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Research Article

ORGANIZATIONAL MATURITY AND ARTIFICIAL INTELLIGENCE ADOPTION IN ROMANIAN TOURISM: AN EMPIRICAL TYPOLOGY

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Abstract

As digital transformation accelerates and artificial intelligence (AI) becomes more accessible, tourism organizations display uneven adoption patterns. This study examines how Romanian tourism organizations cluster based on cultural-strategic profiles and whether objective demographic characteristics are associated with membership in specific maturity profiles. Using survey data from 325 Romanian tourism professionals, the article applies K-means cluster analysis to seven cultural-strategic dimensions: the four archetypes of the Competing Values Framework and the three dimensions of strategic agility. The resulting typology is validated with ANOVA tests on external variables, and associations with organizational demographics are analyzed using chi-square tests and binary logistic regression. The analysis identifies three ordered maturity profiles – Laggards (16.6%), Moderates (36.0%), and Leaders (47.4%)—with medium to large differences across AI adoption, technology-organization-environment (TOE) readiness, digital culture, strategic agility performance, and perceived digital transformation impact. None of the demographic predictors in the logistic model (organization size, geographic scope, respondent experience) significantly predicts Leader membership, and organization type is also non-significant in chi-square analysis. However, geographic scope and organization size have independent effects on actual AI adoption levels. These findings indicate that digital maturity in tourism is closely linked to cultural-strategic capability patterns, while objective resources do not determine profile membership. Given the cross-sectional and self-reported nature of the data, the results should be interpreted as associative rather than causal. The study has implications for policies and managerial interventions that integrate capability-building with measures addressing resource constraints, particularly in SME-dominated tourism contexts.

Keywords: digital maturity; tourism; digital transformation; strategic agility

JEL Classification: L83, O33, M21, Z32

1. Introduction

Tourism is one of the most information-intensive industries and among the most exposed to the pressures of digital transformation. Artificial intelligence (AI), defined as the set of technologies including chatbots, recommendation systems, dynamic pricing algorithms, predictive analytics, review sentiment analysis, process automation, and smart-room systems, is currently one of the most significant sources of transformation for tourism operators' cost structures, customer relationships, and competitive dynamics (Buhalis et al., 2019; Sigala, 2020). However, adoption of these technologies by individual organizations occurs at a highly uneven pace. Within the same market segment, hotel chains may implement AI solutions across the value chain – from booking and revenue management to post-sale service – while small guesthouses may not have progressed beyond telephone reservations. This heterogeneity raises an empirical question that has received insufficient attention in the Romanian literature: What is the typological structure of Romanian tourism organizations regarding their digital maturity and AI adoption, and which organizational factors are most strongly associated with their position within this typology?

The question is both theoretically and practically relevant. Theoretically, the literature has primarily used additive models of AI adoption, treating variables such as organization size, industry sector, and financial resources as direct, parallel predictors. A configurational approach, which identifies coherent organizational profiles, offers an alternative and complementary perspective: organizations may not be distributed uniformly along a continuum from "less mature" to "more mature," but instead tend to cluster into stable profiles that can be ordered along a maturity gradient (Cameron & Quinn, 2011). Identifying these profiles allows for a richer interpretation of the adoption phenomenon and provides a concrete diagnostic tool for practitioners.

From a practical perspective, the Romanian tourism industry is dominated by small and medium-sized enterprises (SMEs), with over 70% of firms classified as micro or small (National Institute of Statistics, 2023). This structure is typical of many emerging economies in Central and Eastern Europe. If the digital maturity of tourism organizations is primarily determined by their size and access to resources – the implicit assumption of the prevailing discourse – then public policy should prioritize financial transfers and infrastructure subsidies. Conversely, if cultural and strategic factors are independently linked to digital maturity, complementary interventions such as management training, support for cultural transformation, and the development of strategic agility capabilities become equally important. This distinction has significant implications for public policy and industry associations.

Unlike widely used digital maturity frameworks, which typically conceptualize maturity as a staged progression or as an aggregate organizational condition, this study develops an empirically derived typology specific to the tourism sector. Rather than assigning organizations to predefined maturity levels, it identifies recurrent cultural-strategic profiles based on the combined configuration of organizational culture and strategic agility. Thus, the article extends existing maturity frameworks by demonstrating that digital maturity in tourism can be understood not only as a linear developmental sequence but also as an empirically observable pattern of cultural and strategic capabilities associated with AI adoption.

This study contributes to the literature in three ways. First, it proposes and empirically validates an ordered typology of Romanian tourism organizations based on a multidimensional cultural and strategic configuration, offering a segmentation with three maturity profiles: Laggards, Moderates, and Leaders. Second, it demonstrates that this typology has substantial associative validity for important outcome variables – concrete AI adoption, perceived digital transformation impact, and anticipated future importance of AI – with effect sizes ranging from medium to large. Third, it shows that profile membership is not significantly associated with objective organizational demographic variables, although some demographic factors independently affect concrete AI adoption levels. This nuanced finding extends the implications for public policy toward complementary interventions focused on the cultural dimension of digital maturity.

The remainder of the article is structured in four sections. Section 2 synthesizes the relevant literature on digital maturity in tourism, AI adoption, and typological approaches to organizations. Section 3 presents the research methodology. Section 4 presents and interprets the results, with tables embedded where they are first discussed. Section 5 presents conclusions, implications, and limitations.

