Artificial Intelligence in Demography:

A study on Demographic Models and the Capacity of Artificial Intelligence

Abstract

With the mounting challenges presented by the intersection of Big Data and increasingly ambitious demographic research, a possible answer lies in the rise of AI especially in the way it relates to data-driven decision making. The support of AI in assessing potential impacts of public policy on targeted population groups at national and intergovernmental levels could reshape the political landscape at a global level. This paper aims to assess how AI is reshaping our access to and understanding of demographic data as well as its potential intersection with public policy in the future. It will assess the current state of demographic research and the limitations that demographers often face like data quality and availability, challenges in measurement especially for migration, data comparability over time especially in places with low amounts of vital registration, and access and privacy constraints especially in the European Union considering the General Data Protection Regulation. A literature review will uncover the advantages of using different AI techniques, especially machine learning and predictive modeling in the case of demographic research, and discuss the ethical use of AI in creating policy recommendations considering transparency and biases in population data. The detailed design of this project will be covered under the methodology section as this assessment will be conducted with a mixed methods approach using both qualitative evidence, in the form of examining perspectives of demographers, AI developers, and EU policymakers, and quantitative evidence, achieved by performing a case study of AI generated demographic reports. The project will then cover the current uses of AI in three demographic databases: Eurostat, World Bank, and ISTAT. The coverage of these databases will include an assessment of the current institutional applications, capabilities in population forecasting and predictive modeling, and the state of automation in statistical reporting. A case study will be performed that reviews the capabilities of AI in understanding a demographer's query, processing the data required, and generating demographic statistics. The study will then review stakeholder perspectives on the use of AI in demography by considering demographers, policymakers, and AI developers positions. These perspectives will include their perspective on whether AI is an opportunity or challenge in the collection and processing of data, the implications of automated forecasting, and its potential for influence on public policymaking. Based upon the results of stakeholder perspectives a section will be dedicated to recommendations to databases that house the data required for demographic research especially the ones considered in the analysis of current applications of AI in demographic databases on how to better implement AI within the database structure with explanations on why these changes would directly impact the field of demographic research. Finally, a discussion will be made on the results of the study and present a list of guidelines for policymakers to consider when utilizing automatically generated demographic data within their policymaking framework.

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1. Introduction

Background of Demography and the Role of Artificial Intelligence

Demography is the scientific study of human populations, focusing on their size, structure, distribution, and change over time through processes such as fertility, mortality, and migration. As a discipline, it emerged from early attempts to apply quantitative methods to social issues, gradually developing into a core social science that informs public policy, economics, public health, and urban planning. The origins of demography are usually traced to the seventeenth century, particularly to the work of John Graunt, whose analysis of London's "Bills of Mortality" demonstrated that births and deaths followed statistical regularities that could be studied scientifically[1]. Graunt's work laid the foundations for life tables and statistical population analysis, which became central tools in demographic research. The term *demography* itself was first used in 1855 by Achille Guillard, though the discipline had already been developing through the work of early "political arithmetic" scholars such as Edmond Halley and Johann Peter Süssmilch[2]. These scholars sought to apply mathematics and probability to population data in order to understand social and political processes. Over time, demography evolved from simple descriptive statistics into a broader analytical field concerned with the causes and consequences of population change. During the nineteenth and twentieth centuries, demography became institutionalized within universities, statistical offices, and international organizations. Advances in census-taking, civil registration systems, and statistical methods allowed researchers to examine population dynamics in greater detail. By the mid-twentieth century, demography had expanded to include theories such as the demographic transition, which describes the shift from high birth and death rates to lower rates as societies industrialize and develop. An important development included the development of multiple regression models that challenged the traditional basis of population forecasting and progression and opened the study of single driving forces for demographic change. This is supported by studies like those conducted by Francesco Billari that shift the paradigm of demography as a "slow" method of analysis focused on fertility mortality and aging into building capabilities to measure "fast" changes in demographic balance like migration, mobility, and shocks[3]. As demographers, we must accept that pursuing traditional methods of "slow" demography based on gradual, cohort-based methods, useful for analytical value in the form of momentum of age structure, generational replacement as an engine of change, and the predictability of long term trends, leaves the theory and policy relevance of

[1] Henry Connor, "John Graunt F.R.S. (1620–1674): The Founding Father of Human Demography, Epidemiology and Vital Statistics," *Journal of Medical Biography* 32, no. 1 (2022): 57–69, https://doi.org/10.1177/09677720221079826

[2] John Rennie Short, *Demography and the Making of the Modern World: Public Policies and Demographic Forces* (Cambridge: Agenda Publishing, 2024), 1–4, https://doi.org/10.1017/9781788217057.001.

[3] Billari, F. C. (2022). Demography: Fast and slow. Population and Development Review, 48(1), 9-30. DOl: 10.1111/padr.12464

demographic analysis weakened[4]. Ability to track and measure demography in terms of "flows" rather than "stocks" is the key to pursuing "fast" demography and include it within demographic research[5]. By framing demography in the context of a more dynamic and mobility oriented perspective we are able to track "fast" demographic change that has significant impact in countries like Germany that was subject to refugee inflows during the 2010s and as a result population dynamics were completely reshaped[6]. The ability to measure both "slow" and "fast" demographic changes provides a compelling challenge to modern demographers because recognizing and developing solutions to pursuing this duality in the field allows for improved demographic theory and policy analysis. Modern demography also integrates insights from sociology, economics, geography, and public health, reflecting its interdisciplinary nature and its role in addressing issues such as aging populations, migration, urbanization, and global inequality.

In recent decades, technological change has significantly transformed demographic research. While traditional demography relied heavily on censuses, surveys, and vital statistics, contemporary researchers increasingly use computational methods and large scale datasets[7]. According to some demographers, the field is in danger of weakening due to an increasing need to adapt conceptually, methodologically, and institutionally to remain politically relevant in a period of rapidly changing global phenomena[8]. Pesando, Dorélien, St-Denis, and Santos argue that there are three driving factors to the diminishing of demographic relevance in politics including institutional visibility and identity (in the sense that demography often exists within a multitude of departments in institutional environments and thus lacks intellectual distinctiveness), persistent inequalities in data availability that shape research agendas, and gaps in training and pedagogy in the profession failing to reflect the interdisciplinary nature of contemporary population issues[9]. The expansion of big data and new digital traces like advertising on social media platforms has opened the field to the reality of shifting global dynamics and population relevancy, an expansion that could be more easily handled with the inclusion of artificial intelligence and machine learning as tools to be used by demographers in their research by simplifying the navigation of datasets and pertinent information as well as providing calculations and forecasting[10]. It is especially necessary in countries with historically limited population metrics like those found in developing countries because of the lack of persistent data meaning digital tracing may be the only way to accurately measure statistics like the study conducted by Rampazzo, Zagheni, Weber, and Testa in which Facebook advertising

[4] Ibid.
[5] Ibid.
[6] Ibid.
[7] C. F. Breen, "New Data Sources for Demographic Research," *Population and Development Review* (2025)
[8] Luca Maria Pesando, Audrey Dorélien, Xavier St-Denis, and Alexis Santos (2023), "Demography as a Field: Where We Came From and Where We Are Headed," *Canadian Studies in Population* 50(3).
[9] Ibid.
[10] Francesco Rampazzo, Emilio Zagheni, Ingmar Weber, and Maria C. Testa, "Mater Certa Est, Pater Numquam: What Can Facebook Advertising Data Tell Us about Male Fertility Rates?" *Proceedings of the International AAAI Conference on Web and Social Media* 12 (2018), https://ojs.aaai.org/index.php/ICWSM/article/view/15078.

data was used to calculate congruencies in male fertility data provided by the UN. Artificial intelligence and machine learning have begun to play a growing role in analyzing population processes and improving demographic forecasts. Machine-learning models are now used to predict fertility preferences and outcomes by identifying complex, non-linear relationships between variables such as education, income, and access to healthcare[11]. These relationships are generally considered too complex for traditional statistical models to capture as effectively or accurately, not to mention the time dedication required to obtain the result is far more while using traditional methods. By combining innovative approaches to digital tracing and modern tools like artificial intelligence and machine learning, obtaining and processing the data required for calculating demographic statistics becomes more reactive to sudden change by responding in real time to shocks, mobility, and migration as well as covering data gaps in developing countries where persistent data is much more difficult to obtain. AI is also being applied to broader demographic questions. Studies have used machine-learning algorithms to classify and forecast fertility rates, helping policymakers design targeted health and education interventions. These models can process large demographic surveys and identify key predictors such as age, family size, and socioeconomic status. Systematic reviews show that since around 2010 there has been rapid growth in the use of AI techniques to forecast fertility transitions and demographic trends at both individual and population levels[12].

Migration research has likewise benefited from AI tools. Machine-learning systems can combine official statistics with new data sources such as online search trends or geolocated events to forecast migration flows and asylum applications with greater accuracy[13]. This reflects the positive influence of the introduction of big data and innovative digital tracing by measuring real time flows in population and providing up to date models that contain pertinent information. These models help governments anticipate sudden migration changes and improve planning for social services and infrastructure. Researchers note that integrating machine learning with traditional demographic models can enhance prediction and account for complex interactions among social, economic, and environmental factors[14] [15].

Data-driven Decision Making and Database Navigation

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[11] Jamilu Sani *et al.*, "Application of Machine Learning Algorithms and SHAP Explanations to Predict Fertility Preference among Reproductive-Age Women in Somalia," *Scientific Reports* (2025).
[12] Shalvi Singh, "Artificial Intelligence Models for Predicting Fertility Transitions: A Systematic Review," *Asian Journal of Research in Computer Science*, May 20, 2025, https://journalajrcos.com/index.php/AJRCOS/article/view/684.
[13] Marcello Carammia, Stefano Maria Iacus, and Teddy Wilkin, "Forecasting Asylum-Related Migration Flows with Machine Learning and Data at Scale," *Scientific Reports* 12 (2022): 1457, https://doi.org/10.1038/s41598-022-05241-8.
[14] Irina Grossman, Kasun Bandara, Tom Wilson, and Michael Kirley, "Can Machine Learning Improve Small Area Population Forecasts? A Forecast Combination Approach," *Computers, Environment and Urban Systems* 95 (July 2022): 101806, https://doi.org/10.1016/j.compenvurbsys.2022.101806
[15] Lasare Samartzidis, Marco Quatrosi, and Angelika von Dulong, "Gender and Age Matter! Identifying Important Predictors for Subjective Well-being Using Machine Learning Methods," *Social Indicators Research* 179 (2025): 955–978, https://doi.org/10.1007/s11205-025-03643-5.

