Artificial Intelligence in Service Industries: Balancing Sustainability, Innovation and Digital Trust in a Cross-Country Perspective

Alexandra Teodora RADU[1]
Andreea Elena NISIPEANU[2]
Antonio Valentin STOIAN[3]

DOI: 10.24818/mer/2026.03-10

ABSTRACT

Artificial intelligence (AI) is increasingly transforming service industries by creating opportunities for innovation, sustainability and digital transformation. This study examines the relationship between AI adoption, innovation capacity, eco-innovation and digital readiness across the 27 European Union Member States (n = 27). The analysis uses comparable country-level data from Eurostat and the European Commission, with AI adoption measured by the percentage of enterprises using at least one AI technology. Innovation capacity, eco-innovation and digital readiness are assessed using the Summary Innovation Index, the Eco-Innovation Index and the share of SMEs that have reached at least a basic level of digital intensity, respectively. The empirical analysis combines descriptive statistics, Pearson and Spearman correlation coefficients and simple linear regression models. The results indicate positive and statistically significant associations between AI adoption and all three dimensions. The strongest relationship is observed between AI adoption and innovation capacity, with a Pearson correlation of 0.8364 and an R^2 of 0.6996. Positive and substantial associations are also identified for eco-innovation ($r = 0.7239$; $R^2 = 0.5241$) and digital readiness ($r = 0.7299$; $R^2 = 0.5328$). The findings suggest that higher AI adoption is associated with stronger innovation, sustainability-oriented performance and digital readiness across EU Member States. However, the cross-sectional design does not allow causal relationships to be established. The study contributes a comparative EU-27 perspective that brings these dimensions together in an integrated analytical framework.

KEYWORDS: *Artificial intelligence; Digital readiness; Eco-innovation; Innovation capacity; Sustainability*

JEL CLASSIFICATION: *O31; O33; Q55*

1. INTRODUCTION

Artificial intelligence (AI) has moved rapidly from an emerging technological capability to an increasingly important component of economic and organisational transformation. Its diffusion across industries is changing the way organisations process information, design services, interact with customers and support decision-making. In service-oriented economies in particular, AI has the potential to influence not only for operational efficiency and service delivery but also broader processes of innovation, digital transformation and sustainability-oriented development. Ameen et al. (2021) highlight the growing importance of AI in shaping customer experiences, while Mariani and Borghi (2024) emphasise its implications for service production and resilient service operations.

[1] The Bucharest University of Economic Studies, Bucharest, Romania, dragomirescualexandra20@stud.ase.ro
[2] The Bucharest University of Economic Studies, Bucharest, Romania, nisipeanuandreea20@stud.ase.ro
[3] The Bucharest University of Economic Studies, Bucharest, Romania, stoianantonio20@stud.ase.ro

The relevance of AI extends beyond the adoption of individual technologies. Its implementation requires complementary resources, including digital infrastructure, organisational capabilities, technological skills and the capacity to redesign existing processes and activities. Huang et al. (2022) emphasise the need to consider AI adoption in hospitality and tourism through a broader assessment framework, while Mingotto et al. (2021) show that the implementation of AI and robotics in service organisations may require significant changes in operations and job design. AI-enabled technologies can therefore be understood as part of a wider technological and organisational environment in which differences in adoption may reflect broader differences in the capabilities of enterprises and national economies.

Existing research has provided extensive insights into AI in service industries, particularly in tourism and hospitality, covering automation, service robots, intelligent systems, customer interactions and organisational transformation. Reviews of the literature demonstrate the substantial growth of research in this area and its increasing thematic diversity (Tussyadiah, 2020; Knani et al., 2022; Kong et al., 2023). Innovation, particularly service innovation, has likewise developed into an important research area, with previous studies examining innovation processes, customer choices and the development of new service solutions (Victorino et al., 2005; Shin & Perdue, 2022). These dimensions are, however, frequently examined separately or from organisational and sector-specific perspectives, while comparatively less attention has been given to their simultaneous relationship with AI adoption at a cross-country level.

The sustainability dimension provides a further perspective on the relationship between technological and organisational transformation. Eco-innovation has become an established area of research in hospitality and tourism, with previous studies examining its antecedents, consequences and role in sustainable development (Sharma et al., 2020; Gürlek & Koseoglu, 2021). More recently, Farmanesh et al. (2025) have examined the relationship between artificial intelligence and green innovation in small and medium-sized enterprises, highlighting the relevance of AI within the broader context of sustainable development. These perspectives suggest that AI adoption may be associated with broader differences in eco-innovation performance across countries, although such relationships should not be interpreted as causal when examined through cross-sectional country-level data.

Against this background, the present study examines the relationship between AI adoption and three complementary dimensions of transformation across the 27 Member States of the EU: innovation capacity, eco-innovation and digital readiness. AI adoption is measured by the share of enterprises using at least one AI technology, while the remaining dimensions are represented by comparable indicators obtained from Eurostat and the European Commission.

The study adopts a quantitative cross-country approach based on descriptive statistics, Pearson and Spearman correlation analyses and simple linear regression models. Rather than seeking to establish causal effects, the analysis investigates whether differences in AI adoption across EU Member States are systematically associated with differences in innovation performance, sustainability-oriented innovation and digital readiness. The empirical analysis therefore considers AI adoption as the main explanatory dimension and examines its association with each of the three outcome dimensions separately.

The study makes two main contributions. First, it brings AI adoption, innovation capacity, eco-innovation and digital readiness together in a single comparative analytical framework, addressing the fragmentation of existing research across technological, sustainability and digital transformation perspectives. Second, it provides evidence on how differences in enterprise-level AI adoption are associated with broader national patterns of technological and socio-economic transformation.

The empirical results reveal consistent positive and statistically significant associations between AI adoption and all three dimensions, with the strongest association in the case of innovation capacity. They support an integrated perspective in which AI adoption forms part of a wider process involving innovation, sustainability and digitalisation, while the cross-sectional design requires these relationships to be interpreted as associations rather than as causal effects.

The remainder of the article is structured as follows. Section 2 reviews the literature on AI; Section 3 presents the research design, data sources, variables and analytical methods; Section 4 reports and discusses the empirical results; and Section 5 concludes.

2. LITERATURE REVIEW

2.1 Artificial Intelligence in Service Industries

Artificial intelligence (AI) has become an increasingly relevant component of service transformation, influencing how organisations design, deliver and manage services. Unlike technological applications that are limited to a particular operational function, AI can support a broad range of activities, including automation, data analysis, prediction, personalisation and direct interaction with customers. Consequently, its adoption has implications not only operational efficiency but also for service quality, organisational capabilities and the overall structure of service delivery.

The development of AI research in tourism and hospitality illustrates the growing importance of these technologies within service industries. Early research concentrated on automation and robotics in customer-facing activities and repetitive operational tasks. Ivanov et al. (2019) examined the progress of robotics in hospitality and tourism, while Tussyadiah (2020) emphasised the growing importance of automation, artificial intelligence and robotics in tourism research, as well as the need to understand how these technologies influence both service operations and human–technology interactions. More recent work has broadened the perspective from robotics towards machine learning, natural language processing, chatbots and other intelligent systems (Chi et al., 2020; Knani et al., 2022; Jabeen et al., 2022).

