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Strategic Readiness for AI and Smart Technology Adoption in Emerging Hospitality Markets: A Tri-Lens Assessment of Barriers, Benefits, and Segments in Albania

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Abstract

The adoption of artificial intelligence (AI) and smart technologies is reshaping global hospitality. However, in emerging markets, uptake remains limited by financial, organizational, and infrastructural barriers. This study examines the digital readiness of 1821 licensed accommodation providers in Albania, a rapidly expanding tourism economy, using an integrated framework that combines the Technology Acceptance Model (TAM), technology–organization–environment (TOE) framework, and Diffusion of Innovations (DOI). Data were collected via a structured survey and analyzed using descriptive statistics, exploratory factor analysis, cluster analysis, and structural equation modeling. Exploratory factor analysis identified a single robust readiness dimension, covering smart automation, environmental controls, and AI-driven systems. K-means segmentation revealed three adopter profiles: Tech Leaders (17.7%), Selective Adopters (43.5%), and Skeptics (38.8%), with statistically distinct but modest mean differences in readiness, reflecting stronger adoption in central urban and coastal hubs compared to weaker uptake in cultural heritage and non-urban regions. Structural modeling showed that environmental competitive pressure strongly enhanced perceived usefulness, which, in turn, drove behavioral intention, whereas perceived ease of use (operationalized as implementation complexity) had negligible effects. Innovation readiness was consistently associated with broader adoption, although intention was translated into actual use only among Tech Leaders. The findings highlight a fragmented digital ecosystem in which enthusiasm for AI exceeds its feasibility, underscoring the need for differentiated policy support, modular vendor solutions, and targeted capacity building to foster inclusive digital transformation.

Keywords: AI adoption; smart technology; digital readiness; technology adoption frameworks; structural equation modeling (SEM); TOE model; TAM; DOI theory; hospitality SMEs; emerging markets; Albania; sustainability

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1. Introduction

The global hospitality industry is undergoing profound digital transformation, driven by the integration of smart technology and artificial intelligence (AI). These innovations enable automation, real-time optimization, and personalized guest experiences, which are essential for service quality, efficiency, and long-term sustainability (Alsharif et al., 2024; Gursoy et al., 2023; Kim et al., 2025). Tools such as AI-powered property management systems, keyless entry, automated chat interfaces, and smart energy controls are reshaping

operational models across the sector (Wong et al., 2023a; Shin et al., 2025; Dwivedi et al., 2023; Nicolau et al., 2024).

However, the diffusion of these technologies is highly variable. In digitally advanced economies, AI and smart technology benefit from supportive ecosystems, robust infrastructure, skilled labor, and digital literacy. By contrast, adoption in emerging markets often lags because of fragmented systems, weak technical capacity, and financial or institutional constraints. These barriers result in a fragmented, short-term-oriented adoption process that lacks long-term sustainability, particularly among small and medium-sized hospitality enterprises (SMHEs), which constitute the backbone of this sector in many developing countries (Chen et al., 2023; Ivanov et al., 2022; Gajić et al., 2024; Khang et al., 2024).

Albania offers a compelling case to examine digital readiness in a fast-growing tourism-driven economy. Accommodation capacity grew by 45% between 2015 and 2023 (INSTAT, 2024), and the country ranked among the top global performers for international-arrival growth in 2023–24 relative to 2019 (AIDA/UNWTO, 2024). However, official provider-level statistics on AI/smart adoption in Albania's accommodation sector have not yet been reported. As a benchmark, EUROSTAT (2025) shows that among EU accommodation enterprises already using AI, ~49% apply it to marketing/sales and ~27% to administration/management, with a lower uptake for operations/finance, while sophisticated cloud services are used by a majority (~75–80%) (EUROSTAT, 2023, 2025). This contrast of rapid growth alongside absent national indicators and likely uneven digital maturity defines the research need and our distinct contribution: we provide national, provider-level evidence (N = 1821) and explicitly link measured readiness to actual use under real feasibility constraints (infrastructure, integration costs, skills).

The existing literature typically applies models such as the Technology Acceptance Model (TAM) or the technology–organization–environment (TOE) framework (Davis, 1989; Tornatzky & Fleischer, 1990). Although useful, these frameworks often fail to account for the interplay between cognitive perceptions, organizational capacity, and environmental enablers (Venkatesh & Davis, 2000; Ifinedo, 2012). While other integrated models, such as UTAUT and UTAUT2 (Venkatesh et al., 2003, 2012), capture intention and behavioral constructs, they remain limited in explaining the structural and environmental constraints that dominate emerging economies. To address these gaps, this study adopts an integrated Tri-Lens framework that synthesizes the TAM, TOE, and the Diffusion of Innovations (DOI) theory (Rogers, 2003), offering a multi-level account that bridges individual attitudes, organizational readiness, and ecosystem-level diffusion.

This integration is not a simple aggregation: the TAM captures psychological and motivational factors, such as perceived usefulness and ease of use; TOE situates adoption within resource and infrastructural constraints; and DOI provides a dynamic classification of adoption maturity. Their combination enables a more holistic explanation of why awareness and positive attitudes often fail to translate into deployment in resource-limited contexts, an issue largely overlooked in earlier research (Mariani, 2019; Majid et al., 2023; Nicolau et al., 2024).

Figure 1 presents the authors' own visualization of an integrated framework that synthesizes the TAM, TOE, and DOI models, which align contextual influences with cognitive mediators and adoption outcomes.

Guided by this Tri-Lens framework, this study pursues a sequential empirical pipeline. Firstly, Exploratory Factor Analysis (EFA) identifies latent readiness factors; secondly, cluster analysis classifies providers into digital adoption profiles; and thirdly, Structural Equation Modeling (SEM), both single-group and multi-group, tests directional pathways across clusters. This design enables theory testing, while capturing the heterogeneity of adoption trajectories in Albania's fragmented hospitality sector.

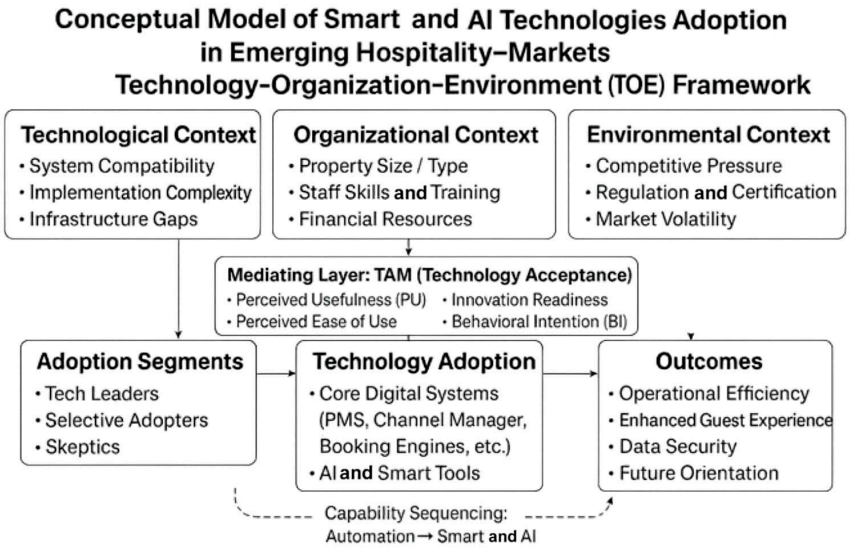

Figure 1. Integrated TOE–TAM–diffusion framework for AI and smart technology adoption in emerging hospitality markets.

Using a national sample of 1821 valid responses from licensed accommodation providers (defined here as hotels, resorts, bed and breakfasts, and guesthouses), this study tested five theory-driven hypotheses:

Environmental Competitive Pressure is hypothesized to enhance Perceived Usefulness (H1), which should enhance Behavioral Intention (H2), leading to Actual Usage (H3). Thus, Innovation Readiness is expected to positively influence Actual Usage (H4). Finally, Perceived Ease of Use (operationalized as implementation complexity) is expected to exert weaker or non-significant effects on Perceived Usefulness and Behavioral Intention (H5).

This study contributes to the literature in three ways: Firstly, it offers a robust theoretical framework, based on cross-disciplinary models. Secondly, it combines national-scale sampling with a sequential pipeline (EFA, clustering, and SEM) to generate replicable empirical insights, which are rarely attempted in emerging markets. Thirdly, it provides policy- and practice-relevant insights into inclusive and sustainable digital transformations in emerging hospitality markets.

2. Literature Review

2.1. AI and Smart Technology in Hospitality

The hospitality sector is at the frontier of digital transformation, increasingly shaped by smart systems and artificial intelligence (AI), which extends beyond traditional ICT into integrated, predictive, and autonomous solutions (Ivanov et al., 2022; Mariani, 2019). These technologies now span back-end functions, such as predictive maintenance, revenue management, and staff scheduling, as well as front-end services, including keyless access, ambient controls, biometric check-ins, and AI-enabled guest communication (Gursoy et al., 2023). Recent studies have highlighted the growing role of robotic process automation (RPA) and generative AI in hotel operations, enabling the automation of repetitive administrative tasks and conversational interfaces such as ChatGPT-based guest services (Yan et al., 2024; Parvez et al., 2025; To & Yu, 2025). Smart property management systems (PMS) are also evolving into AI-enhanced platforms that integrate channel management, personalization, and revenue optimization (Dwivedi et al., 2023). Their adoption signifies a shift from static digital infrastructure to adaptive learning systems that reconfigure guest experiences and operations in real time.

Although AI capabilities in hospitality are advancing rapidly, academic research remains limited in depth and breadth. A bibliometric review by (Peng et al., 2025) shows that while research activity surged post-2020, it remained narrowly focused on technical affordances or guest-facing innovation, often without critically examining the organizational and systemic dynamics of adoption. This gap is particularly evident in small and medium-sized hospitality enterprises (SMHEs), where barriers to integration include not only cost, but also interoperability and digital literacy, which are rarely considered in guest-centered studies (Shin et al., 2025).

On the demand side, guests appreciate smart features such as automated room environments and mobile check-ins for their efficiency and convenience, yet express ambivalence toward fully "human-less" services, which may lack emotional intelligence, personalization, or cultural sensitivity (Wong et al., 2023b). Guest satisfaction is not driven solely by automation, but also by the seamless integration of technology into the hospitality experience, which varies across segments and hotel classes.

On the supply side, providers view AI and smart solutions as levers for operational efficiency, cost control, and workforce optimization. However, adoption remains patchy, especially among small and medium-sized businesses. Barriers include integration complexity, lack of internal IT capabilities, data privacy concerns, and uncertainty around long-term ROI (Ivanov et al., 2022; Buhalis & Leung, 2018). Recent empirical findings further show that even when providers recognize the usefulness of AI tools, their adoption is constrained by implementation complexity, staff training demands, and cybersecurity concerns (Gajić et al., 2024). Crucially, many providers adopt reactively, focusing on proven short-term values, while overlooking the strategic potential of intelligent systems.

Thus, a more comprehensive framework is required that captures not only technological features but also organizational readiness and environmental pressure, especially in resource-limited contexts.

2.2. Insights from Emerging Hospitality Markets

Emerging markets offer a compelling context for investigating the structural, institutional, and behavioral factors shaping technology adoption. In these settings, tourism often plays an important role in economic development, yet providers remain constrained by fragmented infrastructure, informal labor, and limited access to digital capital (Nikopoulou et al., 2023; Sigala, 2020).

Studies from Serbia, Saudi Arabia, and Vietnam have shown that AI adoption in hospitality is frequently motivated by necessity rather than by strategy. In Serbia, hotels adopt AI for cost efficiency, but lack long-term planning (Gajić et al., 2024). In Saudi Arabia, AI and smart technologies are integrated within the national smart tourism agenda, yet their implementation is slowed by inadequate organizational readiness and limited staff capabilities (Alsharif et al., 2024). In Vietnam, SMEs limit their investment in tools with clear payback horizons, avoiding advanced systems owing to perceived risk (Trai et al., 2025). Across these contexts, the pattern is similar: adoption is incremental, fragmented, and opportunistic rather than strategically integrated.

Albania exhibits several unique characteristics. Despite the growing tourism sector and supportive digitalization policies, smart technology adoption remains uneven and opportunistic. Most providers rely on basic connectivity (e.g., websites and booking engines) but lack integration across front-desk, back-office, and guest service systems. Institutional support exists, but organizational readiness varies widely, especially in rural and family-run establishments.

Recent studies conducted in Albania have highlighted the evolving role of digital tools. (Muça et al., 2022) examined how smart technology and e-tourism platforms influ-

ence service delivery and promotion strategies but found that developments are largely promotional rather than operational. This underlines the empirical gap: prior research on Albania has focused on ICT diffusion and e-tourism, but not on multi-level readiness, adoption maturity, or structural adoption pathways (Sánchez et al., 2025), (Nikopoulou et al., 2023). Our results confirm this; while providers recognize benefits, advanced adoption is concentrated among a minority "Tech Leader" group, while the majority operate with selective or minimal digital portfolios.

Thus, emerging markets such as Albania illustrate a paradox: rapid tourism growth and policy support coexist with uneven digital adoption, making them ideal contexts for studying how cognitive, organizational, and environmental factors interact to shape AI readiness.

2.3. Toward a Tri-Lens Framework: Integrating TOE, TAM, and DOI

Given the complex, multi-layered nature of AI and smart technology adoption, no single theoretical lens can capture the full range of influencing factors (Ivanov & Webster, 2020; Sánchez et al., 2025). Therefore, we adopted a Tri-Lens framework that integrates the TAM, TOE, and DOI to provide a holistic account of readiness, perception, and behavior. To make the roles, boundaries, and complementarities explicit, Appendix A Table A1 maps each lens to its level, constructs, indicators, and cross-lens roles.