Artificial intelligence has significant potential to transform how researchers navigate databases and information systems in the future by making discovery, organization, and synthesis far more efficient. Traditional database navigation often relies on keyword searches and manual filtering, which can struggle to handle the exponential growth of scholarly outputs and complex interdisciplinary queries; AI-enhanced information-retrieval systems, by contrast, use machine learning, natural language processing, and neural networks to interpret user intent, rank results by semantic relevance, and personalize recommendations based on prior interactions[16]. These tools can dramatically improve indexing, classification, and retrieval accuracy while reducing the time researchers spend locating relevant sources and datasets. Generative-AI-driven search engines and academic tools already demonstrate this shift: platforms such as Semantic Scholar automatically summarize papers and identify key relationships among studies, while retrieval-augmented generation systems dynamically connect language models to external databases so that answers are grounded in up-to-date scholarly materials rather than static training data[17]. Research on AI-assisted literature navigation shows that systems combining semantic embeddings, bibliographic extraction, and contextual ranking can significantly improve the relevance of retrieved documents and reduce information overload, enabling faster decision-making and exploration of complex knowledge domains. In systematic reviews and horizon-scanning contexts, AI tools can automate large portions of data retrieval and screening, reducing manual workload by over half while maintaining high recall of relevant sources, illustrating the efficiency gains possible when AI helps prioritize and filter database results. Beyond retrieval, AI-enhanced bibliometric and scientometric methods can map research trends, disambiguate authors, predict emerging topics, and recommend collaborations, thereby turning static databases into dynamic knowledge-navigation environments that actively support research planning and innovation. Looking ahead, the integration of large language models and intelligent recommendation systems into academic libraries and research infrastructures could enable conversational database navigation, automated synthesis of literature, and cross-modal searches across text, data, and multimedia, effectively transforming databases from passive repositories into interactive research assistants. While challenges such as bias, transparency, and data governance remain, the trajectory of current research suggests that AI will increasingly help scholars move through vast and fragmented information ecosystems with greater speed, precision, and contextual understanding, reshaping how knowledge is discovered and used across disciplines.

Purpose and Relevance of this Study

The purpose of this study is to determine the current state of artificial intelligence in demographic research (especially its presence within databases), determine whether it is effective

[16] Shireen F. Malo and Adel Al-zebari, "Intelligent Semantic Search for Academic Journals Using AI and NLP Techniques," *Journal of Information Systems Engineering and Management* 10, no. 41s (2025): abstract, https://www.jisem-journal.com/index.php/journal/article/download/7884/3594/21464

[17] "About Semantic Scholar," *Semantic Scholar.*

in providing accurate forecasting and calculations of various demographic statistics (like fertility rates, age-dependency ratio, and net migration rate) as well as propose an automated natural language processing system that can generate policy recommendations on the basis of forecasts and calculations. This being established it is important to dispel the anxieties of readers by stating that such a system should in no way replace genuine demographic experts especially because artificial intelligence is fallible and subject to bias[18]. The proposed system should serve as a regulated tool to be used by demographic experts while conducting their research. Overall, the purpose of this study is to render demographic research easier by intertwining modern technology with demographic researchers themselves and empower them to make compelling arguments for political change to policymakers directly.

This study is relevant because of the ongoing integration of AI into commercial, consumer, and governmental systems in the interest of creating more and more efficient solutions to practically any problem. AI is a hotbed of professional debate and public fear with many convinced that it could replace human labor entirely, especially intellectual labor[19]. Sam Altman, the CEO of OpenAI, has even admitted that without serious regulation AI could be used to spread misinformation and even perform large scale cyber attacks[20]. This study will take a cautiously optimistic stance toward AI in demography which is to say that AI should be fully implemented in the field of demography with the proper guidelines and regulations to make it useful to the global population. Proper guidelines and regulations are important to establish to avoid statistical misrepresentations of data as well as identify and acknowledge bias in data collection which could wholly misrepresent historically marginalized groups.

AI in demography is especially relevant because of the implications of statistical misrepresentations of data that can be automatically processed by artificial intelligence without regard for bias. With proper human oversight AI can be effectively used to generate the graphical and statistical representations of demographic data as well as generate useful policy recommendations based on these automatically generated results when paired with advanced natural language processing mechanisms. This is an urgent area of research because of the rapid, nearly exponential growth of AI and the comparably slow process of regulation that has already resulted in the spread of misinformation[21]. My position is that AI could be used to spread misinformation in the form of poorly founded, biased demographic statistics resulting in policies that adversely affect portions of any given population and consequently the polity as a whole.

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[18] K. Sokol, "Artificial Intelligence Should Support Clinical Decision-Making and Not Replace Clinicians," *PMC Article* (2025)

[19] Channarong Intahchomphoo et al., "Effects of Artificial Intelligence and Robotics on Human Labour: A Systematic Review," *Legal Information Management* 24, no. 2 (2024): 109–124, https://doi.org/10.1017/S1472669624000264

[20] Edward Helmore, "We Are a Little Bit Scared: OpenAI CEO Warns of Risks of Artificial Intelligence," *The Guardian*, March 17, 2023.

[21] "A political consultant faces charges and fines for Biden deepfake robocalls," *NPR*, May 23, 2024.

This is why it is crucial that AI be properly regulated as a tool to be used for properly calculating and forecasting demographic statistics.

The implications of a properly regulated and implemented system of artificial intelligence in demographic research are numerous and could provide a more efficient and accurate way of calculating historically difficult demographic questions like the impact of migrant populations on a polity. I believe that it is imperative that demographers consider the use of properly regulated AI within their research because it would render the process of calculating impacts of various factors like fertility, age dependency, and population aging a rapid process meaning that research could respond to events like pandemics or high volume migration patterns in real time rather than providing a retrospective report. I believe this would signify a paradigmatic change in the field of demography as the information provided could influence policy decisions with reliable evidence.

Research questions

- How is AI currently used in demographic research and databases?
- What is the effectiveness of AI in generating insights for public policy based on automated demographic calculations and forecasting?
- Based on this effectiveness, how should AI be governed to best benefit and protect the private data that feeds demographic statistics of the citizens of any given polity?

2. Literature Review

2.1 AI in Social Sciences and Demography

Digital demography has consolidated over the past decade as a distinct and methodologically innovative subfield within population studies, reflecting the rapid diffusion of digital infrastructures that generate high-volume, high-velocity, and high-variety data. In contrast to traditional demographic sources, such as decennial censuses, household surveys, and civil registration and vital statistics (CRVS) systems, digital demography incorporates passively generated and continuously updated data streams from social media platforms, mobile phone metadata, satellite imagery, and linked administrative registers. The United Nations Global Working Group on Big Data for Official Statistics has repeatedly emphasized that these new data ecosystems can enhance the timeliness and spatial detail of population estimates, particularly in crisis-affected or data-scarce settings where conventional data collection is delayed or incomplete[22]. Likewise, the OECD has documented how big data sources can complement official statistics by providing near real-time indicators of mobility, labor market dynamics, and demographic change, while also cautioning that such integration requires robust methodological

[22] *Using Big Data for Official Statistics*, UN ESCAP (2022)

validation and governance safeguards[23]. Empirically, social media data have been used in experimental demographic research to estimate international migration stocks, analyze diaspora networks, and monitor attitudinal trends related to fertility, aging, and migration governance[24]. Mobile phone data, especially anonymized call detail records, have been deployed to measure internal displacement following natural disasters (e.g., earthquake and hurricane responses), to model commuting systems and seasonal labor mobility, and to capture urbanization trajectories with a temporal resolution unattainable through traditional census instruments[25]. At the same time, satellite-derived night-time light data and high-resolution geospatial imagery have enabled small-area population estimation and infrastructure mapping in low-income regions, often in collaboration with development institutions[26]. Administrative registers including tax files, social security systems, health insurance databases, and educational enrollment records are increasingly linked within secure statistical frameworks to create dynamic population registers that permit longitudinal tracking and continuous demographic accounting[27]. However, both the United Nations Statistics Division and the OECD stress that the integration of digital traces into official statistics demands rigorous quality-assessment frameworks, transparency protocols, metadata standards, and strong privacy-by-design architectures, given the ethical and legal sensitivities associated with personally generated data and algorithmic inference[28] [29].

Institutional case studies further illustrate how digital demography is being operationalized across multilevel governance systems. Eurostat has undertaken methodological pilots within the European Statistical System to integrate mobile network operator data for tourism and cross-border mobility statistics, as well as web-scraped data for price indices, thereby embedding big-data experimentation into formal statistical production processes[30]. These initiatives align with broader European modernization strategies that emphasize interoperability, administrative data reuse, and digital transformation of statistical infrastructures. The United Nations Population Fund has supported the use of geospatial mapping, satellite imagery, and digital enumeration tools to strengthen population estimation in fragile and conflict-affected states, linking digital demography directly to humanitarian logistics and Sustainable Development Goal

[23] OECD, *Statistics and Data Directorate – About* (OECD, 2025)
[24] Dilek Yildiz et al., *Integrating Traditional and Social Media Data to Predict Bilateral Migrant Stocks in the European Union* (2024).
[25] Takahiro Yabe et al., "Mobile Phone Location Data for Disasters: A Review from Natural Hazards and Epidemics," *EPJ Data Science* (2022).
[26] Haorui Duan et al., "High-Resolution Population Mapping Based on SDGSAT-1 Night-Time Light Images and Built-Up Area Extraction," *International Journal of Remote Sensing* (2024)
[27] United Nations, Department of Economic and Social Affairs, Statistics Division, *Handbook on Registers-based Population and Housing Censuses* (New York: United Nations, 2022), 77, https://unstats.un.org/unsd/demographic-social/publication/handbook-registers-phc.pdf
[28] United Nations, Department of Economic and Social Affairs, Statistics Division, *Handbook on the Use of Big Data for Official Statistics* (New York: United Nations, 2023), chapter 2, section 6.
[29] Organisation for Economic Co-operation and Development (OECD), *Good Practice Principles for Data Ethics in the Public Sector* (Paris: OECD Publishing, 2021), chapters 9-15 .
[30] Eurostat, *Feasibility Study on the Use of Mobile Positioning Data for Tourism Statistics* (Luxembourg: Publications Office of the European Union, 2019).

(SDG) monitoring frameworks[31]. The World Bank has invested extensively in combining satellite imagery, machine learning, and administrative microdata to refine poverty mapping and small-area demographic estimation, demonstrating how remote-sensing and geospatial analytics can enhance policy targeting and fiscal allocation in low- and middle-income countries[32]. At the national level, ISTAT represents a leading example of census transformation: its transition toward a register-based census integrates administrative data with sample surveys and experimental big-data sources, reducing respondent burden while improving temporal frequency and coherence[33]. Collectively, these initiatives demonstrate that digital demography constitutes not merely an academic innovation but a structural reconfiguration of official statistics and population research. They also underscore a dual imperative: while big-data methodologies enable more timely, disaggregated, and policy-relevant demographic insights, they simultaneously necessitate strengthened legal compliance mechanisms, algorithmic accountability structures, and public trust safeguards to ensure that innovation in population measurement does not outpace democratic oversight and data protection norms.