The literature indicates that AI applications in service industries can affect several stages of the service process. Automation can be used for routine activities, while data-driven systems can support forecasting, decision-making and personalisation. In hospitality, for example, AI has been associated with automated customer interactions, personalised recommendations, service robots and more efficient operational processes (Huang et al., 2022; Jabeen et al., 2022). Mariani and Borghi (2024) further demonstrate that AI has become relevant to both service production and the development of resilient service operations, suggesting that its role extends beyond isolated technological applications.

The expansion of AI has also changed the relationship between service providers, employees and customers. Rather than simply replacing individual tasks, AI can modify how work is organised and how employees interact with technological systems. Mingotto et al. (2021) show that introducing AI and robotics can require changes in both operations and job design, while Nguyen and Malik (2022) indicate that AI can influence the relationship between knowledge sharing and employee service quality. AI adoption should therefore not be understood as an exclusively technological decision: its effectiveness depends on the organisational environment and employees' ability to adapt.

At the customer level, AI can facilitate more personalised and responsive interactions. Ameen et al. (2021) discuss the changing nature of customer experiences in an environment increasingly influenced by artificial intelligence, while research on service robots and AI-enabled interactions demonstrates that customers evaluate not only the functional performance of these technologies

but also the quality and nature of the interaction itself (Belanche et al., 2020; Letheren et al., 2021). This distinction is important because technological efficiency does not automatically translate into positive service experiences.

The literature therefore presents AI adoption as a multidimensional phenomenon, with implications for operational efficiency, customer experience, employee performance, service quality and organisational transformation. Reviews by Chi et al. (2020), Knani et al. (2022) and Kong et al. (2023) confirm the rapid expansion of AI-related research in tourism and hospitality while showing that the field remains fragmented across different applications, actors and perspectives. This fragmentation creates an opportunity to examine AI adoption not only at the level of individual organisations or consumers but also from a broader cross-country perspective in which the capacity to adopt AI is connected to wider innovation capabilities, digital infrastructure and organisational readiness.

2.2 Artificial Intelligence and Innovation Capacity

Innovation represents an important dimension through which the economic and organisational implications of AI adoption can be understood. In service industries, innovation does not necessarily take the form of a new physical product: it may involve changes in service design, delivery processes, customer interaction, organisational practices or business models. Victorino et al. (2005) demonstrate the importance of service innovation for customers' choices in hospitality, while Valença et al. (2020) propose an innovation radar designed to evaluate innovation in hotels.

The literature on hospitality and tourism service innovation has expanded considerably, with research addressing technological, organisational and market-related dimensions. Shin and Perdue (2022), in their review of hospitality and tourism service innovation, emphasise the diversity of research perspectives and the need for a better understanding of the factors that shape innovation within service organisations. Similarly, Horng et al. (2018) develop a sustainable service innovation framework for the hospitality industry, connecting innovation with broader organisational and sustainability objectives.

AI can contribute to this innovation process by providing capabilities that were previously difficult to achieve through conventional information technologies. AI-based systems can process large volumes of data, identify patterns, support prediction and facilitate personalised services. These capabilities may enable organisations to redesign existing processes or develop new forms of service delivery. Huang et al. (2022) highlight the broad potential of AI within hospitality and tourism and emphasise the importance of considering both technological and managerial dimensions when assessing AI applications.

The relationship between AI and innovation is also visible in service automation. Service robots, chatbots and other intelligent systems can change established processes rather than simply automate individual tasks. Belanche et al. (2020) examine the implementation of service robots and how responsibility and service outcomes are attributed in interactions involving robots, while Mingotto et al. (2021) show that AI and robotics can require organisations to redesign both operations and jobs. Technological adoption may therefore act as a stimulus for organisational innovation when firms adapt their structures to exploit new capabilities.

At the same time, the presence of AI does not necessarily imply a higher level of innovation. The ability to benefit from AI depends on organisational and technological conditions. Research on digital adoption capability in service contexts emphasises the importance of organisational capabilities in achieving service performance through digital technologies (Binsar et al., 2024). In the tourism sector, Carlisle et al. (2023) draw attention to the digital skills divide within the

European tourism industry, suggesting that differences in digital capabilities can influence the extent to which organisations are able to participate effectively in digital transformation.

This perspective is particularly relevant for a cross-country analysis. If AI adoption requires complementary capabilities, differences in adoption across countries may reflect not only differences in access to technology but also differences in innovation ecosystems, skills and digital preparedness. The literature therefore supports the view that AI and innovation are closely connected, but it does not justify assuming that AI adoption automatically produces superior innovation outcomes. A country-level analysis can contribute to this discussion by examining whether differences in AI adoption across EU Member States are associated with differences in innovation performance.

2.3 Artificial Intelligence, Eco-Innovation and Sustainability

The relationship between technological innovation and sustainability has become increasingly important in service industries. Hospitality and tourism are particularly relevant in this respect because their activities involve substantial use of resources and generate environmental, economic and social effects. Sustainability-oriented innovation has therefore gradually become an important research area, although its development has not been uniform across the different dimensions of sustainability.

Gürlek and Koseoglu (2021) provide a broad review of green innovation research in hospitality and tourism, demonstrating the increasing attention given to environmentally oriented innovation. Sharma et al. (2020) similarly examine eco-innovation research in hospitality and identify an increasingly established research stream focused on environmental improvements. These studies show that innovation can contribute to sustainability through changes in resource management, operational processes and environmental practices.

The concept of sustainable service innovation extends this perspective by connecting innovation with the broader sustainability objectives of service organisations. Horng et al. (2018) emphasise the importance of integrating sustainability considerations into service innovation, suggesting that innovation should not be assessed exclusively according to its economic or customer-related effects. Goffi et al. (2022) also demonstrate the relevance of corporate social responsibility to the performance of firms operating in tourism and hospitality, reinforcing the broader connection between organisational practices and sustainability outcomes.

AI introduces a further dimension to this relationship. Intelligent technologies can support the optimisation of operational processes and the use of resources, potentially creating opportunities for more sustainable service delivery. Predictive systems can support more efficient planning, while intelligent automation can reduce repetitive manual processes. From this perspective, AI may function as an enabling technology for sustainability-oriented innovation rather than as a sustainability outcome in itself.

However, the relationship between AI and sustainability should not be considered automatically positive. The adoption of a technology does not guarantee that organisations will use it for environmental or broader sustainability objectives. AI may be introduced primarily to reduce costs, increase productivity or improve customer service, without producing meaningful changes in environmental performance. Consequently, the sustainability effects of AI are likely to depend on how the technology is integrated into organisational strategies and operational practices.

This distinction matters in light of the existing literature. Research on AI in tourism and hospitality has focused strongly on technological applications, customer interactions, service automation and operational performance (Chi et al., 2020; Huang et al., 2022; Jabeen et al., 2022; Knani et al., 2022; Kong et al., 2023), whereas research on eco-innovation has developed largely as a separate stream built around environmental innovation rather than AI-enabled

transformation (Gürlek & Koseoglu, 2021; Sharma et al., 2020). The intersection between the two areas has consequently received comparatively little empirical attention. Reviews of the field confirm this asymmetry: the breadth of AI research in hospitality and tourism is well documented (Jabeen et al., 2022; Knani et al., 2022; Kong et al., 2023), yet sustainability is not positioned as a central empirical dimension of AI adoption within it.

This separation suggests that AI adoption and eco-innovation should be examined together rather than as independent technological and environmental phenomena. A cross-country perspective adds a further contribution, because countries differ in both their technological adoption and their capacity for environmental innovation.