While some prior studies have combined these models, they typically remain conceptual or rely on small samples without a national-scale empirical validation (Ifinedo, 2012). Our study advances this literature by applying the Tri-Lens framework to a large national sample of 1821 Albanian accommodation providers and by combining EFA, clustering, and SEM in a sequential pipeline. We also estimated the multi-group SEM by diffusion segments to examine the moderated pathways.

The TAM explains the cognitive–motivational aspects of adoption, focusing on perceived usefulness (PU) and perceived ease of use (PEOU) as determinants of behavioral intention (BI) (Venkatesh & Davis, 2000; Nikopoulou et al., 2023). TOE provides the structural backdrop, highlighting organizational readiness (ML1) and environmental competitive pressure as feasibility and constraint conditions (Tornatzky & Fleischer, 1990). DOI classifies providers according to adoption timing and diffusion patterns (Rogers, 2003), which we operationalize through three empirically derived segments (Tech Leaders, Selective Adopters, and Skeptics) used for moderation in multi-group SEM.

In our model, organizational and environmental conditions (TOE) shape perceptions (TAM), which in turn drive intention and use. Stronger competitive pressure is expected to increase perceived usefulness, lower implementation complexity is expected to increase perceived usefulness and strengthen intention, higher perceived usefulness should increase intention, and both intention and innovation readiness should increase actual use. We allow these relationships to vary across diffusion segments (DOI: Tech Leaders, Selective Adopters, Skeptics).

Unlike UTAUT/UTAUT2 (Venkatesh et al., 2003, 2012), which are strong on intention but less explicit about infrastructural and institutional barriers, our Tri-Lens alignment is not a simple aggregation. TOE provides the feasibility boundary conditions within which TAM perceptions form, and DOI captures heterogeneity in how intentions translate into actual use across diffusion segments. This multi-level specification helps explain why awareness and positive attitudes often fail to translate into actual usage in resource-limited settings (Mariani, 2019; Majid et al., 2023; Walle et al., 2023).

This framework guided our empirical design: EFA revealed a single readiness dimension, clustering segmented providers into Tech Leaders, Selective Adopters, and Skeptics; and SEM tested the structural pathways across these groups. The resulting model links con-

text, perceptions, and outcomes within one coherent structure, and supports the targeted interpretation of heterogeneity.

3. Materials and Methods

3.1. Theoretical Framework and Research Design

This study adopts an integrated framework that combines the Technology Acceptance Model (TAM), the technology–organization–environment (TOE) framework, and Diffusion of Innovations (DOI) to examine the adoption of AI and smart technologies in Albania's accommodation sector. The TAM (Davis, 1989; Venkatesh & Davis, 2000) captures attitudinal drivers of adoption, particularly Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). In this study, PEOU is explicitly operationalized as implementation complexity, degree of technical expertise, system integration, and staff training required, rather than as interface simplicity. This distinction reflects the reality of adoption in professional hospitality settings where resource limitations and infrastructure constraints shape how ease of use is experienced. The TOE framework (Tornatzky & Fleischer, 1990), (Hameed et al., 2012) situates adoption decisions within the broader technological base, internal capabilities, and environmental pressures, such as competition, certification, and cybersecurity requirements. DOI (Rogers, 2003) complements these perspectives by highlighting the heterogeneity in adoption maturity and positioning providers along a diffusion continuum, from early adopters to skeptics.

Integrating these perspectives allows for a more comprehensive understanding of adoption dynamics by distinguishing between three levels of influence: attitudes toward value (TAM/PU), structural enablers and constraints (TOE readiness and pressure), and diffusion-based adoption maturity (DOI). This triangulation is particularly well suited to transition-economy contexts such as Albania, where fragmented infrastructures, small-firm dominance, and high market volatility create gaps between favorable perceptions of technology and actual implementation (Tussyadiah, 2020; Mariani & Borghi, 2023; Omowole et al., 2024; Šakytė-Statnickė & Budrytė-Ausiejienė, 2025). Guided by this framework, this study addresses three objectives: firstly, to identify latent readiness for AI and smart technologies; secondly, to segment providers based on readiness and adoption orientation; and thirdly, to estimate the structural relationships between implementation complexity (PEOU), readiness, environmental pressure, behavioral intention (BI), and realized adoption (AU). Methodologically, these objectives are pursued through a sequential pipeline: Exploratory Factor Analysis (EFA) is used to derive a readiness factor; clustering is applied to standardized readiness scores to reveal adopter profiles; and Structural Equation Modeling (SEM), both single-group and multi-group, tests adoption pathways consistent with TAM–TOE–DOI while comparing mechanisms across segments.

3.2. Instrument Development and Operationalization of Constructs

A structured questionnaire was developed on the basis of validated constructs from the Technology Acceptance Model (TAM), the technology–organization–environment (TOE) framework, and Diffusion of Innovations (DOI). The instrument was drafted directly in Albanian to ensure conceptual clarity and accessibility to the respondents. Prior to formal administration, terminology and item clarity were pretested with sector representatives during the first phase of regional workshops organized in six tourist destinations in Albania, which also functioned as a practical validation step to confirm that technical expressions (e.g., PMS, booking engine, revenue manager) were widely understood.

The questionnaire combined three item formats: 5-point Likert-scale items measuring perceptions and intentions, binary (yes/no) items capturing actual system use, and categorical questions recording demographic and organizational characteristics. The full

codebook of all items, with wording, coding, and Albanian formulations, is available in the Supplementary Materials.

The survey items were mapped to the theoretical constructs as follows: Within the TAM (Davis, 1989; Venkatesh & Davis, 2000), Perceived Usefulness (PU) was measured by items reflecting operational efficiency, cost reduction, and customer experience (P44_1, P44_2, P44_3, and P48_1). Perceived Ease of Use (PEOU) was operationalized as implementation complexity, including expertise, integration, and training requirements (P34_2, P34_3, P34_5). Behavioral Intention (BI) was measured by items reflecting future investment intentions (P40, P48_2, P48_3, P48_5). Actual Usage (AU) was assessed using binary indicators of core systems (P6, P8, P10, P12, P14, P16, P18, P20, P22, P23, P24, P25, P27, P29). These AU indicators were also aggregated into a formative composite index (AU_comp), while a reflective specification was retained as a robustness check. A full mapping of the TAM constructs to the survey items is provided in Appendix A Table A2.

Within TOE (Tornatzky & Fleischer, 1990), technological dimensions included existing system use (P6–P8, P10–P12, P14–P16, P18–P20, P22–P25, P27, P29–P33) and innovation readiness (ML1, measured by P35–P40, covering willingness to adopt smart and AI-driven systems for automation, control, and optimization). Organizational dimensions included size and resources (Q1, P4, P41) and internal capabilities linked to expertise, training, and internal improvement (P34_5, P44_4, P48_4). The environmental dimensions covered competitive pressure (P18, P27, P45_1–P45_3, P47_3, and P48_6) and regulatory or infrastructural barriers (P34_6, P34_7, and P43). A full mapping of the TOE dimensions to the items is provided in Table A3 in Appendix A.

For SEM analysis, not all items from the initial pool were retained. The final models were estimated using a reduced set of indicators to improve measurement validity and model fit. Specifically, PU was modeled with P44_1–P44_3, PEOU with P34_2, P34_3, and P34_5, ML1 with P35–P40, BI with P48_2 and P48_5, Env_CompPress with P45_1–P45_3, and AU with a composite index based on seven indicators (P6, P10, P12, P14, P16, P18, and P20). Attitude toward using was measured in the initial survey, but was not estimated in the final SEM, as its items overlapped conceptually with ML1 and were subsumed under that construct. Accordingly, attitude toward using was omitted from Appendix A Table A2 to avoid confusion. Other items remain documented in the Supplementary Materials and Appendix A Tables A2 and A3 but were excluded from the final SEM due to weaker loadings, conceptual redundancy, or parsimony considerations.

Constructs were carefully differentiated to ensure conceptual clarity. Innovation Readiness (ML1) is defined as the strategic willingness and preparedness of organizations to adopt AI and smart technologies, reflecting openness to innovation and long-term orientation. In contrast, Perceived Ease of Use (PEOU) was defined as the operational dimension of implementation, referring to the technical expertise required, integration complexity, and staff training demands. This separation allows readiness to be treated as a forward-looking strategic construct, whereas ease of use reflects the immediate operational challenges. To further guard against construct redundancy and multicollinearity, post-estimation Variance Inflation Factor (VIF) diagnostics were conducted (see Section 3.4).

3.3. Data Collection and Sampling

Data were collected between November 2024 and June 2025 using a two-phase mixed method design. In Phase I, regional workshops were organized at six destinations: Berat, Shkodër, Pogradec, Gjirokastër, Sarandë, and Tiranë. These workshops targeted and involved hotel owners and managers, local government officials, vocational school teachers and students, and representatives of tour guides and travel agencies. In addition to fostering discussions on digital transformation in the hospitality sector, the workshops served as

a practical validation stage to ensure that the survey items were well-understood in the Albanian context before formal administration.

In Phase II, the questionnaire was administered digitally with the support of trained enumerators from the Albanian Institute of Statistics (INSTAT). Enumerator training, delivered jointly by INSTAT and the research team, ensured consistent explanation of the questions and minimized misinterpretation, which reduced item non-response. While this procedure enhances data reliability, the presence of enumerators may also introduce social desirability or acquiescence bias. To mitigate this limitation, a common method bias diagnostic (ULMC) was implemented as part of the SEM analysis (Section 3.4).

The sampling frame comprised the entire universe of licensed accommodation providers included in INSTAT's Accommodation Structures Survey. This register combines the Statistical Business Register and the Local Unit Register, covering all statistical units with primary or secondary activities in accommodation. Official classifications follow NVE Rev. 2:55.10 (hotels and similar accommodation), 55.20 (holiday and short-term accommodation), and 55.30 (camping grounds). In practice, within Albania, these correspond to hotels, resorts, bed and breakfasts, and guesthouses, which together constitute the formal accommodation sector. Unregistered or informal accommodation providers were excluded from this study.

From a total population of 2364 accommodation structures, 1821 valid responses were retained after screening for completeness and deduplication across phases, yielding a 77% response rate. Responses were obtained from all 12 prefectures in Albania, with the largest shares being in Vlora (789), Tirana (494), and Shkodër (282). In contrast, peripheral prefectures, such as Dibër (39) and Kukës (38), contributed the smallest number of cases, reflecting their limited tourism infrastructure. A detailed comparison of frame totals and achieved responses by prefecture, property type, and size is provided in the Supplementary Materials. Since no post-stratification weights were applied, the findings should be interpreted as broadly representative of Albania's formal accommodation sector, rather than as weighted national estimates.

All participants were informed that their responses would be solely used for academic research. Informed consent was obtained prior to participation and anonymity and confidentiality were ensured throughout the study.

3.4. Analytical Strategy

All analyses were conducted in R (v4.x) using packages from the psychometric and data science ecosystem, including psych (Revelle, 2024), corrplot, ggplot2 (Wickham, 2016), and dplyr (Wickham et al., 2014). Six readiness items (P35–P40), measured on a 5-point Likert scale, were designed to capture the adoption of smart and AI-driven hospitality technologies. These items covered dimensions such as AI for Customer Data, Smart Environment, Reservation Automation, Security Innovation, Operational Innovation, and AI for Operations.

Exploratory Factor Analysis (EFA): Prior to factor analysis, diagnostic procedures were conducted. As the readiness indicators were ordinal, a polychoric correlation matrix was estimated as the appropriate input (Garrido et al., 2013; Holgado–Tello et al., 2010). The sampling adequacy was confirmed using the Kaiser–Meyer–Olkin (KMO) index (Kaiser, 1974), and the suitability of the correlation matrix was verified using Bartlett's test of sphericity (Bartlett, 1954). Factor retention was determined using parallel analysis (PA) with 1000 Monte Carlo replications (Horn, 1965; Hayton et al., 2004). Both the scree plot and PA criteria supported a one-factor solution, which was estimated using the minimum residual (minres) extraction method. For robustness, an alternative two-factor solution with oblimin rotation was also tested, but the results confirmed that the one-factor solution was superior

and was retained for subsequent analyses. Reliability was evaluated using Cronbach's α (Cronbach, 1951) and McDonald's ω (McDonald, 2013). This solution was conceptualized as a single readiness dimension, termed the Adoption of Smart and AI-Driven Hospitality Technology. Appendix A Tables A4–A9 and Figure A1 present the results.

Cluster Analysis: Standardized factor scores from the readiness dimension (ML1) were used to classify accommodation providers. K-means clustering was applied with the optimal cluster number selected through triangulation using the Elbow method (Thorndike, 1953), average silhouette width (Rousseeuw, 1987), and the Gap statistic (Tibshirani et al., 2001). A three-cluster solution was retained, identifying the profiles of Tech Leaders, Selective Adopters, and Skeptics. Cluster membership and validation statistics are reported in Appendix A Tables A2–A4 and A10.

Structural Equation Modeling (SEM). Adoption pathways were examined using structural equation models estimated with the Weighted Least Squares Mean and Variance-adjusted (WLSMV) estimator, which is appropriate for ordinal indicators (Brown, 2015; Byrne, 2016). The full lavaan syntax used for the measurement and structural models is provided in the R scripts in the Supplementary Materials. All categorical variables were declared ordered with thresholds freely estimated from the data, implying an estimation based on polychoric and tetrachoric correlations. The full set of threshold estimates is reported in Appendix A Table A11.

To assess common method bias, an unmeasured latent method construct (ULMC) diagnostic was conducted, in which a latent method factor was loaded on all reflective items. The Fit indices and method loadings for this model are reported in Appendix A Tables A12 and A13.