2. Literature review

2.1 Digital maturity and AI adoption in tourism

The concept of digital maturity reflects the extent to which an organization has integrated digital technologies into its processes, customer relationships, and strategic decisions (Kane et al., 2017; Westerman et al., 2014). In the tourism industry, digital maturity is consistently associated with financial performance, customer satisfaction, and the capacity to withstand external shocks, as demonstrated by organizations' experiences during the COVID-19 pandemic (Pencarelli, 2020; Sigala, 2020). AI-based technologies now represent the frontier of digital maturity; their implementation requires not only acquiring technical systems but also restructuring processes, retraining staff, and reorganizing data flows. Recent reviews show that AI and generative AI research in tourism and hospitality has expanded rapidly, yet the field still exhibits fragmented applications and remains at an early stage of managerial consolidation regarding how organizations translate AI potential into routines, capabilities, and performance outcomes (Li et al., 2025; Liao et al., 2025). Recent tourism-focused conceptual work also suggests that digital innovation should not be viewed as purely technological, as organizational culture shapes how digital tools are interpreted, integrated, and translated into performance outcomes in tourism firms (Diaconescu et al., 2025).

Pencarelli (2020) and Buhalis et al. (2019) note that, despite AI's transformative potential for tourism, effective adoption among small and medium-sized operators remains limited, and the literature on determining factors is still developing. Existing studies identify a wide range of barriers, including lack of technical competencies, uncertainty about return on investment, cultural resistance, and privacy concerns (Tsaih & Hsu, 2018). However, most of these studies have treated barriers as isolated independent variables, without exploring whether they cluster coherently around distinct organizational profiles. This view is further supported by recent Romanian evidence showing that AI acceptance and use intensity depend not only on perceived usefulness, but also on organizational AI readiness, psychological safety, trust, and technostress (Țuclea & Poenaru, 2026).

2.2 Theoretical framework: organizational culture and strategic agility

To characterize the cultural-strategic configuration of organizations, the article draws on two complementary theoretical frameworks. The first is the Competing Values Framework (CVF; Cameron & Quinn, 2011; Quinn & Rohrbaugh, 1983), which identifies four cultural archetypes along the flexibility-stability and internal-external orientation axes: Clan culture (emphasizing collaboration, mentoring, and employee development), Adhocracy culture (emphasizing innovation, risk-taking, and experimentation), Market culture (emphasizing results and competition), and Hierarchy culture (emphasizing processes, rules, and stability). In the international literature, adhocracy culture has been associated with higher levels of innovative technology adoption, although study results are mixed and depend on sectoral context (Hartnell et al., 2011). This tourism-specific perspective aligns closely with the present study, as Diaconescu et al. (2025) explicitly connect CVF culture types to digital innovation and suggest that adhocracy-oriented cultures are especially conducive to digitalization, whereas hierarchical cultures may be less supportive of such change.

The second framework is the strategic agility model of Doz & Kosonen (2010), which conceptualizes agility as the result of three meta-capabilities: strategic sensitivity (the capacity to perceive emerging opportunities and threats), leadership unity (the capacity of the leadership team to commit to coherent decisions under uncertainty), and resource fluidity (the capacity to redistribute resources rapidly across units and priorities). Strategic agility has been identified in recent studies as a facilitator of digital transformation, particularly for organizations operating in turbulent environments (Doz, 2020). Recent evidence from tourism and hospitality further suggests that digital leadership can strengthen organizational outcomes through strategic agility and organizational learning culture, reinforcing the relevance of combining cultural and agility-based perspectives in this study (Jasim et al., 2024).

2.3 The typological approach

Unlike variable-by-variable approaches, the typological (or configurational) approach posits that organizations exhibit internal coherence: relevant dimensions tend to covary and form recurring profiles, and performance depends more on the coherence of the profile than on high scores for isolated dimensions (Fiss, 2011). In the technology adoption literature, similar typologies have been proposed by Westerman et al. (2014) with their four profiles: Beginners, Conservatives, Fashionistas, and Digirati, and by Kane et al. (2017), with the Early, Developing, and Maturing profiles. In the tourism industry, however, empirical typologies of digital maturity that focus specifically on AI adoption and examine profile independence from organizational demographic characteristics remain scarce, presenting an opportunity for the contribution offered in this article.

Building on this literature, this article formulates two research questions: RQ1. Do Romanian tourism organizations empirically segment into a small number of coherent cultural-strategic profiles, ordered along a maturity gradient, with associative validity for AI adoption and digital transformation impact variables? RQ2. Is profile membership associated with objective demographic characteristics of the organization (size, type, geographic scope, respondent experience), or do these demographics primarily affect concrete adoption outcomes independently of profile?

3. Methodology

3.1 Data source and sample

This study employs a cross-sectional quantitative design using a self-administered online survey conducted in January 2026. The questionnaire was distributed through professional channels, industry associations, and specialist networks to ensure sectoral diversity. Participation was voluntary and anonymous. After verifying response integrity, the final sample consists of 325 Romanian tourism professionals. The complete demographic profile of the sample - including organization type, size, geographic scope, gender, age, experience, education, and the respondent's functional domain - is presented in Table 1.

