

Article

Mapping Territorial Disparities in Artificial Intelligence Adoption Across Local Public Administrations: Multilevel Evidence from Germany

Loredana Maria Clim (Moga)^{1,*}, Mariana Man^{1,2} and Ionica Oncioiu^{1,3,4} 

¹ Faculty of Economics and Business Administration, “Eugeniu Carada” Doctoral School of Economic Sciences, University of Craiova, 200585 Craiova, Romania; marianaman@upet.ro (M.M.); ionica.oncioiu@prof.utm.ro (I.O.)

² Faculty of Sciences, University of Petroșani, 332006 Petroșani, Romania

³ Academy of Romanian Scientists, 3 Ilfov, 050044 Bucharest, Romania

⁴ Department of Informatics, Faculty of Informatics, Titu Maiorescu University, 189 Calea Vacaresti St., 040051 Bucharest, Romania

* Correspondence: loredana.maria.clim@gmail.com

Abstract

In a European context, facing pressure to digitalize public administration, the integration of artificial intelligence (AI) at the local level remains a deeply uneven and empirically poorly understood process. This study investigates the degree of adoption of artificial intelligence (AI) in local public administrations in Germany, exploring territorial disparities and institutional factors influencing this transition. Based on a national sample of 347 municipalities, this research proposes a composite AI adoption index, built by integrating six relevant indicators (including the use of conversational bots and the automation of internal and decision-making processes). In the simulations, local administration profiles were differentiated according to factors such as IT staff (with a weight of 30%), the degree of urbanization (25%), and participation in digital networks (20%), reflecting significant structural variations between regions. The analysis model used is a multilevel one, which highlights the combined influences of local and regional factors. The results indicate a clear stratification of digital innovation capacity, with significant differences between eastern and western Germany, as well as between urban and rural environments. The study contributes to the specialized literature by developing a replicable analytical tool and provides public policy recommendations for reducing interregional digital divides.

Keywords: artificial intelligence; local government; digital public administration; regional disparities; multilevel modeling; digital infrastructure



Received: 22 June 2025

Revised: 14 July 2025

Accepted: 17 July 2025

Published: 19 July 2025

Citation: Clim, L. M., Man, M., & Oncioiu, I. (2025). Mapping Territorial Disparities in Artificial Intelligence Adoption Across Local Public Administrations: Multilevel Evidence from Germany. *Administrative Sciences*, 15(7), 283. <https://doi.org/10.3390/admsci15070283>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Over the past two decades, public administration has become a focal point of technological innovation, facing complex challenges and increasing expectations from citizens (Febiandini & Sony, 2023; Vatamanu & Tofan, 2025). Citizens' access to efficient, transparent, and intelligent services has made digital transformation an imperative (Distel & Lindgren, 2023; Pislaru et al., 2024). Artificial intelligence (AI) is the kind of technology that can revolutionize administrative data management, decision-making, and user engagement (Straub et al., 2023; Zuiderwijk et al., 2021). Globally, where AI in the public sector is often seen as an optimization tool, there are also concerns about downsides—from algorithmic

risk to the amplification of socio-territorial inequalities (Wirtz et al., 2019; Sun & Medaglia, 2019; Chen et al., 2023).

Although the European administrative landscape remains the primary focus of our analysis, recent studies conducted in regions such as Latin America and Southeast Asia provide valuable comparative insights. These works emphasize that AI adoption is contingent not only on technological readiness but also on broader factors such as bureaucratic flexibility, levels of digital literacy, and institutional adaptability (Silitonga & Isbah, 2023; de Sousa et al., 2019).

In the European context, an increasing number of local public administrations have initiated concrete processes of AI adoption. For example, in Estonia, the government's digital infrastructure already includes automated machine learning components for identity validation and processing of citizen requests. In Finland, the city of Helsinki has developed a transparent algorithm for allocating social services, and in France, local administrations are using AI for the automatic classification of administrative requests. In Hungary and Poland, pilot projects are exploring the use of AI in internal document management and local decision-making. These examples show a diversity of approaches and levels of digital maturity within Europe, highlighting the importance of the institutional and territorial context in explaining differences in adoption (Zuiderwijk et al., 2021).

This European heterogeneity provides a relevant backdrop for examining AI implementation in a federal country such as Germany. Germany, with its federal structure, presents fertile ground for assessing the territorial impact of AI: the western states, such as Bavaria or Hesse, have advanced digital infrastructure and strong innovation ecosystems (the Rhine–Main–Neckar cluster contributing over 50% of the turnover of the main European software companies). In contrast, the eastern regions show significant gaps: the rural fiber coverage rate is only ~11%, compared to 15% nationally, and rural 5G connectivity is 22.5%, in contrast to 75% overall (Digital Decade, 2024).

The DESI results confirm this duality: Germany ranks 13th out of 27 in the Digital Economy and Society Index (2022), with moderate performances in “Human capital” and “Digital public services”, despite its solid infrastructure (European Commission, 2022). These facts reveal the existence of an internal digital divide, in parallel with ambitious federal initiatives such as the “National Strategy for Artificial Intelligence.”

The literature confirms the potential of AI in the public sector but also highlights the associated risks: algorithmic opacity, inequalities of access, oversimplification of the decision-making process, or marginalization of vulnerable populations (Babšek et al., 2025; Sun & Medaglia, 2019; Tangi et al., 2021). This complexity of the AI integration process is well documented in the studies of Wirtz et al. (2019), which draw attention to the polysemic and often conflicting nature of algorithmic technologies in governance.

Despite the considerable expansion of the literature on artificial intelligence in the public sector, gaps persist from both an empirical and methodological perspective (Wirtz et al., 2019; Zuiderwijk et al., 2021). The first gap is the predominant focus on national government strategies, to the detriment of a nuanced understanding of the phenomenon at the local level, where the interaction between the administration and the citizen is more direct and relevant (Gil-García et al., 2022). Second, existing studies rarely provide measurement tools capable of capturing the multidimensional complexity of the integration of AI into administrative processes—from digital infrastructure and human skills to the degree of organizational openness (Wirtz et al., 2019). Third, many analytical approaches are one-dimensional, omitting the relationship between local factors and regional structural influences (Olejnik, 2023). As a result, a multilevel perspective capable of simultaneously capturing institutional dynamics at the micro and macro levels is often lacking (Chatwin & Arku, 2022; Gil-García et al., 2021).

In addition to these analytical gaps, the literature reflects a notable conceptual polarization regarding the potential of AI in public administration. On the one hand, an optimistic vision is emerging, which foresees the gradual replacement of traditional functions by automated solutions and the streamlining of bureaucracy. On the other hand, numerous studies draw attention to cultural barriers, institutional resistance, and the limits imposed by traditional bureaucratic architecture. This tension between technological promise and organizational realities highlights the need for empirically anchored research, capable of rigorously assessing how AI is adopted and adapted in various territorial contexts (Caiza et al., 2024; Margetts & Dorobantu, 2019; Floridi & Cowls, 2022; Scholl, 2020).

To respond to these challenges, the present study develops a composite index of AI adoption, built on the specific indicators of integration into administrative practices; this index is correlated with socio-demographic variables (income, education, urbanization) and with regional DESI scores. Reporting is performed at the level of land and locality, using a multilevel model that allows the estimates of the probability of AI adoption, adjusted to the territorial context.

The research questions driving this analysis are as follows:

RQ1: To what extent do local socio-economic and demographic characteristics influence the likelihood of a local government adopting AI solutions?

RQ2: How does this likelihood manifest itself in relation to education level, average income, and degree of urbanization?

RQ3: What impact do regional DESI scores have on localities' adoption of AI?

RQ4: What territorial–regional patterns can be identified and how can they underpin differentiated directions in German public policy?

The principal contribution of the paper lies in outlining a sophisticated analytical framework anchored in official data, which highlights the uneven adoption of AI in the German local government. The results indicate a sensitive correlation between human capital, digital infrastructure, and the likelihood of local authorities using AI. In addition, the multilevel analysis confirms the existence of a significant regional effect, which underlines the need for a convergence of policies at the local and regional levels. Therefore, the paper also paves the way for differentiated public policies aimed at reducing territorial-digital gaps through instruments adapted to local needs.