2.2 Digital Demography and Big Data

Digital demography has emerged over the past decade as a distinct and methodologically innovative subfield within population studies, driven by the rapid expansion of large-scale digital traces generated through everyday technologies. Unlike traditional demographic data sources, such as censuses, household surveys, and civil registration systems, digital demography incorporates passively generated and continuously updated data from social media platforms, mobile phone metadata, satellite imagery, and linked administrative registers. Scholars associated with the United Nations Global Working Group on Big Data for Official Statistics have emphasized that these new data streams offer unprecedented opportunities to improve "the timeliness, accuracy, and responsiveness of population statistics, particularly in contexts where conventional data collection is infrequent or disrupted"[34]. Similarly, the OECD has documented how big data can complement official statistics by providing near real-time indicators of mobility, labor markets, and demographic change, while also underscoring the methodological and governance challenges involved[35]. Social media data, for example, have been used in experimental research to estimate migration stocks and flows, track diaspora networks, and

[31] United Nations Population Fund (UNFPA), *State of World Population 2021: My Body Is My Own* (New York: UNFPA, 2021), 11.
[32] World Bank, *Poverty and Shared Prosperity 2022: Correcting Course* (Washington, DC: World Bank, 2022), 9.
[33] Istituto Nazionale di Statistica (ISTAT), *Censimento permanente della popolazione e delle abitazioni – Settima edizione* (Rome: ISTAT, 1 October 2024),
[34] United Nations Global Working Group on Big Data for Official Statistics, *A World That Counts: Mobilising the Data Revolution for Sustainable Development* (New York: United Nations, 2014), and United Nations Global Working Group on Big Data for Official Statistics, *Handbook on the Use of Big Data for Official Statistics* (New York: United Nations, 2023)
[35] Organisation for Economic Co-operation and Development (OECD), *OECD Framework for the Governance of Emerging Technologies* (Paris: OECD Publishing, 2023).

measure public sentiment related to fertility, aging, and migration policies[36]. Mobile phone data, especially call detail records and anonymized location pings, have enabled researchers to map internal displacement after natural disasters, model commuting and seasonal mobility patterns, and analyze urbanization processes with spatial precision not possible through decennial censuses[37]. Administrative registers, including tax, health, education, and social security databases, are increasingly linked within secure statistical infrastructures to create continuous population registers, supporting dynamic demographic monitoring rather than static cross-sectional snapshots. However, leading international bodies consistently stress that the integration of such data requires rigorous quality assessment frameworks, transparency standards, and safeguards for privacy and informed consent, given the ethical sensitivities surrounding personally generated digital traces[38].

Concrete institutional initiatives demonstrate how digital demography is being operationalized within official statistical systems and development institutions. Eurostat has conducted methodological work and pilot projects using mobile network data to estimate tourism flows and cross-border mobility, as well as web-scraped data to enhance price and economic statistics, reflecting the broader European effort to modernize statistical production under the European Statistical System[39]. The United Nations Population Fund has supported the integration of geospatial technologies, satellite imagery, and digital mapping tools into population estimation and humanitarian planning, particularly in fragile states where census data are outdated or incomplete; such efforts align with UN-wide strategies to leverage big data for the Sustainable Development Goals[40] [41]. The World Bank has likewise invested in combining satellite imagery, geospatial analytics, and administrative microdata to refine poverty mapping and small-area population estimates, demonstrating how big data can improve targeting and resource allocation in low- and middle-income countries[42]. At the national level, ISTAT has been at the forefront of census transformation in Europe, transitioning toward a register-based census model that integrates administrative records with survey data and experimental big-data sources, including mobile data, to enhance demographic accuracy and reduce respondent burden[43]. Collectively, these cases illustrate that digital demography is not merely an academic trend but a structural transformation in how population data are produced and used. They also highlight the dual imperative confronting statistical agencies: to harness the analytical power of big data for more timely and policy-relevant demographic insights, while simultaneously strengthening data

[36] Luca Pappalardo et al., "Using Digital Trace Data to Study Migration and Mobility," *EPJ Data Science* 10 (2021), 30.
[37] Takahiro Yabe et al. "Mobile Phone Location Data for Disasters" (2022).
[38] United Nations, *Handbook on the Use of Big Data for Official Statistics,* (2023), chapter 2, section 6.
[39] Eurostat, *Mobile Network Data for Official Statistics: ESSnet Big Data II Results* (Luxembourg: Publications Office of the European Union, 2021), 23.
[40] United Nations Population Fund (UNFPA), *State of World Population 2023: 8 Billion Lives, Infinite Possibilities* (New York: UNFPA, 2023).
[41] United Nations, *Handbook on the Use of Big Data for Official Statistics,* (2023), chapter 2, section 11.
[42] World Bank, *World Development Report 2021: Data for Better Lives* (Washington, DC: World Bank, 2021), 27.
[43] Istituto Nazionale di Statistica (ISTAT), *Uso dei Big Data nella statistica ufficiale* (Rome: ISTAT, 2021).

governance architectures that ensure methodological robustness, legal compliance, and public trust.

2.3 AI and Public Policy

AI in public policymaking: where it is being used and why it matters

AI is moving from "experimental" to operational across the public policy cycle by moving forward with agenda setting, policy design, implementation, monitoring, and evaluation. Governments are increasingly facing high-volume, high-velocity information environments (administrative data, service logs, satellite imagery, text-heavy consultations, etc.). In practice, agencies deploy machine learning to triage cases and allocate resources (e.g., fraud detection, inspection targeting, service demand forecasting), natural language processing to process unstructured text (public comments, legal documents, citizen complaints), and optimization/recommendation systems to support operational decisions (queue management, staffing, routing, eligibility checks). The main policy value proposition is not "automation for the sake of automation," but improved timeliness, consistency, and analytical reach especially when human decision-makers must interpret complex evidence under time constraints.

At the same time, the adoption path in government is shaped by accountability expectations that are often stricter than in the private sector: public authorities must be able to justify decisions, ensure non-discrimination, maintain legal defensibility, and protect citizens' rights. This is why AI governance platforms, tools that operationalize oversight, transparency, and controls, are now central to public-sector AI scale-up. For example, IBM positions watsonx.governance as an end-to-end toolkit for governing and monitoring AI (including generative AI), emphasizing automated monitoring, risk controls, and policy-driven transparency to support regulated and mission-critical environments[44]. Similarly, OneTrust AI Governance is marketed around inventorying AI use cases and models, monitoring risk, reducing bias through oversight, and generating audit-ready documentation features aimed at enabling governance teams to keep pace with rapid AI deployment[45]. In other words, the public-sector AI story is increasingly about institutional capacity: building systems that can demonstrate responsible use at scale, not merely proof-of-concept performance.

Regulatory compliance mechanisms: Why they are foundational and what "good" looks like

Regulatory compliance in AI is not a paperwork afterthought; it is the operational backbone that enables lawful, sustainable deployment. In the EU context, the EU AI Act is explicitly risk-based and imposes strict obligations on "high-risk" systems and separate obligations for

[44] IBM, *watsonx.governance: Govern AI Models for Trust and Transparency* (Armonk, NY: IBM, 2023).
[45] OneTrust, *OneTrust AI Governance: Manage Risk and Build Trust in AI Systems* (Atlanta, GA: OneTrust, 2023).

general-purpose AI including requirements for risk management, data quality, logging/traceability, technical documentation, human oversight, robustness, accuracy, and cybersecurity[46]. In addition, the Act provides for significant penalties—up to €35 million or 7% of worldwide annual turnover for certain infringements (with lower tiers for other violations), which makes compliance mechanisms material to organizational risk management rather than simply ethical "best practice"[47].

A useful way to conceptualize compliance mechanisms is to treat them as controls mapped to the AI lifecycle. Under the EU AI Act's framework for high-risk systems, providers must implement a risk management system as a continuous process, not a one-time assessment[48]. They must also implement a quality management system that institutionalizes compliance through documented policies, procedures, and governance of modifications—effectively making compliance repeatable and auditable[49]. High-risk systems must undergo conformity assessment procedures before being placed on the market or put into service, anchoring compliance in verifiable technical documentation and assessment pathways[50].

In practice, "compliance mechanisms" that stand up to regulatory scrutiny usually include a large variety of regulating systems. One of which is an AI system and model inventory (system-of-record): a maintained register of models/use cases, owners, data sources, intended purpose, risk classification, and deployment status—necessary for demonstrating oversight and for responding rapidly to regulator queries[51]. Documented risk assessments and testing is another compliance mechanism that includes bias evaluation, performance validation, robustness and cybersecurity testing, and where relevant adversarial testing and red-teaming; importantly, these should be repeatable and versioned[52]. Traceability and logging includes the logging of activity to enable reconstruction of system behavior and decisions, which is essential for complaint handling, incident investigation, and audit[53]. Human oversight design is based upon clear human-in-the-loop or human-on-the-loop processes, escalation paths, and training, so that accountability remains anchored in institutional roles rather than outsourced to an algorithm[54]. Another compliance mechanism is incident management and continuous monitoring which includes post-deployment monitoring for drift and harmful outcomes, with defined thresholds and response playbooks. This aligns strongly with the logic of risk management as an ongoing

[46] REGULATION (EU) 2024/1689 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL, Laying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act), 2024 O.J. (L 1689) Article 4.
[47] Ibid, Article 99.
[48] Ibid, Article 9.
[49] Ibid, Article 7.
[50] Ibid, Article 43.
[51] OneTrust, "AI Model Inventory," *OneTrust Glossary* (2024).
[52] European Union, *Regulation (EU) 2024/1689 (Artificial Intelligence Act)*, arts. 9, 12, 15.
[53] Ibid, Articles 12, 16, 72-73.
[54] Ibid, Article 14.

process[55]. Procurement and third-party controls are the final example of compliance mechanisms and include contractual requirements for documentation, testing evidence, transparency, and security all of which are crucial because governments often deploy vendor models[56].

Two widely used anchors for implementing these controls are the EU AI Act obligations for legal compliance and risk management frameworks for operational maturity. The NIST AI Risk Management Framework (AI RMF 1.0) is a prominent reference point in practice because it is designed to be usable across contexts and organizes activities into four functions GOVERN, MAP, MEASURE, MANAGE which translate directly into governance operating models[57]. Governance platforms often explicitly position themselves as tools to operationalize such frameworks through workflows and evidence capture. OneTrust, for instance, describes aligning with NIST's AI RMF and embedding oversight into lifecycle approvals via customizable workflows and integrations[58]. IBM's watsonx.governance similarly emphasizes end-to-end governance with monitoring and risk controls, and it highlights availability in regulated government contexts including FedRAMP-authorized offerings on AWS GovCloud, relevant for U.S. public-sector procurement[59].

The deeper point for public policy is this: compliance mechanisms are capacity-building instruments. They allow agencies to justify decisions, detect and correct harms, maintain legitimacy, and scale innovation without accumulating unacceptable legal and political risk.

AI in politics: risks to democratic processes (deepfakes, disinformation, and real-world cases)

The political domain presents a distinct risk profile because democratic legitimacy depends heavily on the integrity of the information environment and on citizens' ability to attribute speech and intent to real actors. AI-generated and AI-amplified content can erode these conditions in at least three ways including synthetic media that impersonates candidates or officials (deepfakes), industrialized persuasion and microtargeting that accelerates disinformation, and "liar's dividend" dynamics where authentic evidence is dismissed as fake because deepfakes are plausible.

A well-documented example is the New Hampshire "Biden" robocall incident in January 2024. The U.S. Federal Communications Commission (FCC) described illegal robocalls that used a generative-AI voice message imitating President Joe Biden and encouraging potential voters not

[55] Ibid, Article 9.
[56] Matthew Hickok, "Public Procurement of Artificial Intelligence Systems: New Risks and Future Directions," *AI & Society* (2022).
[57] National Institute of Standards and Technology (NIST), *Artificial Intelligence Risk Management Framework (AI RMF 1.0)* (Gaithersburg, MD: NIST, 2023), 3.
[58] OneTrust, *OneTrust AI Governance: Operationalize Responsible AI and Manage AI Risk* (Atlanta, GA: OneTrust, 2023)
[59] IBM, *watsonx on AWS: Secure and Compliant Deployment Options* (2024).

to vote in the primary[60]. The FCC announced a $6 million fine connected to this "election interference" deepfake robocall scheme, illustrating how existing communications law can be mobilized against AI-enabled voter deception even before comprehensive AI election regulation is in place[61]. From a policymaking standpoint, the case is instructive because it links technical manipulation in the form of voice cloning and caller ID spoofing to concrete enforcement levers like telecom compliance obligations, penalties, and deterrence.