Such an association should nevertheless be interpreted carefully. A positive relationship would indicate that countries with higher AI adoption also tend to perform better in eco-innovation, but it would not demonstrate that AI causes improvements in sustainability. Other national characteristics, including innovation capacity, digital infrastructure and institutional conditions, may contribute to the observed differences . This is particularly important when using secondary cross-sectional data.

2.4 Digital Readiness and Digital Trust in AI-Enabled Services

The ability to adopt AI is closely related to the broader digital environment in which organisations operate. Digital transformation requires more than access to individual technologies. Organisations and economies need appropriate infrastructure, digital skills, organisational capabilities and the ability to integrate digital solutions into existing activities. Consequently, digital readiness is an important contextual condition for the effective adoption of AI.

Research in tourism and hospitality illustrates the importance of these complementary capabilities. Carlisle et al. (2023) identify a digital skills divide in the European tourism industry, indicating that differences in digital competencies can affect the capacity of organisations to participate in technological transformation. Binsar et al. (2024) similarly focus on digital adoption capability and its relationship with service performance, highlighting the importance of organisational capabilities in transforming digital technologies into practical outcomes.

The relationship between AI and digital readiness is therefore potentially bidirectional. A stronger digital environment can facilitate AI adoption by providing the necessary infrastructure, skills and organisational capabilities; increasing AI adoption may in turn contribute to further digital transformation. From a country-level perspective, AI adoption should be considered as part of a wider digital transformation process rather than as an isolated technological indicator.

Digital transformation also raises questions that extend beyond technological capacity. When AI becomes directly involved in customer interactions, organisations increasingly rely on systems that collect, process and generate information on behalf of both firms and consumers. As a result, trust becomes an important dimension of AI-enabled service delivery.

Research on AI-based service interactions shows that customer responses depend on more than technological functionality. Ameen et al. (2021) emphasise the changing nature of customer experiences in the age of artificial intelligence, while Cheng and Jiang (2020) examine the role of perceived privacy risk, satisfaction, loyalty and continued use in interactions with AI-driven chatbots. These findings indicate that the quality of an AI-enabled service depends partly on customers' perception of whether the interaction is useful, reliable and sufficiently safe.

Trust is also related to the characteristics of the AI interface itself. Pizzi et al. (2023) examine how anthropomorphism and gaze direction influence willingness to disclose personal information in chatbot interactions, and Letheren et al. (2021) investigate anthropomorphism

in AI service robot interactions. These findings are relevant because increased personalisation and human-like interaction may improve engagement while simultaneously raising questions about privacy, transparency and the appropriate boundaries of automated service interactions.

The literature also identifies potential drawbacks of AI-enabled services. Castillo et al. (2021) examine service interactions in which AI can contribute to value co-destruction from the customer perspective, while Belanche et al. (2024) explicitly address the potential negative consequences of AI in services. These contributions demonstrate that AI adoption can create risks as well as benefits. Problems related to service failures, inappropriate automation, privacy concerns or inadequate interactions may weaken customer confidence and reduce the value created by technological adoption.

Digital trust should therefore be understood as complementary to digital readiness rather than as a substitute for it. A country may have strong technological capabilities and high levels of digital adoption while still facing challenges associated with trust, privacy, security or acceptance of AI-enabled services. Conversely, trust in digital technologies may facilitate their adoption when users and organisations perceive AI systems as reliable and appropriately governed.

For the present study, this distinction is particularly relevant. The available country-level indicators capture technological adoption and digital preparedness more directly than the multidimensional concept of digital trust. Digital trust is therefore treated as a conceptual dimension of responsible AI-enabled service transformation, while the empirical analysis focuses on indicators for which comparable observations can be established across the 27 EU Member States, rather than reducing trust to a single measure that may not represent its individual components.

Overall, the literature suggests that the transition towards AI-enabled services involves at least three interconnected dimensions: the capacity to adopt AI, the ability to integrate it into broader digital and innovation systems, and the conditions under which users and organisations are willing to trust and use AI-based services. These three dimensions provide the basis on which AI adoption is examined from a broader European perspective in the present study.

2.5 Research Gap and Analytical Framework

The literature reviewed above reveals a growing body of research on artificial intelligence in service industries, particularly in tourism and hospitality, covering AI applications, service robots, chatbots, customer experiences, employee perspectives and operational transformation (Chi et al., 2020; Ivanov et al., 2019; Knani et al., 2022; Jabeen et al., 2022; Kong et al., 2023).

Three limitations remain. First, much of the literature examines AI at the level of individual technologies, organisations, employees or consumers, which provide valuable insight into specific mechanisms but offers little evidence on differences between national environments. Second, innovation, sustainability and digital transformation are frequently investigated as related but separate research streams; work on green and eco-innovation in hospitality, for example, has developed independently from much of the AI literature (Gürlek & Koseoglu, 2021; Sharma et al., 2020). Third, although trust, privacy, anthropomorphism and the negative consequences of AI have received increasing attention, these issues are generally investigated through firm-level or consumer-level studies rather than from a comparative country-level perspective (Cheng & Jiang, 2020; Pizzi et al., 2023; Belanche et al., 2024).

This fragmentation creates a need for a broader empirical perspective connecting technological adoption with innovation, sustainability and digital transformation — particularly in the European Union, where Member States share a common institutional framework but continue to display substantial differences in technological adoption, innovation performance and digital capabilities. The present study therefore treats AI adoption as the central technological

dimension and examines its relationship with innovation capacity, eco-innovation and digital readiness, while incorporating digital trust as a conceptual dimension that qualifies the interpretation of AI-enabled transformation.

The study's analytical logic follows from this. Higher AI adoption may be associated with stronger innovation capacity, because AI provides analytical, predictive and automation capabilities that support the redesign of services and organisational processes. AI adoption may also be associated with eco-innovation where intelligent technologies are integrated into resource optimisation and sustainability-oriented practices. Finally, AI adoption is expected to be related to digital readiness, because implementation requires complementary digital infrastructure, skills and organisational capabilities. These expectations underpin the three research questions set out in the introduction.

These relationships should not automatically be interpreted as causal. AI adoption occurs within broader national innovation and digital ecosystems, and countries with stronger economic and technological capabilities may simultaneously exhibit higher AI adoption, innovation and digital readiness. The empirical analysis therefore focuses on the association between these dimensions across the EU-27 rather than claiming that AI adoption alone determines national innovation or sustainability performance.

The study contributes by bringing these dimensions together in a single cross-country framework. While previous research has provided detailed evidence on specific AI applications and service contexts, comparatively little attention has been given to how AI adoption differs across European countries and how those differences relate simultaneously to innovation, eco-innovation and digital readiness. Examining the 27 EU Member States with comparable secondary data provides a broader view of the position of AI within the transformation of service-oriented economies.

3. DATA AND METHODOLOGY

3.1 Research Design and Data Sources

This study employs a quantitative cross-country research design to examine the relationships between artificial intelligence (AI) adoption, innovation, eco-innovation and digital readiness across the 27 Member States of the European Union. The analysis is conducted at the country level and relies on secondary data obtained from official European statistical and institutional sources.

The EU-27 countries were selected as the units of analysis to ensure a consistent and comparable cross-country framework. Indicators were selected according to two main criteria: their relevance to the dimensions investigated and the availability of comparable data for the EU Member States. The analysis focuses on 2024 as the main reference period, while differences in reference years between individual indicators are reported explicitly where applicable.