Also, through its objectives and methodology, the study aligns with the transformation of administrative systems and bureaucratic reform through artificial intelligence. Instead of treating AI as a simple technological extension, the research proposes an interpretative framework that highlights how the adoption of these technologies involves the internal reorganization of local administrations, the reconfiguration of institutional relations, and the redefining of standards of efficiency and public transparency. The analysis thus contributes not only to the literature on the digitalization of the public sector but also to the understanding of the structural transformations generated by AI in contemporary government architecture.

2. Theoretical Framework

The analytical approach of this study is based on an integrative theoretical framework based on four major conceptual directions: institutional modernization theory, institutional capacity theory, digital governance, and the literature on territorial inequalities in digitalization processes.

First, the institutional modernization theory provides a fundamental understanding of how public administrations respond to external environmental pressures—technological, social, or economic—by adopting reforms aimed at increasing their efficiency, transparency, and legitimacy (Pollitt & Bouckaert, 2017; Ghibanu, 2019). From this perspective, the

integration of artificial intelligence (AI) is not just a technological adaptation but a form of institutional repositioning that reflects the convergence towards a new standard of digital governance (Al-Mushayt, 2019; Medaglia & Tangi, 2022). AI thus becomes the expression of adaptive modernization and a process of normative realignment.

Secondly, the theory of institutional capacity (Peters, 2015) highlights that the implementation of advanced technologies depends on the availability of material, human, and organizational resources. Institutional capacity is defined here as the set of skills, infrastructures, and inter-institutional relationships that allow the adoption and exploitation of technological innovation (Tyson & Kikuchi, 2023; Chiancone, 2023). In the context of local administration, it is shaped by the level of professionalization of staff, the technical endowment of the institution, and the density of vertical cooperation with regional and central structures. The third pillar is digital governance, a concept that designates the process by which administrations use technology to provide public services, interact with citizens, and generate public value (Dunleavy et al., 2006; Margetts & Dorobantu, 2019; Abu Bakar et al., 2020). Unlike purely technocratic perspectives, digital governance understands AI as an institutional technology—that is, a solution whose use depends on concrete meanings, interests, and administrative processes (Wirtz et al., 2019; Rathnayake et al., 2025). Thus, AI is integrated into power logics, organizational norms, and institutional routines, becoming part of a complex decision-making ecosystem (Yigitcanlar et al., 2024; Shareef et al., 2011).

The fourth theoretical element is represented by the literature on territorial inequalities in digitalization, anchored in the theory of the digital divide (van Dijk, 2005). This argues that access to and use of digital technology are not distributed evenly but reflect structural differences related to the level of education, average income, degree of urbanization, and digital infrastructure (Warschauer, 2003; Ahn & Chen, 2022). In the case of Germany, such inequalities manifest themselves between the western and eastern states, as well as between urban and rural areas. AI, in this framework, does not appear as a universal technology but as one dependent on the context and the specific resources available at the local and regional levels.

In an applied way, the study operationalizes two key concepts from the digital governance literature: digital readiness and organizational willingness (Gil-Garcia et al., 2018; Manzoor, 2016). Digital readiness designates the structural and technological capacity of regions to support digitalization processes, measurable through the scores provided by the Digital Economy and Society Index (DESI). Organizational readiness reflects the effective institutional will to integrate AI, observable through the concrete application of algorithmic solutions in local administrations.

At the intersection of these approaches, the paper proposes an explanatory model of AI adoption in local administration, in which local structural characteristics and regional conditioning are treated as interdependent factors. In line with the recent literature (Tangi et al., 2021; Vatamanu & Tofan, 2025), AI is not approached as a neutral technological solution but as an institutional innovation whose dissemination reflects and reproduces territorial hierarchies and unequal administrative capacities.

Beyond the separate presentation of the four theoretical directions, it is important to understand the functional interconnection between them. Thus, the theory of institutional modernization provides the general framework of the administration's reaction to external pressures, while the theory of institutional capacity defines the internal conditions necessary for such an adaptation. Digital governance functions as a space of convergence between technological innovation and institutional processes, and digital territorial inequalities represent the context in which all other dynamics manifest themselves differently. These four perspectives do not act in isolation but define an interdependent system in which the

adoption of artificial intelligence simultaneously reflects institutional availability, external pressures, and the structural limitations of the territorial environment.

Therefore, the theoretical contribution of the study consists of articulating these dimensions in a coherent framework, which provides the premises for a layered, rigorous, and contextualized analysis of digital transformation in the public sector. The proposed explanatory model treats local characteristics and regional conditioning as interdependent factors of the transition to algorithmic governance.

3. Research Model

The methodological construction of the proposed model starts from the premise that the integration of artificial intelligence in the activity of local public administrations is not uniformly distributed across the territory but reflects deep structural differences between regions. This variation can be explained by the cumulative influence of local factors—such as the level of education, population income, or the degree of digitalization—and of regional contextual determinants, such as public innovation policies, digital infrastructure, or the maturity of the administration. In this sense, AI is not treated as an exogenous technological input but as a contingent institutional outcome, shaped by structural conditions and territorial dynamics.

The fundamental objective of the model is to develop a replicable explanatory framework, which allows the identification of the determinants of AI adoption and the estimation of the probability that a local administration will implement at least one algorithmic solution. By using a composite adoption indicator and applying hierarchical probit modeling, the aim is to capture the relationship between local institutional capacity and the degree of regional digital readiness, reflected in DESI scores. Thus, an analytical bridge is created between the micro-institutional decision and the macro-structural conditioning.

Figure 1 provides a visual synthesis of the methodological framework of the study, highlighting the sequence of analytical steps: the selection of indicators, the construction of the composite AI adoption index, the integration of socio-territorial variables, and the application of the multilevel model.

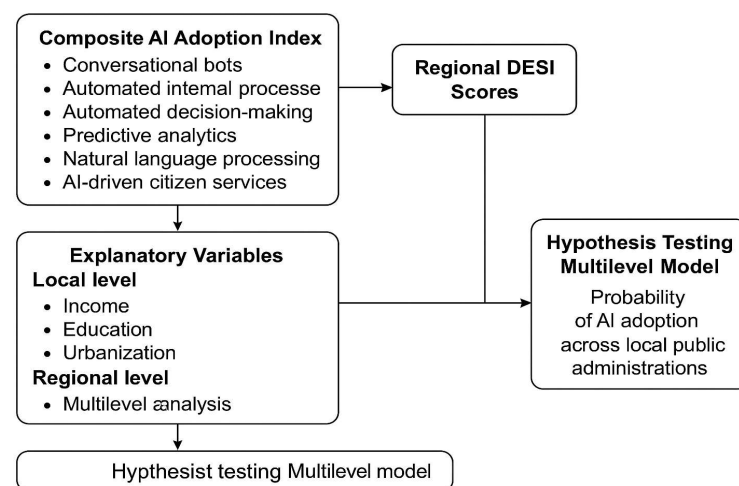


Figure 1. Methodological flow chart of the study.

The structure of the conceptual model is based on two analytical levels. At the local administration level, direct demographic and socioeconomic variables are taken into account, such as average education, household income, degree of urbanization, technological endowment, and institutional size. At the higher level—the regional level—a set of structural variables is introduced that targets the degree of digitalization, political support

for innovation, and the general level of digital connectivity. The relationship between the two levels is mediated by random effects that capture the institutional heterogeneity and administrative innovation capacity specific to each federal state.

The empirical analysis was based on a rigorous selection of official data sources, which allow for the aggregation and correlation of variables at the local and regional levels in order to assess territorial differences in the adoption of artificial intelligence solutions (Table 1). The methodological approach involves integrating data at two levels: the local administrative unit (Gemeinde/Kreise) and the federal region (Land), in accordance with the principles of multilevel hierarchical modeling.