A second widely cited case occurred around Slovakia's 2023 election, where AI-generated audio circulated shortly before voting, purporting to capture public figures discussing election manipulation. UNESCO's media literacy materials and multiple investigative accounts treat the episode as an instructive illustration of how synthetic audio can exploit timing and platform dynamics in electoral contexts[62]. Importantly, the risk here is not only whether a deepfake "swings" an election, a claim that can be hard to prove, but that it raises verification costs for journalists, regulators, and the public at precisely the moment when rapid, reliable attribution is most needed.

A third set of examples concerns large-scale elections where misinformation travels primarily through social platforms and messaging channels. During India's 2024 election period, Reuters reported viral deepfake videos involving Bollywood stars that appeared to criticize the prime minister and support the opposition, amplifying concerns about AI manipulation in political communication[63]. This illustrates a broader pattern, specifically that synthetic media can be used not only to impersonate politicians, but also to weaponize the perceived credibility of cultural figures and trusted messengers.

These cases point toward several governance imperatives for democratic resilience that can hopefully deter future intrusions of AI in the influence of democratic elections. The first imperative is provenance and disclosure including clear labeling for synthetic media and political advertising transparency requirements, backed by auditing and enforcement capacity not merely voluntary platform policy. UNESCO's guidelines also stipulate a rapid-response verification ecosystem which would include coordination among electoral authorities, telecom regulators, platforms, and civil society fact-checkers especially during "quiet periods" or information blackouts[64]. Drawing from the findings of the FCC another imperative is platform and telecom accountability especially because disinformation is often a distribution problem as much as a generation problem; the FCC-focused response shows that intermediaries can be required to

[60] Federal Communications Commission (FCC), "FCC Declares AI-Generated Voices in Robocalls Illegal under the Telephone Consumer Protection Act," Declaratory Ruling, February 8, 2024.
[61] Federal Communications Commission (FCC), "FCC Proposes $6 Million Fine for Illegal AI-Generated Robocalls Impersonating President Biden," Notice of Apparent Liability for Forfeiture, May 2024.
[62] UNESCO, *Guidelines for the Governance of Digital Platforms and Elections* (Paris: UNESCO, 2023).
[63] Meryl Sebastian. "AI and deepfakes blur reality in India elections" (BBC Asia: May 2024), https://www.bbc.com/news/world-asia-india-68918330
[64] UNESCO, *Guidelines for the Governance of Digital Platforms and Elections* (Paris: UNESCO, 2023).

tighten controls where legal authority exists[65]. A final imperative is public-sector communications hardening which would necessitate authentication of official communications channels, pre-bunking strategies, and citizen education of media literacy to reduce susceptibility to synthetic persuasion.

Taken together, AI in politics is not merely a "technology threat"; it is an institutional stress test. The same generative capabilities that can support civic services and policy analysis can also be repurposed to undermine trust, distort public discourse, and complicate accountability making governance, compliance, and enforcement design central to any credible public-sector AI strategy.

Population-level AI raises distinct ethical stakes

AI systems trained or deployed on population-level data sit at a particularly sensitive intersection of scale and power. Their outputs including risk scores, resource-allocation recommendations, projections, "hotspot" maps, or eligibility triage can shape real-world distributions of benefits and burdens across communities. This creates a dual ethical obligation: first, to ensure the AI system is technically trustworthy meaning it is valid, robust, and monitored; and second, to ensure it is institutionally accountable meaning it is governed, contestable, and aligned with rights-based constraints. Risk-management approaches such as the NIST AI Risk Management Framework (AI RMF 1.0) explicitly elevate "trustworthiness" characteristics including fairness, accountability, transparency, and privacy as design and governance requirements rather than optional add-ons[66].

A core challenge is that population data is rarely neutral. Demographic and administrative systems encode legal categories, policy priorities, and institutional practices; digital-trace data reflects platform incentives and unequal technology access; and "ground truth" labels like fraud, risk, and compliance often reflect enforcement patterns rather than objective phenomena. NIST's treatment of bias is useful here because it frames bias as broader than representation alone, distinguishing systemic bias that is embedded in institutions and social context, computational or statistical bias found in data and modeling artifacts, and human-cognitive bias which is how people interpret and operationalize model outputs[67].

Ethical frameworks in practice: lessons from Pegasystems "The AI Manifesto"

In applied settings, organizations often translate high-level ethics into operating principles and control points. Pegasystems "The AI Manifesto" is a notable example because it articulates nine principles that connect AI strategy, human oversight, and responsible deployment[68]. These

[65] Federal Communications Commission, "FCC Proposes $6 Million Fine" (May 2024).
[66] NIST, *Artificial Intelligence Risk Management Framework,* 8.
[67] Ibid, 17.
[68] Pegasystems, *The Pega AI Manifesto: Nine Principles for Responsible AI* (Cambridge, MA: Pegasystems, 2023)

principles emphasize, among other themes, that AI should be embedded in actionable decisions and workflows rather than treated as a stand-alone experiment; that "augmented intelligence" should keep humans in control; that organizations should balance "left-brain" analytical AI with "right-brain" generative AI; and that ethical requirements including transparency, accountability, fairness, and privacy-friendliness should be operationalized within tools and processes rather than treated as aspirational slogans[69].

For population-level applications, several of the Manifesto's principles map cleanly onto public-interest safeguards including human control and oversight, outcomes-and-decisions orientation, and ethics beyond compliance. Population analytics often feeds high-impact decisions including benefits, services, policing priorities, health interventions. Keeping humans "in the loop" is not just a safety measure; it is an accountability bridge that preserves contestability and institutional responsibility[70]. Starting from policy outcomes forces explicit articulation of what counts as success and for whom, reducing the risk that the model optimizes proxy metrics such as cost reduction at the expense of equity or rights[71]. The Manifesto explicitly argues that ethics cannot be reduced to "what is allowed" and should instead ask "what should be done" an important stance in social policy contexts where lawful data use may still be socially harmful, stigmatizing, or legitimacy-eroding[72].

The practical takeaway is not that one vendor document should become a universal standard, but that a principle-based framework is only meaningful if it is translated into lifecycle controls that include model documentation, bias testing, monitoring, auditability, and user-facing explanation mechanisms.

Transparency: what it enables and why it becomes difficult under GDPR constraints

In the EU, transparency is not merely a norm; it is an enforceable legal requirement. GDPR Article 12 establishes that information provided to data subjects must be concise, accessible, and written in clear language[73]. When personal data is collected directly or indirectly, controllers must provide specific disclosures, and critically for AI must inform individuals about the existence of automated decision-making in relevant cases and provide "meaningful information about the logic involved," as well as the significance and envisaged consequences for the individual[74].

Where a decision is "solely automated" and produces legal or similarly significant effects, GDPR Article 22 provides additional protections commonly discussed as a "right not to be subject to"

[69] Ibid.
[70] Ibid.
[71] Ibid.
[72] Ibid.
[73] European Union, *Regulation (EU) 2016/679 (General Data Protection Regulation)*, art. 12.
[74] Ibid, Articles 13, 14.

such decisions, subject to exceptions and safeguards[75]. Guidance and commentary from EU data protection institutions highlight the practical implications of these provisions for automated decision-making and profiling, including the need to design safeguards and transparency pathways[76] [77].

Why transparency is hard in population-level AI

Even when transparency is required, it is not straightforward to deliver especially at population scale because of several tensions that render data opaque. Large-scale predictive systems (e.g., ensemble models, deep learning, or complex rule + ML hybrids) can be difficult to explain faithfully. Yet GDPR's emphasis is not on disclosing source code; it is on providing "meaningful information" about logic and consequences. Legal and scholarly debates note that the GDPR does not necessarily demand a complete technical explanation of system functionality, but it does require an informative account that is meaningful to the data subject in context[78]. The proprietary nature of AI models also poses a challenge to transparency. Operational AI systems may incorporate proprietary models or sensitive fraud-detection signals and over-disclosure can facilitate gaming or reveal commercially sensitive information. This creates a recurrent governance problem, namely how to provide sufficient transparency to meet legal and ethical obligations while preserving security and legitimate confidentiality interests, a tension often surfaced in discussions around access requests and automated decision-making[79]. Another challenge to transparency are population analytics which often affect groups without making "solely automated" decisions about individuals. Many population-level uses do not produce individual determinations but still influence service distribution like where clinics are placed and which neighborhoods are targeted for inspections[80]. GDPR rights are primarily individual-facing, so institutions must often go beyond GDPR minima publishing model cards, impact assessments, and audit summaries to achieve democratic legitimacy and procedural fairness. The "transparency paradox" also poses a challenge to transparency by revealing that a larger amount of information can obscure relevant and useful information. More information does not always produce more understanding. GDPR itself recognizes digital-literacy constraints by requiring clear, plain language, meaning transparency must be designed as communication in the form of layered explanations, visual summaries, and plain-language consequence statements not merely documentation dumps[81].

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[75] Ibid, Article 22.
[76] European Data Protection Board (EDPB), *Guidelines 05/2022 on the Use of Facial Recognition Technology in the Area of Law Enforcement* (Brussels: EDPB, 2022)
[77] European Data Protection Board, *Guidelines on Automated Individual Decision-Making and Profiling under Regulation 2016/679* (revised and endorsed 2021)
[78] European Union, *Regulation (EU) 2016/679 (General Data Protection Regulation)*, art. 13.
[79] Callum Duckmanton, "Automated Decision Making: The Impact of the Data (Use and Access) Act 2025 and a Recent CJEU Judgment," *Burges Salmon (Passle)*, June 25, 2025.
[80] Virginia Eubanks, *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor* (New York: St. Martin's Press, 2018).
[81] European Union, *Regulation (EU) 2016/679 (General Data Protection Regulation)*, art. 12.

In short, transparency is essential because it underpins contestability, trust, and lawful processing; but it is also constrained by model complexity, institutional incentives, and the practical limits of what can be communicated meaningfully at scale.

Data availability, coverage, and "who is missing"

Population-level bias is frequently rooted in unequal data availability and uneven coverage across social groups. Digital-trace sources such as social media platforms, smartphone applications, and mobile-phone metadata are generated through voluntary participation and mediated by access to infrastructure, devices, and skills, which leads to systematic overrepresentation of younger, wealthier, and more digitally connected populations[82] [83]. These structural imbalances shape the evidentiary base used in policy analysis and algorithmic systems, meaning that even large datasets can offer only a partial view of the population. In governance contexts where such data inform resource allocation, public health monitoring, or urban planning, gaps in coverage may translate into skewed assessments of need or risk, reinforcing longstanding concerns about participation bias in computational social science[84].

Research on social media participation has highlighted this problem through the concept of "omitted voices." Individuals who are absent from platforms or who participate less frequently or less visibly are often systematically different along socio-demographic dimensions such as age, education, and socioeconomic status, producing biased inferences when platform data are treated as representative of the broader public [85]. Methodological scholarship and policy assessments further stress that platform-derived data are not only selective but also "noisy," shaped by platform affordances, algorithmic amplification, and shifting user practices, all of which complicate generalization beyond the user base from which the data are drawn[86]. These limitations highlight the importance of combining platform data with complementary sources and documenting uncertainty when drawing population-level conclusions.