The conceptual specification followed a Tri-Lens framework integrating the TAM, TOE, and DOI (Venkatesh & Davis, 2000; Rogers, 2003; Hameed et al., 2012). Six latent constructs were modeled: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Innovation Readiness (ML1), Behavioral Intention (BI), Actual Use (AU), and Environmental Competitive Pressure (Env_CompPress). PEOU was operationalized as implementation complexity, capturing technical expertise, integration challenges, and staff training requirements.

Given the applied focus on realized deployment, Actual Use (AU) was modeled primarily as a composite observed index (AU_comp), aggregating seven technologies: PMS, CRM, website builder, booking engine, payment gateway, revenue manager, and guest messaging. This approach treats AU as a formative construct, representing a portfolio of adoption practices. As a robustness check, AU was also modeled reflectively; its measurement properties and comparative fit are reported in Appendix A Tables A14 and A15.

Model adequacy was evaluated using multiple indices, including χ^2, df, χ^2/df, CFI, TLI, RMSEA, and SRMR, following the established guidelines (Hair et al., 2022; Kline, 2016; Schumacker & Lomax, 2015). To further ensure model stability, Variance Inflation Factors (VIFs) were computed for all structural predictors, both pooled and by cluster. All VIFs fell below the conventional cut-off of 10, with only BI and Environmental Competitive Pressure in the AU_comp regression showing moderate collinearity (VIF $\approx$ 6). This level is acceptable and does not threaten the estimate reliability (Hair et al., 2022). Finally, a multi-group SEM was conducted to test the measurement and structural invariance across the three readiness-based clusters. The Fit indices, difference tests, and group-specific paths are reported in Appendix A Tables A14–A16.

The study complied with ethical standards for social science research and AI tool usage. AI has only been used for editing, not for generating or analyzing data (Porsdam Mann et al., 2024).

4. Results

4.1. Descriptive Statistics: Adoption, Benefits, and Barriers

4.1.1. Adoption of Core Technologies

The adoption of core digital technologies remains uneven across Albania's accommodation sector (N per item = 1689–1728; missing $\leq$ 4%) (see Figure 2 and Appendix A Table A17). Among the 1681–1728 valid responses per item, the most widely used systems were channel managers (884 responses, 51.3%) and property management systems (PMS) (643 responses, 37.2%). Moderate uptake was observed for booking engines (n = 425, 25.0%), payment gateways (n = 328, 19.2%), and website builders (n = 253, 14.8%).

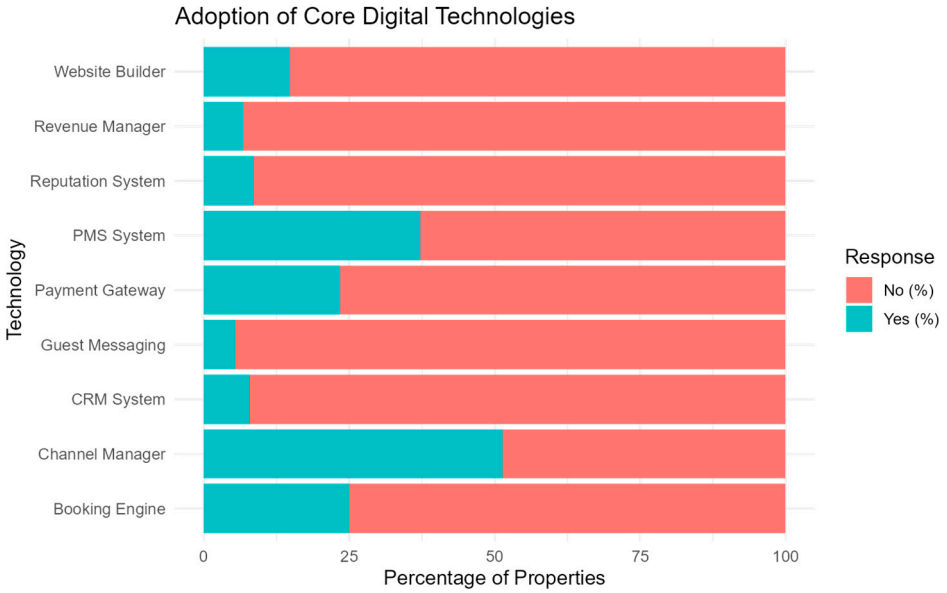

Figure 2. Adoption rates of Core Digital Hospitality Systems: Proportion of accommodation providers reporting adoption versus non-adoption of core systems, including PMS, channel manager, CRM, booking engine, payment gateway, guest messaging, revenue manager, reputation system, and website builder.

In contrast, specialized systems remain a niche. CRM systems (n = 135, 7.9%), revenue managers (n = 91, 5.3%), and guest messaging tools (n = 107, 6.3%) reported low penetration. Reputation systems (n = 155, 9.1%) also remain limited; these tools are primarily provider-facing, consolidating guest ratings, and reviews from online travel platforms. Overall, the data confirm that while distribution-related infrastructure is increasingly embedded, advanced optimization and engagement solutions are still in the early stages of diffusion. Similar patterns of uneven adoption between distribution-oriented and advanced management systems have been reported in other developing hospitality markets (Pergelova et al., 2024; Šakytė-Statnickė & Budrytė-Ausiejienė, 2025; Nikopoulou et al., 2023).

4.1.2. Adoption of AI and Smart Technologies

The adoption of AI-enabled and smart technologies is even more restricted, with only a few tools exceeding a 20% penetration rate (N per item = 1647–1701; missing $\leq$ 5%) (see Figure 3, Appendix A Table A18). The most widely used were security cameras and motion sensors (n = 1167 of 1682, 69.4%), reflecting the strong prioritization of safety and monitoring. Moderate adoption was observed for keyless door management (n = 469, 27.8%), energy-saving sensors (n = 411, 24.4%), and smart lighting and thermostat controls (n = 364, 21.6%).

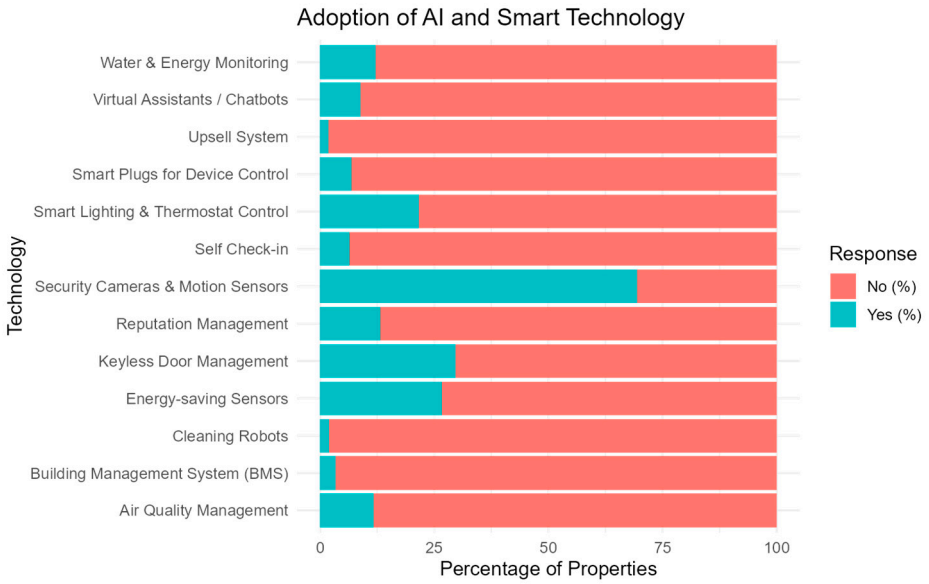

Figure 3. Adoption of Smart and AI-Enabled Hospitality Technologies: Proportion of accommodation providers reporting adoption versus non-adoption of smart and AI tools, including self-check-in, keyless door management, energy-saving sensors, chatbots, cleaning robots, and building management systems.

In contrast, capital-intensive or complex solutions, such as building management systems (BMS) (n = 71, 4.2%), cleaning robots (n = 58, 3.4%), and virtual assistants/chatbots (n = 145, 8.6%), are rarely adopted. Within this category, reputation management platforms (n = 223, 13.2%) stand apart from basic reputation systems, whereas the latter focuses on consolidating ratings. Reputation management tools integrate more advanced digital engagement such as automated monitoring, sentiment analysis, and proactive brand interaction. These patterns are consistent with international findings, where SMEs often adopt affordable security or energy-saving tools but face constraint scaling toward high investment or AI-driven systems (Pergelova et al., 2024; Buhalis & Leung, 2018; Dayour et al., 2023).

4.1.3. Perceived Benefits of AI and Smart Technology

Despite limited adoption, respondents strongly endorsed the benefits of AI and smart technologies (N per item = 1616–1659; missing $\leq$ 6%) (see Figure 4, Appendix A Table A19). Across constructs, more than two-thirds of providers agreed that such technologies would deliver strategic or operational improvements. The most frequently cited benefits were energy sustainability (n = 1271 of 1637, 77.6%), guest experience (n = 1280 of 1659, 77.2%), operational efficiency (n = 1254 of 1642, 76.4%), and data security (n = 1236 of 1640, 75.4%). Future-oriented outcomes were also widely recognized, with future competitiveness (n = 1205 of 1616, 74.6%) and Integration Readiness (n = 1192 of 1620, 73.6%) endorsed at similarly high levels.

These results highlight a perception–adoption gap: providers largely recognize the long-term strategic value of AI and smart solutions, yet the implementation lags considerably. This gap underscores the fact that decision-makers are not resistant in principle but constrained in practice, echoing global evidence that awareness often outpaces deployment in resource-limited contexts (Pergelova et al., 2024; Vrontis et al., 2022; Mariani & Borghi, 2023). Item-level details are reported in Supplementary Table S2: Perceived Benefits by Item.

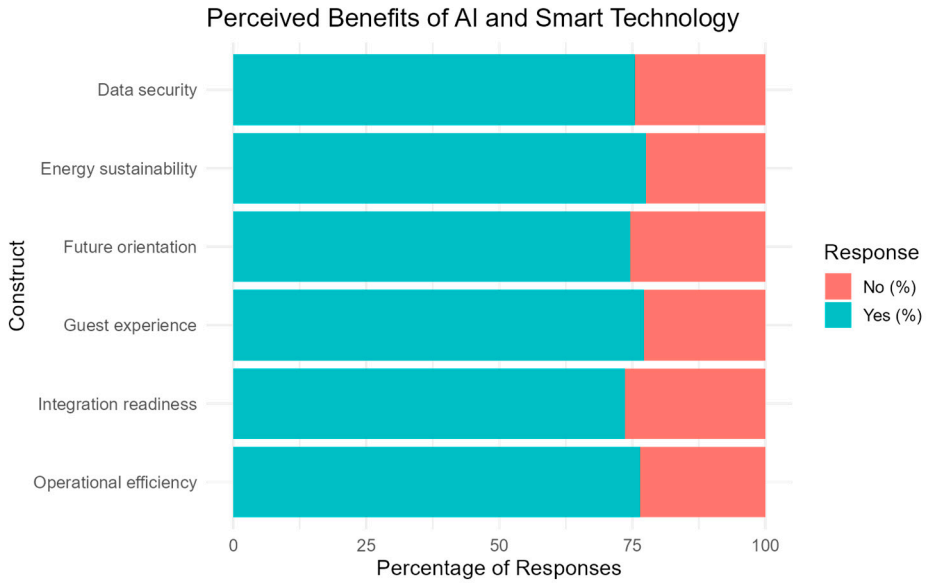

Figure 4. Perceived Benefits of Smart and AI-Driven Hospitality Technologies: Proportion of accommodation providers recognizing benefits in operational efficiency, integration readiness, guest experience, future orientation, energy sustainability, and data security.

4.1.4. Perceived Barriers to Integration of AI and Smart Technology

Respondents also identified substantial barriers to adoption, dominated by financial and infrastructural constraints (N per item = 1627–1648; missing $\leq$ 4%) (see Figure 5, Perceived Barriers to AI and Smart Technology, Appendix A Table A20: Perceived Barriers to AI and Smart Technology). The most widely cited obstacles were high implementation and maintenance costs (n = 1204 of 1648, 73.1%), lack of financial resources for initial investments (n = 1176 of 1645, 71.5%), and complexity of integration with existing systems (n = 1103 of 1634, 67.5%).

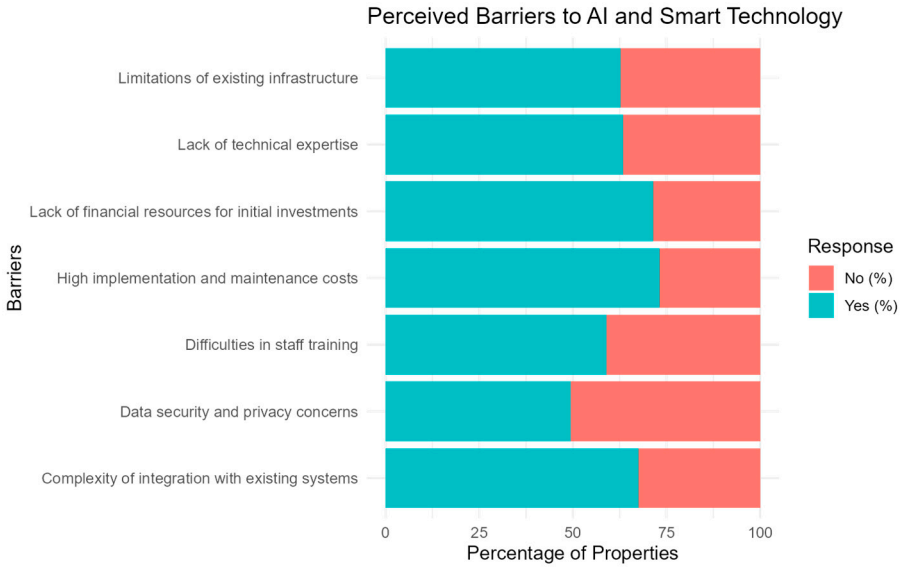

Figure 5. Reported Barriers to the Adoption of Smart and AI-Driven Hospitality Technologies: Proportion of accommodation providers citing barriers including infrastructure limitations, lack of technical expertise, financial constraints, high costs, staff training difficulties, data security concerns, and system integration complexity.