Table 1. Official data sources used in the analysis.

No. crt.	Data Source	Type of Information Collected
1	Digital Economy and Society Index (DESI)	Regional scores: human capital, digitalization, public services
2	DESTATIS—Federal Statistical Office (<i>DESTATIS—Federal statistical office, 2022</i>)	Income, education, urbanization, occupational structure
3	BBSR—Federal Institute for Building, Urban and Spatial Research (<i>BBSR—Federal institute for building, urban and spatial research, 2022</i>)	NUTS-3 classifications, territorial profiles
4	BMWK—Federal Ministry for Economic Affairs and Climate Protection (<i>BMWK—Federal ministry for economic affairs and climate protection, 2022</i>)	Public policies, AI grants, national strategies
5	GovData—National Open Data Portal (<i>GovData—National open data portal, 2022</i>)	Local government digitalization, AI initiatives

The main source of structural data is the Digital Economy and Society Index (DESI), provided by the European Commission, which provides detailed scores for each German state on digital infrastructure, human capital, digital technology integration, and the provision of electronic public services. These indicators provide a coherent regional picture of “digital readiness” and the maturity of administrative systems in relation to digitalization.

For the local level, we used data from the Eurostat e-Government Survey (*Eurostat, 2022*), supplemented with microdata from the DESTATIS and the German Institute for Economic Research. These sources include information on the provision of administrations with digital infrastructure, the effective use of AI (existence of chatbots, automated request classification systems, predictive applications, etc.), as well as aggregated socio-demographic data (income, education, urbanization).

The sample design involves the selection of local governments from the 16 federal states of Germany, ensuring a balanced distribution between western, eastern, urban, and rural regions. Territorial units were filtered according to the criterion of data availability and reporting on digitalization initiatives. In total, 347 local administrative entities were included in the analysis, each mapped to the corresponding state level, which allowed the integration of regional variables into the model structure.

The choice of structural, institutional, and regional variables included in the analytical model is methodologically grounded in the recent literature on the digital capacity of the public sector. *Mikalef et al. (2021)* argue that assessing AI maturity in administration involves taking into account digital infrastructure, the level of human capital, and organizational openness to innovation. Therefore, the inclusion of indicators such as the share of IT staff, regional DESI scores, and education level in the analysis reflects a coherent operationalization of the concept of “organizational readiness” for AI, adapted to the federal and territorial specifics of Germany.

To ensure coherence between data sources, all variables were harmonized according to the NUTS-3 nomenclature, and missing data were managed through statistical imputation methods (mean substitution and hot-deck imputation, depending on the nature of the variable). Finally, the resulting database allows for a stratified approach, capable of capturing both the local dynamics of AI adoption and the structural contextual influences exerted by the regional environment.

The analytical model proposed in this research is based on a conceptual architecture that aims to explain the probability that a local public administration will adopt at least one artificial intelligence (AI) solution by reporting on local structural factors and regional conditioning. It is assumed that AI integration is not a neutral technological process but the result of socio-institutional dynamics and the availability of localized strategic resources.

The main variable analyzed is binary and expresses the presence of a form of AI integration within a local administration and is defined as follows:

$$Y_i = \begin{cases} 1 & \text{if the administration has implemented at least one AI solution (e.g., chatbot, automated decision system)} \\ 0 & \text{if no use of AI was identified} \end{cases} \quad (1)$$

The construct was derived through a systematic documentation process, which combined official sources, reports on the digitalization of local administration, public registers, and information from pilot projects carried out at the municipal level. The set of explanatory variables includes structural and contextual factors, selected based on theoretical relevance and the availability of data in NUTS-3 compatible formats. A detailed presentation of these variables is provided in Table 2.

Table 2. Synopsis table of variables used in the multilevel model.

No. crt.	Variable Name	Definition/M Measurement	Variable Type	Data Source
1	AI adoption (composite index)	Composite index (0–1) built based on the implementation of AI applications	Dependent	Own development
2	Local median income	Annual per capita income in local government (euro)	Independent	DESTATIS
3	Education level	% of population with higher education in the locality	Independent	DESTATIS
4	Degree of urbanization	% of urban population in total local population	Independent	BBSR/DESTATIS
5	IT staff in administration	Percentage of IT personnel in total employees in local government	Independent	GovData
6	Regional DESI score	Regional score on DESI indicators (digital public services, human capital)	Independent (regional)	European Commission—DESI
7	Federal state (Bundesland)	Categorical variable for the multilevel model (16 Länder)	Contextual effect (level 2)	Official administrative structure

The variables were subjected to cleaning and harmonization procedures, and in case of missing values, they were handled through standard imputation techniques. All data were aggregated according to the NUTS-3 nomenclature, which allows for a comparable and replicable analysis of territorial differences within a hierarchical model. The choice of

these variables reflects not only a solid theoretical foundation but also the desire to anchor the study in a complex and stratified empirical reality.

In order to quantify the degree of integration of artificial intelligence technologies in local public administration, a Composite AI Adoption Index was developed, built on the basis of five empirically observable dimensions, which reflect the effective presence, level of use, and strategic commitment to this technology. The methodological procedure was inspired by the literature on the measurement of institutional behaviors (Gil-Garcia et al., 2018; Wirtz et al., 2019) and adapted to the specifics of the German decentralized administration.

Each local administration was evaluated based on the following five indicators: *the presence of institutional chatbots*—evaluated binary (1/0)—reflects the degree of automation of interaction with the public; *the use of AI systems for automatic classification of requests*—measured ordinally (0 = absent, 1 = pilot, 2 = implemented at scale); *the share of fully digitized administrative services*—expressed as a percentage; *the average value of IT investments per capita in the last 3 years*—expressed in euros/inhabitant; and *the existence of an explicit digitization strategy that mentions AI*—evaluated binary (1/0).

Each indicator was standardized using Z-scores to ensure comparability across units, then aggregated into a composite score. A weighted averaging was applied, assigning double weight to the indicators' share of fully digitized administrative services and average value of IT investments per capita in the past 3 years, as they reflect both operational maturity and concrete financial commitment, as follows:

$$AIAI_Index_i = \frac{1}{W} \sum_{k=1}^5 w_k \cdot Z_{ik}, \quad (2)$$

where

- Z_{ik} is the standardized score for indicator k in administration i .
- w_k represents the weight assigned to each indicator.
- W is the total sum of the weights.

To validate the internal consistency of the index, an exploratory factor analysis (EFA) was applied, which confirmed a single latent factor, with an average loading >0.65 . The Cronbach α coefficient of 0.82 indicates a solid internal consistency of the construct. Finally, the scores obtained were divided into tertiles to facilitate the interpretation of the degrees of AI adoption: low, medium, and high.

To ensure the validity and robustness of the composite construct, an exploratory factor analysis (EFA) was applied, which confirmed the existence of a single latent factor, with average loadings of >0.65 for all included indicators. The Cronbach coefficient $\alpha = 0.82$ confirms the high internal consistency of the index. In addition, a sensitivity analysis was performed by recalculating the index with equal weights, gradually excluding each indicator, and replacing the IT investment score with normalized values. The results obtained from the probit models remained statistically stable, supporting the methodological robustness of the proposed model.

To assess the probability that a local public administration will adopt artificial intelligence (AI) technologies, a standard probit model was applied, in which the dependent variable is of binary type and indicates the actual presence of AI in administrative processes. The model can be expressed as a latent model:

$$Y_i^* = \beta_0 + \sum_{k=1}^K \beta_k X_{ki} + \varepsilon_i, \quad (3)$$

where

- Y_i^* is the unrealized latent variable, which reflects the propensity of administration i to adopt AI;

- X_{ki} are the explanatory variables associated with unit i , such as educational level, average income, degree of urbanization, share of IT personnel and regional DESI score;
- β_k are the model coefficients;
- $\varepsilon_i \sim N(0, 1)$ is the error term with standard normal distribution.