Table 1. Demographic profile of the sample (N = 325)

Characteristic	Category	n	%
Organization type	Accommodation (hotel/resort/guesthouse)	106	32.6
	Travel agency / tour operator	82	25.2
	HoReCa	78	24.0
	Transport	29	8.9
	DMO / promotion association	13	4.0
	Other tourism services	9	2.8
	Tourism technology provider	8	2.5
Organization size	Micro (1-9 employees)	96	29.5
	Small (10-49 employees)	135	41.5
	Medium (50-249 employees)	61	18.8
	Large (250+ employees)	24	7.4
	Don't know	9	2.8
Geographic scope	Local / regional	170	52.3
	National	87	26.8
	International (Europe)	49	15.1
	International (extra-Europe)	16	4.9
	Don't know	3	0.9
Respondent gender	Female	204	62.8
	Male	121	37.2
Respondent age	18-24 years	105	32.3
	25-34 years	103	31.7
	35-44 years	64	19.7
	45-54 years	45	13.8
	55+ years	8	2.5
Experience in tourism	< 5 years	146	44.9
	5-10 years	112	34.5
	11-20 years	47	14.5
	> 20 years	20	6.2
Education	Bachelor's degree	144	44.3
	Master's degree	117	36.0
	Post-secondary / vocational	21	6.5
	High school	24	7.4
	PhD	12	3.7
	Other professional qualifications	7	2.2
Functional domain	Management	59	18.2
	Restaurant / bar / catering	57	17.5
	Front office / reception	45	13.8
	Reservations / ticketing	44	13.5
	Marketing / sales	41	12.6
	Finance / accounting	28	8.6
	Housekeeping / maintenance	14	4.3
	IT / technology	12	3.7

Characteristic	Category	n	%
	Tour guiding / animation	12	3.7
	Human resources	7	2.2
	Other	6	1.8

Source: Authors' calculations

The sample broadly represents the main segments of the Romanian tourism industry, with a strong presence of accommodation, travel agencies, and HoReCa, dominated by SMEs (71.0%) and primarily oriented toward the local and national market. Most respondents are female (62.8%), have higher education (84.0% with a bachelor's degree or higher), and span a wide age range (64.0% under 35 years), with diverse functional roles from operational positions (front office, F&B, reservations) to managerial and strategic functions. The sample is convenience-based rather than probabilistic; while sectoral and demographic distributions generally correspond to the population structure of Romanian tourism, generalization should be approached with caution. Respondent age and functional domain were examined in supplementary analyses; due to fragmented subgroup sizes and limited relevance to the main research questions, they are not included in the main models.

3.2 Measurement

All perceptual constructs were measured using 7-point Likert scales. Concrete AI adoption was measured on a 5-point stage scale (1 = not under consideration; 5 = fully implemented), with the "not applicable / do not know" option recoded as missing.

Organizational culture was measured with 16 items (4 per CVF archetype) adapted from Cameron and Quinn (2011). Strategic agility was measured with 12 items (4 per dimension) adapted from Doz and Kosonen (2010). AI adoption was measured with 10 items representing concrete applications: customer chatbots, personalized recommendations, dynamic pricing, predictive analytics, smart-room systems, automated reservations, sentiment analysis, fraud detection, marketing automation, and robotic process automation. TOE readiness (Technology-Organization-Environment; Tornatzky & Fleischer, 1990) was measured with 12 items (4 per dimension). Digital transformation impact was measured with 7 items covering perceived benefits in customer experience, operational efficiency, revenues, competitiveness, innovation capacity, employee engagement, and data-driven decision-making. Digital culture was measured with 6 items capturing day-to-day norms and practices oriented toward data and technology. Strategic agility performance was measured with 6 items, and culture facilitating AI with 6 additional items. Future AI importance was measured with a single item on a 1–10 scale. Barriers and required cultural changes were measured as multi-select items (maximum of three options).

Descriptive statistics and reliability indicators for the multi-item scales are presented in Table 2. All scales showed excellent internal consistency, with Cronbach's α coefficients ranging from .915 (Clan culture) to .972 (digital transformation impact), well above the conventional .70 threshold (Nunnally & Bernstein, 1994). Kaiser-Meyer-Olkin measures ranged from .918 to .954 across construct groups, and Bartlett's tests of sphericity were significant at $p < .001$ in all cases, supporting the suitability for factor analysis (Kaiser, 1974). Harman's single-factor test indicated that the first unrotated factor accounted for 54.3% of the variance, slightly exceeding the conventional 50% threshold. However, this result is not considered definitive, as current methodological literature notes that Harman's single-factor test is, at best, a limited screening tool rather than a comprehensive assessment of common method bias. Therefore, common method bias was addressed using both procedural and inferential approaches: anonymous administration, varied response anchors, separation of predictor and criterion items within the questionnaire, neutrally worded items, and the emergence of multiple factors rather than a single dominant factor. Additionally, the results show both strong and null relationships across different analyses, rather than a uniformly inflated pattern. However, because the data are cross-sectional and self-reported by a single respondent per organization, residual common method bias cannot be ruled out and remains an explicit limitation of the study.