AI adoption represents the main explanatory dimension of the study and is measured through the share of enterprises using at least one AI technology. The other dimensions capture innovation capacity, eco-innovation/sustainability and digital readiness. The exact indicators, measurement units, reference years and data sources are presented in Table 1.

Table 1. Variables, Indicators and Data Sources

Variable	Role in the analysis	Indicator	Unit of measurement	Reference year	Data source
AI Adoption	Main explanatory variable	Enterprises using at least one AI technology	% of enterprises	2024	Eurostat (ISOC_EB_AI)
Innovation Capacity	Dependent variable	Summary Innovation Index	Index (EU = 100)	2024	European Commission – European Innovation Scoreboard
Eco-Innovation / Sustainability	Dependent variable	Eco-Innovation Index	Index (EU-27 = 100)	2024	European Commission – Eco-Innovation Index
Digital Readiness	Dependent variable	SMEs with at least a basic level of digital intensity	% of enterprises	2024 framework (2023 data)	European Commission – State of the Digital Decade (DESI)

Source: Authors' elaboration based on data from Eurostat and the European Commission (2024a, 2024b, 2024c).

For transparency and reproducibility, Table 2 presents the country-level observations for all variables included in the study, recorded for each of the 27 EU Member States.

Table 2. Country-Level Dataset for the EU-27 (2024; digital readiness 2023)

No.	EU Member State	AI Adoption	Innovation	Eco-Innovation / Sustainability	Digital Readiness
1	Austria	20.27	127.9	177.1	57.93
2	Belgium	24.71	136.0	109.2	74.46
3	Bulgaria	6.47	50.6	58.8	28.41
4	Croatia	11.76	76.6	96.6	55.97
5	Cyprus	7.90	116.9	97.6	67.28
6	Czechia	11.26	98.7	125.6	49.30
7	Denmark	27.58	149.3	177.5	75.33
8	Estonia	13.89	115.3	116.5	55.93
9	Finland	24.37	140.6	180.8	85.59
10	France	9.91	114.4	144.0	51.97
11	Germany	19.75	122.8	140.7	61.38
12	Greece	9.81	85.3	91.0	43.26
13	Hungary	7.41	77.6	64.4	53.16
14	Ireland	14.90	124.5	121.2	66.11
15	Italy	8.20	98.6	150.1	60.69
16	Latvia	8.83	59.0	114.7	48.19
17	Lithuania	8.76	92.0	114.7	59.99
18	Luxembourg	23.73	123.3	175.1	57.85
19	Malta	17.30	96.8	99.2	76.49
20	Netherlands	23.06	138.3	133.1	82.72
21	Poland	5.90	72.5	69.7	50.04
22	Portugal	8.63	91.8	113.2	53.61

No.	EU Member State	AI Adoption	Innovation	Eco-Innovation / Sustainability	Digital Readiness
23	Romania	3.07	37.4	80.2	26.78
24	Slovakia	10.78	71.6	98.9	42.19
25	Slovenia	20.89	100.1	121.5	50.36
26	Spain	11.31	98.9	127.2	60.53
27	Sweden	25.09	146.2	165.2	79.91

Source: Authors' elaboration based on data from Eurostat and the European Commission (2024a, 2024b, 2024c).

The dataset was assembled by matching observations at country level: for each Member State, the value of the AI adoption indicator is matched with the corresponding values of the innovation, eco-innovation/sustainability and digital readiness indicators. Measurement units and reference periods were checked and retained as reported in the original sources — percentage indicators are retained as percentages and index-based indicators on their original scales, without transformations that would not be methodologically justified.

A further criterion was the availability of observations for the complete EU-27 sample. An indicator that does not provide sufficiently comparable observations for all Member States was not used as a core variable, because the purpose of the study is a consistent cross-country comparison rather than a maximum number of indicators.

The final dataset therefore consists of 27 country-level observations and four analytical variables, providing the basis for the descriptive, correlation and regression analyses presented below.

3.2 Variables and Measurement

The analysis is based on four variables. AI adoption is the main explanatory variable, while innovation capacity, eco-innovation/sustainability and digital readiness are treated as outcome dimensions. The selection of indicators was guided by their availability at country level and their comparability across the EU-27.

AI Adoption is measured by the percentage of enterprises using at least one artificial intelligence technology. The indicator is obtained from Eurostat and refers to enterprises with at least 10 people employed, excluding the financial sector, with 2024 as the reference year. It captures the extent to which AI technologies have been incorporated into enterprise activities and therefore provides the basis for examining differences in adoption across Member States.

Innovation Capacity is measured using the Summary Innovation Index (SII) from the European Innovation Scoreboard 2024, a composite measure of the innovation performance of EU Member States expressed on an index scale relative to the EU benchmark. The original index values are retained without transformation, allowing differences in overall innovation performance to be compared with differences in AI adoption.

Eco-Innovation/Sustainability is represented by the Eco-Innovation Index 2024, provided by the European Commission, which measures countries' performance in developing innovations that reduce environmental pressures, improve resource efficiency and strengthen environmental performance. The 2024 values are retained in their original form.

Digital Readiness is measured using the indicator "SMEs with at least a basic level of digital intensity" from the European Commission's 2024 State of the Digital Decade framework (DESI indicators), expressed as the percentage of SMEs that have reached at least a basic level of digital intensity on the basis of a defined set of digital technologies. Although the indicator is included within the 2024 framework, the underlying observations refer to 2023; this distinction

is maintained explicitly in the dataset in order to avoid treating data from different reference periods as observations from the same year.

3.3 Analytical Methods

The empirical analysis proceeds in three steps. First, descriptive statistics — mean, median, minimum, maximum and sample standard deviation (n − 1) — summarise each variable's distribution across the 27 Member States. Second, the strength and direction of each bivariate relationship are assessed using the Pearson correlation coefficient and, because AI adoption departs from a normal distribution (Shapiro–Wilk $W = 0.912$, $p = 0.025$, against $p > 0.35$ for each of the three outcome variables), the Spearman rank correlation coefficient is reported alongside it as a distribution-free check; Spearman coefficients are computed on average ranks, so that tied observations are handled consistently. Third, three simple ordinary least squares models of the form $Yi = \alpha + \beta AIi + \varepsilon i$ are estimated, where Yi denotes innovation capacity, eco-innovation and digital readiness respectively. For each model, the slope, intercept, coefficient of determination, standard error of the slope, t-statistic and two-tailed p-value on 25 degrees of freedom are reported. Statistical significance is assessed at the 5% level. All calculations were performed on the country-level observations presented in Table 2.

3.4 Methodological Considerations and Limitations

Several methodological considerations should be taken into account when interpreting the results. First, the analysis is conducted at country level using a relatively small sample of 27 Member States; the findings therefore describe cross-country patterns within the European Union and should not be interpreted as evidence of firm-level or individual-level relationships.

Second, the indicators differ in their measurement scales and, in one case, in their reference year: AI adoption, innovation capacity and eco-innovation are based on the 2024 reference period, whereas the digital readiness indicator included in the 2024 State of the Digital Decade framework refers to 2023. These differences are reported explicitly and taken into account when interpreting the results.