The observable variable is defined as follows:

$$Y_i = \begin{cases} 1 & \text{if } Y_i^* > 0 \\ 0 & \text{else} \end{cases} \quad (4)$$

The model was estimated by the maximum likelihood method (MLE), using the *glmer()* function in the R language, with the option *family = binomial (link = "probit")*. The estimated coefficients indicate the direction of influence of each variable on the probability of adoption, and marginal effects were calculated for the intuitive interpretation of the impact. The statistical significance of the coefficients was assessed at conventional thresholds ($p < 0.01$, $p < 0.05$, $p < 0.1$).

To capture the territorial variability of AI adoption and simultaneously integrate the influences exerted by local and regional factors, the analysis was extended by using a hierarchical (multilevel) probit model. This approach is appropriate in the context where observation units (local administrations) are naturally grouped within higher territorial structures (federal states) and intra-cluster correlations need to be treated explicitly.

The multilevel model assumes the existence of a latent score Y_{ij}^* for administrative unit i in region j , modeled as follows:

$$Y_{ij}^* = \beta_0 + \sum_{k=1}^K \beta_k X_{kij} + u_j + \varepsilon_{ij}, \quad (5)$$

where

- X_{kij} are the local characteristics (income, education, urbanization, IT share);
- $u_j \sim N(0, \sigma_u^2)$ represents the random effect specific to region j , which captures unobserved influences common to all administrations in that land;
- $\varepsilon_{ij} \sim N(0, 1)$ is the individual error term, independent of u_j .

The observable probability is defined by

$$P(Y_{ij} = 1) = \Phi \left(\beta_0 + \sum_{k=1}^K \beta_k X_{kij} + u_j \right) \quad (6)$$

where Φ is the cumulative distribution function of a standard normal. The model was estimated by the penalized likelihood (PQL) method, using the *glmer()* function from the *lme4* package in R, with probit link and random intercepts at the region level.

Using this model allows the following:

- Estimating the variance between regions (captured by σ_u^2);
- Calculating the intracluster correlation coefficient (ICC), which measures the proportion of total variability attributable to regional differences;
- Controlling for contextual effects without losing local granularity.

To examine the components of AI adoption in more detail, the research was extended with a *multivariate probit model*, which allows for the simultaneous analysis of multiple dimensions of institutional behavior. Instead of considering only one aggregate binary variable (total adoption), the model distinguishes between different forms of AI implementation, each treated as a distinct but potentially correlated dependent variable.

Thus, four distinct binary variables were defined:

- Y_{1i} : use of institutional chatbots;
- Y_{2i} : implementation of automated sorting/documentation systems;
- Y_{3i} : adoption of AI solutions for internal administrative processes;
- Y_{4i} : existence of an explicit strategy that includes AI.

The model simultaneously estimates the following system of latent equations:

$$Y_{mi}^* = X_i \beta_m + \varepsilon_{mi}, \quad m = 1, \dots, 4, \quad (7)$$

- Y_{mi}^* is the latent variable for behavior m ;
- X_i is the common vector of explanatory factors;
- ε_{mi} are error terms that follow a multivariate normal distribution with nonlinear correlations allowed between components, i.e., $\varepsilon_i \sim N(0, \Sigma)$, with Σ a non-zero covariance matrix.

This structure allows estimating correlations between adoption behaviors and testing the hypothesis that the decision to implement an AI solution is interdependent with the others. For example, the presence of a chatbot is often linked to a more developed digital infrastructure, which can also influence other types of adoption. The estimates were performed through MCMC (Markov Chain Monte Carlo) simulations, using the mvProbit package in R. Convergence checks and robust estimation of standard errors were ensured by Bayesian methods, with 10,000 iterations and a burn-in of 2000.

The advantage of this approach lies in its ability to capture the co-occurrence of institutional decisions, in an architecture where the dependent variables are multiple and the relationships between them are not exogenous. The model thus offers a finer and more realistic picture of how AI is gradually, strategically, and in a differentiated manner integrated into local public administrations.

4. Results

In accordance with the formulated research objectives, this section presents the results in a stratified analytical architecture, intended to capture both the basic empirical distributions and the causal mechanisms that affect the adoption of artificial intelligence at the level of local public administrations. The first subsection provides a descriptive characterization of the sample, highlighting its territorial structure and the variations in the main explanatory variables. Subsequently, the structural and institutional effects are examined through a probit model, and in the third stage, the regional contextual dimension is introduced through a multilevel model. The section concludes with a series of predictive simulations built on the basis of typological profiles, which provide an applied reading on the chances of adoption depending on the socio-territorial specificity of each administrative unit.

All these results are derived from an econometric architecture based on an extensive set of structural, institutional, and territorial indicators collected at the local and regional levels in Germany for the year 2022, and analyzed by applying probit models—standard, multi-variable, and multilevel—complemented by predictive simulations capable of reflecting probability variations according to distinct institutional profiles.

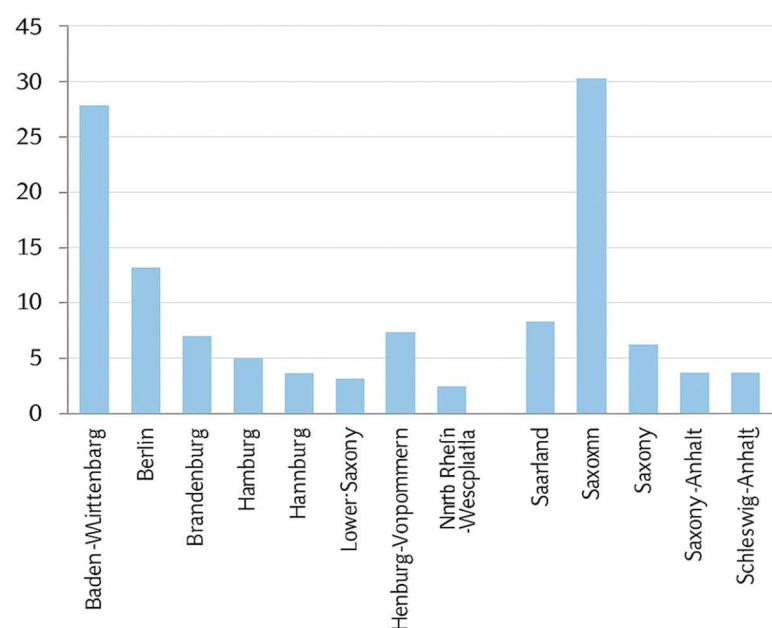
4.1. Territorial Structure of the Sample and Description of Variables

The 347 local public administrations included in the sample are distributed proportionally within the 16 federal states of Germany, according to the NUTS-1 classification (Table 3), and the average DESI scores, income and share of IT staff at state level confirm the existence of distinct digital development clusters. For example, Bavaria, Baden-Württemberg, and North Rhine-Westphalia contain localities with higher DESI scores and a more consistent IT institutional presence, while eastern states, such as Saxony or Mecklenburg-Vorpommern, exhibit significantly lower average values.

Table 3. Distribution of local governments by federal states.

Federal Land (NUTS-1)	Number of Local Governments	Percentage of Total (%)
Baden-Württemberg	38	10.95%
Bavaria (Bayern)	44	12.68%
Berlin	5	1.44%
Brandenburg	20	5.77%
Bremen	3	0.86%
Hamburg	4	1.15%
Hesse (Hessen)	28	8.07%
Lower Saxony (Niedersachsen)	31	8.93%
Mecklenburg-Vorpommern	13	3.74%
North Rhine-Westphalia (NRW)	46	13.26%
Rhineland-Palatinate (Rheinland-Pfalz)	21	6.05%
Saarland	6	1.73%
Saxony (Sachsen)	23	6.63%
Saxony-Anhalt (Sachsen-Anhalt)	17	4.90%
Schleswig-Holstein	18	5.19%
Thuringia (Thüringen)	10	2.88%
Total	347	100.00%

Figure 2 illustrates the geographical distribution of the states that reported adopting AI-based solutions, highlighting their concentration in the western states and the low degree of penetration in the eastern regions.