Table 2. Descriptive statistics and reliability of multi-item scales

Construct	k items	M	SD	Min	Max	α
Strategic sensitivity	4	5.11	1.41	1.00	7.00	.927
Leadership unity	4	5.29	1.40	1.00	7.00	.930
Resource fluidity	4	5.00	1.44	1.00	7.00	.932
Clan culture	4	5.43	1.30	1.00	7.00	.915
Adhocracy culture	4	5.01	1.48	1.00	7.00	.929
Market culture	4	5.33	1.34	1.00	7.00	.917
Hierarchy culture	4	5.33	1.37	1.00	7.00	.930
AI adoption (1-5)	10	3.49	1.19	1.00	5.00	.955
TOE - Technology	4	4.86	1.72	1.00	7.00	.951
TOE - Organization	4	4.74	1.71	1.00	7.00	.948
TOE - Environment	4	4.70	1.69	1.00	7.00	.951
Digital transformation impact	7	4.89	1.66	1.00	7.00	.972
Culture facilitating AI	6	5.05	1.51	1.00	7.00	.961
Digital culture	6	4.86	1.60	1.00	7.00	.955
Strategic agility performance	6	5.09	1.45	1.00	7.00	.958

Note: AI adoption is measured on a 1-5 stage scale; all other constructs on 1-7 Likert scales.
Source: Authors' calculations

3.3 Analytic strategy

Organizational segmentation was performed using K-means cluster analysis on seven standardized cultural-strategic variables (Z-scores): the four CVF archetypes and the three strategic agility dimensions. K-means was selected because the study aimed for a parsimonious and interpretable partition based on continuous standardized variables, making partition-based clustering appropriate for this segmentation goal. Alternative methods, such as hierarchical clustering, are useful for exploratory analysis, and model-based clustering may offer additional distributional assumptions and fit criteria; however, K-means was used here because it provides a transparent and widely accepted approach for theory-guided profile segmentation. We acknowledge that K-means can be sensitive to initial seeds and that cluster solutions may vary with different initializations. Therefore, the three-cluster solution was chosen based on the elbow heuristic, profile interpretability, dimensional balance, and theoretical coherence. External validity of the typology was assessed using one-way analysis of variance (ANOVA) on variables not included in cluster construction, with effect size measured by η^2 and pairwise differences evaluated using Tukey HSD post hoc tests. For ANOVAs with organization type as a factor, only the four major categories (Accommodation, Travel agency/tour operator, HoReCa, Transport; combined $n = 295$) were included; smaller categories (DMO/promotion associations, technology providers, other tourism services) were excluded due to insufficient subgroup sizes for reliable variance estimation. The association between the typology and objective demographic variables was tested using chi-square tests of independence (including all original categories, even the smaller groups), with Cramér's V as the measure of association strength. To further strengthen the analysis, a binary logistic regression was conducted with membership in the Leader profile (0/1) as the dependent variable, and organization size, respondent experience, and geographic scope as ordinal predictors, using McFadden's pseudo-R^2 as the measure of fit. Organization type was retained as a categorical demographic variable and tested separately via chi-square due to the lack of a natural ordinal coding. All significance tests used $\alpha = .05$.

4. Results

4.1 Empirical typology of tourism organizations

The within-cluster sum of squares criterion indicated an inflection between $k = 2$ and $k = 3$ (from 1154.4 to 899.5), followed by only marginal improvements for $k = 4$ (796.3) and $k = 5$ (729.3). The three-cluster solution was retained because it provided the most interpretable and theoretically coherent partition while maintaining parsimony. Table 3 shows the centroids for the seven clustering dimensions and the validation variables.

It is important to note that the three profiles do not exhibit qualitatively distinct internal logics on the seven clustering dimensions. Instead, they form an ordered maturity gradient: scores increase nearly monotonically from Laggards to Moderates to Leaders on each cultural-strategic dimension. The clustering procedure thus identifies three coherent maturity levels of perceived cultural-strategic capability, not three different types of cultural-strategic configurations. This interpretation is consistent with the developmental logic of digital maturity models (Kane et al., 2017; Westerman et al., 2014), in which organizations progress through ordered stages rather than alternate between qualitatively different configurations. We use the term "profiles" throughout the article in this ordinal sense.

Table 3. Centroids of the three profiles (K-means, k = 3)

Variable	Laggards (n = 54; 16.6%)	Moderates (n = 117; 36.0%)	Leaders (n = 154; 47.4%)
Clustering variables (*M*, scale 1-7)			
Clan culture	3.59	5.06	6.35
Adhocracy culture	3.03	4.43	6.14
Market culture	3.31	5.11	6.21
Hierarchy culture	3.29	5.05	6.25
Strategic sensitivity	3.34	4.59	6.13
Leadership unity	3.27	4.89	6.30
Resource fluidity	3.13	4.42	6.09
External validation (*M*)			
AI adoption (1-5)	2.77	3.49	3.76
TOE - Technology (1-7)	2.84	4.51	5.83
TOE - Organization (1-7)	2.77	4.32	5.75
TOE - Environment (1-7)	3.01	4.41	5.51
Digital transformation impact (1-7)	3.20	4.45	5.83
Digital culture (1-7)	3.29	4.34	5.81
Strategic agility performance (1-7)	3.45	4.65	6.00
Future AI importance (1-10)	6.00	6.98	7.90

Source: Authors' calculations

Profile 1 – Laggards (n = 54, 16.6%) are characterized by uniformly low scores on all seven cultural-strategic dimensions, with raw means ranging from 3.03 (adhocracy culture) to 3.59 (clan culture). This profile has the lowest AI adoption (M = 2.77 on the 1–5 scale), the most modest TOE readiness, and attributes the least importance to AI for the future of organizational competitiveness (M = 6.00 on the 1–10 scale).