Third, the cross-sectional nature of the dataset limits the extent to which causal relationships can be established. Observed associations between AI adoption and the other dimensions should therefore be interpreted as statistical associations rather than evidence that higher AI adoption directly causes improvements in innovation, eco-innovation or digital readiness.

Finally, composite indicators such as the Summary Innovation Index and the Eco-Innovation Index provide broad representations of complex dimensions but may conceal differences between their individual components. Despite these limitations, the selected indicators provide a consistent basis for comparing the EU-27 Member States and for examining the relationship between AI adoption, innovation, sustainability and digitalisation.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1 Descriptive Results and Cross-Country Comparison

The first stage of the empirical analysis examines the descriptive characteristics of the four variables. Table 3 presents the mean, median, minimum, maximum and standard deviation for the 27 EU Member States, and provides an overview of the distribution and cross-country variation of each dimension.

Table 3. Descriptive Statistics of the Selected Variables

Variable	Mean	Median	Minimum	Maximum	Standard Deviation
AI Adoption (%)	14.28	11.31	3.07	27.58	7.18
Innovation Capacity	102.33	98.90	37.40	149.30	29.75
Eco-Innovation	120.88	116.50	58.80	180.80	34.77
Digital Readiness (%)	58.35	57.85	26.78	85.59	14.73

Source: Authors' calculations based on data presented in Table 2.

The descriptive statistics reveal substantial differences across the EU-27 Member States in all four dimensions considered in the analysis. The mean AI adoption rate is 14.28%, while the median is lower, at 11.31%, indicating that the distribution is influenced by countries with relatively high levels of AI adoption. The difference between the minimum value of 3.07% and the maximum value of 27.58%, together with a standard deviation of 7.18 percentage points, indicates considerable heterogeneity in the diffusion of AI technologies across the EU-27.

Innovation capacity also displays substantial cross-country variation, with values ranging from 37.40 to 149.30 and a standard deviation of 29.75. The mean value of 102.33 is relatively close to the median of 98.90, suggesting a comparatively balanced distribution around the central values, despite the wide range between the lowest- and highest-performing countries.

Eco-innovation shows the greatest dispersion among the index-based indicators. The Eco-Innovation Index ranges from 58.80 to 180.80, with a mean of 120.88 and a standard deviation of 34.77. This variation indicates pronounced differences in eco-innovation performance among EU Member States. Digital readiness ranges from 26.78% to 85.59%, with a mean of 58.35% and a median of 57.85%. The close proximity of these two measures suggests a relatively balanced distribution, although the observed range still points to significant differences in digitalisation levels across countries.

4.2 AI Adoption and Innovation

Table 4. Correlation and Regression Results for AI Adoption and Innovation Capacity

Measure	Result
Pearson correlation (r)	0.8364
Spearman correlation (ρ)	0.8272
Regression coefficient (β)	3.4671
Intercept	52.8254
R^2	0.6996
Standard error of β	0.4543
t-statistic	7.6310
p-value	5.50×10^{-8}

Source: Authors' calculations based on data presented in Table 2.

Table 4 presents the correlation and regression results for the relationship between AI adoption and innovation capacity across the EU-27 Member States. The Pearson correlation coefficient is 0.8364, indicating a strong positive linear association between the two variables. The Spearman correlation coefficient is also high and positive ($\rho = 0.8272$), which is consistent with the Pearson result and indicates that the positive relationship is maintained when observations

are ranked. The relatively small difference between the two coefficients further supports the consistency of the observed association.

The simple linear regression results reinforce this finding. The estimated regression coefficient for AI adoption is 3.4671, indicating that a one-percentage-point increase in the share of enterprises using AI is associated, on average, with a 3.47-point increase in the Innovation Capacity index. The coefficient of determination (R^2) is 0.6996, meaning that approximately 70% of the cross-country variation in innovation capacity is accounted for by the linear model including AI adoption. The estimated coefficient is statistically significant ($t = 7.6310$, $p < 0.001$), providing strong statistical evidence of a positive association between the two variables.

These results should not be interpreted as evidence of a causal effect, since the analysis is based on cross-sectional country-level observations. Rather, they indicate that EU Member States with higher levels of AI adoption tend to have higher levels of innovation capacity.

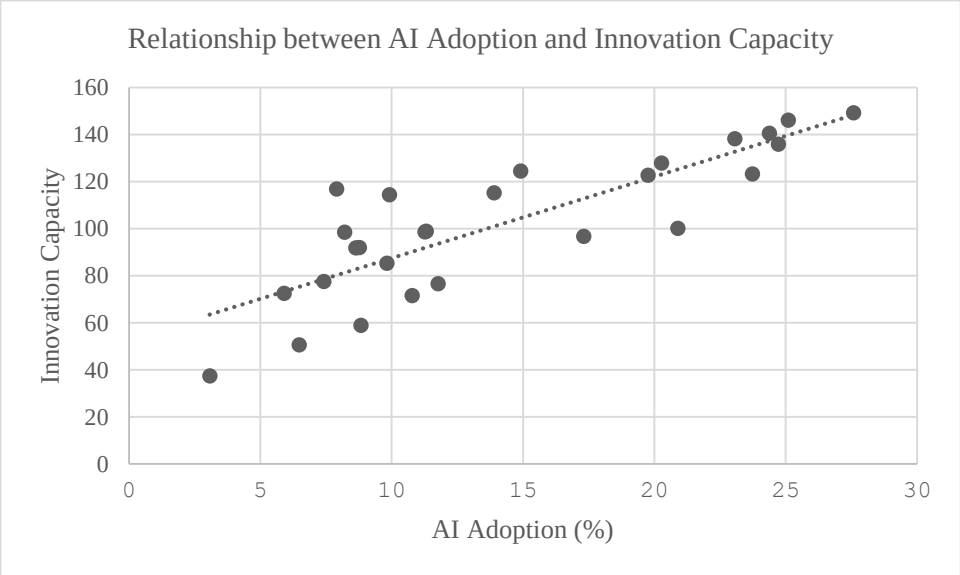


Figure 1. Relationship between AI Adoption and Innovation Capacity

Source: Authors' calculations based on data presented in Table 2.

Figure 1 illustrates this relationship. The upward-sloping trendline ($f(x) = 3.4671x + 52.8254$; $R^2 = 0.6996$) and the distribution of observations around it are consistent with the correlation and regression results reported in Table 4.

4.3 AI Adoption, Eco-Innovation and Sustainability

Table 5. Correlation and Regression Results for AI Adoption and Eco-Innovation

Measure	Result
Pearson correlation (r)	0.7239
Spearman correlation (ρ)	0.7025
Regression coefficient (β)	3.5075
Intercept	70.7972
R^2	0.5241
Standard error of β	0.6685
t-statistic	5.2468
p-value	1.97×10^{-5}

Source: Authors' calculations based on data presented in Table 2.

The relationship between AI adoption and eco-innovation is also positive and relatively strong. The Pearson correlation coefficient is 0.7239, while the Spearman coefficient is 0.7025. Both measures indicate a positive association, although the slightly lower Spearman coefficient suggests that the relationship is somewhat less pronounced when observations are ranked. Nevertheless, the difference between the two coefficients remains relatively limited, supporting the overall direction of the relationship.

The regression analysis produces a positive coefficient of 3.5075. This indicates that a one-percentage-point increase in AI adoption is associated, on average, with a 3.51-point increase in the Eco-Innovation Index. The R^2 value of 0.5241 shows that approximately 52.4% of the cross-country variation in eco-innovation is accounted for by the simple linear model. The coefficient is statistically significant ($t = 5.2468$, $p < 0.001$), indicating that the observed positive association is statistically significant at conventional levels.