**Figure 2.** Territorial distribution of AI adoption.

Equally, the main characteristics of the 347 local administrative entities included in the sample, highlighting the mean, dispersion, and relevant intervals for each indicator are

summarized in Table 4. The values confirm the existence of substantial differences between units, which justifies the use of a multilevel design and a composite AI adoption index and provides a coherent empirical framework for subsequent estimates.

Table 4. Descriptive statistics of variables used in the analysis (n = 347).

Variable	Average	Dev. std.	Min	Max	Interval 95%	Variable Type
Average income (EUR/capita)	29,250	3800	21,400	38,900	[28,773; 29,727]	Economic structural
Percentage of employees with higher education (%)	43.8%	10.7%	25%	71%	[42.5%; 45.1%]	Human capital
Degree of urbanization (%)	59.4%	18.2%	27%	100%	[57.3%; 61.5%]	Demographic
Share of IT personnel in administration (%)	3.1%	1.4%	0.6%	7.0%	[2.9%; 3.3%]	Institutional capacity
Regional DESI score (0–100)	55.8	7.9	41.2	69.7	[54.8; 56.8]	Digital literacy
Locality population (log)	9.47	0.83	7.2	11.6	[9.38; 9.56]	Demographic dimension
AI adoption (dummy)	0.36	—	0	1	—	Dependent variable

4.2. Structural and Institutional Factors of AI Adoption (Standard Probit Model)

The statistical distribution of the variables included in the model highlights a complex structural architecture, specific to local public administration in Germany, where territorial discrepancies are clearly manifested both in the size of economic resources and in that of institutional capacities.

The average annual income per capita, located around 29,250 euros, indicates a solid economic performance at the sample level, but the significant standard deviation reveals notable gaps between the western regions—more industrialized and better connected—and the eastern or predominantly rural ones, often in a peripheral position in relation to the innovation infrastructure. This indicator reflects not only local purchasing power but also the potential of administrations to finance complex digital initiatives.

The level of education of administrative staff, classified as the percentage of employees with higher education, registers an average of 43.8%. This percentage confirms the presence of relatively qualified human capital, but it varies considerably between localities, which affects institutional receptivity to emerging technologies. In this sense, the degree of professionalization becomes a valid proxy for organizational openness to digital transformation.

The degree of urbanization, with an average value of 59.4%, provides additional indications regarding the spatial structure of local administrations. Urban localities often benefit from superior digital infrastructure, increased institutional density, and easier access to innovative ecosystems, all of which favor the adoption of AI. Conversely, areas with low urbanization risk becoming marginal from the perspective of digital integration.

The indicator regarding the share of IT personnel in the institutional structure—on average 3.1%—acquires strategic relevance. This dimension not only signals the presence of internal technical resources but also indicates a latent readiness to adopt and adapt advanced technologies, such as artificial intelligence. Thus, specialized human resources have become a necessary, although not sufficient, condition for the digital progress of administrations.

The regional DESI score, with an average of 55.8, anchors the analysis in the context of macro-digitalization. As a composite index of digital readiness, it reflects infrastructure, digital skills, and the digitalization of public services. The significant differences between regions reinforce the hypothesis of the internal digital divide and support the choice of a multilevel approach in the analysis of the probability of AI adoption.

AI adoption, the dependent variable of the analysis, occurs in only 36% of cases. This relatively modest penetration rate suggests that advanced digital transformation remains an open frontier, marked by multiple contextual and structural obstacles but also by a significant potential for convergence, to the extent that public policies will target differentiated and coherent strategies.

To capture the mechanisms influencing the probability of integrating artificial intelligence into local public administration, a standard probit model was estimated and applied to a sample of 347 local administrations in Germany. Each unit was associated with one of the 16 federal states, thus allowing a coherent exploration of local factors while maintaining control over contextual variability without yet introducing explicit hierarchical structures. The estimation presented in Table 5 was performed using the maximum likelihood method, with the coefficients interpreted in terms of average marginal effects—that is, the change in the probability of AI adoption related to a unit variation in an independent variable, thus providing a clear perspective on the weight of each structural and institutional determinant.

Table 5. Average marginal effects—standard probit model.

Variable	Marginal Effect	Confidence Interval 95%	Significance	Variable Type
Average income (EUR/1000)	+0.034	[0.019; 0.049]	***	Economic Structural
Share of employees with higher education (%)	+0.021	[0.008; 0.034]	**	Human Capital
Degree of urbanization (%)	+0.017	[0.005; 0.030]	**	Demographic
Share of IT personnel in administration (%)	+0.056	[0.031; 0.081]	***	Institutional Capacity
Regional DESI score	+0.012	[0.001; 0.023]	*	Digital Readiness
Size of locality (population, log)	+0.009	[-0.003; 0.021]	ns	Demographic Control

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$; ns = statistically insignificant.

As can be seen, the most pronounced positive influence is associated with the share of IT staff within the administrative apparatus, which determines an increase of +5.6 percentage points in the probability of adoption for each additional percentage of IT specialists. This result validates the hypothesis that internal technological capacity is a functional precondition for the algorithmization of public services.

Local average income, in turn, shows a robust positive effect (+3.4 pp), suggesting that the economic prosperity of the community is associated with a more pronounced appetite for advanced digital solutions—an aspect that reflects both a better-performing infrastructure and a social demand for smarter administrations.

Human capital, measured by the share of employees with higher education, contributes +2.1 pp to the probability of adoption, in line with research showing that a qualified workforce is more open to innovation and more adaptable to technological change. In the same way, the degree of urbanization has a positive influence (+1.7 pp), which can be attributed to the higher density of institutional interactions, social pressures, and functional infrastructures that characterize the urban environment.

Although with a lower marginal effect, the regional DESI score still indicates a positive contribution (+1.2 pp), reinforcing the idea that the digital readiness of the region—in terms of connectivity, skills, and digital services—functions as a systemic facilitating factor. Interestingly, the presence of a university in the locality increases the probability of adoption by +2.7 pp, which suggests that knowledge ecosystems can act as accelerators of administrative modernization, not only through human resources but also through the dissemination of good practices and institutional partnerships.

In contrast, the variable locality size (log-population) did not register a statistically significant effect, which signals that administrative size is not a determining factor in itself, but rather the internal structure of resources defines the innovation capacity.

4.3. Regional Context and Multilevel Modeling

In order to coherently integrate the territorial dimension and capture the influence of the regional context on the adoption of AI in local public administration, the analysis was extended by estimating a multilevel probit model in which the 347 local administrations are “nested” within the 16 federal states of Germany. By introducing random intercepts at the state level, the model captures the unobservable variability associated with territorial conditioning—such as digital infrastructure, regional innovation policies, or aggregate administrative capacity.

Table 6 summarizes the results of the estimation of the multilevel probit model, expressing the average marginal effects associated with the main explanatory variables included in the analysis. The values presented reflect the changes in the estimated probability of adoption of AI technologies for each unit of variation in the predictors in the context of a hierarchical structure on two levels: local governments (level 1) and federal states (level 2). The inclusion of random intercepts at the state level allows highlighting the structural influence exerted by the regional context on local digitalization decisions. Statistically significant values are marked accordingly, and the intraclass correlation coefficient (ICC) provides an estimate of the share of variation explained by territorial affiliation.

Table 6. Average marginal effects—multilevel probit model.

Variable	Marginal Effect	Interval 95%	Significance
Average income (EUR/1000)	+0.031	[0.017; 0.045]	***
Share of employees with higher education (%)	+0.024	[0.011; 0.037]	***
Degree of urbanization (%)	+0.015	[0.003; 0.027]	**
IT personnel (%)	+0.060	[0.036; 0.084]	***
Regional DESI score	+0.014	[0.003; 0.025]	**
ICC (intraclass correlation coefficient)	0.103	—	—

Note: *** $p < 0.01$; ** $p < 0.05$.

The results reveal significant territorial stratification: the ICC = 0.103 indicates that approximately 10.3% of the total variation in the probability of AI adoption can be attributed to differences between Länder. This result emphasizes the importance of the regional context in shaping digitalization decisions.