Profile 2 – Moderates (n = 117, 36.0%) show intermediate scores across all dimensions, with raw means between 4.42 (resource fluidity) and 5.11 (market culture). AI adoption is moderate (M = 3.49), corresponding to the pilot or early implementation stage.

Profile 3 – Leaders (n = 154, 47.4%) are characterized by high scores across all dimensions, with raw means ranging from 6.09 (resource fluidity) to 6.35 (clan culture). AI adoption is the highest (M = 3.76), TOE readiness is substantially more developed, digital culture is strongest (M = 5.81), and the importance attributed to AI for the future is the highest (M = 7.90).

4.2 Validation of the typology

The validation variables used in this section vary in their conceptual distance from the clustering variables. Some, such as TOE readiness, digital culture, culture facilitating AI, and strategic agility performance, are conceptually close to the cultural-strategic dimensions used to construct the profiles and should be interpreted primarily as relational or nomological reinforcement rather than as fully independent external validators. In contrast, variables such as concrete AI adoption, future AI importance, demographic characteristics, and perceived barriers provide more distal validation evidence. The results are therefore interpreted in a graduated manner, distinguishing between proximal reinforcement and more external forms of validation.

The associative validity of the typology is supported by ANOVA tests on variables not used in cluster construction, as shown in Table 4. Differences among the three profiles are statistically significant at $p < .001$ for all tested variables, with effect sizes (η^2) ranging from .087 (AI adoption) to .429 (strategic agility performance). According to Cohen's (1988) conventional thresholds, two of the nine effects are in the medium range (AI adoption and future AI importance), while the remaining seven are in the large range. The largest differences between profiles are observed for strategic agility performance (η^2 = .429), TOE - Organization (η^2 = .408), TOE - Technology (η^2 = .396), and digital culture (η^2 = .366). Tukey HSD post hoc tests confirm that all three pairs of clusters differ significantly on these dimensions (all $p < .001$). Notably, the smaller effect for AI adoption itself (η^2 = .087) is consistent with the fact that AI adoption is a behavioral variable influenced by multiple proximal factors beyond cultural-strategic configuration, including resource availability, sectoral characteristics, and external pressures.

Table 4. One-way ANOVAs on external variables for typology validation

Dependent variable	*F*(2, 322)	*p*	η^2	Effect size
AI adoption	14.12	< .001	.087	medium
TOE - Technology	105.35	< .001	.396	large
TOE - Organization	111.15	< .001	.408	large
TOE - Environment	64.38	< .001	.286	large
Digital transformation impact	86.65	< .001	.350	large
Culture facilitating AI	100.58	< .001	.385	large
Digital culture	93.14	< .001	.366	large
Strategic agility performance	120.84	< .001	.429	large
Future AI importance	16.05	< .001	.091	medium

Note: Cohen's (1988) thresholds: η^2 = .01 (small), .06 (medium), .14 (large).
All Tukey HSD pairwise tests significant at p < .001. Variables in Table 4 differ in conceptual proximity to the clustering dimensions; accordingly, some results are interpreted as relational reinforcement, while others provide more distal validation evidence.
Source: Authors' calculations

4.3 Profile membership and objective demographics

A theoretically relevant result is that membership in the three profiles is neither significantly associated with nor meaningfully predicted by the tested objective demographic variables of the organizations. Table 5 presents both chi-square tests of independence (Panel A) and a binary logistic regression predicting membership in the Leader profile (Panel B).

Table 5. Association of profiles with objective demographic characteristics

Panel A - Chi-square tests of independence

Demographic variable	χ^2	df	*p*	Cramér's *V*	Interpretation
Organization type	12.76	12	.387	.140	very weak
Organization size	9.86	8	.275	.123	very weak
Geographic scope	6.98	8	.539	.104	very weak
Respondent experience	7.66	6	.264	.109	very weak

Panel B - Binary logistic regression: P(Leader) ~ demographic characteristics (N = 314)

Predictor	*B*	*SE*	*z*	*p*	*OR*	95% CI
(Constant)	0.046	0.356	0.13	.897	1.047	[0.52, 2.10]
Organization size	-0.067	0.141	-0.47	.637	0.936	[0.71, 1.23]
Respondent experience	0.037	0.128	0.29	.776	1.037	[0.81, 1.33]
Geographic scope	-0.038	0.138	-0.28	.781	0.963	[0.73, 1.26]

Note: McFadden's pseudo-R^2 = .001; Log-likelihood = -217.08. Predictor variables coded ordinally (size: 1 = micro, 4 = large; experience: 1 = under 5 years, 4 = over 20 years; scope: 1 = local, 4 = international outside Europe).
Source: Authors' calculations.