The results suggest that countries characterised by higher levels of AI adoption also tend to exhibit stronger eco-innovation performance. However, the cross-sectional design does not support a causal interpretation of this association. Other country-level factors may contribute to both AI adoption and eco-innovation performance.

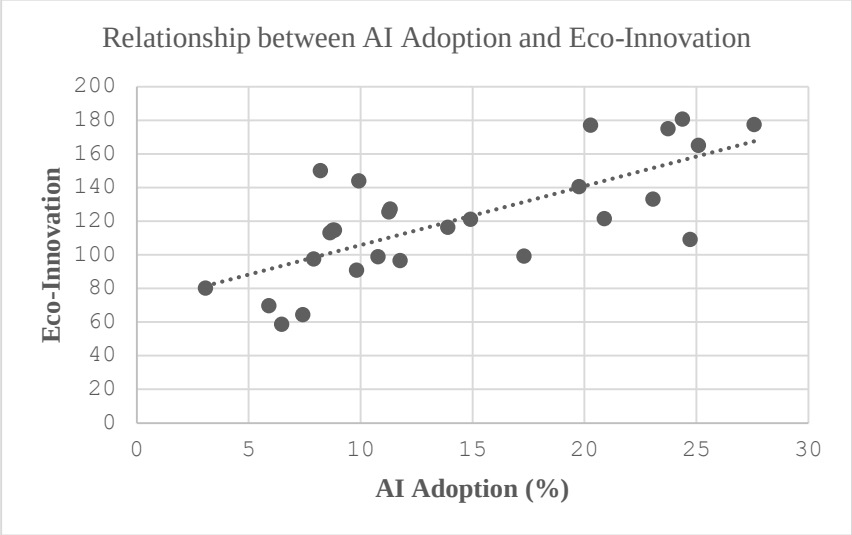


Figure 2. Relationship between AI Adoption and Eco-Innovation

Source: Authors' calculations based on data presented in Table 2.

Figure 2 illustrates this relationship. The upward-sloping trendline ($f(x) = 3.5075x + 70.7972$; $R^2 = 0.5241$) and the distribution of observations around it are consistent with the correlation and regression results reported in Table 5.

4.4 AI Adoption and Digital Readiness

Table 6. Correlation and Regression Results for AI Adoption and Digital Readiness

Measure	Result
Pearson correlation (r)	0.7299
Spearman correlation (ρ)	0.6557
Regression coefficient (β)	1.4981
Intercept	36.9575
R^2	0.5328
Standard error of β	0.2806
t-statistic	5.3395
p-value	1.55×10^{-5}

Source: Authors' calculations based on data presented in Table 2.

The third relationship examined is that between AI adoption and digital readiness. The Pearson correlation coefficient is 0.7299, indicating a strong positive linear association. The Spearman coefficient is somewhat lower, at 0.6557, although it remains positive and substantial. The larger difference between the Pearson and Spearman coefficients compared with the previous two relationships suggests that the association may be somewhat more sensitive to the distribution of the observations. Nevertheless, both measures point in the same positive direction.

The regression results confirm the positive direction of the relationship. The estimated coefficient for AI adoption is 1.4981, indicating that a one-percentage-point increase in AI adoption is associated, on average, with approximately a 1.50-percentage-point difference in the share of SMEs that have reached at least a basic level of digital intensity. The R^2 value of 0.5328 indicates that approximately 53.3% of the observed cross-country variation in digital readiness is accounted for by the linear model. The coefficient is statistically significant ($t = 5.3395$, $p < 0.001$), confirming that the positive association is statistically significant.

Overall, the results indicate that EU Member States with higher levels of AI adoption tend to have higher levels of digital readiness. Nevertheless, as in the previous analyses, this finding indicates an association rather than causality.

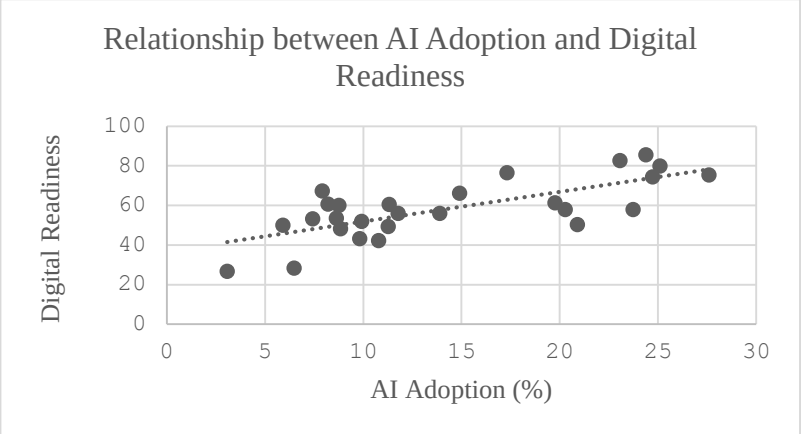


Figure 3. Relationship between AI Adoption and Digital Readiness

Source: Authors' calculations based on data presented in Table 2.

Figure 3 illustrates this relationship. The upward-sloping trendline ($f(x) = 1.4981x + 36.9575$; $R^2 = 0.5328$) and the distribution of observations around it are consistent with the correlation and regression results reported in Table 6.

4.5 Integrated Discussion of Findings

The empirical findings provide consistent evidence of positive associations between AI adoption and all three dimensions examined. All correlation coefficients are positive, and all regression coefficients are statistically significant at conventional levels, with the strongest relationship being observed for innovation capacity ($r = 0.8364$; $R^2 = 0.6996$) and substantial relationships for eco-innovation ($R^2 = 0.5241$) and digital readiness ($R^2 = 0.5328$). Countries characterised by higher levels of enterprise AI adoption therefore tend to perform better across the broader dimensions of technological and economic transformation considered here.

The particularly strong association between AI adoption and innovation capacity is consistent with the broader literature, which identifies AI as an important technological capability for improving service processes, efficiency, competitiveness and innovation. Previous research in service industries has highlighted the role of AI and other digital technologies in areas such as service quality, resource utilisation, flexibility and innovation (Iranmanesh et al., 2022). The present findings extend this perspective by showing that the relationship is also visible across the EU-27, although the cross-sectional nature of the analysis means the results should be interpreted as an association rather than as evidence that AI adoption directly causes higher innovation capacity.

The positive relationship between AI adoption and eco-innovation also supports the view that AI can contribute to sustainability when it is incorporated into processes and business models oriented towards more efficient resource use and environmental objectives. The literature identifies several ways in which AI can support sustainability, while also emphasising that its environmental and social benefits cannot be considered automatic. In particular, AI can contribute to sustainable solutions through process optimisation, resource allocation and innovation, but its environmental footprint and potential social risks must also be considered (Farmanesh et al., 2025; Toderas, 2025). The empirical result, with an R^2 of 0.5241, therefore indicates a meaningful cross-country association between AI adoption and eco-innovation, although the simple model leaves considerable variation unexplained.