Additional barriers included lack of technical expertise (n = 1039 of 1638, 63.4%), limitations of existing infrastructure (n = 1033 of 1644, 62.8%), and difficulties in staff

training (n = 964 of 1633, 59.0%). Concerns about privacy and data security, while relevant, were less prominent (n = 806 of 1627, 49.5%). These findings are consistent with prior studies highlighting high costs, skill shortages, and integration challenges as decisive barriers in hospitality digitalization (Pergelova et al., 2024; Mariani & Borghi, 2023),

4.2. Exploratory Factor Analysis and Adoption Segmentation

4.2.1. Exploratory Factor Analysis (EFA)

An EFA of the six readiness items (P35–P40; analysis N = 1,671, listwise deletion applied) indicated a single, well-defined latent dimension. Sampling adequacy was excellent (overall KMO = 0.941; item MSAs = 0.935–0.947), and Bartlett's test confirmed factorability, $\chi^2(15) = 12{,}255.52$, $p < 0.001$ (Appendix A Table A4). Parallel analysis using polychoric correlations supported a one-factor solution: the first observed eigenvalue (4.987) clearly exceeded its simulated counterpart (0.491), whereas the second observed eigenvalue (0.053) closely matched its simulated value (0.051) (Appendix A Table A5, Figure A1).

The one-factor minres model (no rotation) yielded uniformly strong standardized loadings: P35 = 0.925, P36 = 0.903, P37 = 0.900, P38 = 0.916, P39 = 0.919, and P40 = 0.906 (Appendix A Table A6). Communalities ranged 0.81–0.86 and with a total explained variance of 83.1% (Appendix A Tables A7 and A8). Reliability was excellent (Cronbach's $\alpha = 0.953$; McDonald's $\omega_t = 0.967$; Appendix A Table A9), exceeding conventional psychometric criteria (Nunnally & Bernstein, 1994).

For robustness, we also estimated a two-factor solution with oblimin rotation. Factor MR1 accounted for 83% of the variance, whereas MR2 accounted for only 3%. All six items loaded strongly on MR1 (0.81–0.95) with only trivial cross-loadings, and the two factors correlated moderately (r = 0.31) (Appendix A Table A21). Given these results, the one-factor specification was retained as the most parsimonious and theoretically coherent.

Residual correlation diagnostics (Appendix A Table A22) confirmed low non-systematic residuals, further supporting the unidimensionality.

Therefore, we interpret this factor as Adoption Readiness for Smart and AI-Driven Hospitality Technology (ML1), encompassing automation, environmental control, security, and guest-facing innovation.

4.2.2. Cluster Analysis

Heterogeneity in readiness was examined by applying k-means clustering to standardized readiness scores (ML1_z). Three complementary diagnostics informed the choice of cluster number. Firstly, the Elbow plot (Appendix A, Figure A2) shows a marked reduction in within-cluster variance through k = 3, with diminishing returns thereafter, suggesting that the three clusters capture most of the data structure. Secondly, the Gap statistic (Appendix A, Figure A3) indicated a relative maximum at k = 3, with only marginal gains for higher k values (4–6), supporting the three-cluster solution as the most parsimonious and defensible choice. Thirdly, the Silhouette curve (Appendix A, Figure A4) shows that the clustering quality is already acceptable at k = 3 (average silhouette ≈ 0.59), with modest improvements at k = 4–5. Given the convergence of the Elbow and Gap criteria on k = 3, together with the conceptual interpretability of three distinct profiles, k = 3 was retained despite the slightly higher silhouette at a larger k.

The retained profiles (analysis N = 1671) were Tech Leaders (n = 296, 17.7%), Selective Adopters (n = 726, 43.4%), and Skeptics (n = 649, 38.8%) (Appendix A Table A10). The mean standardized readiness scores confirmed ordered separation (Figure 6), with Tech Leaders having the highest (mean = 1.56, CI [1.51, 1.61]), Selective Adopters moderate (mean = 0.26, CI [0.24, 0.29]), and Skeptics the lowest (mean = −1.00, CI [−1.03, −0.97]).

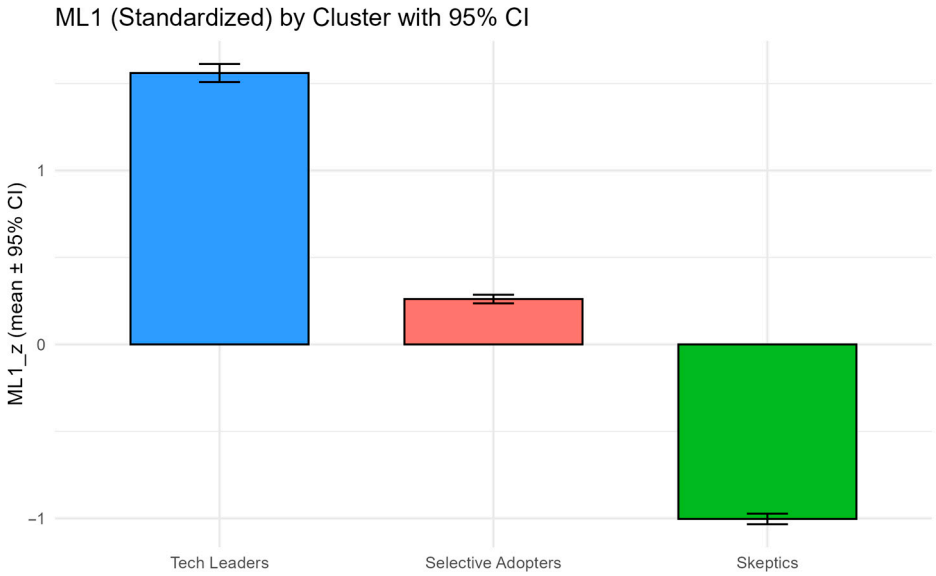

Figure 6. Cluster Means of ML1 Standardized Factor Scores with 95% Confidence Intervals.

The Kruskal–Wallis test confirmed significant differences in readiness across clusters ($\chi^2(2) = 1440.18$, $p < 0.001$). Post hoc Dunn tests further established that all three groups were statistically distinct: Tech Leaders > Selective Adopters ($Z = -15.43$, $p < 0.001$), Selective Adopters > Skeptics ($Z = 26.51$, $p < 0.001$), and Tech Leaders > Skeptics ($Z = -35.59$, $p < 0.001$) (Appendix A Tables A23 and A24).

To anchor these profiles in concrete practice, Figure 7: Smart and AI Systems by Cluster compares the selected technologies. Across all groups, security sensors are the modal adoption (67–72%; Tech Leaders 71%, Selective Adopters 72%, Skeptics 67%). The second tier comprises keyless entry (25–33%; 30/33/25%), energy sensors (25–30%; 27/30/25%), and smart lighting (19–25%). Advanced or capital-intensive tools remain uncommon in every segment: BMS (3–4%), cleaning robots (1–3%), and chatbots are below 15% (13/9/9%). Thus, while the levels differ moderately (Tech Leaders ≥ Selective ≥ Skeptics on several items), all clusters share a consistent pattern: emphasis on safety/efficient devices with limited penetration of complex automation.

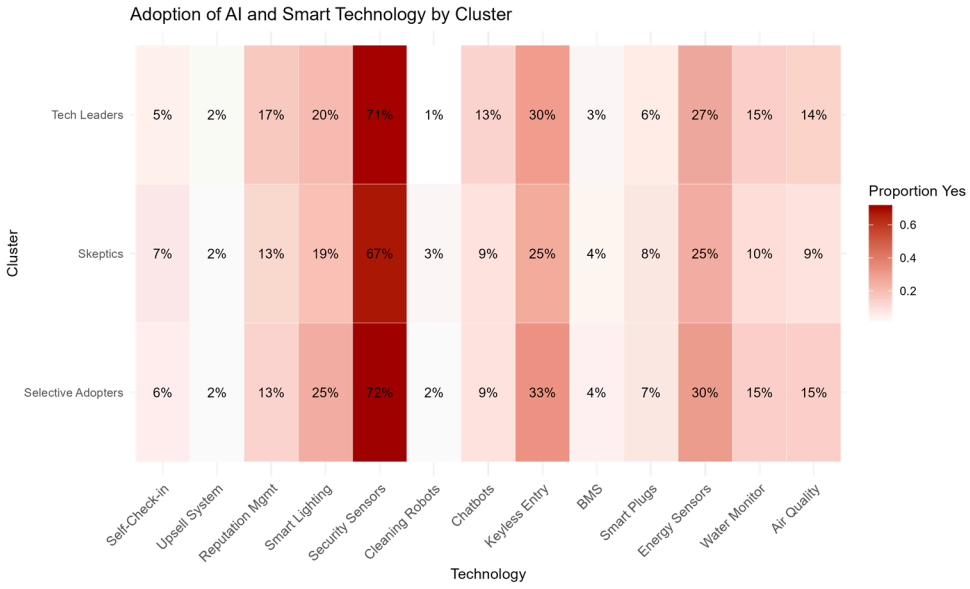

Figure 7. Heatmap of smart/AI technology adoption rates by cluster.

This integrative, two-step design, deriving a psychometrically sound readiness factor and then segmenting providers based on that factor, provides the empirical basis for the multi-group SEM in Section 4.3, where adoption pathways are formally tested across the three readiness-based clusters.

4.3. Structural Equation Modeling (SEM)

4.3.1. Model Specification and Fit

The structural equation model was estimated within the integrated TAM–TOE–DOI framework, encompassing six latent constructs. Perceived Usefulness (PU) is modeled as a function of Perceived Ease of Use (PEOU), Innovation Readiness (ML1), Environmental Competitive Pressure (Env_CompPress), Behavioral Intention (BI) as a function of PU and PEOU; and Actual Use either as a reflective latent (AU) or as a formative composite index (AU_comp) summarizing adoption across seven core systems (PMS, CRM, website builder, booking engine, payment gateway, revenue manager, and guest messaging). In this study, PEOU captures the implementation complexity (technical expertise, integration demands, and staff training). All coefficients reported are standardized (β). The models were estimated using WLSMV, treating ordinal/binary indicators as ordered with freely estimated thresholds.

The composite AU model fits best (CFI = 0.998, TLI = 0.998, RMSEA = 0.023, SRMR = 0.036, $\chi^2(125) = 213.75$; $\chi^2/df = 1.71$), outperforming the reflective AU model (CFI = 0.995, TLI = 0.995, RMSEA = 0.031, SRMR = 0.060, $\chi^2(241) = 558.12$; $\chi^2/df = 2.31$). Therefore, the direct comparison (Appendix A Tables A25 and A26, and Figures A5 and A6) motivates the interpretation of the results with AU_comp, while retaining the reflective specification in the appendix as a robustness check.

4.3.2. Measurement Model

Reflective constructs show high standardized loadings (Appendix A Table A27): PU—customer experience 0.97, operational efficiency 0.92, cost reduction 0.89; PEOU—tech expertise 0.96, integration complexity 0.87, staff training 0.88; ML1—0.82–0.90 (AI for customer data 0.86; smart environment 0.82; reservation automation 0.87; security innovation 0.90; operational innovation 0.90; AI for operations 0.88); BI—single platform 0.96, AI personalization 0.95; Env_CompPress—improve security 0.89, certified technology 0.97, cyber training 0.92 (Appendix A Table A27). The thresholds were within the expected range (Appendix A Table A11). The ULMC diagnostic indicated an excellent fit (CFI = 1.000 [0.999974], RMSEA = 0.006, SRMR = 0.025; Appendix A Table A12) with small method effects (Appendix A Table A13). The reflective AU block also shows acceptable measurement quality (six of seven indicators ≥ 0.80; payment gateway 0.64), consistent with lower empirical usage. The coverage and item distributions are summarized in Appendix A Table A28. Appendix A Table A29 indicates that 1494 providers had valid responses for all seven AU items.

4.3.3. Structural Model Findings

The composite model paths (Table 1; Figure 8) indicate that Env_ComPress → PU (β = 0.865), ML1 → PU (β = −0.119), PEOU → PU (β = 0.036), and PU → BI (β = 0.861) had the strongest effects. Additional paths included ML1 → AU_comp (β = 0.314), PEOU → BI (β = 0.047), BI → AU_comp (β = −0.027), and Env_CompPress → AU_comp (β = −0.070). The explained variance was high for PU ($R^2 = 0.860$) and BI ($R^2 = 0.785$), but more modest for AU_comp ($R^2 = 0.126$). For the reflective AU model, $R^2(AU) = 0.177$ (see Appendix A, Figure A6, Table A30). Full parameter estimates, including SEs, test statistics, p-values, and confidence intervals, are reported in Supplementary Materials.

Table 1. Parameter Estimates for the Composite AU SEM Model (WLSMV Estimation).