Chi-square tests show no significant associations between profile and organization type ($\chi^2(12)$ = 12.76, p = .387, V = .140), organization size ($\chi^2(8)$ = 9.86, p = .275, V = .123), geographic scope ($\chi^2(8)$ = 6.98, p = .539, V = .104), or respondent experience ($\chi^2(6)$ = 7.66, p = .264, V = .109). All Cramér's V values are below the .15 threshold, indicating very weak associations. The binary logistic regression in Panel B supports this: coefficients for organization size (B = -0.067, p = .637), experience (B = 0.037, p = .776), and geographic scope (B = -0.038, p = .781) are all non-significant, and McFadden's pseudo-R^2 is .001, indicating that objective demographic variables explain virtually none of the variance in Leader status.

This result must be interpreted carefully, especially regarding demographic effects. In recent academic and policy discussions, AI adoption in tourism and related service industries is often framed as partly shaped by organizational resources and capabilities, with SMEs commonly seen as facing stronger barriers due to limited digital capabilities, skills, and complementary assets (Arroyabe et al., 2024). Our data partially nuance this narrative. On one hand, demographic factors have independent and statistically significant effects on concrete AI adoption when treated as a continuous variable: the effect of size is significant (ANOVA $F(3, 291) = 3.34$, $p = .020$, $\eta^2 = .033$, with a Tukey difference of 0.75 units between micro and large firms), and the effect of geographic scope is even stronger ($\eta^2 = .066$; see Section 4.5). On the other hand, these objective resource and exposure factors do not translate into segregation of profiles: 47.9% of micro firms and 51.1% of small firms are classified as Leaders, compared to 45.8% of large firms and 41.0% of medium firms. Similarly, firms with local activity are distributed across profiles in proportions very similar to firms with international activity (49.4% Leaders for local versus 49.0% Leaders for international-Europe). For organization type, transport (65.5% Leaders) and technology providers (62.5%) are over-represented, but not to a degree that gives the chi-square test statistical significance ($p = .387$).

The careful reading of these patterns is therefore not that "resources do not matter for AI adoption" – they clearly do, in measurable ways, for adoption levels – but rather that objective resources do not predetermine membership in the cultural-strategic Leader profile. Organizations with similar levels of resources end up in different maturity profiles, and organizations with different resource endowments can end up in the same profile. This suggests that profile membership reflects something other than resource availability – likely the quality of management, leadership decisions, and the contingent history of organizational culture development – while resources continue to play a complementary role in shaping the depth and breadth of actual AI implementations.

4.4 Perceived barriers and required cultural changes

Table 6 shows the frequencies of the eight main barriers and their association with profile membership. The most frequently cited barrier is insufficient internal resources (time, people, budget), reported by 42.8% of respondents, followed by uncertainty about AI's benefits or return on investment (35.1%) and lack of internal technical competencies (31.4%). Profiles differ significantly on only one barrier: cultural resistance to change is mentioned by 35.7% of respondents in the Leader profile, compared to 18.5% in the Laggard profile ($\chi^2(2) = 8.29$, $p = .016$).

Table 6. Frequency of barriers across organizational profiles

Barrier	Laggards (%)	Moderates (%)	Leaders (%)	Total (%)	$\chi^2(2)$	*p*
Insufficient internal resources	35.2	46.2	42.9	42.8	1.82	.403
Uncertainty about ROI	33.3	35.9	35.1	35.1	0.11	.948
Lack of technical competencies	31.5	38.5	26.0	31.4	4.81	.090
Data security / privacy	33.3	31.6	31.2	31.7	0.09	.957
Customer acceptance concerns	20.4	29.1	33.1	29.5	3.14	.208
IT integration difficulties	31.5	27.4	26.0	27.4	0.61	.737
Cultural resistance to change	**18.5**	**23.1**	**35.7**	**28.3**	**8.29**	**.016**
Lack of clear digital strategy	9.3	17.1	21.4	17.8	4.11	.128

Note: Percentages refer to respondents who selected the barrier (multiple selection, max. 3). The only significant association is with cultural resistance.
Source: Authors' calculations

This seemingly paradoxical result can be interpreted as evidence of a higher level of organizational consciousness among Leaders: in organizations that have begun to actively implement AI, cultural frictions become visible and acknowledged, while in laggard organizations the issue remains latent because implementation has not yet begun. For all other barriers, differences between profiles are not significant (all p > .05). The universality of these barriers is itself a relevant finding: they represent systemic challenges of the tourism industry rather than problems specific to any particular segment.

Regarding cultural changes identified as necessary for effective AI adoption (Table 7), respondents most frequently cite orientation toward continuous learning (40.9%), greater risk tolerance and experimentation (39.4%), and increased data and digital literacy (37.5%). None of these seven cultural changes shows significant differences between profiles (all p > .40), suggesting an industry consensus on the necessary directions for cultural evolution.

Table 7. Frequency of required cultural changes for AI adoption

Cultural change	Laggards (%)	Moderates (%)	Leaders (%)	Total (%)	$\chi^2(2)$	*p*
Orientation toward continuous learning	40.7	38.5	42.9	40.9	0.53	.766
Risk tolerance and experimentation	33.3	39.3	41.6	39.4	1.13	.567
Data and digital literacy	38.9	34.2	39.6	37.5	0.88	.643
Leadership commitment	33.3	41.0	35.7	37.2	1.22	.542
Change management	24.1	30.8	31.8	30.2	1.17	.557
Innovative mindset	27.8	26.5	33.1	29.8	1.52	.467
Cross-departmental collaboration	22.2	27.4	23.4	24.6	0.77	.682

Source: Authors' calculations.