A similar positive pattern is observed for digital readiness. The Pearson correlation of 0.7299 and the R^2 of 0.5328 indicate that countries with higher AI adoption also tend to exhibit higher levels of basic digital readiness among SMEs, a relevant point because AI adoption does not occur independently of the broader digital environment. The larger difference between the Pearson and Spearman coefficients for this relationship suggests that its strength is somewhat more sensitive to the distribution of country-level observations, although both measures remain positive.

The findings should also be interpreted in relation to the digital trust dimension emphasised in the literature review. Digital trust was not included as a quantitative variable in the present empirical model because the selected dataset does not provide a directly comparable country-level indicator for this dimension. It therefore remains a conceptual component of the study rather than an empirically tested variable. This distinction is important because previous research indicates that trust, perceived usefulness, perceived risk and other factors can influence acceptance of AI-enabled services. Trust has been identified as a significant predictor of behavioural intentions in several AI contexts, although its influence may vary according to the application and circumstances of use (Liu & Tao, 2022; Zhang et al., 2021; Zarifis et al., 2021).

Taken together, the results support the central perspective of the study: AI adoption is associated with a broader process of digital, innovative and sustainability-oriented transformation rather than an isolated technological development. At the same time, the literature indicates that technological progress needs to be accompanied by responsible implementation, transparency and trust, particularly in service environments where AI interacts

directly with users. This integrated perspective is consistent with the identified research gap, as existing studies frequently examine AI adoption, sustainability and trust separately rather than within a single cross-country framework.

5. CONCLUSIONS

This study examined the relationship between AI adoption and three dimensions of technological and socio-economic transformation across the 27 EU Member States: innovation capacity, eco-innovation and digital readiness. Using comparable country-level data from Eurostat and the European Commission, it combined descriptive statistics, Pearson and Spearman correlation coefficients and simple linear regression to examine these relationships.

The empirical results indicate positive and statistically significant associations between AI adoption and all three dimensions considered. The strongest relationship was identified between AI adoption and innovation capacity. The Pearson correlation coefficient reached 0.8364, while the regression model produced an R^2 of 0.6996, indicating that approximately 70% of the observed cross-country variation in innovation capacity is accounted for by the linear model including AI adoption. The relationship with eco-innovation was also positive and substantial, with a Pearson correlation coefficient of 0.7239 and an R^2 of 0.5241. Similarly, AI adoption was positively associated with digital readiness, with a Pearson correlation coefficient of 0.7299 and an R^2 of 0.5328. In all three models, the estimated regression coefficients were statistically significant at $p < 0.001$.

These findings answer the three research questions positively. Higher levels of AI adoption are associated with higher innovation capacity, stronger eco-innovation performance and higher levels of digital readiness across EU Member States. The consistency of the Pearson and Spearman results supports the overall direction of these relationships, although the strength of the association varies across the three dimensions.

From a theoretical perspective, the findings reinforce the view that AI adoption should be considered as part of a broader process of digital and organisational transformation. The particularly strong relationship with innovation capacity suggests that countries with wider diffusion of AI among enterprises tend to operate within innovation environments that are better positioned to integrate advanced technologies. The positive association with eco-innovation further indicates that AI adoption and sustainability-oriented innovation may develop in parallel. However, the results should not be interpreted as evidence that AI adoption directly causes improvements in innovation or sustainability, since the analysis is based on cross-sectional country-level data.

The findings also have practical implications for policymakers and organisations in service industries. Policies aimed at increasing AI adoption should be accompanied by measures that strengthen the wider digital capabilities required for effective technology integration. Investments in digital skills, technological infrastructure and innovation capacity may help create conditions for AI to generate broader economic and organisational benefits. At the same time, the sustainability dimension should remain part of AI-related strategies, since technological development may create environmental and social costs alongside its potential benefits. The responsible use of AI therefore requires attention to efficiency and innovation as well as transparency, privacy, fairness and accountability.

Digital trust is an additional consideration. Although it was not included as a quantitative variable because a directly comparable country-level indicator was not available in the selected dataset, the literature reviewed here indicates that trust is an important condition for the acceptance of AI-enabled services. Future empirical research could complement the present framework by incorporating measurable indicators of digital trust and responsible AI.

Several limitations should be acknowledged. The analysis is based on just 27 country-level observations, which limits the statistical generalisability of the findings and prevents conclusions at the firm or individual level. In addition, the cross-sectional design does not permit causal relationships to be established. The indicators also refer to slightly different measurement periods, as the digital readiness measure is based on 2023 data within the 2024 State of the Digital Decade framework, whereas the other main indicators use 2024 data. Finally, composite indicators such as the Summary Innovation Index and the Eco-Innovation Index capture broad dimensions of national performance and may therefore conceal differences between their individual components.

Future research could address these limitations by extending the analysis across several years and applying panel-data methods to investigate how changes in AI adoption relate to changes in innovation, sustainability and digital readiness over time. Further work could also examine differences between service industries, include firm-level observations, incorporate quantitative measures of digital trust, privacy, transparency and responsible AI, and extend the geographical scope beyond the EU-27.

Overall, the study shows that AI adoption is positively associated with innovation capacity, eco-innovation and digital readiness across the EU-27. The results support an integrated perspective in which artificial intelligence is examined not as an isolated technological phenomenon but as part of a wider transformation involving innovation, sustainability and digitalisation. At the same time, the absence of causal evidence and the limited country-level sample highlight the need for further research before stronger conclusions about the effects of AI adoption can be drawn.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge The Bucharest University of Economic Studies for providing the opportunity to present this research at The International Conference on Economics – Challenges and Opportunities.

REFERENCES

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior, 114,* 106548. https://doi.org/10.1016/j.chb.2020.106548

Belanche, D., Belk, R. W., Casaló, L. V., & Flavián, C. (2024). The dark side of artificial intelligence in services. *The Service Industries Journal, 44*(3–4), 149–172. https://doi.org/10.1080/02642069.2024.2305451

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020). Service robot implementation: A theoretical framework and research agenda. *The Service Industries Journal, 40*(3–4), 203–225. https://doi.org/10.1080/02642069.2019.1672666

Binsar, F., Rahim, R. K., Hamsal, M., & Mursitama, T. N. (2024). Determinants of digital adoption capability for service performance in Indonesian hospitals: A conceptual model. *Journal of System and Management Sciences, 14*(2), 188–213. https://doi.org/10.33168/JSMS.2024.0212

Carlisle, S., Ivanov, S., & Dijkmans, C. (2023). The digital skills divide: Evidence from the European tourism industry. *Journal of Tourism Futures, 9*(2), 240–266. https://doi.org/10.1108/JTF-07-2020-0114

Castillo, D., Canhoto, A. I., & Said, E. (2021). The dark side of AI-powered service interactions: Exploring the process of co-destruction from the customer perspective. *The*

Service Industries Journal, 41(13–14), 900–925. https://doi.org/10.1080/02642069.2020.1787993

Cheng, Y., & Jiang, H. (2020). How do AI-driven chatbots impact user experience? Examining gratifications, perceived privacy risk, satisfaction, loyalty, and continued use. *Journal of Broadcasting & Electronic Media, 64*(4), 592–614. https://doi.org/10.1080/08838151.2020.1834296

Chi, O. H., Denton, G., & Gursoy, D. (2020). Artificially intelligent device use in service delivery: A systematic review, synthesis, and research agenda. *Journal of Hospitality Marketing & Management, 29*(7), 757–786. https://doi.org/10.1080/19368623.2020.1721394