Path (lhs → rhs)	Estimate	SE	Z	*p*-Value	95% CI Lower	95% CI Upper	Std. Loading (β)
PU = ~P44_1	0.339	0.026	12.88	<0.001	0.287	0.391	0.906
PU = ~P44_2	0.330	0.026	12.91	<0.001	0.280	0.381	0.883
PU = ~P44_3	0.357	0.028	12.62	<0.001	0.302	0.413	0.954
PEOU = ~P34_2	0.964	0.017	55.65	<0.001	0.930	0.998	0.964
PEOU = ~P34_3	0.865	0.021	41.53	<0.001	0.824	0.905	0.865
PEOU = ~P34_5	0.879	0.019	47.28	<0.001	0.842	0.915	0.879
RL1 = ~P35	1.071	0.038	28.23	<0.001	0.997	1.145	0.869
RL1 = ~P36	1.063	0.043	24.92	<0.001	0.979	1.146	0.819
RL1 = ~P37	1.152	0.045	25.47	<0.001	1.064	1.241	0.874
RL1 = ~P38	1.139	0.041	27.57	<0.001	1.058	1.220	0.896
RL1 = ~P39	1.140	0.041	27.98	<0.001	1.060	1.220	0.899
RL1 = ~P40	1.086	0.039	27.82	<0.001	1.010	1.163	0.878
BI = ~P48_2	0.444	0.027	16.45	<0.001	0.391	0.497	0.957
BI = ~P48_5	0.440	0.027	16.51	<0.001	0.388	0.492	0.949
Env_CompPress = ~P45_1	0.892	0.013	66.58	<0.001	0.865	0.918	0.892
Env_CompPress = ~P45_2	0.972	0.008	116.94	<0.001	0.956	0.988	0.972
Env_CompPress = ~P45_3	0.923	0.011	84.21	<0.001	0.901	0.944	0.923
PU ← PEOU	0.096	0.090	1.07	0.287	−0.081	0.273	0.036
PU ← RL1	−0.317	0.058	−5.50	<0.001	−0.430	−0.204	−0.119
PU ← Env_CompPress	2.312	0.229	10.11	<0.001	1.864	2.760	0.865

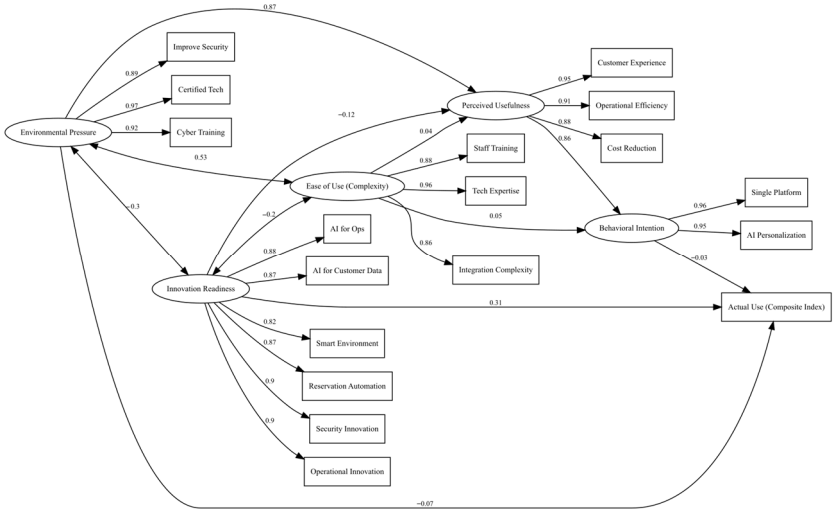

Figure 8. Structural Equation Model Results (Composite AU Specification).

The significant effects included Environmental Competitive Pressure → Perceived Usefulness (β = 0.865), Perceived Usefulness → Behavioral Intention (β = 0.861), and Innovation Readiness → Actual Use (β = 0.314). Explained variance: PU (R^2 = 0.860), BI (R^2 = 0.785), and AU_comp (R^2 = 0.126).

To assess possible construct overlap, Variance Inflation Factors (VIFs) were computed for all the structural predictors (Appendix A Table A31). Across the equations, the maximum VIFs ranged from 1.4 to 6.4. The AU_comp regression showed moderate collinearity between BI and Environmental Competitive Pressure (VIF ≈ 6), but this level remained below the conventional threshold of 10 and did not threaten estimate stability (Hair et al., 2022). All other predictors had VIFs below 2, confirming that Innovation Readiness and PEOU are empirically distinct from related constructs.

Indirect effects were evaluated within the WLSMV framework using model-implied estimates and their robust standard errors (full parameter estimates are reported in the Supplementary Materials). This approach provides consistent tests of mediation effects for ordinal indicators, as recommended in SEM applications with categorical data (Brown, 2015; Muthén & Muthén, 2017).

4.3.4. Multi-Group SEM

Invariance testing across readiness clusters indicated excellent configural, metric, and structural fit (Appendix A Table A14), with chi-square difference tests confirming no significant loss of fit (Appendix A Table A15; $p = 0.142$ and 0.144). Group-specific estimates from the configural model (Appendix A, Table A16) reveal distinct adoption patterns. For Tech Leaders, Behavioral Intention was a strong predictor of Actual Use ($\beta = 0.584$, $p = 0.044$), complemented by a positive effect of Innovation Readiness ($\beta = 0.354$, $p < 0.001$) and a negative effect of Environmental Competitive Pressure ($\beta = -0.639$, $p = 0.024$). Among Selective Adopters, Innovation Readiness significantly predicted Actual Use ($\beta = 0.278$, $p < 0.001$), whereas Behavioral Intention did not. For Skeptics, Innovation Readiness again showed a significant effect ($\beta = 0.381$, $p < 0.001$), while Behavioral Intention remained non-significant. In this group, Environmental Competitive Pressure strongly influenced Perceived Usefulness ($\beta = 0.880$, $p < 0.001$) but did not translate into higher adoption. The group-specific explained variances are reported in the Supplementary Materials.

5. Discussion

This study provides a structured, theory-driven investigation of digital readiness in Albania's accommodation sector by integrating the Technology Acceptance Model (TAM), technology–organization–environment framework (TOE), and Diffusion of Innovations (DOI). By combining descriptive statistics, factor analysis, segmentation, and structural modeling, the findings illuminate both robust patterns, such as high perceived benefits but weak uptake, and more tentative dynamics, such as cluster-specific adoption strategies that require cautious interpretation given modest mean differences.

5.1. Operational Digitalization vs. Strategic AI Readiness

The descriptive findings (Section 4.1) reveal a pronounced divide between operational digitalization and strategic AI readiness. Foundational systems such as channel managers (51.3%) and property management systems (37.2%) have achieved a relatively broad uptake, reflecting their status as "minimum digital baselines," which enable participation in distribution networks dominated by online travel agencies (OTAs). Their diffusion underscores the necessity of operational digital tools for market survival, rather than strategic differentiation.

By contrast, the adoption of more advanced systems is limited. Revenue managers (5.3%), guest messaging (6.3%), and smart environmental controls such as thermostats and lighting (21.6%) exemplify technologies with clear strategic potential but weak penetration. This divergence suggests that adoption decisions in Albania are less constrained by perceived usefulness, which is consistently high and more constrained by TOE-related bottlenecks such as high costs, integration challenges, and shortages of skilled personnel.

Theoretically, this divide illustrates how the TAM explains high attitudinal readiness, TOE highlights structural inhibitors, and DOI situates slow uptake within an "early majority" stage rather than true early adoption. Comparative studies in transition economies, including Serbia, Vietnam, and the Baltic states, report similar "two-speed" digital ecosystems, where core tools become normalized while AI-driven solutions remain aspirational

without systemic enablers (Gajić et al., 2024; Trai et al., 2025; Šakytė-Statnickė & Budrytė-Ausiejienė, 2025).

These dynamics also reflect the sectoral structure. Albania's accommodation sector is dominated by small and medium-sized enterprises, which often lack the resources and managerial capacity to integrate complex systems. As in other emerging economies, this structural composition helps explain why digital maturity tends to plateau at the operational level (Pergelova et al., 2024). In summary, operational digitalization is robust, but strategic AI readiness is tentative and contingent on broader financial, infrastructural, and policy support.

5.2. High Perceived Benefits, Strong Structural Constraints

Despite the low adoption, the perceived benefits of AI and smart technologies are strong and widespread. Most providers expect improvements in energy sustainability (77.6%), guest experience (77.2%), and operational efficiency (76.4%), whereas substantial shares anticipate gains in data security (75.4%) and competitiveness (74.6%) (Appendix A Table A19). These results reinforce the TAM construct of Perceived Usefulness: accommodation managers and owners clearly recognize the strategic value of these technologies for both operational and competitive outcomes (Dwivedi et al., 2023; Mariani & Borghi, 2023).

However, the translation to actual use is constrained by systemic obstacles. High implementation and maintenance costs (73.1%), lack of financial resources (71.5%), and integration complexity (67.5%) were the most frequently cited barriers, followed by shortage of technical expertise (63.4%) and staff training challenges (59.0%) (Appendix A Table A20). Privacy and security concerns, although not negligible (49.5%), were less salient, suggesting that feasibility and resource limitations outweigh ethical and regulatory issues.

This perception–adoption gap is a robust finding echoed in Central and Eastern Europe, where SMEs recognize benefits but remain stuck in incremental digitalization without subsidies or vendor support (Pergelova et al., 2024; Tussyadiah, 2020; Soomro et al., 2025). DOI theory interprets Albania's firms as "early majority," interested but hesitant.

SEM adds nuance; while innovation readiness showed a modest positive effect on actual use ($\beta = 0.314$), behavioral intention did not translate into adoption. This highlights that readiness helps but is not sufficient on its own, as financial and infrastructural barriers remain decisive. Possible explanations include measurement errors (self-reports inflate readiness), sample composition (dominated by small firms with limited resources), and interaction effects (readiness is constrained by finances). This paradox, where firms feel "ready" but cannot act, is consistent with prior evidence that enthusiasm often exceeds feasibility (Ali et al., 2022; Wang & Mohamed, 2025; Phaphoom et al., 2017).

Thus, while the TAM explains why adoption is desired, TOE clarifies why it frequently fails, and DOI situates hesitation within diffusion dynamics. This finding should be treated as robust in terms of barriers and perceived benefits, but tentative regarding the causal interpretation of the readiness–use gap.

5.3. Segmentation Reveals Divergent Digital Pathways

The integration of exploratory factor analysis and cluster segmentation (Section 4.2) identified three adopter profiles: Tech Leaders (17.7%), Selective Adopters (43.5%), and Skeptics (38.8). Statistical tests confirmed the separation despite modest mean differences, suggesting systematic differences in readiness.

Tech Leaders scored the highest, reflecting broad adoption across domains such as security innovations, environmental monitoring, operational optimization, and selected guest automation. Their stronger presence in urban hubs (e.g., Tirana) and premium

coastal destinations (e.g., Sarandë, Himara, Durrës, Shkodër) underscores location-specific environmental factors. Crosstabs in Appendix A Table A32 show that Tech Leaders were relatively evenly distributed across property sizes, while regional disparities were more decisive, consistent with DOI's 'early adopters' who combine resources and competitive pressure.

Selective Adopters hold an intermediate position. They favored technologies such as security sensors and energy management, but nearly one-third lacked a PMS or booking engines. Appendix A Table A32 confirms that Selective Adopters were the modal group across all property size categories (≈38–47%), reflecting TOE's budget-driven incrementalism.

Skeptics displayed the lowest readiness, with a fragile digital baseline. Appendix A Table A32 shows that they were widespread across all property sizes and were particularly prevalent in certain peripheral municipalities (e.g., Dibër), while also representing a substantial share in some coastal destinations (e.g., Sarandë and Shkodër). This pattern highlights how structural barriers combine with attitudinal inertia in both rural and urban contexts.

Two crosscutting findings were noteworthy. Firstly, cluster membership is relatively stable across property sizes (Appendix A Table A32), indicating that even micro and small firms can achieve leadership when strategically resourced. Secondly, regional disparities were far more pronounced (Appendix A Table A32), underscoring the environmental dimensions of TOE.

From a policy perspective, these segmentation results provide useful insights but should be interpreted with caution for fine-grained strategy design, given the modest mean differences. Nonetheless, they point to clear structural divides, particularly between major urban centers and peripheral or less-central regions and between areas with stronger versus weaker infrastructure.

5.4. Innovation Readiness and Environmental Pressure Drive Adoption

In the pooled model, Environmental Competitive Pressure emerged as the dominant antecedent of Perceived Usefulness ($\beta = 0.87$, $p < 0.001$), which in turn strongly predicted Behavioral Intention ($\beta = 0.86$, $p < 0.001$). This aligns with TAM and TOE accounts, highlighting how external competition shapes perceptions of strategic value. In contrast, Perceived Ease of Use, measured here as implementation complexity, showed negligible associations with PU ($\beta = 0.04$, n.s.) and BI ($\beta = 0.05$, n.s.), indicating that in this setting, feasibility concerns are secondary when usefulness is perceived as high.

Innovation Readiness (ML1) played a dual role: it was negatively associated with PU ($\beta = -0.12$, $p < 0.001$), suggesting stricter evaluation standards among more capable firms, but positively linked to breadth of adoption ($\beta = 0.31$, $p < 0.001$). The BI → AU path was not significant overall, although it emerged clearly among Tech Leaders ($\beta \approx 0.58$).

Multi-group SEM further indicated that Tech Leaders follow the full TAM sequence, whereas Selective Adopters and Skeptics rely more directly on readiness. This pattern suggests that the intention–behavior link is contingent on the maturity stage. While the enabling role of readiness in broadening adoption appears robust, pathway magnitudes should be interpreted cautiously, given the modest explanatory power for AU ($R^2 \approx 0.13$–0.18).

5.5. Policy and Practice Implications

These findings have important implications for policymakers, vendors, training providers, and local stakeholders.