4.5. Demographic effects on outcomes

While cultural-strategic profiles are not associated with demographics, certain outcome variables show independent demographic effects (Table 8). Geographic scope has the strongest effect on concrete AI adoption ($F(3, 295) = 6.96$, $p < .001$, $\eta^2 = .066$): organizations with international European activity report the highest adoption levels ($M = 3.99$), followed by international extra-European ($M = 3.91$), national ($M = 3.67$), and local ($M = 3.22$). This finding aligns with the literature on technology transfer through external pressures: organizations exposed to international customer expectations and global industry practices adopt digital technologies more quickly (Oliveira & Martins, 2011).

Table 8. Demographic effects on outcomes (significant ANOVAs only, N = 325)

Factor	Dependent variable	*F*	df	*p*	η^2
Geographic scope	AI adoption	6.96	3, 295	< .001	.066
Geographic scope	Future AI importance	4.21	3, 318	.006	.038
Organization size	AI adoption	3.34	3, 291	.020	.033
Organization type	TOE - Organization	3.83	3, 291	.010	.038
Organization type	TOE - Environment	3.66	3, 291	.013	.036
Organization type	TOE - Technology	3.07	3, 291	.028	.031
Organization type	Adhocracy culture	3.04	3, 291	.029	.030
Respondent experience	Future AI importance	4.42	3, 321	.005	.040

Note: Only effects significant at p < .05 shown. For organization type ANOVAs, only the four major categories (Accommodation, Travel agency / tour operator, HoReCa, Transport) were retained (df = 3, 291); the smaller categories (DMO/promotion association, technology providers, other tourism services; combined n = 30) were excluded due to subgroup sizes too small for reliable variance estimation. No significant gender differences on any dependent variable (all p > .15; Cohen's d ≤ .16).
Source: Authors' calculations

Organization size has a significant but more modest effect on AI adoption ($\eta^2 = .033$). Organization type significantly affects TOE dimensions: transport firms report higher scores for all three TOE dimensions and for adhocracy culture, while HoReCa firms report the lowest scores on these dimensions. These differences likely reflect sectoral characteristics: the capital intensity and operational complexity of transport require greater technological readiness than food service. Respondent experience has an interesting effect on the importance attributed to AI for future competitiveness ($F(3, 321) = 4.42$, $p = .005$, $\eta^2 = .040$): respondents with more than 20 years of experience attribute the highest future importance to AI ($M = 8.80$ out of 10), compared to those with under 5 years ($M = 7.36$). This finding may indicate that senior professionals, having experienced multiple previous technological waves, internalize the logic of technological disruption more fully. No significant differences were found by gender on any outcome variable (all $p > .15$, Cohen's $d \leq .16$), supporting the invariance of results across respondents.

5. Discussion

Three aspects of the results merit deeper discussion. The first is the ordered nature of the identified profiles. The three profiles do not represent qualitatively distinct cultural-strategic configurations but rather coherent maturity levels along a single ordered gradient: Laggards score uniformly low, Moderates uniformly intermediate, and Leaders uniformly high on each of the seven cultural-strategic dimensions used for clustering. This pattern aligns with the developmental logic of digital maturity models (Kane et al., 2017; Westerman et al., 2014), in which organizations progress through ordered stages. The implication is therefore more modest than in studies that identify sharply distinct organizational types: the analysis captures an ordered gradient of cultural-strategic maturity that is strongly associated with digital outcomes. Even so, this gradient remains practically useful because it provides a more informative diagnostic lens than a single aggregated maturity indicator.

The second aspect concerns the relationship between profile membership and demographic variables. The two findings of this study must be interpreted together: profile membership is not significantly associated with size, type, geographic scope, or experience, but these same variables exert independent statistical effects on concrete AI adoption when modeled directly. This reconciliation is important. Resources and exposure to international markets shape the extent to which organizations actually deploy AI, but they do not predetermine the cultural-strategic configuration through which the organization approaches digital transformation. This interpretation aligns with recent managerial research in hospitality, which shows that AI adoption is influenced by both facilitating and inhibiting organizational conditions and that its effects extend to workforce transformation and the evolving skill requirements of frontline employees (Shin et al., 2025). A possible explanation, suggested by the literature on organizational agility (Doz, 2020), is that the determining factors of cultural-strategic profile are largely endogenous to the organization: the quality of the management team, historical leadership decisions, and the contingencies of organizational culture formation. These variables are not directly observable through standard demographics but manifest indirectly through scores on cultural-strategic dimensions. This interpretation is also compatible with recent evidence showing that younger entrants to the labor market attach substantial importance to organizational culture when evaluating employers, suggesting that cultural quality may influence not only internal adaptability but also the attraction and retention of human capital relevant for digital transformation (Diaconescu, 2024). The implication for future research is that causal models of digital maturity should integrate variables regarding organizational leadership history and firm adaptation trajectories, alongside static characteristics of size and sector.