European Commission. (2024a). *EU eco-innovation index 2024*. Directorate-General for Environment. https://green-forum.ec.europa.eu/eco-innovation_en

European Commission. (2024b). *European innovation scoreboard 2024*. Directorate-General for Research and Innovation. https://research-and-innovation.ec.europa.eu/knowledge-publications-tools-and-data/publications/all-publications/european-innovation-scoreboard-2024_en

European Commission. (2024c). *Report on the state of the Digital Decade 2024*. https://digital-strategy.ec.europa.eu/en/library/report-state-digital-decade-2024

Eurostat. (2024). *Artificial intelligence by size class of enterprise* (ISOC_EB_AI) [Data set]. European Commission. https://ec.europa.eu/eurostat/databrowser/view/isoc_eb_ai/default/table?lang=en

Farmanesh, P., Solati Dehkordi, N., Vehbi, A., & Chavali, K. (2025). Artificial intelligence and green innovation in small and medium-sized enterprises and competitive-advantage drive toward achieving sustainable development goals. *Sustainability, 17*(5), 2162. https://doi.org/10.3390/su17052162

Goffi, G., Masiero, L., & Pencarelli, T. (2022). Corporate social responsibility and performances of firms operating in the tourism and hospitality industry. *The TQM Journal, 34*(6), 1626–1647. https://doi.org/10.1108/TQM-06-2021-0166

Gürlek, M., & Koseoglu, M. A. (2021). Green innovation research in the field of hospitality and tourism: The construct, antecedents, consequences, and future outlook. *The Service Industries Journal, 41*(11–12), 734–766. https://doi.org/10.1080/02642069.2021.1929930

Horng, J. S., Liu, C. H. S., Chou, S. F., Tsai, C. Y., & Hu, D. C. (2018). Developing a sustainable service innovation framework for the hospitality industry. *International Journal of Contemporary Hospitality Management, 30*(1), 455–474. https://doi.org/10.1108/IJCHM-12-2015-0727

Huang, A., Chao, Y., de la Mora Velasco, E., Bilgihan, A., & Wei, W. (2022). When artificial intelligence meets the hospitality and tourism industry: An assessment framework to inform theory and management. *Journal of Hospitality and Tourism Insights, 5*(5), 1080–1100. https://doi.org/10.1108/JHTI-01-2021-0021

Iranmanesh, M., Ghobakhloo, M., Nilashi, M., Tseng, M.-L., Yadegaridehkordi, E., & Leung, N. (2022). Applications of disruptive digital technologies in hotel industry: A systematic review. *International Journal of Hospitality Management, 107*, 103304. https://doi.org/10.1016/j.ijhm.2022.103304

Ivanov, S., Gretzel, U., Berezina, K., Sigala, M., & Webster, C. (2019). Progress on robotics in hospitality and tourism: A review of the literature. *Journal of Hospitality and Tourism Technology, 10*(4), 489–521. https://doi.org/10.1108/JHTT-08-2018-0087

Jabeen, F., Al Zaidi, S., & Al Dhaheri, M. H. (2022). Automation and artificial intelligence in hospitality and tourism. *Tourism Review, 77*(4), 1043–1061. https://doi.org/10.1108/TR-09-2019-0360

Knani, M., Echchakoui, S., & Ladhari, R. (2022). Artificial intelligence in tourism and hospitality: Bibliometric analysis and research agenda. *International Journal of Hospitality Management, 107*, 103317. https://doi.org/10.1016/j.ijhm.2022.103317

Kong, H., Wang, K., Qiu, X., Cheung, C., & Bu, N. (2023). 30 years of artificial intelligence (AI) research relating to the hospitality and tourism industry. *International Journal of Contemporary Hospitality Management, 35*(6), 2157–2177. https://doi.org/10.1108/IJCHM-03-2022-0354

Letheren, K., Jetten, J., Roberts, J., & Donovan, J. (2021). Robots should be seen and not heard… sometimes: Anthropomorphism and AI service robot interactions. *Psychology & Marketing, 38*(12), 2393–2406. https://doi.org/10.1002/mar.21575

Liu, K., & Tao, D. (2022). The roles of trust, personalization, loss of privacy, and anthropomorphism in public acceptance of smart healthcare services. *Computers in Human Behavior, 127*, 107026. https://doi.org/10.1016/j.chb.2021.107026

Mariani, M. M., & Borghi, M. (2024). Artificial intelligence in service industries: Customers' assessment of service production and resilient service operations. *International Journal of Production Research, 62*(15), 5400–5416. https://doi.org/10.1080/00207543.2022.2160027

Mingotto, E., Montaguti, F., & Tamma, M. (2021). Challenges in re-designing operations and jobs to embody AI and robotics in services: Findings from a case in the hospitality industry. *Electronic Markets, 31*(3), 493–510. https://doi.org/10.1007/s12525-020-00439-y

Nguyen, T.-M., & Malik, A. (2022). Impact of knowledge sharing on employees' service quality: The moderating role of artificial intelligence. *International Marketing Review, 39*(3), 482–508. https://doi.org/10.1108/IMR-02-2021-0078

Pizzi, G., Vannucci, V., Mazzoli, V., & Donvito, R. (2023). I, chatbot! The impact of anthropomorphism and gaze direction on willingness to disclose personal information and behavioral intentions. *Psychology & Marketing, 40*(7), 1372–1387. https://doi.org/10.1002/mar.21813

Sharma, T., Chen, J., & Liu, W. Y. (2020). Eco-innovation in hospitality research (1998–2018): A systematic review. *International Journal of Contemporary Hospitality Management, 32*(2), 913–933. https://doi.org/10.1108/IJCHM-01-2019-0002

Shin, H., & Perdue, R. R. (2022). Hospitality and tourism service innovation: A bibliometric review and future research agenda. *International Journal of Hospitality Management, 102*, 103176. https://doi.org/10.1016/j.ijhm.2022.103176

Toderas, M. (2025). Artificial intelligence for sustainability: A systematic review and critical analysis of AI applications, challenges, and future directions. *Sustainability, 17*(17), 8049. https://doi.org/10.3390/su17178049

Tussyadiah, I. (2020). A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in

Tourism. *Annals of Tourism Research, 81*, 102883. https://doi.org/10.1016/j.annals.2020.102883

Valença, M. N., Sobral, M. F. F., Andrade Lima, T. L. D., & Farias, D. D. M. P. (2020). Innovation radar in hospitality: A new procedure to evaluate the innovation in hotels. *Journal of Hospitality and Tourism Technology, 11*(2), 313–326. https://doi.org/10.1108/JHTT-10-2017-0119

Victorino, L., Verma, R., Plaschka, G., & Dev, C. (2005). Service innovation and customer choices in the hospitality industry. *Managing Service Quality: An International Journal, 15*(6), 555–576. https://doi.org/10.1108/09604520510634023

Zarifis, A., Kawalek, P., & Azadegan, A. (2021). Evaluating if trust and personal information privacy concerns are barriers to using health insurance that explicitly utilizes AI. *Journal of Internet Commerce, 20*(1), 66–83. https://doi.org/10.1080/15332861.2020.1832817

Zhang, S., Meng, Z. X., Chen, B. B., Yang, X., & Zhao, X. R. (2021). Motivation, social emotion, and the acceptance of artificial intelligence virtual assistants—Trust-based mediating effects. *Frontiers in Psychology, 12*, 728495. https://doi.org/10.3389/fpsyg.2021.728495