Tiered policy support: Adoption readiness is unevenly distributed. Appendix A Table A32 shows that Skeptics and Selective Adopters represent the majority across property sizes,

particularly in micro and small establishments, and are predominant in key tourist destinations. This included cultural heritage sites (Berat, Gjirokastër, and Korça), seaside destinations (Himara and Lezha), and the lakeside hub of Pogradec. In contrast, Tech Leaders are relatively more concentrated in major urban hubs and premium coastal centers, such as Tirana, Durrës, Saranda, Shkodër, and Vlora. This confirms that "who needs what" varies by both size and region: Skeptics require foundational infrastructure, Selective Adopters need incremental support, and Tech Leaders are best positioned to pilot AI-enabled tools.

Vendor solutions: Figure 7, a heatmap of cluster-specific adoption rates, confirms the clustered uptake of selected tools: security sensors are widely adopted (~67–72%), while keyless entry remains moderate (25–33%), underscoring selective adoption pathways. Vendors should design modular bundles tailored to cluster profiles and destination types. For Skeptics with micro and small properties, "starter packages" should include a PMS, booking engines, and payment gateways to establish basic digital baselines. For Selective Adopters, bundles should be extended to reputation management tools, energy-saving sensors, and keyless entry. Tech Leaders, especially in Tirana, Durrës, Sarandë, Shkodër, and Vlorë, can be targeted with advanced systems such as revenue managers, guest messaging, and chatbots. Crosstabs (Appendix A Table A32) revealed a particularly low coverage of core systems among Skeptics, making them priority targets for vendor-designed modular systems.

Capacity building: Human resource gaps remain critical. Training must be accessible to micro- and small-scale firms that dominate the Skeptic and Selective Adopter clusters (Appendix A Table A32). In the regional workshops, beyond hotel owners and managers, we engaged local officials, vocational schoolteachers and students, and travel agency representatives. Teachers showed a strong interest in updating curricula to reflect new digital trends in hospitality, while students and agencies sought practical skills to align themselves with industry demands. This reinforces the fact that training strategies must be cluster-specific and embedded in broader local ecosystems, preparing the next-generation workforce alongside current operators.

Monitoring readiness: Cluster-based segmentation offers a tool for longitudinal monitoring. Policy instruments should link incentives (e.g., grants, tax credits, or preferential financing) to measurable adoption milestones, gradually moving firms along the Skeptic $\rightarrow$ Selective Adopter $\rightarrow$ Tech Leader trajectory. Regular updates should also be shared with vocational institutions and local governments to align skills pipelines with technology adoption.

Global and strategic implications: Compared to developed economies, Albania illustrates how ease of use is secondary to feasibility and resources. This contextual contribution, demonstrating how the TAM, TOE, and DOI interact under infrastructural constraints and limited financing, represents one of the key theoretical additions of this study.

5.6. Limitations and Future Research

Although this study offers new insights, it has several limitations. Firstly, reliance on self-reported data may overstate the level of reported readiness owing to optimism bias. Secondly, although the sample size was large, it was restricted to Albania; hence, generalizability to other emerging tourism markets remains limited and requires further comparative validation. Thirdly, the cluster solution, while statistically validated, reflected relatively modest mean differences; therefore, segmentation-based strategies should be treated as tentative.

Future research could address these limitations by employing longitudinal designs to track digital transformation over time, cross-country comparisons to situate Albania within

broader regional trajectories, and mixed method approaches that integrate qualitative insights into organizational strategies and cultural dynamics. Such work would refine the understanding of the interplay between the TAM, TOE, and DOI under resource-constrained conditions, and guide more precise policy interventions.

6. Conclusions

This study examines digital readiness and technology adoption in Albania's accommodation sector by applying an integrated TAM–TOE–DOI framework. By addressing the empirical gap in how small and medium-sized hospitality enterprises in emerging tourism markets adopt smart and AI-enabled tools, this study provides one of the first large-scale, nationally grounded analyses for this context. This study combined descriptive statistics, exploratory factor analysis (EFA), cluster-based segmentation, and structural equation modeling (SEM) using data from 1821 licensed hotels, guesthouses, and resorts (with valid N values ranging from 1600 to 1700 depending on the item) collected between November 2024 and June 2025.

The results reveal a fragmented digital ecosystem, with widespread adoption of core operational systems (e.g., PMS, channel managers, and booking engines), but limited penetration of advanced AI and smart tools such as chatbots, revenue managers, and robotics. This "two-speed" environment highlights that technological diffusion in Albania is driven less by perceptions of usefulness, which are uniformly high, and more by structural constraints such as financial costs, integration complexity, and skill shortages. In theoretical terms, this underscores the complementarity of the TAM, TOE, and DOI frameworks: the TAM accounts for high attitudinal readiness; TOE captures systemic obstacles; and DOI situates adoption maturity within an "early majority" stage rather than early adoption.

Segmentation analysis identified three adopter profiles: Tech Leaders (17.7%), Selective Adopters (43.5%), and Skeptics (38.8%), with systematic but moderate differences in readiness. Tech Leaders combined broader adoption with stronger representation in urban hubs and premium coastal destinations, while Selective Adopters pursued incremental and pragmatic adoption pathways, and Skeptics lagged with fragile digital baselines concentrated in cultural heritage and non-urban regions. Crosstabulation (Appendix A Table A32) further showed that property size was not decisive, whereas regional context was highly influential. These patterns highlight that execution roadmaps must differentiate between urban hubs, where larger hotels and Tech Leaders can pilot advanced AI tools, and rural or heritage regions, where Skeptics and smaller family-run providers require foundational infrastructure and subsidized starter bundles. Selective Adopters, distributed across sizes, are best served with modular add-ons and targeted training, which allows gradual progression.

The SEM results showed that environmental competitive pressure strongly enhanced perceived usefulness ($\beta \approx 0.87$), which, in turn, drove behavioral intention ($\beta \approx 0.86$). Perceived ease of use, operationalized as implementation complexity, had negligible overall effects. Innovation readiness played a dual role: it was negatively associated with perceived usefulness, but positively linked to actual usage breadth. The link between behavioral intention and actual use was insignificant in the pooled sample but significant among Tech Leaders, suggesting that intention translates into behavior only at higher maturity levels. These results demonstrate that innovation readiness is a consistent enabler of adoption, whereas environmental pressure raises awareness without guaranteeing deployment.

From a practical perspective, this study highlights that digital transformation pathways are uneven and contextually embedded. Therefore, policymakers should design tiered interventions tailored to the cluster profiles and regional conditions. In practice,

this means prioritizing advanced pilots for Tech Leaders in urban hubs. These include AI-driven revenue management platforms for dynamic pricing and demand forecasting, generative AI guest messaging and concierge systems, predictive energy and maintenance management through smart BMS, service robots for check-in or housekeeping, and AI-enhanced sentiment analysis for reputation management. Selective Adopters should be supported with modular mid-level solutions, such as AI-driven reputation and review management systems, smart energy optimization through IoT sensors and predictive analytics, mobile keyless entry, and guest engagement platforms that enable personalized offers and upselling. Finally, Skeptics in rural and heritage regions should gain access to essential baseline systems, such as lightweight cloud-based PMS with OTA integration, booking engines, secure digital payment gateways, and basic CRM modules, delivered through micro-finance schemes or shared digital platforms. Vendors should align with this staged logic by offering scalable bundles for each cluster, whereas training institutions should differentiate between basic digital literacy for small providers and advanced AI/data skills for larger hotels. Together, these measures could gradually shift Skeptics toward Selective Adopters and Tech Leaders, supporting the sustainable digital transformation of Albania's hospitality sector.

This study had several limitations that must be noted. Firstly, reliance on self-reported survey data may introduce optimism bias in perceived readiness. Secondly, although the sample was large and covered the formal accommodation sector, the findings are specific to Albania and may not be generalizable to other emerging economies. Thirdly, three-cluster segmentation showed statistically significant but modest mean differences, indicating that strategies based on cluster profiles should be treated as indicative rather than definitive.

Therefore, future research should pursue three directions: longitudinal designs to capture trajectories of digital transformation over time, cross-country comparisons to Albania within broader regional and global patterns, and mixed method approaches that integrate qualitative insights into organizational strategies, guest perceptions, and cultural dynamics. Such work would refine the theoretical integration of the TAM, TOE, and DOI and guide more precise interventions under conditions of infrastructural and institutional constraints.

In summary, this study advances the understanding of AI and smart technology adoption in emerging hospitality economies by validating an integrated multi-level framework and demonstrating how attitudinal readiness, organizational constraints, and diffusion maturity interact in shaping adoption outcomes. While operational digitalization is now widespread in Albania, strategic AI readiness remains constrained by systemic obstacles. Bridging this gap will require sustained, coordinated action across policy, practice, and research to ensure that enthusiasm for smart technologies translates into sustainable, inclusive transformation.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/tourhosp6040187/s1; Table S1: survey codebook (Albanian/English wording, coding, anchors); Table S2: perceived benefits, item-level counts, and percentages (CSV); Table S3: SEM (composite AU) parameter estimates and fit indices (CSV); Table S4: multi-group SEM (configural) fit indices and R^2 (CSV); Dataset S1: de-identified survey dataset (XLSX); Code S1: data preparation and descriptives (R); Code S2: EFA and k-means clustering (R); Code S3: CFA/SEM (TAM–TOE–DOI) with ULMC (R).

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Institutional Review Board Statement: The study was approved by the Ethics Committee of the University of Tirana (protocol code NO.1007/1, date of approval: 5 July 2024).

Informed Consent Statement: Informed consent was obtained from all the subjects involved in the study.

Data Availability Statement: The de-identified dataset is provided in Dataset S1. The survey codebook (Table S1) and R scripts (Code S1–S3) are available in the Supplementary Materials.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AU	Actual Usage (composite index of core systems)
BI	Behavioral Intention
CFI	Comparative Fit Index
χ^2	Chi-square statistic
df	Degrees of Freedom
DOI	Diffusion of Innovations
EFA	Exploratory Factor Analysis
ICT	Information and Communication Technology
INSTAT	Albanian Institute of Statistics
KMO	Kaiser–Meyer–Olkin
ML1	Readiness for Smart and AI-Driven Hospitality Technology
OTA	Online Travel Agency
PEOU	Perceived Ease of Use (implementation complexity)
PMS	Property Management System
PU	Perceived Usefulness
RMSEA	Root Mean Square Error of Approximation
RMSR	Root Mean Square Residual
ROI	Return on Investment
SEM	Structural Equation Modeling
SI	Strategic Intent
SMHEs	Small and Medium-sized Hospitality Enterprises
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
TLI	Tucker–Lewis Index
TOE	Technology–Organization–Environment
ULMC	Unmeasured Latent Method Construct
VIF	Variance Inflation Factor

Appendix A

Table A1. Cross-framework map (levels, boundaries, and interactions).

Lens	Level	Construct (This Study)	Conceptual Domain	Boundary Rule	Measurement	SEM Role	Cross-Lens Interactions
TAM	Individual	Perceived Usefulness (PU)	Beliefs about performance gains from smart/AI tech	No readiness or adoption items	Reflective	Mediator	Env_CompPress → PU → BI
TAM	Individual	Perceived Ease of Use (PEOU) (implementation complexity)	Implementation burden (Expertise, integration, training)	Not capability/ willingness; no adoption items	Reflective	Predictor of PU & BI (expected −)	PEOU → PU, BI (−)
TAM	Individual	Behavioral Intention (BI)	Intention to invest/deploy	No adoption or readiness items	Reflective	Proximal driver of AU	PU → BI → AU_comp (varies by segment)
TOE	Organizational	Innovation Readiness (ML1)	Strategic preparedness/ willingness	Not intention; not complexity; no adoption items	Reflective EFA→CFA	Direct driver; basis for segments	ML1 → AU_comp; segmentation source
TOE	Environmental	Environmental Competitive Pressure	External market/ regulatory pressure	No internal capability/ readiness/ adoption items	Reflective	Exogenous antecedent to PU	Env_CompPress → PU (indirect to BI/AU)
TOE	Technological	Actual Use (AU_comp)	Breadth/depth of adopted tool stack	Not used as indicators elsewhere	Composite (formative)	Outcome	Endpoint of PU/BI and ML1 effects
DOI	System/Market	Adoption segments (k-means on ML1)	Diffusion maturity profiles	Not modeled as latent; no indicators	Grouping (moderator)	Moderates path coefficients (multi-group SEM)	Tests heterogeneity (e.g., BI → AU_comp)

Table A2. Mapping of TAM Constructs to Survey Items.

TAM Construct	Item Codes	Description
Perceived Usefulness (PU)	P44_1, P44_2, P44_3, P48_1	Belief that technology improves efficiency, reduces costs, enhances experience
Perceived Ease of Use (PEOU)	P34_2, P34_3, P34_5	Complexity: expertise, integration, training
Behavioral Intention (BI)	P40, P48_2, P48_3, P48_5	Intention to invest in AI and automation
Actual Usage (AU)	P6, P8, P10, P12, P14, P16, P18, P20, P22, P23, P24, P25, P27, P29	Use of PMS, CRM, website builders, booking engines, etc.

Table A3. Mapping of TOE Dimensions to Survey Items.

TOE Dimension	Sub-Dimension	Item Codes	Description
Technological	Existing Technology Use	P6–P8, P10–P12, P14–P16, P18–P20, P22–P25, P27, P29–P33	Core systems (PMS, CRM, channel managers, sensors, BMS, etc.)
Technological	Innovation Readiness (RL1)	P35–P40	Willingness to adopt AI/smart systems
Organizational	Size and Resources	Q1, P4, P41	Rooms, type, budget
Organizational	Internal Capabilities	P34_5, P44_4, P48_4	Staff skills, training, improvement needs
Environmental	Competitive Pressure	P18, P27, P45_1–P45_3, P47_3, P48_6	Security, reputation, trust
Environmental	Regulatory and Infrastructure	P34_6, P34_7, P43	Infrastructure, privacy, lack of integration

Table A4. Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity.