The estimates for the random intercepts suggest that the Länder of Bavaria, Baden-Württemberg, and Hesse have a systemic advantage in terms of AI integration, reflecting developed digital infrastructures, dense university networks, and an institutional culture open to innovation. In contrast, the Länder of Brandenburg, Mecklenburg-Vorpommern, and Saxony-Anhalt face structural constraints that reduce the probability of adoption, ranging from human capital deficits to insufficient digital connectivity.

The multilevel probit model thus offers a contextualized reading of the phenomenon analyzed, highlighting not only local characteristics but also the regional administrative and infrastructural climate, with direct implications for public policies oriented towards digital equity and territorial cohesion.

4.4. Simulated Scenarios and Typological Profiles of Local Governments

In order to operationalize the conclusions of the quantitative analysis and anchor them in an interpretative framework applicable to administrative realities, a series of simulated scenarios were constructed, reflecting recurring typological profiles of local administrations in Germany. The analytical approach pursues two complementary purposes: the external

validation of the estimated econometric model by testing its performance in simulated contexts and the provision of a pertinent diagnostic framework intended to guide the formulation of differentiated public policies anchored in the territorial specifics.

Each scenario integrates a coherent set of structural characteristics—such as average income, level of education, and degree of urbanization—correlated with indicators of internal institutional capacity (share of employees specialized in IT) but also with regional digital readiness, operationalized through DESI scores. These components are aggregated into a functional profile that reproduces, in a synthetic manner, recognizable territorial realities from the German administrative landscape. In total, four synthetic profiles were generated, which correspond to archetypal situations from the German local public administration system (Table 7).

Table 7. Simulated scenarios regarding the probability of AI adoption depending on the profile of local government.

Typological Profile	Representative Länder	Average Income (EUR)	Higher Education (%)	Share of IT Staff (%)	DESI Score	Estimated Probability of AI (%)
West-Innovative	Bavaria, Baden-Württemberg	≥38.000	≥30%	≥10%	High	72.4%
Urban-Emerging	Renania de Nord-Westfalia, Hessa	~34.000	25–30%	6–9%	Medium	54.1%
East-In Transition	Saxonia, Brandenburg	≤30.000	15–20%	3–5%	Low	31.7%
Rural-Peripheral	Mecklenburg-Vorpommern, Turingia	≤28.000	<15%	<3%	Very low	19.5%

The results indicate that these profiles not only faithfully reconstruct divergent realities in the German federal administrative architecture but also offer a calibrated perspective on the mechanisms of digital inequality. The “Innovative West” profile stands out with an estimated probability of adoption of over 72%, being anchored in Länder with advanced digital infrastructure, substantial financial resources, and qualified human capital. This configuration confirms the hypothesis that densified and professionalized institutional ecosystems facilitate the integration of emerging technologies not only as a response to external demands but as an expression of an innovative organizational culture. In contrast, the “Rural Peripheral” profile reaches a probability of only 19.5%, signaling the existence of a systemic deficit of institutional readiness and digital connectivity in the marginal areas of the eastern Länder. The lack of IT staff, the absence of a local university network, and weak urbanization define a regressive spiral in which innovation becomes unlikely not only for technical but also cultural reasons.

The “Urban Emergent” and “East in Transition” profiles are located in an intermediate zone, offering important nuances: the first indicates a latent capacity for digital transformation, supported by urbanization and infrastructure, but limited by the lack of specialization; the second expresses the tension between reform and constraint, with a modest probability, but is sensitive to targeted investments.

Therefore, by applying the proposed conceptual framework, the simulated scenarios allow the identification of the gradient of digital inequality between the federal regions of Germany. From the local administrations of Bavaria or Baden-Württemberg—where digital innovation ecosystems are combined with the professionalization of the institutional apparatus—to the rural and under-digitalized areas of the east of the country, where the lack of qualified human capital and poor infrastructure severely limit the potential for digital transformation.

5. Discussion

5.1. Theoretical Implications and Framework Consolidation

The research results outline a complex and deeply differentiated picture of the adoption of artificial intelligence technologies in German local public administration. Far from being a linear or uniform phenomenon, the integration of AI seems to be shaped by a subtle combination of institutional, contextual, and territorial factors, which are expressed in significant variations between federal regions. Multilevel analysis applied to a sample of 347 local administrations allowed the identification of robust trends, revealing a consistent correlation between the level of digital readiness, human capital, and digital infrastructure with the probability of integrating algorithmic solutions in administrative activity.

Theoretically, the study advances an integrative perspective that brings together complementary research directions: institutional modernization theory, digital governance literature, and the analysis of territorial inequalities. Through this synthesis, AI is not interpreted as a simple technological extension but as an expression of the organizational capacity to respond to exogenous pressures—be they technological, social, or normative—in an adaptive and contextualized way. The results obtained confirm that regional inequalities do not constitute mere statistical gaps, but reflect distinct institutional configurations, in which the availability for innovation is closely linked to the degree of professionalization, the density of administrative networks, and the organizational culture specific to each state.

In doing so, this study not only confirms existing assumptions from prior research but also contributes a territorialized reading of AI adoption, integrating the macro-level conditions of digital readiness with the meso-level dynamics of institutional capacity—a connection often neglected in current public administration theory. Moreover, by consolidating diverse strands of the literature into a coherent analytical framework, this research advances a replicable model for understanding algorithmic governance as a spatially contingent and institutionally embedded phenomenon.

5.2. Methodological Foundations and Practical Implications

From a methodological point of view, the construction of a composite AI adoption index, corroborated with the successive application of probit models—standard, multilevel, and multivariable—provides a rigorous analysis platform, capable of capturing the nuances of the decision-making process at the local level. This layered statistical architecture strengthens the internal validity of the findings, enabling the identification of context-sensitive effects often overlooked in linear modeling frameworks.

The integration of the simulated components into the general model allows for an operational transposition of the results, facilitating a pragmatic understanding of the adoption mechanisms and offering a valuable tool for the formulation of differentiated public policies. In particular, scenario simulations offer an evidence-based mechanism for anticipating the administrative behavior of diverse institutional profiles, making the model directly useful for policy experimentation and calibration.

At the same time, interpreting the results through the proposed theoretical framework allows for a thorough and coherent reading of the AI adoption process. For example, the significant influence of IT personnel and education level validates the hypotheses of the institutional capacity theory, while the differentiated effects between regions (confirmed by the ICC) support the theory of digital territorial inequalities. The positive correlation with the DESI score expresses the degree of regional digital readiness, specific to digital governance, and the role of innovative urban institutions reflects the processes described in the theory of institutional modernization. Thus, the empirical results align with the integrated theoretical model, providing a layered explanation of the administrative decision-making dynamics.

The practical consequences of this research are particularly relevant for the development of administrative intervention strategies. The simulated typologies, which reflect recognizable regional profiles, provide a functional map of institutional diversity and the degree of digital maturity. For example, for local administrations located in western regions, which have advanced digital infrastructure, qualified human capital, and an organizational culture receptive to innovation, it is necessary to strengthen the capacity for algorithmic experimentation. According to Okewu et al. (2019), these entities can benefit from public policies that stimulate partnerships with research centers, ethical assessment of the use of AI in decision-making processes and the progressive integration of generative solutions in relations with citizens. Hence, the model not only diagnoses but also strategically informs interventions that address the uneven territorial landscape of AI deployment in the public sector.

5.3. Strategic Recommendations for Fair Algorithmic Governance

Urban administrations in regions in transition, where urbanization is high, but institutional capacity remains fragile, should be supported through continuous professionalization programs, attracting digital skills and encouraging inter-institutional collaborations. In these cases, it is appropriate to create local administrative innovation hubs, which would function as facilitators of algorithmic adoption in local administration.

For administrations in the eastern regions, which face systemic structural challenges—including infrastructure and staffing deficits—public policies need to be compensatory. Investments in basic connectivity, support for the recruitment and retention of IT staff, and interregional cooperation mechanisms are needed to jointly access relevant expertise and technologies.