Mobile-phone data illustrates a similar tension between promise and limitation. Call detail records and mobility traces have been widely promoted as tools for filling statistical gaps, particularly in low- and middle-income settings where survey infrastructures are costly or infrequent and real-time indicators are scarce [87] [88]. At the same time, official-statistics guidance and empirical research consistently note that ownership and usage patterns are uneven across

[82] Eszter Hargittai, "Potential Biases in Big Data: Omitted Voices on Social Media," *Social Science Computer Review* 38, no. 1 (2020): 10–24.
[83] United Nations Population Fund, *The Future of Population Data: ICPD30 Think Piece* (New York: UNFPA, 2024).
[84] National Academies of Sciences, Engineering, and Medicine, *Social Media and Democracy: The State of the Field, Prospects for Reform* (Washington, DC: National Academies Press, 2020).
[85] Hargittai, "Potential Biases in Big Data," 2020.
[86] National Academies, *Social Media and Democracy*, 2020.
[87] United Nations Population Fund, *Future of Population Data*, 2024.
[88] Roland Hosner, Zachary Strain-Fajth, and Veronique Lefebvre, *Bias Estimates for Mobile Phone Data (MPD)-Derived Mobility Statistics in Low- and Middle-Income Countries* (Flowminder Foundation, 2025).

gender, age, rural–urban divides, and socioeconomic status, while practices such as phone sharing and multi-SIM ownership introduce additional interpretive challenges [89]. Consequently, analysts emphasize the need for calibration, weighting, and validation against census or survey benchmarks to mitigate bias and avoid misrepresenting population dynamics.

Taken together, these findings underscore that issues of data availability and coverage are inseparable from questions of who is missing in digital datasets. The absence of certain populations whether due to infrastructural barriers, digital exclusion, cultural norms, or deliberate disengagement creates blind spots that can shape evidence and decision-making [90]. Rather than treating digital-trace data as comprehensive substitutes for traditional statistics, recent scholarship frames them as complementary sources whose limitations must be explicitly acknowledged and documented [91]. Within debates on data availability, the key insight is that representativeness is not guaranteed by scale: even vast digital datasets remain socially situated artefacts that reflect patterns of access, participation, and power.

Administrative data bias and institutional feedback loops

Administrative registers can appear comprehensive because they cover large portions of the population and are produced through routine institutional processes. However, recent research on government data and public-sector AI emphasizes that such datasets reflect administrative visibility rather than social reality, since records are generated only when individuals interact with institutions and according to categories defined by policy and bureaucracy[92]. Consequently, populations outside formal systems including undocumented migrants, informal workers, unhoused individuals, or those avoiding state contact may be missing or only partially represented. Contemporary public-sector AI scholarship highlights that these coverage gaps are not incidental but stem from structural features of administrative data ecosystems, including data quality limitations, incomplete integration across agencies, and institutional reporting incentives[93].

Beyond coverage bias, administrative labels themselves are shaped by policy frameworks and enforcement practices. Eligibility flags, compliance indicators, and risk classifications often emerge from institutional definitions of need, deviance, or vulnerability rather than neutral observation. Empirical work on government data demonstrates that predictive models trained on administrative records can inherit historical disparities embedded in those datasets, with fairness interventions frequently unable to overcome biases rooted in the underlying data distribution and

[89] United Nations Population Fund, *Future of Population Data*, 2024.
[90] Hargittai, "Potential Biases in Big Data," 2020.
[91] United Nations Population Fund, *Future of Population Data*, 2024.
[92] Anastasija Nikiforova et al., "Responsible AI Adoption in the Public Sector: A Data-Centric Taxonomy of AI Adoption Challenges," (2025).
[93] Ibid.

institutional history[94]. These findings underscore that administrative bias is frequently upstream of modeling choices, rooted in the social and organizational processes through which government data are produced.

These dynamics create the conditions for institutional feedback loops. When administrative data inform predictive tools that guide inspections, surveillance, or service allocation, the resulting interventions generate additional records for the same populations already visible in the data. Over time, this recursive process can reinforce the apparent concentration of risk or need in specific communities, blurring the distinction between prevalence and institutional attention. Recent research on responsible AI adoption in the public sector similarly identifies data quality, governance fragmentation, and path-dependent administrative processes as key drivers of biased outcomes and persistent inequalities in automated decision-making[95].

Policy frameworks increasingly recognize these dynamics as forms of systemic bias. The NIST AI Risk Management Framework and related guidance stress that harmful bias may arise from "non-representative training data" and from the amplification of historical and societal inequalities embedded in institutional datasets[96]. From a European perspective, emerging digital-government and AI governance frameworks including the Data Governance Act, Data Act, and the EU AI Act explicitly acknowledge the need for dataset quality, traceability, and bias monitoring, reflecting concerns that administrative and operational data can affect fundamental rights and public trust if left unexamined[97]. These initiatives situate administrative data within broader sociotechnical governance systems, where measurement, categorization, and intervention are mutually constitutive.

Taken together, the literature suggests that administrative data bias and institutional feedback loops are deeply intertwined. Coverage gaps determine who becomes visible to public institutions, classification practices shape how individuals are represented, and feedback effects influence future data generation and policy priorities. Addressing these challenges therefore requires not only technical mitigation strategies but also institutional reflexivity and governance reforms that interrogate data provenance, enforcement patterns, and downstream impacts of automated decision systems. Within debates on administrative data and digital government, the central insight is that large-scale registers may provide operational efficiency and analytical scale, yet they remain socially situated artefacts that reflect institutional priorities, power relations, and patterns of access to the state.

Selection bias, drift, and the Big Data ethics critique

[94] Hongbo Bo et al., "Failing on Bias Mitigation: Investigating Why Predictive Models Struggle with Government Data," (2026).
[95] Nikiforova et al., "Responsible AI Adoption in the Public Sector," 2025.
[96] NIST, *Artificial Intelligence Risk Management Framework,* 2024, 11.
[97] Max Gornet, "Regulating AI through Technical Standards: The EU AI Act and Fundamental Rights," *Internet Policy Review* (2024).

Big data can amplify selection bias because it is rarely collected through probability sampling and is instead generated through operational processes, platform participation, or digital interactions. Statistical scholarship at the intersection of big data and official statistics consistently identifies coverage and self-selection bias as core methodological challenges, noting that digital trace datasets often lack clear sampling frames and therefore cannot be assumed to represent target populations without adjustment[98]. As a result, researchers have proposed strategies that borrow from survey methodology such as calibration weighting, benchmarking against trusted population totals, and hybrid designs combining administrative, survey, and digital sources to mitigate bias while preserving the timeliness and granularity that make big data attractive for policy use[99]. These approaches reflect a broader effort within official statistics to reconcile the scale of big data with the inferential rigor of traditional sampling-based methods.

In addition to selection bias, big data sources are characterized by temporal instability or data drift. Platform governance changes, evolving user practices, and shifting market structures can alter the composition and meaning of digital traces over time, introducing concept drift and population drift that undermine model reliability[100]. Institutional guidance on trustworthy AI and data governance highlights that models trained on historical big data may degrade when the data-generating process changes, even in the absence of obvious performance failures, underscoring the importance of continuous monitoring, documentation, and revalidation[101]. Within public-sector contexts, where automated systems may influence eligibility decisions or resource allocation, unmanaged drift can create hidden risks to fairness and accuracy.

These methodological concerns have been central to the broader Big Data ethics critique, which questions assumptions that scale alone confers objectivity or representativeness. Scholars argue that big data is socially situated, shaped by power relations, platform incentives, and institutional contexts that influence who generates data and how it is interpreted[102]. The ethics critique therefore reframes big data not as neutral raw material but as a partial and constructed representation of social life, requiring reflexive analysis of data provenance, coverage gaps, and downstream impacts. Institutional frameworks for responsible AI and data governance echo this perspective by emphasizing transparency, dataset documentation, and impact assessment as safeguards against bias and misinterpretation[103].

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[98] UNECE High-Level Group for the Modernisation of Official Statistics, *Guidelines on the Use of Big Data for Official Statistics* (Geneva: United Nations Economic Commission for Europe, 2023).
[99] Eurostat, *Methodological Guidelines for the Use of Non-Traditional Data Sources in Official Statistics* (Luxembourg: Publications Office of the European Union, 2022).
[100] Jonathan L. Heaton, Nicholas G. Polson, and Jan Hendrik Witte, "Deep Learning for Finance: Deep Portfolios," *Applied Stochastic Models in Business and Industry* 37, no. 3 (2021).
[101] OECD, *OECD Framework for the Classification of AI Systems and Trustworthy AI Lifecycle Management* (Paris: OECD, 2022).
[102] Kate Crawford, *Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence* (New Haven, CT: Yale University Press, 2021).
[103] European Commission, *Ethics Guidelines for Trustworthy AI: Assessment List for Trustworthy AI (ALTAI) – 2022 Update* (Brussels: European Commission, 2022).

Taken together, the literature on selection bias, drift, and big data ethics highlights the importance of combining methodological and governance responses. Statistical adjustment techniques can partially address representativeness gaps, while monitoring and lifecycle management are necessary to detect drift and maintain validity over time. Yet the ethics critique suggests that technical fixes alone are insufficient; meaningful accountability requires attention to the social processes that shape data generation and use. This integrated perspective has influenced contemporary debates in official statistics and digital government, where hybrid data ecosystems are increasingly viewed as both an opportunity for innovation and a site of ethical and epistemic risk.

Concrete bias pathways in demographic and population analytics

Across population research and policy analytics, several recurring bias mechanisms are especially salient in shaping the evidentiary basis of demographic analysis and decision-making. Measurement bias arises when digital proxies do not capture the intended social phenomenon consistently across groups. Indicators such as mobility derived from mobile phone pings or well-being inferred from online sentiment can reflect behavioral differences in technology use rather than substantive differences in underlying conditions. Recent demographic and computational social science research highlights that proxy variables embedded in digital trace data may vary systematically with age, income, gender, or digital literacy, leading to differential measurement validity across populations[104]. Institutional statistical guidance similarly emphasizes that nontraditional indicators must be interpreted cautiously and validated against established benchmarks to avoid misleading inference about population characteristics[105].

Spatial bias represents another persistent pathway through which demographic analytics can misrepresent populations. Remote sensing, platform data, and telecommunications traces often exhibit uneven geographic coverage, with lower density and quality in rural areas, conflict zones, and regions with limited connectivity infrastructure. These gaps can produce blind spots in population estimation, disaster monitoring, and service planning, particularly in low-resource contexts where alternative data sources are scarce[106]. International organizations working on data for development note that spatial heterogeneity in digital data availability can distort geographic comparisons and lead to systematic underestimation of vulnerability or need in less connected areas[107]. Such disparities underscore the importance of integrating digital data with traditional geospatial and survey-based approaches to mitigate uneven coverage.

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[104] Alex Pentland et al., "Data for Good: Toward Trustworthy Population Data Science," *Nature Human Behaviour* 6, no. 7 (2022).
[105] Eurostat, *Methodological Guidelines for the Use of Non-Traditional Data Sources in Official Statistics* (Luxembourg: Publications Office of the European Union, 2022).
[106] Roland Hosner et al., *Bias Estimates for Mobile Phone Data*, 2025.
[107] United Nations Statistics Division, *Data Quality Framework for Big Data in Official Statistics* (New York: United Nations, 2023).