	Variable	Value	df	Chi-Square	*p*-Value	N
KMO	Overall KMO	0.941	–	–	–	–
KMO by Item	P35	0.935	–	–	–	–
KMO by Item	P36	0.936	–	–	–	–
KMO by Item	P37	0.947	–	–	–	–
KMO by Item	P38	0.944	–	–	–	–
KMO by Item	P39	0.939	–	–	–	–
KMO by Item	P40	0.943	–	–	–	–
Bartlett	Bartlett's Test	–	15	12,255.52	<0.001	1671

Table A5. Parallel Analysis: Observed vs. Simulated Eigenvalues.

Component	Observed Eigen	Simulated Eigen	Obs − Sim
1	4.987	0.491	4.496
2	0.053	0.051	0.003
3	0.014	0.024	−0.010
4	−0.009	0.001	−0.010
5	−0.023	−0.021	−0.001
6	−0.036	−0.054	0.018

Table A6. Factor Loadings for One-Factor Solution (Minres Extraction).

Item	RL1
P35	0.925
P36	0.903
P37	0.900
P38	0.916
P39	0.919
P40	0.906

Table A7. Communalities of Readiness Items.

Item	Communality
P35	0.856
P36	0.815
P37	0.810
P38	0.840
P39	0.845
P40	0.821

Table A8. Variance Explained by One-Factor Solution.

Measure	RL1
SS loadings	4.987
Proportion Var	0.831

Table A9. Reliability Analysis of Readiness Construct (Cronbach's α and McDonald's ω).

Cronbach's Alpha (α)			
Cronbach's α	Standardized α	Number of Items	N (Observations)
0.953	0.954	6	1671
McDonald's Omega (ω)			
Omega Total	Omega Hierarchical	Number of Items	N (Observations)
0.967	–	6	1671

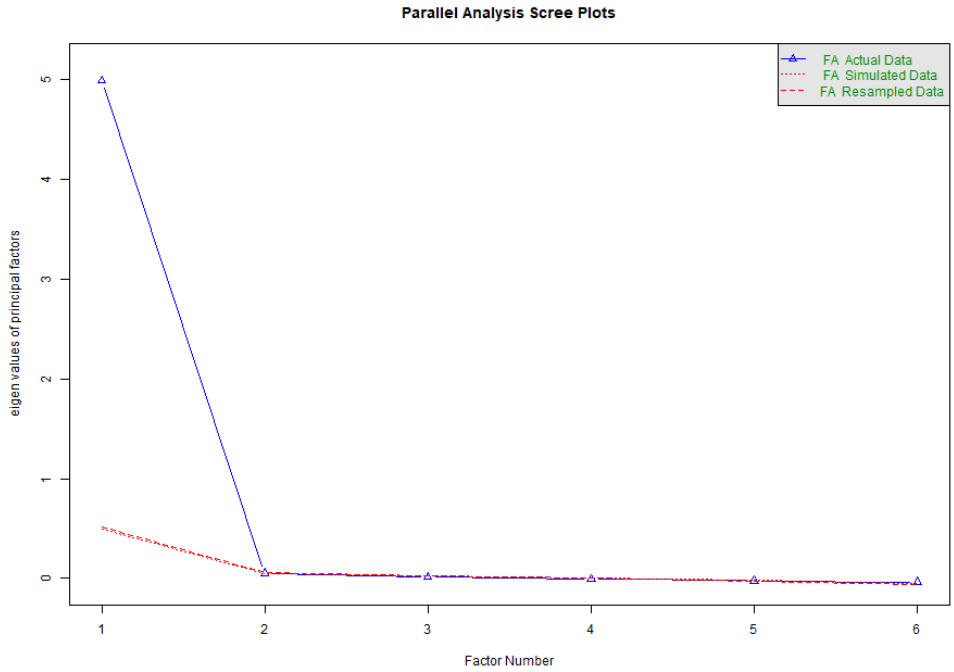

Figure A1. Parallel Analysis Scree Plot for Readiness Indicators.

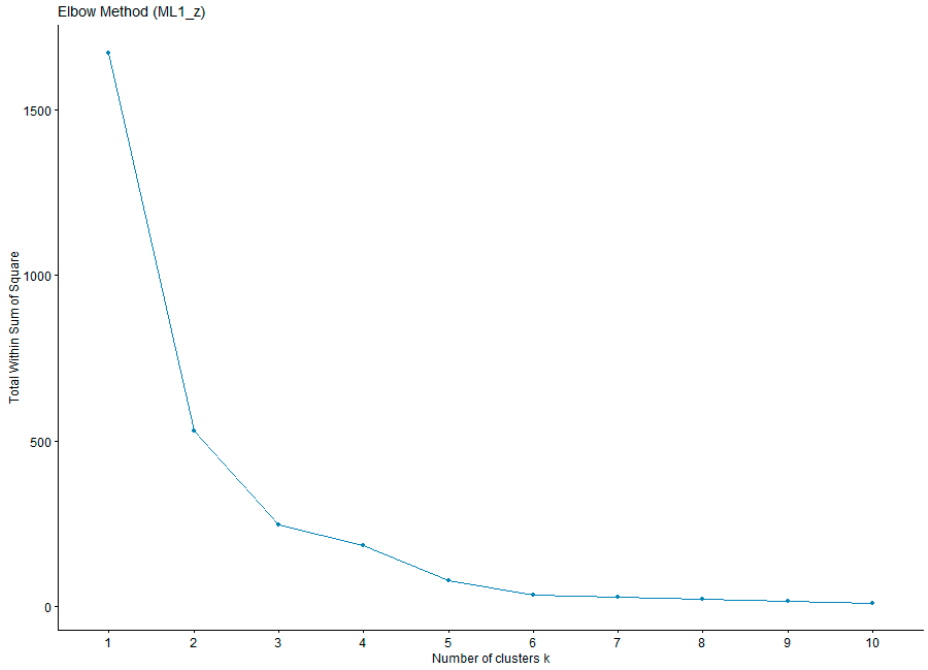

Figure A2. Elbow Method for Determining the Optimal Number of Clusters.

Table A10. Cluster Membership, Descriptive Statistics, and Centers (ML1 Factor Scores).

Cluster Membership (Sample Sizes and Percentages)		
Cluster Label	N	Percent (%)
Tech Leaders	296	17.7
Selective Adopters	726	43.4
Cluster Label	N	Percent (%)

Table A10. *Cont.*

Cluster Centers (K-means Solution, ML1 Standardized Scores)				
Cluster Label	N	Mean (ML1_z)	95% CI Lower	95% CI Upper
Tech Leaders	296	1.560	1.508	1.612
Selective Adopters	726	0.261	0.236	0.286
Skeptics	649	−1.003	−1.034	−0.973

Cluster Centers (K-means Solution, ML1 Standardized Scores)		
Cluster	Center (ML1_z)	Label
1	0.261	Selective Adopters
2	1.560	Tech Leaders
3	−1.003	Skeptics

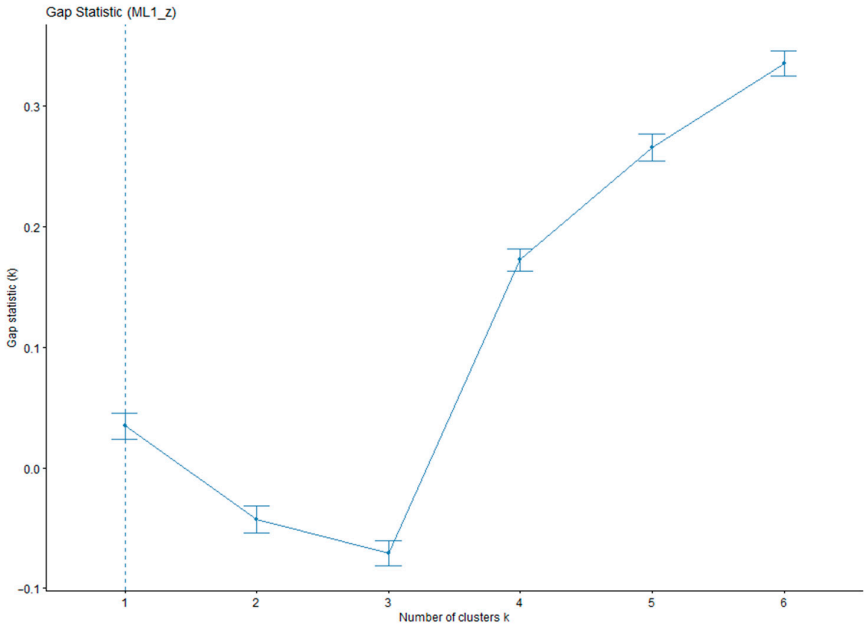

Figure A3. Gap statistic for determining the optimal number of clusters.

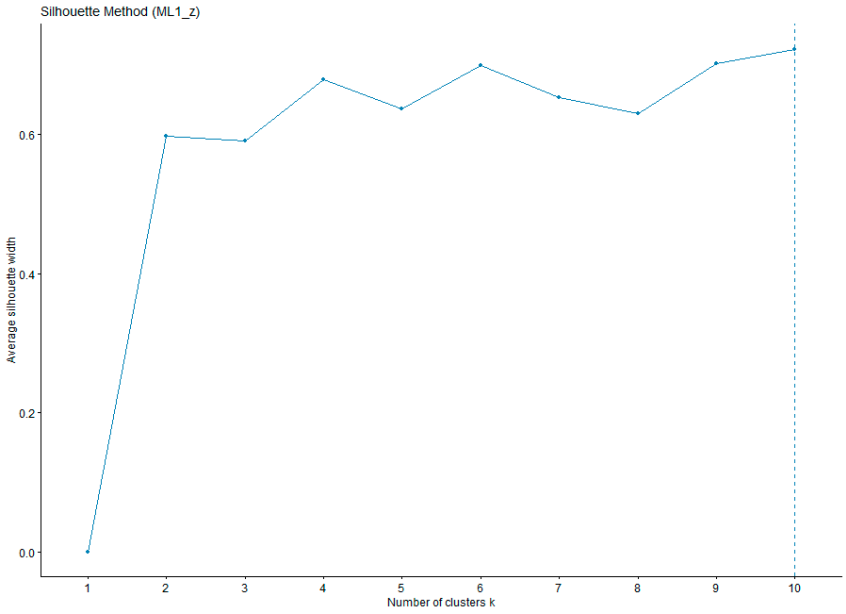

Figure A4. Silhouette Method for Determining the Optimal Number of Clusters.

Table A11. Threshold Estimates for Ordinal Indicators (WLSMV Estimation).

Item	Threshold	Estimate	SE
P44_1	t1	0.405	0.035
P44_2	t1	0.650	0.037
P44_3	t1	0.743	0.038
P34_2	t1	0.368	0.035
P34_3	t1	0.499	0.035

Table A12. Model Fit Indices for CFA with ULMC Specification.

Fit Index	Value
CFI	1.000
TLI	1.000
RMSEA	0.006
SRMR	0.025

Table A13. Method Factor Loadings in ULMC Specification.

Indicator	β (Estimate)	SE	z	*p*-Value
P44_1	0.064	0.054	1.184	0.236
P44_2	−0.197	0.049	−4.021	<0.001
P44_3	0.117	0.054	2.150	0.032
P34_2	0.321	0.054	5.914	<0.001
P34_3	−0.045	0.051	−0.877	0.380

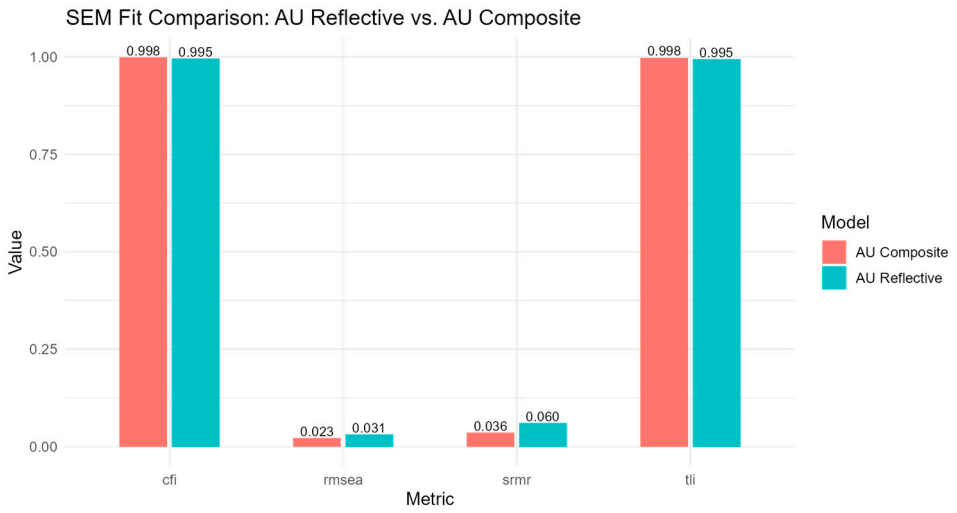

Figure A5. Model Fit Indices Across SEM Specifications. Comparison of CFI, TLI, RMSEA, and SRMR indices between AU-reflective and AU-composite measurement specifications.

Table A14. Multi-Group SEM Model Fit Indices.

