simulation environments allow managers to practice interpreting AI outputs without operational risk	Legacy property management systems at independent and smaller chain properties provide limited analytics functionality, reducing the operational urgency for reskilling; fragmented data across PMS, POS, and HR systems creates a technical environment where analytical skills are difficult to apply even when they are present
Organizational	Large branded chains have established learning and development functions that can integrate AI literacy content into onboarding and continuing education programs; hotel operators with dedicated revenue management and analytics teams can transfer knowledge to operational managers through structured internal coaching programs	Most U.S. hotel properties are managed by general managers and department heads with operational expertise in service quality and labor management rather than data interpretation; high employee turnover rates documented above 70% annually in some segments reduce the return on reskilling investments and discourage sustained training programs (AHLA, 2025b)
Environmental	Competitive pressure from branded chains that have already deployed AI-driven operations creates external urgency for independent operators to develop comparable workforce capabilities; AHLA and HSMAI industry associations have developed accessible analytics certification and training programs that lower the environmental barrier to reskilling at the property level	Staffing shortages documented at 64.9% of hotels (AHLA, 2025b) mean that training time competes directly with operational coverage needs; the absence of accreditation or regulatory requirements for AI literacy in hotel management creates no external mandate for reskilling investment

Sources: Tornatzky and Fleischer (1990); Nikopoulou et al. (2023); Shin et al. (2025); Kumawat et al. (2025); AHLA (2025a, 2025b); CoStar Group (2024); HSMAI Academy (2024).

5.2 A Three-Level Reskilling Framework

Based on the TOE analysis in Table 3 and the reskilling demands documented in Section 4, Table 4 proposes a three-level reskilling framework calibrated to the operational realities of U.S. hotel properties at different scales and AI deployment levels.

Table 4. Three-Level Workforce Reskilling Framework for AI-Enabled U.S. Hotel Operations

Reskilling Level	Target Workforce Segment	Core Competency Being Built	Delivery Mechanism
Level 1: Operational AI Literacy	All hotel managers and supervisors regardless of department or property type	Ability to read and question data outputs from the AI systems deployed in their department: RevPAR dashboards, scheduling platform recommendations, procurement reports, and guest feedback summaries	CHIA certification program (CoStar Group, 2024); HSMAI Hotel Data Analytics Essentials course; property-level BI dashboard training integrated into onboarding
Level 2: Human-AI Collaboration Skills	Department heads and operational managers at branded chain properties where AI systems are fully deployed	Ability to identify when AI recommendations are contextually incorrect, override algorithmic outputs with justified rationale, and lead their teams through AI-assisted operational decisions	Internal coaching by revenue management and analytics specialists; practitioner-led modules through AHLA Foundation hospitality apprenticeship programs; scenario-based simulation using live property data
Level 3: Algorithmic Oversight and Ethics	General managers, area managers, and corporate operations staff responsible for AI system governance across multiple properties	Ability to evaluate whether AI systems are generating appropriate recommendations, identify systemic bias or data quality failures in automated outputs, and apply data governance principles including GDPR and CCPA compliance in operational contexts	CAHTA certification program (CoStar Group, 2024); AACSB-aligned executive education programs at hospitality schools; industry association governance frameworks developed by AHLA and HSMAI

Sources: Becker (1964); Schultz (1961); Shin et al. (2025); Kumawat et al. (2025); AHLA (2025a); CoStar Group (2024); HSMAI Academy (2024); AACSB (2020).

Level 1 is the non-negotiable baseline. Every hotel manager and supervisor working in an AI-enabled operational environment should be able to read and question data outputs from the systems deployed in their department. This does not require advanced data science training; it requires the ability to interpret a RevPAR dashboard, understand what a scheduling platform recommendation means and why it was generated, and recognize when a procurement alert is signaling a problem. The CHIA certification program (CoStar Group, 2024) and HSMAI Academy's Hotel Data Analytics Essentials course provide accessible pathways to this baseline competency for working hotel managers. Level 2 builds the human-AI collaboration capacity that Shin et al. (2025) identified as among the most critical and systematically absent competencies in current hotel management. Level 3 addresses the governance and ethics dimension that Kumawat et al. (2025) identified as the frontier of effective AI adoption, equipping managers to govern AI systems that collect guest data, generate algorithmic performance assessments, and make automated recommendations affecting worker compensation.

5.3 Barriers to Reskilling Effectiveness

Table 5 maps the five primary barriers constraining reskilling effectiveness in U.S. hotel operations, organized by TOE dimension.