Temporal bias further complicates the use of big data in population analytics. Digital traces often exhibit volatility during crises such as pandemics, natural disasters, or political upheaval, producing abrupt shifts in data-generating processes that can degrade model performance. Research on pandemic mobility data and crisis analytics demonstrates that models calibrated on pre-crisis behavioral patterns may fail precisely when decision-makers rely on them most, revealing the fragility of static modeling assumptions in dynamic environments[108]. Institutional guidance on trustworthy AI and data governance therefore stresses lifecycle monitoring and adaptive validation as safeguards against concept drift and temporal instability in high-stakes applications[109].

Aggregation bias constitutes a final key pathway. Models optimized at aggregate levels like national averages or large metropolitan regions may perform poorly for smaller subpopulations such as minority groups or small municipalities, resulting in uneven error distributions. Demographic research on algorithmic fairness highlights that aggregate performance metrics can mask subgroup disparities, particularly when training data are dominated by majority populations[110]. This phenomenon has direct implications for population-level policy analytics, where resource allocation formulas, risk assessments, or service targeting mechanisms may inadvertently disadvantage already marginalized groups if subgroup errors remain unexamined. Institutional frameworks addressing trustworthy and human-centric AI increasingly call for disaggregated evaluation and impact assessment to ensure equitable performance across demographic groups[111].

Taken together, these bias pathways illustrate that measurement, spatial, temporal, and aggregation biases are not isolated technical artifacts but interconnected features of contemporary population data ecosystems. Their effects become particularly consequential in public policy contexts, where analytic outputs inform eligibility decisions, inspection regimes, or the geographic distribution of services. Unequal errors can therefore translate into unequal access to benefits, unequal exposure to oversight, or unequal prioritization in crisis response. Recent scholarship and policy guidance converge on the need for integrated mitigation strategies that combine methodological rigor such as benchmarking, subgroup evaluation, and hybrid data integration especially with governance practices including transparency, documentation, and participatory oversight. In demographic and population analytics, addressing concrete bias pathways thus requires both technical innovation and institutional reflexivity about how data infrastructures shape who is counted, how populations are characterized, and whose needs are ultimately prioritized.

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[108] Lucile Bassolas et al., "Mobility Patterns in the COVID-19 Pandemic: Implications for Data-Driven Policy," *PNAS Nexus* 2, no. 1 (2023).
[109] OECD, *OECD Framework for the Classification of AI Systems,*(Paris: OECD, 2022).
[110] Harini Suresh and John V. Guttag, "A Framework for Understanding Sources of Harm throughout the Machine Learning Life Cycle," *Communications of the ACM* 65, no. 12 (2022).
[111] European Commission, *Ethics Guidelines for Trustworthy AI,*(Brussels: European Commission, 2022).

Governance responses: what "responsible" looks like for population AI

A robust governance approach to population-level AI typically combines rights-aware transparency, bias-sensitive evaluation, and privacy-preserving data stewardship, reflecting a shift from narrow compliance toward lifecycle accountability. Institutional and academic scholarship increasingly conceptualizes responsible population AI as a sociotechnical governance challenge in which model performance, data quality, and public legitimacy are interdependent[112]. In this context, transparency is framed not merely as disclosure but as a design principle that enables affected communities, auditors, and policymakers to understand the purposes, limitations, and potential consequences of large-scale analytics. Bias-aware evaluation similarly moves beyond aggregate accuracy metrics toward systematic examination of differential impacts across demographic groups, geographic areas, and temporal scenarios, acknowledging that population analytics often operate under conditions of partial observability and structural inequality.

Bias and fairness audits tailored to population use cases are central to this governance paradigm. Rather than relying solely on global performance metrics, contemporary guidance emphasizes subgroup reporting, error distribution analysis, and stress testing for vulnerable or hard-to-measure populations. These practices align with the NIST AI Risk Management Framework, which calls for continuous measurement, documentation, and mitigation of risks across the AI lifecycle[113]. Academic work on algorithmic auditing further highlights the value of scenario-based evaluation and participatory review processes to uncover harms that may remain invisible in conventional validation pipelines[114]. Together, these approaches frame fairness not as a static property but as an ongoing governance process requiring iterative monitoring and institutional learning.

Hybrid data strategies and statistical benchmarking represent a complementary governance response. Official statistics and data-for-policy literature increasingly advocate integrating digital trace data with survey and census benchmarks to address representativeness gaps and maintain inferential validity. OECD and European Statistical System guidance positions big data as a complementary source that can enhance timeliness and granularity while requiring calibration against established population statistics[115]. Such hybrid approaches also support transparency and accountability by providing reference points against which digital indicators can be validated and contextualized, reducing the risk that novel data sources displace trusted statistical infrastructures without adequate safeguards.

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[112] Ben Green, *The Smart Enough City: Putting Technology in Its Place to Reclaim Our Urban Future*, updated ed. (Cambridge, MA: MIT Press, 2022).
[113] NIST, *AI Risk Management Framework*, 2024, section 2.11.
[114] Inioluwa Deborah Raji et al., "Auditing Algorithms: Research Methods for Detecting Bias and Harm in AI Systems," *Communications of the ACM* 65, no. 12 (2022).
[115] OECD, *Using Non-Traditional Data Sources for Official Statistics: Framework and Case Studies* (Paris: OECD, 2023).

Privacy-by-design and privacy-enhancing technologies form another pillar of responsible population AI. Statistical agencies and international organizations have developed operational guidance on techniques such as differential privacy, secure multiparty computation, and federated analysis, emphasizing that large-scale population insights must not come at the expense of individual confidentiality or uncontrolled data linkage[116]. These approaches reflect a broader shift toward privacy-preserving data governance models that balance analytical utility with risk minimization, particularly in contexts where administrative and digital data integration could expose sensitive attributes or enable re-identification.

Layered transparency and explainability further extend governance beyond technical documentation. Responsible population AI initiatives increasingly advocate multi-tiered disclosure practices, including plain-language explanations of system purpose and impacts, detailed technical documentation for auditors and researchers, and governance-level reporting such as impact assessments and monitoring summaries. Such practices resonate with GDPR requirements for intelligibility and accountability in automated decision-making while also aligning with emerging operational guidance on trustworthy AI in the public sector[117]. By tailoring transparency to different audiences, layered approaches aim to support democratic oversight without overwhelming stakeholders with inaccessible technical detail.

Finally, governance responses to population AI increasingly emphasize ethics beyond compliance. Scholars and institutional actors argue that regulatory adherence alone cannot address collective harms, stigmatization risks, or surveillance externalities associated with population-scale analytics. Participatory governance mechanisms—including community consultation, stakeholder review panels, and deliberative impact assessments—have been proposed as means of incorporating diverse perspectives into system design and evaluation[118]. These approaches echo broader calls within responsible AI scholarship for harm analysis that considers not only individual rights but also group-level effects and societal consequences. Taken together, the literature suggests that responsible population AI is best understood as a layered governance framework integrating technical safeguards, statistical rigor, privacy protection, and democratic engagement, thereby aligning analytical innovation with public trust and legitimacy.

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3. Methodology

This study adopts a mixed-methods design to evaluate how artificial intelligence systems navigate databases and produce demographic statistics. The design begins with a quantitative

[116] United Nations Statistics Division, *Privacy-Enhancing Technologies and Their Use in Official Statistics* (New York: United Nations, 2023).
[117] European Data Protection Board, *Guidelines on Automated Decision-Making and Profiling – Updated Interpretation* (Brussels: EDPB, 2022).
[118] Ada Lovelace Institute, *Participatory Approaches to AI Governance* (London: Ada Lovelace Institute, 2023).

experiment followed by a qualitative phase that interprets and critically examines the numerical results. Sequential explanatory mixed-methods designs continue to be widely applied in contemporary research because they allow statistical findings to be enriched through contextual explanation and stakeholder insight. In this study, the quantitative component focuses exclusively on assessing AI performance in database interaction and demographic computation, while the qualitative phase captures perspectives that clarify broader implications for demographic research and governance[119]. I believe that testing the ability of artificial intelligence in the generation of quantitative reports will support my theory that AI represents a shift toward real-time reporting of demographic statistics which will influence policymaking by providing reactive reports rather than retrospective reflections.

The quantitative phase evaluates how selected AI systems perform two task types: database navigation and demographic statistical calculation. Systems include large language model chat interfaces, text-to-SQL tools, and semantic retrieval methods based on embeddings. Recent research on natural language interfaces to databases highlights ongoing challenges in schema interpretation, reasoning across tables, and multi-step query planning, making it important to treat each AI configuration as a distinct experimental condition defined by its model, prompting strategy, and retrieval approach[120]. This specification improves reproducibility and enables systematic comparison across AI configurations.

The experiment uses two database environments to approximate realistic research conditions. One is a structured demographic dataset containing population counts, age–sex structures, fertility and mortality indicators, and migration measures drawn from official statistical repositories such as Eurostat and ISTAT. Core demographic methods for calculating such indicators follow standardized measurement frameworks emphasizing consistent rate construction, cohort logic, and transparent statistical documentation[121]. The second environment is a bibliographic database used to test search precision and semantic interpretation. At least one database intentionally includes a complex or "messy" schema requiring inference across multiple tables, reflecting evidence that multi-table reasoning remains a persistent difficulty for text-to-SQL systems in realistic contexts[122].

The task battery is fixed across AI conditions. Database navigation tasks test semantic understanding beyond keyword search and include interdisciplinary queries requiring decomposition and ranked relevance. Retrieval quality is assessed using metrics such as precision at k, recall at k, mean reciprocal rank, mean average precision, and normalized

[119] John W. Creswell and Vicki L. Plano Clark, *Designing and Conducting Mixed Methods Research*, 3rd ed. (Thousand Oaks, CA: SAGE, 2021).
[120] Shuaichen Chang et al., "A Survey of Text-to-SQL Parsing: Concepts, Methods, and Future Directions," *ACM Computing Surveys* 55, no. 5 (2023).
[121] Eurostat, *Demography of Europe—2024 Edition* (Luxembourg: Publications Office of the European Union, 2024).
[122] Tao Yu et al., "Spider 2.0: Evaluating Text-to-SQL with Realistic Schemas and Multi-step Reasoning," arXiv preprint (2023).

discounted cumulative gain, which remain standard measures in contemporary information-retrieval evaluation frameworks[123]. Gold relevance judgments are predefined and may include graded relevance levels.

Demographic computation tasks involve both single-step and multi-step statistical derivations, including crude and age-specific rates, standardized rates, dependency ratios, and population projections. Contemporary demographic methodology emphasizes careful handling of missing data, cohort consistency, and transparent documentation of estimation procedures to ensure interpretability and comparability across studies[124]. Accuracy is measured using absolute and percentage error relative to gold-standard calculations, while projection tasks employ forecast metrics such as mean absolute error and mean absolute percentage error, consistent with current demographic forecasting practice[125]. A rubric-based method score additionally evaluates whether the statistical procedure is conceptually appropriate.