In the case of isolated rural administrations, where resources are limited and the level of digitalization is minimal, it is recommended to form territorial consortia for shared digitalization, implement open-source solutions with government support, and develop inter-municipal mentoring networks. Only through such interventions can the transition to an inclusive algorithmic administration be supported, capable of responding to the requirements of equitable governance in the territory.

A further strategic dimension concerns interoperability and the adoption of open standards across local and regional administrations. Ensuring that AI solutions are compatible, modular, and adaptable to local needs enhances not only efficiency but also resilience and institutional sovereignty in digital transformation efforts. In line with the calls made by Pencheva et al. (2020), public policies on AI should not be uniform but contextually calibrated, taking into account the institutional specificity and real resources of each local administration.

Furthermore, any public policy strategy aimed at promoting the adoption of AI must be supported by a robust monitoring and evaluation framework. This framework should integrate both quantitative indicators—such as adoption rates, service efficiency gains, or digital equity indices—and the qualitative assessments of organizational adaptability, user satisfaction, and ethical safeguards. In the absence of such feedback loops, algorithmic governance risks not only perpetuating but even deepening existing institutional asymmetries.

Beyond the concrete recommendations, the research also opens up relevant perspectives for the specialized literature. By focusing on the territorial dimension of AI adoption and by combining a rigorous quantitative approach with a sophisticated theoretical framework, this study invites a reconceptualization of the digitalization of public administration not as a simple technological transformation but as a differentiated institutional process, deeply shaped by the context in which it takes place. In this sense, local administrations can no longer be treated as passive implementers of technologies imposed from above

but become reflexive actors of algorithmic governance, with a strategic autonomy whose recognition is indispensable for the success of any digital modernization initiative.

6. Conclusions

The present study provided a detailed empirical radiography of the mechanisms shaping the adoption of artificial intelligence (AI) technologies in local public administration in Germany, in a complex federal context marked by deep structural and territorial inequalities. By using a multilevel methodological design, which integrates both local variables and regional conditionings, this research was able to highlight the fact that digitalization processes are not uniformly distributed but reflect heterogeneous institutional configurations and structural capacities.

The results obtained indicate a significant relationship between the level of human capital, digital infrastructure, and the probability of integrating AI into administrative processes. The share of IT staff and regional DESI scores appear as relevant predictors of institutional capacity, while local economic and demographic variables—such as average income and degree of urbanization—substantially influence organizational openness to innovation. The multilevel model also demonstrated significant interregional variation, which highlights the need to adapt public policies to territorial specificity and existing institutional networks. These findings are consistent with previous research on digital capacity in public institutions (Gil-García et al., 2021), which emphasized the role of both technical infrastructure and human competencies in shaping innovation trajectories in government.

By formulating simulated scenarios, the research managed to translate quantitative data into an applicable analytical tool, capable of underpinning differentiated political decisions and supporting strategies to reduce digital divides. This practical contribution complements the theoretical value of the paper, which proposes an integrated framework for understanding digital transformation processes in the public sector at the intersection of institutional resources, territorial dynamics, and contextual factors.

In the long term, the analysis opens up relevant perspectives for the development of a European comparative research agenda in the field of public administration digitalization, emphasizing the role of AI not only as a disruptive technology but as a vector of structural reform. Thus, local administrations are no longer simple implementation entities but become strategic actors of algorithmic governance, with the potential to actively shape the future of public administration. This perspective aligns with recent shifts in the literature on algorithmic governance (Yarovoy, 2023; Vatamanu & Tofan, 2025), where public administrations are increasingly analyzed as mediators of algorithmic accountability, rather than passive adopters of technology.

While the analytical construction is methodologically robust, certain empirical and conceptual limitations remain, especially related to the absence of qualitative validation and the use of aggregate data that cannot capture intra-organizational diversity. First, the use of aggregated data at the local and regional level—although valuable for territorial modeling—may mask significant variations at the intra-institutional or inter-organizational level. AI adoption, as a complex process, is influenced not only by structural and institutional variables but also by subtle organizational dynamics, difficult to quantify in the absence of a qualitative component.

Secondly, DESI scores, although useful as synthetic indicators of digital readiness, do not fully capture the particularities of the local administrative context, being constructed mainly for comparisons between states, not between sub-national units. Also, the model does not yet integrate normative or cultural variables, such as resistance to change, organizational climate, or the attitudes of key actors in local administrations.

Regarding the future of research, a promising direction is the integration of mixed methodological designs, combining multilevel quantitative analysis with semi-structured interviews, comparative case studies, and organizational ethnography techniques. Another line of development consists of extending the current model by including temporality—either through longitudinal studies or dynamic simulations—to capture the evolution of AI adoption over time and institutional reactions to public policies of digital stimulation. As [Gil-Garcia et al. \(2018\)](#) suggest, future research should delve deeper into the dimension of public perception of AI, integrating qualitative analyses that assess the impact of algorithms on the legitimacy of administrative processes.

Last but not least, it is worth exploring in depth the ethical and democratic legitimacy dimension of AI in public administration, as well as investigating how algorithmic solutions can strengthen or, conversely, erode citizens' trust in state institutions. As such, the integration of ethical design principles and algorithmic transparency standards becomes imperative—not only to legitimize AI use in public administration, but to foster democratic resilience in an increasingly automated policy environment ([Floridi & Cowls, 2022](#); [Wirtz et al., 2019](#)).

Author Contributions: Conceptualization, L.M.C. and I.O.; methodology, M.M. and I.O.; software, I.O.; validation, L.M.C., M.M. and I.O.; formal analysis, L.M.C., M.M. and I.O.; investigation, M.M. and I.O.; resources, L.M.C., M.M. and I.O.; data curation, L.M.C., M.M. and I.O.; writing—original draft preparation, L.M.C. and I.O.; writing—review and editing, I.O.; visualization, L.M.C., M.M. and I.O.; supervision, I.O.; project administration, I.O. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
DESI	Digital Economy and Society Index
DESTATIS	Federal Statistical Office
NUTS	Nomenclature of Territorial Units for Statistics
BBSR	Federal Institute for Building, Urban and Spatial Research
BMWK	Federal Ministry for Economic Affairs and Climate Protection
GovData	Open Government Data
EFA	Exploratory Factor Analysis
MCMC	Markov Chain Monte Carlo

References

- Abu Bakar, K. A., Ibrahim, R., & Yunus, Y. (2020). Digital government evolution and maturity models: A review. *Open International Journal of Informatics*, 8(2), 70–87.
- Ahn, M. J., & Chen, Y.-C. (2022). Digital transformation toward AI-augmented public administration: The perception of government employees and the willingness to use AI in government. *Government Information Quarterly*, 39(2), 101664. [[CrossRef](#)]
- Al-Mushayt, O. S. (2019). Automating e-government services with artificial intelligence. *IEEE Access*, 7, 146821–146829. [[CrossRef](#)]
- Babšek, M., Ravšelj, D., Umek, L., & Aristovnik, A. (2025). Artificial intelligence adoption in public administration: An overview of top-cited articles and practical applications. *AI*, 6(3), 44. [[CrossRef](#)]