Table 5. Barriers to Workforce Reskilling Effectiveness in U.S. Hotel Operations

Barrier	TOE Dimension	Manifestation in U.S. Hotel Operations	Evidence
High employee turnover limiting reskilling return on investment	Organizational	With turnover rates historically above 70% annually in some hotel segments, reskilling investments produce diminishing returns when trained employees leave before deploying their new skills	AHLA (2025b); Kumawat et al. (2025)
Staffing shortages reducing time available for training	Environmental	64.9% of hotels reporting staffing shortages means managers are deployed in operational coverage roles rather than development activities; training competes directly with daily service delivery	AHLA (2025b); Shin et al. (2025)
Fragmented data systems limiting the application of analytical skills	Technological	At independent and smaller chain properties, PMS, POS, HR, and financial systems operate without integration; even managers with analytical literacy cannot apply those skills when the data environment is fragmented	Nikopoulou et al. (2023)
Absence of industry-wide reskilling standards or mandates	Environmental	Neither AHLA, HSMAI, nor accreditation bodies currently require demonstrable AI literacy as a condition of employment or certification in hotel management; without a mandate, reskilling investment remains discretionary	AACSB (2020)
Wage competition consuming capital that could fund reskilling	Organizational	With total compensation projected at $128.47 billion in 2025 (AHLA, 2025a) and wages 25.6% above 2019 levels, hotel operators facing margin pressure have limited discretionary capital for workforce development investment	AHLA (2025a, 2025b); Bowen and Morosan (2018); Becker (1964)

Sources: AHLA (2025a, 2025b); Shin et al. (2025); Kumawat et al. (2025); Nikopoulou et al. (2023); Bowen and Morosan (2018); Becker (1964); AACSB (2020).

The barriers in Table 5 share a common structural feature: they are all amplified by the same conditions that are driving AI adoption. Higher compensation costs reduce the discretionary capital available for reskilling investment. Staffing shortages reduce the time available for training. High turnover reduces the return on individual reskilling investments. The industry is simultaneously facing the strongest external pressure to reskill its workforce and the weakest internal conditions for doing so, a structural problem that individual operators cannot solve in isolation.

6. PROPOSED EMPIRICAL VALIDATION METHODOLOGY

The three-level reskilling framework and five hypothesized barriers in this paper require empirical validation using primary data from U.S. hotel operations. Table 6 presents the variable definitions, measurement approaches, and data sources for a proposed mixed-methods empirical study.

Table 6. Variable Definitions and Measurement Approaches for Empirical Validation

Variable	Operationalization	Data Source	Benchmark
IV: AI-driven operational intelligence adoption	Composite index: AI systems deployed by domain, AI-assisted decision percentage, automation coverage score, and system integration depth (12-item survey scale)	Hotel operator survey; technology vendor audit; PMS and scheduling platform configuration records	AHLA (2025a) AI deployment benchmarks; Nikopoulou et al. (2023) digital maturity framework
DV: Workforce reskilling outcomes	Reskilling program completion rate; analytics literacy assessment score; AI override accuracy rate; BI dashboard reading proficiency test; labor cost variance accuracy in scheduling (adapted from Shin et al., 2025)	HR training records; property analytics assessment scores; operational KPI records	CHIA assessment standards (CoStar Group, 2024); AHLA Foundation competency frameworks
Moderator 1: Organizational capacity	Presence of L&D function; internal analytics coaching availability; employee turnover rate at property; training hours available per manager per quarter	HR records; operator management structure audit	AHLA (2025b) turnover benchmarks; AACSB (2020) analytics competency standards
Moderator 2: Environmental conditions	Competitive intensity score; staffing shortage severity; presence of industry reskilling mandates or accreditation requirements	Operator records; AHLA (2025b) industry surveys	AHLA (2025a, 2025b) industry benchmarks
Moderator 3: Technological readiness	Analytics platform integration score; PMS-POS data connectivity; embedded training module availability; CHIA or CAHTA certification access	Technology audit; CoStar Group (2024) certification records	TOE framework (Tornatzky and Fleischer, 1990) adoption readiness dimensions
Control variables	Property type (branded chain vs. independent); property scale (rooms); geographic market; star rating	Operator records; STR benchmarking data	CoStar Group (2024) property classification standards

Sources: Becker (1964); Tornatzky and Fleischer (1990); Nikopoulou et al. (2023); Shin et al. (2025); Kumawat et al. (2025); CoStar Group (2024); AACSB (2020); AHLA (2025a, 2025b).