The practical implication for Romanian tourism SMEs is neither pessimistic nor naively optimistic: there is no structural predetermination to remain in the Laggard profile, as about half of micro and small firms already belong to the Leader profile. However, smaller firms face genuine resource-related disadvantages in actual adoption levels that complementary policy interventions should address. This relative democratization of cultural-strategic maturity is also consistent with anecdotal observations from the industry. In recent years, many boutique guesthouses and small travel agencies have implemented AI solutions – from WhatsApp-integrated chatbots to dynamic pricing algorithms – sometimes ahead of large hierarchical chains, while large operators still retain advantages in the scale and sophistication of their AI deployments. In the Romanian hospitality literature, competitiveness has long been linked to service quality, cost control, human resources, innovation, and technology (Emilian et al., 2009). This supports treating AI adoption as part of a broader organizational capability and competitiveness bundle rather than as an isolated technical choice.

The third aspect concerns the pattern of cultural resistance across profiles. The finding that respondents in the Leader profile mention cultural resistance to change more frequently than those in the Laggard profile aligns with recent literature suggesting that recognizing a problem is itself a form of organizational maturity (Cameron & Quinn, 2011). In organizations that have not begun effective AI implementation, cultural resistance remains invisible because there is no active process to generate it. In organizations actively implementing AI, cultural frictions become visible, are discussed, and serve as resources for reflection. Rather than indicating a weakness among Leaders, this critical awareness may be a distinctive marker of their maturity. However, this interpretation should be considered exploratory until qualitative follow-up research examines how organizations at different maturity levels experience and articulate cultural resistance. More broadly, recent Romanian evidence also suggests that organizational conditions such as psychological safety, trust, and technostress influence employees' acceptance and intensity of AI use, reinforcing the idea that the human side of digital transformation matters alongside structural and technological conditions (Ţuclea & Poenaru, 2026).

Conclusions

This study examined the typological structure of Romanian tourism organizations in terms of their digital maturity and AI adoption. The results offer a threefold contribution.

Empirically, the article proposes and validates an ordered typology with three maturity profiles: Laggards (16.6%), Moderates (36.0%), and Leaders (47.4%), based on a multidimensional configuration of organizational culture and strategic agility dimensions. The associative validity of the typology is supported by significant differences of medium to large magnitude (η^2 between .087 and .429) across AI adoption variables, TOE readiness, digital culture, agility performance, and digital transformation impact. The typology thus provides a practically useful and empirically grounded diagnostic tool for researchers, managers, and decision-makers in the tourism industry.

Theoretically, the article advances digital maturity research in tourism by demonstrating that organizations cluster into ordered cultural-strategic maturity profiles rather than differing only on isolated variables. However, the findings should be interpreted with caution. Given the cross-sectional, self-reported, and conceptually related nature of some measures, the reported relationships are best understood as strong associations rather than causal effects.

In public policy and managerial practice, the findings support a complementary reorientation of the dominant discourse. Although demographic factors influence actual AI adoption, they do not predetermine membership in the Leader profile. Public policies to stimulate digital transformation in tourism should therefore combine two approaches: one focused on cultural and strategic capabilities, including managerial training, cultural change, and digital competence development; and another focused on resource and infrastructure constraints, particularly for micro and small firms operating in local markets. This conclusion is also consistent with recent evidence from tourism SMEs, which suggests that digital transformation yields stronger performance benefits when technology adoption is embedded in a strategic digitalization plan rather than treated as a stand-alone technical upgrade (Succurro, 2026). It also aligns with recent OECD guidance, which emphasizes that AI-related tourism policies should support trustworthy diffusion, skills development, and SME capacity-building, rather than focusing solely on technology availability (OECD, 2024).

The study has several limitations. First, the cross-sectional design does not permit causal inferences; the observed relationships should be interpreted as associations, and future longitudinal studies could test causal direction. Second, all measurements are self-reported by a single respondent per organization, and clustering and validation variables are conceptually adjacent, as both assess organizational capabilities and outcomes using the same instrument. Therefore, common method bias is a moderate concern that future studies should address through multi-source designs, such as involving managers from multiple departments or pairing self-reports with objective adoption indicators. Future studies should address this issue more rigorously through multi-source designs and, where feasible, explicit statistical controls such as marker-variable or latent method-factor approaches. Third, the sample is Romanian, so generalization to other tourism contexts – especially Central and Eastern European markets with similar industry structures – requires replication. Fourth, the analysis of barriers revealed few significant differences between profiles, suggesting that future research could usefully explore intra-profile differences, for example, through qualitative interviews with organizations from the same profile that exhibit different evolution trajectories.

Future research directions include extending the typology through international comparative studies, longitudinal testing of profile stability, investigating micro-foundational factors that explain profile membership (such as leadership quality, firm historical trajectories, and critical organizational events), and studying the impact of specific interventions – training programs, mentoring, and technical assistance – on the mobility of organizations between profiles. In the broader context of digital ecosystems and the transformation of the European tourism industry, ordered maturity typologies such as the one proposed here can serve as a starting point for designing empirically informed sectoral policies and operational diagnostic tools for professional associations and individual organizations.

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Abbreviations: The following abbreviations are used in this manuscript: artificial intelligence (AI); technology-organization-environment (TOE); Competing Values Framework (CVF); destination management organization (DMO); small and medium-sized enterprises (SMEs); food and beverage (F&B); Organization for Economic Co-operation and Development (OECD).

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