- BBSR—Federal institute for building, urban and spatial research. (2022). Available online: https://www.bbsr.bund.de/BBSR/EN/home/_node.html (accessed on 27 January 2025).
- BMWK—Federal ministry for economic affairs and climate protection. (2022). Available online: <https://www.bmwk.de/Navigation/EN/Home/home.html> (accessed on 29 January 2025).
- Caiza, G., Sanguña, V., Tusa, N., Masaquiza, V., Ortiz, A., & Garcia, M. V. (2024). Navigating governmental Choices: A comprehensive review of artificial intelligence's impact on decision-making. *Informatics*, 11(3), 64. [CrossRef]
- Chatwin, R., & Arku, G. (2022). Multilevel governance and the role of local governments in digital innovation. *Journal of Urban Affairs*, 44(5), 732–749.
- Chen, Y.-C., Ahn, M. J., & Wang, Y.-F. (2023). Artificial intelligence and public values: Value impacts and governance in the public sector. *Sustainability*, 15, 4796. [CrossRef]
- Chiancone, C. (2023). *Understanding the role of AI in government decision making*. Available online: <https://www.linkedin.com/pulse/understanding-role-ai-government-decision-making-chris-chiancone> (accessed on 13 January 2025).
- de Sousa, W. G., de Melo, E. R. P., Bermejo, P. H. d. S., Farias, R. A. S., & Gomes, A. O. (2019). How and where is artificial intelligence in the public sector going? A literature review and research agenda. *Government Information Quarterly*, 36(4), 101392. [CrossRef]
- DESTATIS—Federal statistical office. (2022). Available online: https://www.destatis.de/DE/Home/_inhalt.html (accessed on 27 January 2025).
- Digital Decade. (2024). *Digital decade 2024: Broadband coverage in Europe 2023*. Available online: <https://digital-strategy.ec.europa.eu/en/library/digital-decade-2024-broadband-coverage-europe-2023> (accessed on 22 January 2025).
- Distel, B., & Lindgren, I. (2023). A matter of perspective: Conceptualizing the role of citizens in e-government based on value positions. *Government Information Quarterly*, 40(4), 101837. [CrossRef]
- Dunleavy, P., Margetts, H., Bastow, S., & Tinkler, J. (2006). *Digital era governance: IT corporations, the state, and e-government*. Oxford University Press.
- European Commission. (2022). *Digital economy and society index (DESI) 2022—Country report: Germany*. European Commission. Available online: <https://digital-strategy.ec.europa.eu/en/policies/desi-germany> (accessed on 22 January 2025).
- Eurostat. (2022). *Digital economy and society statistics—E-government survey*. European Commission. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=E-government_statistics (accessed on 31 January 2025).
- Febianini, V. V., & Sony, M. S. (2023). Analysis of public administration challenges in the development of artificial intelligence industry 4.0. *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, 4(2), 164–168. [CrossRef]
- Floridi, L., & Cows, J. (2022). Ethics and governance of artificial intelligence: Public anxieties and regulatory challenges. *Journal of Information, Communication and Ethics in Society*, 20, 45–62.
- Ghibanu, I. A. (2019). Strategies and Techniques of Organizational Image Building. *Postmodern Openings*, 10(1), 193–199. [CrossRef] [PubMed]
- Gil-Garcia, J. R., Dawes, S. S., & Pardo, T. A. (2018). Digital government and public management research: Finding the crossroads. *Public Management Review*, 20(5), 633–646. [CrossRef]
- Gil-García, J. R., Dawes, S. S., Pardo, T. A., & Sayogo, D. S. (2021). Digital government and AI: Understanding adoption patterns in multilevel contexts. *Government Information Quarterly*, 38(3), 101589.
- Gil-García, J. R., Sayogo, D. S., & Mellouli, S. (2022). Local government and artificial intelligence: Institutional readiness and policy implications. *Information Polity*, 27(2), 221–235.
- GovData—National open data portal. (2022). Available online: <https://www.govdata.de/> (accessed on 29 January 2025).
- Manzoor, A. (2016). Emerging role of big data in public sector. In *Big data: Concepts, methodologies, tools, and applications* (pp. 1–12). IGI Global.
- Margetts, H., & Dorobantu, C. (2019). Rethink government with AI. *Nature*, 568(7751), 163–165. [CrossRef] [PubMed]
- Medaglia, R., & Tangi, L. (2022, October 4–7). *The adoption of artificial intelligence in the public sector in Europe: Drivers, features, and impacts* [Conference session]. ICEGOV'22: Proceedings of the 15th International Conference on Theory and Practice of Electronic Governance, Guimarães, Portugal.
- Mikalef, P., Krogstie, J., Pappas, I. O., & Giannakos, M. (2021). Investigating the effects of big data analytics capabilities on firm performance: The mediating role of dynamic capabilities. *Information & Management*, 58(6), 103434. [CrossRef]
- Okewu, E., Misra, S., Okewu, J., Damaševičius, R., & Maskeliūnas, R. (2019). An intelligent advisory system to support managerial decisions for a social safety net. *Administrative Sciences*, 9, 55. [CrossRef]
- Olejnik, K. (2023). Regional disparities and digital transformation in decentralized governance. *Regional Studies*, 57(3), 377–392.
- Pencheva, I., Esteve, M., & Mikhaylov, S. J. (2020). Big Data and AI—A transformational shift for government: So, what next for research? *Public Policy and Administration*, 35(1), 24–44. [CrossRef]
- Peters, B. G. (2015). *Advanced introduction to public policy*. Edward Elgar Publishing.
- Pislaru, M., Vlad, C. S., Ivascu, L., & Mircea, I. I. (2024). Citizen-centric governance: Enhancing citizen engagement through artificial intelligence tools. *Sustainability*, 16(7), 2686. [CrossRef]

- Pollitt, C., & Bouckaert, G. (2017). *Public management reform: A comparative analysis—Into the age of austerity* (4th ed.). Oxford University Press.
- Rathnayake, A. S., Nguyen, T. D. H. N., & Ahn, Y. (2025). Factors influencing AI chatbot adoption in government administration: A case study of Sri Lanka's digital government. *Administrative Sciences*, 15, 157. [\[CrossRef\]](#)
- Scholl, H. J. (2020). Digital government: Looking back and ahead on a fascinating domain of research and practice. *Digital Government: Research and Practice*, 1(1), 1–12. [\[CrossRef\]](#)
- Shareef, M. A., Kumar, V., Kumar, U., & Dwivedi, Y. K. (2011). e-Government Adoption Model (GAM): Differing service maturity levels. *Government Information Quarterly*, 28(1), 17–35. [\[CrossRef\]](#)
- Silitonga, F., & Isbah, M. F. (2023). Artificial intelligence and the future of work in the Indonesian public sector. *Jurnal Ilmu Sosial dan Humaniora*, 12(2), 296–308. [\[CrossRef\]](#)
- Straub, V. J., Morgan, D., Bright, J., & Margetts, H. (2023). Artificial intelligence in government: Concepts, standards, and a unified framework. *Government Information Quarterly*, 40(4), 101881. [\[CrossRef\]](#)
- Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of artificial intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly*, 36(2), 368–383. [\[CrossRef\]](#)
- Tangi, L., Benedetti, M., Gastaldi, L., & Noci, G. (2021). Investigating the use of artificial intelligence in public services: Evidence from the Italian context. *Government Information Quarterly*, 38(1), 101546. [\[CrossRef\]](#)
- Tyson, A., & Kikuchi, E. (2023). *Growing public concern about the role of artificial intelligence in daily life*. Pew Research Center.
- van Dijk, J. A. G. M. (2005). *The deepening divide: Inequality in the information society*. SAGE Publications.
- Vatamanu, A. F., & Tofan, M. (2025). Integrating artificial intelligence into public administration: Challenges and vulnerabilities. *Administrative Sciences*, 15(4), 149. [\[CrossRef\]](#)
- Warschauer, M. (2003). *Technology and social inclusion: Rethinking the digital divide*. MIT Press.
- Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector—Applications and challenges. *International Journal of Public Administration*, 42(7), 596–615. [\[CrossRef\]](#)
- Yarovoy, T. (2023). Opportunities and risks of the use of artificial intelligence in public administration. *Economic Synergy*, (2), 36–47.
- Yigitcanlar, T., David, A., Li, W., Fookes, C., Bibri, S. E., & Ye, X. (2024). Unlocking artificial intelligence adoption in local governments: Best practice lessons from real-world implementations. *Smart Cities*, 7, 1576–1625. [\[CrossRef\]](#)
- Zuiderwijk, A., Chen, Y. C., & Salem, F. (2021). Implications of the use of artificial intelligence in public governance: A systematic literature review and a research agenda. *Government Information Quarterly*, 38(3), 101577. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.