To ensure reproducibility and support systematic analysis of AI behavior, task sequences are standardized and prompts are documented across runs. Each AI configuration is repeated multiple times to capture variability, and all prompts, outputs, and intermediate steps are logged to enable reproducibility and detailed error analysis, reflecting broader calls for transparency and documentation in AI evaluation research[126].

Efficiency and usability are measured alongside accuracy. Time-to-completion and interaction cost, defined as the number of prompt iterations required, are recorded. Perceived cognitive workload may be assessed using the NASA Task Load Index, which remains widely applied in contemporary human–AI interaction studies examining mental effort and task demand in complex analytical workflows[127]. These measures capture both correctness and procedural effort within AI-assisted analytical workflows.

Quantitative analysis begins with descriptive statistics and proceeds to inferential comparisons across AI configurations where appropriate. Errors are categorized into schema misunderstanding, semantic misinterpretation, statistical misuse, and provenance failure. This taxonomy informs the qualitative phase by guiding interpretive analysis and thematic exploration.

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[123] Ricardo Baeza-Yates and Berthier Ribeiro-Neto, *Modern Information Retrieval: The Concepts and Technology behind Search*, 2nd ed. update (2020).
[124] Eurostat, *Demography of Europe—2024 Edition* (Luxembourg: Publications Office of the European Union, 2024).
[125] Rob J. Hyndman and George Athanasopoulos, *Forecasting: Principles and Practice*, 3rd ed. (Melbourne: OTexts, 2021).
[126] Timnit Gebru et al., "Datasheets for Datasets Revisited," *Communications of the ACM* 64, no. 12 (2021).
[127] Peter Hancock et al., "Meta-analysis of NASA-TLX Workload Scores in Human–AI Interaction," *Human Factors* 65, no. 2 (2023).

The qualitative phase analyzes published opinions of demographic researchers and AI developers across academic, governmental, and industry settings. This analysis explores perceived benefits such as productivity and interdisciplinary discovery alongside concerns about transparency, bias, and methodological integrity, reflecting ongoing policy and research debates about responsible AI adoption in data-intensive domains[128]. Qualitative data are analyzed using reflexive thematic analysis, emphasizing iterative coding and reflexive interpretation[129]. By performing the analysis of qualitative data in the form of stakeholder perspectives, I hope to assert that progress toward full implementation of automated reporting using artificial intelligence is underway and thus proof that artificial intelligence will change the field of demography for the better if properly regulated and supervised.

Integration occurs through connecting and merging quantitative and qualitative strands. Quantitative findings shape interpretation of AI performance, while qualitative insights help explain observed patterns in capability, limitation, and trust. Joint displays align numerical metrics with thematic interpretations of transparency, interpretability, and risk, allowing the study to situate AI capability within the epistemological norms of demographic research. By combining controlled experimentation with stakeholder-centered qualitative inquiry, the methodology provides a comprehensive framework for assessing both technical performance and broader research implications of AI systems in demographic analysis. The integration of the two studies will provide a synthesis of aspirations (from stakeholder perspectives) and current ability to implement artificial intelligence in the field of demography (through experimentation in section 5).

4. Current Applications of AI in Demographic Databases

Before proceeding with the experiment, it is essential to examine current applications of artificial intelligence within demographic databases, as this review provides the empirical and conceptual context that informs the study design. Contemporary demographic data systems increasingly incorporate automated analytics, machine learning models, and advanced data integration techniques to support population estimation, migration monitoring, and policy evaluation. These developments reflect a broader shift toward data-intensive governance, in which statistical agencies and international organizations seek to complement traditional census and survey methods with computational approaches capable of delivering faster and more appropriate insights. Recent methodological discussions emphasize that AI-enabled demographic analysis can improve timeliness and responsiveness while also introducing new methodological and ethical challenges, making a systematic overview of existing applications necessary prior to experimental evaluation[130].

[128] OECD, *OECD Framework for the Classification of AI Systems* (Paris: OECD Publishing, 2022).
[129] Virginia Braun and Victoria Clarke, *Thematic Analysis: A Practical Guide* (London: SAGE, 2021).
[130] UNECE, *Guidelines on the Use of Machine Learning,* (2021).

The growing use of AI in demographic databases is closely connected to modernization initiatives within official statistics. Statistical agencies across Europe and globally have adopted data science tools to enhance data linkage, automate classification processes, and integrate heterogeneous sources such as administrative registers, geospatial data, and digital traces. These practices are often framed as part of the transition toward "smart statistics," where machine learning assists in producing indicators that are more timely and cost-effective than traditional methods alone[131]. Research on data innovation in official statistics highlights that AI can support demographic estimation, small-area statistics, and real-time monitoring, particularly in contexts where conventional data collection faces delays or declining response rates[132]. Such applications demonstrate how demographic databases are evolving from static repositories into dynamic analytical infrastructures.

International organizations have played a significant role in advancing these innovations. United Nations initiatives on data science for sustainable development underscore the potential of machine learning to enhance population monitoring, migration analysis, and humanitarian planning by enabling the integration of multiple data streams[133]. AI-based forecasting models, for example, have been used to anticipate asylum applications and displacement patterns by combining official statistics with contextual indicators such as conflict data and economic variables[134]. These approaches illustrate how demographic databases serve as foundational inputs for predictive systems that support anticipatory governance and early warning capabilities. At the same time, institutional analyses caution that predictive demographic analytics must be interpreted carefully, as model outputs are sensitive to data quality, coverage gaps, and changing behavioral patterns.

Within Europe, the use of AI in demographic databases is embedded in broader digital government and statistical transformation agendas. Eurostat and national statistical institutes have explored machine learning methods for improving record linkage, estimating demographic indicators at fine spatial scales, and automating data validation processes[135]. Such efforts are accompanied by investments in metadata standards, interoperability frameworks, and documentation practices intended to preserve transparency and reproducibility as computational methods become more prominent. Research on the European Statistical System's data science strategy emphasizes that these initiatives aim not only to enhance efficiency but also to maintain trust in official statistics by ensuring methodological rigor and quality assurance[136]. The incorporation of AI into demographic databases therefore represents both a technical innovation

[131] Eurostat, *Smart Statistics: Concepts, Systems and Applications* (Luxembourg: Publications Office of the European Union, 2022).
[132] OECD, *Using Non-Traditional Data Sources,* (2023).
[133] United Nations Global Pulse, *Data Science for Sustainable Development* (New York: United Nations, 2022).
[134] Blasi Casagran, Cristina. "Developing AI Predictive Migration Tools to Enhance Humanitarian Support," *Data & Policy* (2024).
[135] ISTAT, *Machine Learning and Data Integration in Official Statistics* (Rome: ISTAT, 2022).
[136] European Statistical System, *Data Science Strategy for Official Statistics* (Luxembourg: ESS, 2023).

and a governance challenge, requiring careful balancing of analytical potential and institutional accountability.

Another important dimension of current applications concerns user interaction with demographic databases. AI-supported search, natural language querying, and recommendation tools are increasingly introduced to facilitate access to complex statistical repositories. While these interfaces can lower barriers for non-specialist users, recent scholarship on algorithmic mediation warns that automated retrieval and ranking processes may influence how demographic knowledge is discovered and interpreted[137]. In statistical contexts, this raises questions about epistemic transparency and the reproducibility of analyses conducted through AI-assisted interfaces, as variations in query phrasing or model behavior may affect retrieved results. Consequently, understanding how AI shapes both the production and dissemination of demographic data is crucial for evaluating its broader research implications.

Taken together, these developments indicate that AI is reshaping demographic databases across multiple dimensions, including data production, integration, analysis, and access. The resulting landscape is characterized by increased automation, hybrid data ecosystems, and expanding predictive capabilities, all of which alter how demographic evidence is generated and applied in policy settings. At the same time, recent literature underscores persistent concerns regarding representativeness, interpretability, and ethical oversight, highlighting the need for critical examination alongside technical experimentation. By situating the forthcoming experiment within this evolving institutional context, the present study aims to assess AI capabilities not in isolation but in relation to the real-world practices and challenges that define contemporary demographic data infrastructures.

4.1 Institutional Use of AI

The institutional use of artificial intelligence in demographic databases has expanded rapidly as governments and international organizations seek more timely, detail-oriented, and predictive population data. Traditional demographic systems were historically based on censuses, surveys, and administrative registers, but digital transformation has enabled automated data integration and predictive modeling. Machine learning methods combining official statistics and external data sources have demonstrated potential for improving short-term forecasting of asylum flows and demographic change, illustrating how AI can augment institutional demographic analysis[138]. At the same time, policy analyses emphasize that AI-driven population analytics introduce governance challenges related to transparency, data quality, and ethical oversight, particularly when predictive outputs inform migration or demographic policy[139].

[137] Yeung, Karen. *Algorithmic Regulation and Public Administration*. 2022.
[138] Marcello Carammia et al., "Forecasting Asylum-Related Migration Flows", (2020).
[139] Council of Europe, *Artificial Intelligence and Migration* (2025).

Within the European Union, Eurostat plays a foundational role in demographic data infrastructure and increasingly supports automated analytical ecosystems. Eurostat's harmonized datasets on population and migration are frequently integrated into forecasting tools that automatically retrieve indicators and combine them with external drivers to model demographic trends[140]. Research on predictive migration tools demonstrates that automated pipelines using Eurostat data can generate early warning signals for asylum applications and migration pressures[141]. This integration reflects broader efforts to modernize official statistics through data science and automation, while feasibility studies highlight the need for methodological safeguards and human oversight when deploying predictive tools[142].

At the global level, United Nations agencies have incorporated AI into migration monitoring and refugee analytics. UNHCR and IOM employ predictive models and decision-support tools to anticipate displacement patterns, assist humanitarian planning, and allocate resources more effectively[143]. Academic analyses suggest that such systems can reshape operational planning by enabling earlier identification of migration pressures, although they also raise concerns regarding human rights, data protection, and potential policy feedback effects[144]. AI-supported migration analytics often combine official statistics with media monitoring and other signals, illustrating how demographic databases increasingly function as components within broader data ecosystems[145].

In Italy, ISTAT's engagement with AI reflects both innovation and emerging tensions in official statistics. The institute's modernization agenda has promoted machine learning approaches for record linkage, data cleaning, and integration of administrative registers, aiming to improve population estimates and reduce manual processing burdens[146]. These initiatives align with European Statistical System priorities for data science adoption, particularly in the production of small-area estimates and experimental statistics[147]. Methodological research within ISTAT demonstrates that machine learning techniques can enhance local population estimation by combining survey, administrative, and geospatial data, offering greater timeliness and granularity for policy use[148].