The proposed empirical design uses a two-phase approach. Phase 1 deploys a cross-sectional survey of hotel general managers and department heads at a minimum of 120 U.S. hotel properties, stratified by property type (branded chain versus independent) and property scale (under 100 rooms, 100 to 299 rooms, 300 rooms and above), measuring AI deployment adoption levels, reskilling program investment, and reskilling outcome scores. Phase 2 extracts operational KPI data from participating properties, including RevPAR variance, labor cost per occupied room, and food cost percentage, to test whether AI adoption combined with structured reskilling investment generates measurably better operational performance than AI adoption without reskilling investment. The primary empirical prediction is that the relationship between AI-driven operational intelligence adoption and operational performance is positively moderated by reskilling program quality, such that operators who invest in structured reskilling alongside AI deployment outperform operators who deploy AI systems without corresponding workforce development investment.

7. DISCUSSION

Five findings from this review carry implications for hotel operators, workforce development policy, and future research.

The reskilling demand generated by AI adoption in U.S. hotel operations is domain-specific, operational, and teachable. It is not about training hotel managers to become data scientists. It is about training them to govern the AI systems already deployed in their properties. The competencies documented in Table 2 are specific enough to be taught, assessed, and certified through existing programs including CHIA and HSMAI Academy. The problem is not that the reskilling tools do not exist; it is that the organizational and environmental conditions for using them at scale are currently inadequate.

The workforce crisis and the reskilling problem are the same problem expressed in different terms. The industry's inability to resolve staffing shortages through wage increases alone is consistent with what Human Capital Theory predicts when capability mismatches are the binding constraint rather than compensation levels. A manager who lacks the analytical skills to run an AI-enabled hotel department is less valuable to the employer regardless of what they are paid. Addressing the reskilling deficit would improve both workforce productivity and retention by increasing the competence-based satisfaction that research consistently associates with lower turnover in knowledge-intensive roles (Kumawat et al., 2025).

The barriers to reskilling are predominantly organizational and environmental rather than technological. The tools are available. What is missing is the organizational architecture for deploying them systematically: internal coaching programs, protected training time, industry-coordinated reskilling standards, and accreditation requirements that create external incentives for the investment. This finding is consistent with the TOE framework prediction that organizational capacity and environmental conditions are the binding constraints on technology adoption outcomes in hospitality (Nikopoulou et al., 2023).

The reskilling problem has a national scale consequence that individual operator decisions cannot address. The global travel and tourism sector contributed $10.9 trillion to global GDP in 2024 and supported 357 million jobs worldwide (WTTC, 2025). The U.S. hotel industry employs 2.17 million workers and projects total compensation of $128.47 billion in 2025 (AHLA, 2025a). When managers across this industry cannot effectively govern the AI systems deployed in their properties, the aggregate productivity and quality consequences extend beyond individual hotels to the competitive position of the U.S. hospitality sector.

The reskilling response requires coordination across actors that current market incentives do not align. Hotel operators face the mobility problem identified by Becker (1964): reskilling investments benefit mobile workers more than the investing firm. Industry associations can lower the per-operator cost of reskilling through group certifications and shared training infrastructure. Accreditation bodies can create the external mandates that shift reskilling from discretionary to required. Without this coordination, the reskilling gap will persist and widen as AI deployment continues to accelerate.

8. CONCLUSION

This systematic review examined the relationship between AI-driven operational intelligence adoption as the independent variable and workforce reskilling outcomes as the dependent variable in U.S. hotel operations. Four conclusions stand out.

AI deployment in U.S. hotel operations is generating five specific reskilling demands across revenue management analytics, workforce scheduling analytics, procurement analytics, guest data management, and business intelligence dashboard literacy that the industry's current training and development practices do not systematically address. The consequence is an operational risk problem: managers who cannot govern AI systems will generate errors that are invisible until they accumulate into measurable performance failures.

The barriers to reskilling are organizational and environmental rather than technological. The certification programs, simulation tools, and industry training resources required to address the reskilling gap are available and accessible. The barriers are high turnover rates reducing investment returns, staffing shortages reducing training time, fragmented data systems limiting skill application, the absence of industry reskilling standards, and wage competition consuming the capital that could fund development programs.

The three-level reskilling framework proposed in this paper provides a practical, sequenced pathway from baseline BI literacy through human-AI collaboration skills to algorithmic oversight and ethics competency. Its implementation requires coordination across hotel operators, industry associations, accreditation bodies, and technology vendors rather than investment by any single actor alone.

Future research should empirically test the proposed framework using the mixed-methods design outlined in Section 6. Comparative studies measuring reskilling outcomes at properties that have implemented structured AI literacy programs against those that have not would provide the causal evidence that this systematic review cannot supply. The 2.17 million workers in the U.S. hotel industry stand to benefit directly from the development of that evidence base.

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Corresponding Author: Salami Abdul Mohammed