Model	CFI	TLI	RMSEA	SRMR	χ^2	Df
Configural	1.000	1.001	0.000	0.044	306.51	375
Metric (loadings equal)	1.000	1.000	0.000	0.053	406.96	409
Structural (loadings + regressions equal)	0.999	0.999	0.016	0.055	471.74	425

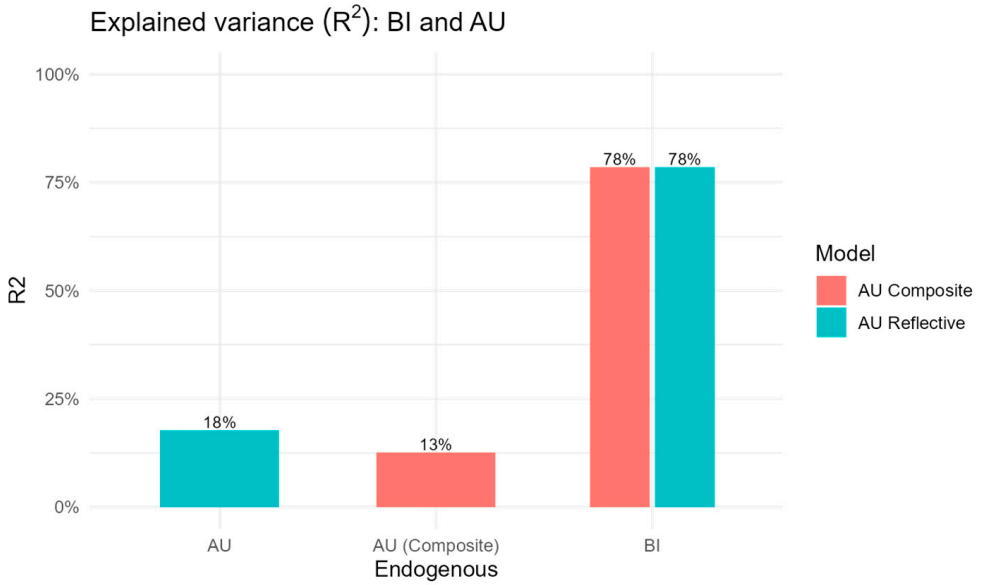

Figure A6. Explained Variance (R^2) Across SEM Specifications. Proportion of variance explained (R^2) for Adoption Use (AU), AU (composite), and Behavioral Intention (BI) under reflective and composite specifications.

Table A15. Chi-Square Difference Tests for Multi-Group Invariance.

Comparison	χ^2	df	χ^2 diff	df diff	*p*-Value
Configural	306.51	375	–	–	–
Metric	406.96	409	42.86	34	0.142
Structural	471.74	425	21.98	16	0.144

Table A16. Key Structural Paths in Multi-Group SEM (Configural Model, Composite Specification).

Group	Path	Estimate	SE	z	*p*-Value	β (Std.)
Tech Leaders	PU ← PEOU	0.015	0.226	0.065	0.948	0.005
Tech Leaders	PU ← RL1	−0.540	0.200	−2.699	0.007	−0.180
Tech Leaders	PU ← Env_CompPress	2.606	0.775	3.361	0.001	0.866
Tech Leaders	BI ← PU	0.943	0.365	2.588	0.010	0.973
Tech Leaders	BI ← PEOU	−0.233	0.252	−0.923	0.356	−0.080

Table A17. Adoption of Core Digital Hospitality Systems.

Technology	Count Yes	Count No	Total N	Yes (%)	No (%)
PMS System	643	1085	1728	37.2	62.8
Channel Manager	884	840	1724	51.3	48.7
CRM System	135	1581	1716	7.9	92.1
Website Builder	253	1453	1706	14.8	85.2
Booking Engine	425	1277	1702	25.0	75.0
Payment Gateway	328	1377	1705	19.2	80.8
Guest Messaging	107	1595	1702	6.3	93.7
Revenue Manager	91	1618	1709	5.3	94.7
Reputation System	155	1556	1711	9.1	90.9

Table A18. Adoption of Smart and AI-Enabled Hospitality Technologies.

Technology	Count Yes	Count No	Total N	Yes (%)	No (%)
Self-Check-in	109	1592	1701	6.4	93.6
Upsell System	32	1657	1689	1.9	98.1
Reputation Management	223	1464	1687	13.2	86.8
Smart Lighting and Thermostat Ctrl	364	1321	1685	21.6	78.4
Security Cameras and Motion Sensors	1167	515	1682	69.4	30.6
Keyless Door Management	469	1216	1685	27.8	72.2
Energy-saving Sensors	411	1274	1685	24.4	75.6
Smart Plugs for Device Control	139	1546	1685	8.3	91.7
Cleaning Robots	58	1629	1687	3.4	96.6
Virtual Assistants/Chatbots	145	1541	1686	8.6	91.4
Building Management System (BMS)	71	1615	1686	4.2	95.8
Air Quality Management	212	1473	1685	12.6	87.4

Table A19. Perceived Benefits of Smart and AI-Driven Hospitality Technologies.

Construct	Count Yes	Count No	Total N	Yes (%)	No (%)
Data security	1236	404	1640	75.4	24.6
Energy sustainability	1271	366	1637	77.6	22.4
Future orientation	1205	411	1616	74.6	25.4
Guest experience	1280	379	1659	77.2	22.8
Integration readiness	1192	428	1620	73.6	26.4
Operational efficiency	1254	388	1642	76.4	23.6

Table A20. Reported Barriers to the Adoption of Smart and AI-Driven Hospitality Technologies.

Barrier	Yes (n, %)	No (n, %)	Total N
High implementation and maintenance costs	1204 (73.1%)	444 (26.9%)	1648
Lack of technical Expertise	1039 (63.4%)	599 (36.6%)	1638
Complexity of integration with existing systems	1103 (67.5%)	531 (32.5%)	1634
Lack of financial resources for investments	1176 (71.5%)	469 (28.5%)	1645
Difficulties in staff training	964 (59.0%)	669 (41.0%)	1633
Data security and privacy Concerns	806 (49.5%)	821 (50.5%)	1627
Limitations of existing Infrastructure	1033 (62.8%)	611 (37.2%)	1644

Table A21. Two-Factor Exploratory Factor Analysis (Oblimin Rotation) Results and Model Fit Statistics (N = 1671; polychoric correlations; minres extraction).

Factor Correlations and Factor Score Adequacy		
Measure	MR1	MR2
Factor correlations	1.00 0.31	0.31 1.00
Factor score adequacy		
Correlation of regression scores with factors	0.99	0.82
Multiple R^2 of scores with factors	0.97	0.67
Minimum correlation of possible factor scores	0.94	0.35
Model Fit Statistics		
Fit Statistic	Value	Notes
Mean item complexity	1.1	Average complexity of item loadings
Null model df	15	Objective function = 7.35
Null model χ^2	12,255.52	$p < 0.001$
Two-factor model df	4	Objective function = 0.01
Likelihood χ^2	16.3	$p = 0.0026$
Empirical χ^2	0.86	$p = 0.93$
RMSR	0.00	Root Mean Square of Residuals
df-corrected RMSR	0.01	Adjusted RMSR
Tucker–Lewis Index (TLI)	0.996	Excellent fit
RMSEA	0.043	90% CI [0.023, 0.066]
BIC	−13.38	Bayesian Information Criterion
Fit (off-diagonal)	1.00	Based on off-diagonal residuals

Table A22. Residual Correlation Matrix of Readiness Items (EFA One-Factor Solution). (N = 1671; polychoric correlations; minres extraction).

Item	P35	P36	P37	P38	P39	P40
P35	0.144	0.019	−0.006	−0.006	−0.010	0.004
P36	0.019	0.185	0.024	−0.014	−0.014	−0.016
P37	−0.006	0.024	0.190	0.001	−0.003	−0.014
P38	−0.006	−0.014	0.001	0.160	0.010	0.009
P39	−0.010	−0.014	−0.003	0.010	0.155	0.017
P40	0.004	−0.016	−0.014	0.009	0.017	0.170

Table A23. Kruskal–Wallis Test of Readiness Differences Across Clusters.

Test Statistic (χ^2)	df	*p*-Value
1440.18	2	<0.001

Table A24. Post hoc Dunn Test Pairwise Comparisons of Readiness Across Clusters.

Comparison	Z	Unadjusted *p*-Value	Adjusted *p*-Value
Selective Adopters − Skeptics	26.51	<0.001	<0.001
Selective Adopters − Tech Leaders	−15.43	<0.001	<0.001
Skeptics − Tech Leaders	−35.59	<0.001	<0.001

Table A25. Model Fit Indices for the Composite AU Model (WLSMV Estimation).

Fit Index	Value
CFI	0.998
TLI	0.998
RMSEA	0.023
SRMR	0.036
Chi-Square	213.75
Df	125
Chi-Square/df	1.71

Table A26. Model Fit Indices for the Reflective AU Model (WLSMV Estimation).

Fit Index	Value
CFI	0.995
TLI	0.995
RMSEA	0.031
SRMR	0.060
Chi-Square	558.12
df	241
Chi-Square/df	2.32

Table A27. Standardized Loadings for Reflective Constructs (CFA). (PU, PEOU, ML1, BI, Environmental Competitive Pressure).

Construct	Indicator	Standardized Loading (β)
PU–Perceived Usefulness	Customer Experience	0.972
	Operational Efficiency	0.921
	Cost Reduction	0.891
PEOU–Perceived Ease of Use	Tech Expertise	0.964
	Integration Complexity	0.866
	Staff Training	0.878
ML1–Adoption Readiness	AI for Customer Data	0.862
	Smart Environment	0.819
	Reservation Automation	0.872
	Security Innovation	0.902
	Operational Innovation	0.903
	AI for Operations	0.879
BI–Behavioral Intention	Single Platform	0.957
	AI Personalization	0.949
Env_CompPress–Environmental Competitive Pressure	Improve Security	0.893
	Certified Technology	0.972
	Cyber Training	0.922

Table A28. Indicators Summary: Coverage and Item Distributions.

Item	N (Non-Missing)	N (Missing)	% Yes (1)	% No (0)
P6	1582	89	35.2	0.0
P10	1570	101	8.3	0.0
P12	1562	109	15.7	0.0
P14	1557	114	26.5	0.0
P16	1557	114	24.5	0.0
P18	1547	124	7.4	0.0
P20	1545	126	6.0	0.0

Table A29. Distribution of Providers by Number of Completed AU Items (N = 1569 providers; counts indicate how many AU items were answered per provide).

Number of AU Items Completed (Contributed)	Frequency (n)
0	75
1	17
2	7
3	7
4	14
5	15
6	40
7 (all items answered)	1,494

Table A30. Explained Variance (R^2) for Composite and Reflective AU SEM Models (WLSMV Estimation).

Endogenous Variable	R^2 (Composite Model)	R^2 (Reflective Model)
P44_1	0.820	0.820
P44_2	0.780	0.775
P44_3	0.911	0.905
P34_2	0.929	0.920
P34_3	0.748	0.748
P34_5	0.772	0.780
P35	0.755	0.769
P36	0.671	0.675
P37	0.764	0.768
P38	0.803	0.776
P39	0.809	0.794
P40	0.770	0.769
P48_2	0.916	0.918
P48_5	0.900	0.903
P6	–	0.644
P10	–	0.776
P12	–	0.833
P14	–	0.682
P16	–	0.410
P18	–	0.914
P20	–	0.852
P45_1	0.795	0.798
P45_2	0.945	0.952
P45_3	0.852	0.849
PU	0.860	0.859
BI	0.785	0.785
AU_comp/AU	0.126	0.177

Table A31. Variance Inflation Factors (VIF) for Structural Predictors.

Dependent Variable	Predictor	VIF
PU	Innovation Readiness (ML1)	1.6
	Perceived Ease of Use (PEOU)	1.4
	Environmental Competitive Pressure	1.9
BI	Perceived Usefulness (PU)	1.7
	Perceived Ease of Use (PEOU)	1.8
AU_comp	Behavioral Intention (BI)	6.4
	Environmental Competitive Pressure	6.0
	Innovation Readiness (ML1)	1.9
	Perceived Ease of Use (PEOU)	1.7

Table A32. Cluster Membership by Property Size and Region.

Cluster Membership by Property Size				
Room Size Category	Tech Leaders (n, %)	Selective Adopters (n, %)	Skeptics (n, %)	Total (N)
Micro (<10)	130 (17.1%)	317 (41.7%)	313 (41.2%)	760
Small (11–20)	83 (17.5%)	223 (47.1%)	167 (35.3%)	473
Medium (21–50)	62 (18.3%)	138 (40.8%)	138 (40.8%)	338
Large (>50)	21 (16.8%)	48 (38.4%)	56 (44.8%)	125
Cluster Membership by Region (Selected Municipalities)				
Region	Selective Adopters (n, %)	Skeptics (n, %)	Tech Leaders (n, %)	
Berat	28 (52.8%)	20 (37.7%)	5 (9.4%)	
Dibër	14 (58.3%)	10 (41.7%)	0 (0.0%)	
Durrës	61 (54.5%)	30 (26.8%)	21 (18.8%)	
Elbasan	17 (34.0%)	29 (58.0%)	4 (8.0%)	
Gjirokastër	10 (62.5%)	6 (37.5%)	0 (0.0%)	
Himarë	64 (63.4%)	28 (27.7%)	9 (8.9%)	
Korçë	31 (35.2%)	45 (51.1%)	12 (13.6%)	
Lezhë	40 (54.1%)	21 (28.4%)	13 (17.6%)	
Pogradec	10 (45.5%)	8 (36.4%)	4 (18.2%)	
Sarandë	104 (33.7%)	137 (44.3%)	68 (22.0%)	
Shkodër	71 (38.6%)	78 (42.4%)	35 (19.0%)	
Tiranë	80 (37.6%)	97 (45.5%)	36 (16.9%)	
Vlorë	42 (50.0%)	36 (42.9%)	6 (7.1%)	

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