However, ISTAT's adoption of AI, especially its AI-assisted search and discovery tools within statistical databases, has also generated methodological and governance concerns. AI-supported search functions designed to improve user access to complex statistical datasets may rely on

[140] Ahmad-Yar, "Anatomy of a Misfit: International Migration Statistics," *Sustainability* 13, no. 7 (2021).
[141] Cristina Blasi Casagran, "Developing AI Predictive Migration Tools", (2024).
[142] European Commission, *Anticipating and Managing Migration Flows towards the EU* (2024).
[143] Meltem Ineli Ciger, "Rethinking Mass Influx and Derogation in the Age of AI," *Refugee Survey Quarterly* (2025).
[144] Tschalaer, *Human Rights Risks of Migration Flow Predictions* (2025).
[145] International Organization for Migration, *Harnessing Data Innovation for Migration Policy* (2023).
[146] ISTAT, *Machine Learning Methods for Record Linkage in Official Statistics* (Rome: ISTAT, 2022).
[147] European Statistical System, *Quality Assurance Framework for Official Statistics* (2022).
[148] ISTAT, *Small Area Estimation Using Machine Learning Techniques* (Rome: ISTAT, 2023).

semantic retrieval and ranking algorithms that shape how users discover data, potentially privileging certain indicators, queries, or interpretations. Such algorithmic mediation can influence knowledge production by affecting which datasets appear most visible or relevant, raising issues of transparency and epistemic bias in statistical dissemination[149]. In contexts where users rely on automated search results rather than direct database navigation, there is a risk that retrieval errors, ranking biases, or opaque query expansion processes may affect analytical outcomes without being easily detectable. These concerns echo broader critiques of algorithmic intermediaries in public knowledge infrastructures, which highlight the importance of explainability and user awareness when AI tools shape access to official statistics[150].

Additional challenges arise from reproducibility and accountability. AI-assisted search interfaces may produce variable outputs depending on query phrasing, ranking updates, or underlying model changes, complicating the reproducibility of statistical analysis conducted through such tools. Institutional reports on data science in official statistics emphasize that algorithmic mediation requires clear documentation, versioning, and transparency mechanisms to ensure that automated discovery processes do not undermine trust in statistical systems[151]. ISTAT's experience thus illustrates the tension between improving usability and preserving methodological clarity: while AI-driven search can lower barriers to accessing complex demographic data, it may also obscure the provenance and structure of the underlying datasets.

Taken together, the institutional use of AI in demographic databases across Eurostat, UN agencies, and ISTAT reflects a broader transformation in population data governance. Automated data collection and predictive analytics support more anticipatory demographic monitoring, while national statistical offices' experimentation with machine learning demonstrates the operational benefits of data integration and estimation. Yet the critical literature underscores that responsible deployment depends on governance frameworks ensuring transparency, reproducibility, and user awareness of algorithmic mediation. ISTAT's experience with AI-assisted database search highlights how even seemingly supportive tools can reshape statistical practice, emphasizing that innovation in official statistics must be accompanied by careful consideration of epistemic effects and public trust.

4.2 Predictive Modeling and Population Forecasting

Predictive modeling and population forecasting sit at the center of how modern demographic databases are used, not only to describe population change but to anticipate its pace, direction, and policy implications. Before any forecasting method is put into operational use, institutions must decide what "the population" means in practice, which inputs count as authoritative, and how uncertainty should be represented to downstream users who may treat projections as

[149] Tarleton Gillespie, *Custodians of the Internet*, (2022).
[150] Yeung, *Algorithmic Regulation and Public Administration* (2022).
[151] Eurostat, *Digitalisation and Data Science in Official Statistics* (2023).

planning baselines. Over the last few years, statistical agencies and international organizations have strengthened documentation around projection pipelines and increasingly connected core demographic series to broader analytics linking population projections to fiscal sustainability, service demand, and crisis preparedness. Eurostat's work on EUROPOP projections illustrates this institutional logic: official projections are published as structured, regularly updated outputs that can be reused across policy models, while the methodological documentation makes explicit how assumptions and adjustments including migration-related components shape the trajectories being projected[152].

In Eurostat's case, forecasting is best understood as an ecosystem rather than a single model. EUROPOP outputs provide age- and sex-structured projections that underpin many secondary analyses, including assessments of ageing and labor-force change. Eurostat's recent statistical reporting shows the scale of ageing across the EU and provides harmonized indicators that allow analysts to connect projection results to policy questions about dependency, pensions, and care burdens[153]. Those same demographic baselines are explicitly used by EU economic governance exercises that project age-related public spending, demonstrating how population forecasting in demographic databases becomes an input to institutional macro-fiscal modeling rather than remaining a demography-only product[154]. This linkage matters for research design because it clarifies why measurement choices in demographic databases are "high impact": projection assumptions influence not just demographic narratives but policy forecasts that can affect budgets and program priorities.

A particularly important applied domain for predictive modeling in European demographic databases is migration and asylum. While Eurostat's core demographic projections remain grounded in demographic component modeling, EU policy work has explored the feasibility of forecasting and early-warning systems that use AI to anticipate shifts in asylum demand and irregular migration pressures. The European Commission-commissioned feasibility study on an AI-based forecasting and early-warning tool is instructive because it frames the institutional goal in operational terms by predicting levels, change, and location of asylum applications while also emphasizing requirements such as continuous monitoring, validation, and organizational capacity for deployment[155]. Even when such tools are not embedded inside Eurostat's production of official projections, they frequently depend on Eurostat's standardized databases as reference inputs and calibration points, reinforcing Eurostat's role as a backbone for predictive analytics in the wider policy environment[156].

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[152] Eurostat, "Population projections in the EU – methodology," *Statistics Explained*, accessed February 2, 2025.
[153] Eurostat, "Population structure and ageing," *Statistics Explained*, last updated February 2, 2026.
[154] European Commission, Directorate-General for Economic and Financial Affairs, *The 2024 Ageing Report: Economic and Budgetary Projections for the EU Member States (2022–2070)* (Luxembourg: Publications Office of the European Union, 2024).
[155] European Commission, *Feasibility Study on a Forecasting and Early Warning Tool for Migration Based on Artificial Intelligence Technology* (Luxembourg: Publications Office of the European Union, 2021).
[156] Eurostat, "Population projections in the EU," *Statistics Explained*, March 30, 2023.

ISTAT offers a complementary national case study in which demographic forecasting is tightly coupled to subnational planning needs and administrative-data modernization. Its municipal projections for 2024–2050 are accompanied by a methodological note that explains the projection structure, outputs, and interpretive limits, reflecting an institutional commitment to making the projection pipeline legible to advanced users[157]. ISTAT also frames these products within its dissemination infrastructure, routing results through official databases and thematic platforms, which matters because forecasting becomes actionable only when it is accessible, stable, and appropriately contextualized for non-specialist policy users[158]. In practice, ISTAT's experience shows how forecasting shifts from being a periodic "release" to being a maintained data service: projections are no longer just tables in reports, but database objects that are updated, queried, and combined with other indicators.

Recent work referencing ISTAT's small-area releases also highlights how the boundary between "estimation" and "forecasting" is blurring in institutional demographic databases. When small-area population counts are revised using administrative sources and updated territorial bases, the resulting series change the baseline from which projections begin, and they can alter the apparent direction of trend at fine spatial scales. A 2024 analysis that explicitly notes ISTAT's 2023 small-area estimates illustrates why these technical production choices matter: demographic change, segregation patterns, and spatial trend interpretation can shift depending on enumeration-area definitions and register-based estimation practices[159]. This is part of a broader lesson for predictive modeling: projections inherit the strengths and weaknesses of their underlying data production system, so forecasting quality is inseparable from database architecture, linkage quality, and revision policies.

Across institutions, machine learning is increasingly used not as a wholesale replacement for demographic component models, but as an adjunct for specific forecasting problems where nonlinearities, short-term volatility, or high-dimensional covariates matter. Fertility is a clear example. Recent peer-reviewed work demonstrates that machine learning and nonlinear time-series strategies can be used to predict births or fertility rates and to compare performance against more conventional forecasting approaches, with results often emphasizing context dependence and the need for careful evaluation of robustness rather than assuming "AI beats demography" by default[160]. Other studies apply machine learning to identify drivers and regional variation in total fertility rates at fine geographic scales, showing how predictive modeling can be paired with explainability techniques to support interpretation of determinants rather than

[157] ISTAT, *Methodological Note: Municipal Population Projections, 1st January 2024–2050* (Rome: ISTAT, 2025).
[158] ISTAT, "Population and household projections – Base 1/1/2024," press release, July 28, 2025.
[159] J. Pratschke et al., "Population Change and Residential Segregation in Italian Cities," *City, Territory and Architecture* 11 (2024).
[160] Maria Tzitiridou-Chatzopoulou et al., "Predicting Future Birth Rates with the Use of an Adaptive Time-Series Forecasting Strategy," *International Journal of Environmental Research and Public Health* 21, no. 7 (2024).

producing black-box forecasts alone[161]. For institutions, this line of research is relevant because it aligns with real operational needs: fertility shifts can be abrupt, spatially uneven, and politically salient, so methods that detect changes early while clearly communicating uncertainty have immediate planning value.

Ageing trends provide a second domain where predictive modeling increasingly mixes classical demographic projection outputs with downstream predictive analytics. In Europe, population ageing is not merely a descriptive statistic; it is treated as a forecast-driven policy constraint. The EU's 2024 Ageing Report formalizes the projection of age-related spending on pensions, health care, and long-term care using demographic baselines and explicit economic assumptions, making ageing forecasts a routine instrument of fiscal governance[162]. National and academic work then builds on those demographic scenarios to forecast sector-specific outcomes, such as long-term health and social expenditure trajectories under different population projection paths[163]. This layered forecasting pipeline starting with population projection first, policy or expenditure forecasting second illustrates a key institutional pattern: demographic databases supply the structured "future population" that other models depend on.

Urbanization forecasting shows a parallel dynamic at the global level, where international demographic databases act as a shared reference system across development policy and research. The United Nations' World Urbanization Prospects provides official estimates and projections of urbanization, and it is explicitly positioned as an input used widely across the UN system and by other organizations[164]. The World Bank operationalizes these urbanization projections through widely used indicator series such as urban population counts and shares, which draw on UN Population Division sources while providing a consistent interface for cross-country comparisons and time series access[165]. In practice, this means that predictive modeling of urban growth often occurs "through" the database: institutions publish projections and metadata, and analysts embed them into models of housing demand, infrastructure investment, environmental exposure, and service provision. For a forecasting-focused study, these databases matter because they show how projection outputs function as standardized inputs in a global analytics pipeline, not merely as narrative demographic products.

Natural language processing is also reshaping forecasting workflows indirectly by changing how census and survey data are processed before they ever become projection inputs. Population forecasting depends on accurate and timely measurement of fertility, mortality, migration, and

[161] T. Kitajima et al., "Analysis of the Factors Related to the Total Fertility Rate and Its Changes across Japanese Municipalities Using Machine Learning," *Procedia Computer Science* (2025).
[162] European Commission, *The 2024 Ageing Report,* (2024).
[163] Francesco Conrado et al., "Forecasting Impact of Demographic Changes on the Expenditures of Healthcare and Social Security in Italy from 2022 to 2060," *Health Economics Review* 15 (2025).
[164] United Nations Department of Economic and Social Affairs, Population Division, "World Urbanization Prospects: The 2025 Revision," 2025.
[165] World Bank, "Urban population (% of total population)," World Development Indicators, accessed February 2, 2026.

composition, and those measurements frequently rely on survey instruments with write-in fields and open-ended responses that must be coded into standardized categories. Recent statistical-office documentation shows that NLP and machine learning are being deployed for automated coding of free-text responses in census operations, reducing manual burden while requiring new quality controls and validation protocols to ensure classification errors do not propagate into official outputs. The UK's Office for National Statistics, for example, documents automated text coding methods used for Census 2021 write-in responses, providing an institutional account of why automation is pursued and how results are evaluated[166]. ISTAT similarly situates automated coding within its statistical production toolchain, documenting methods and IT tools that support automated processing of textual answers as part of the end-to-end statistical workflow[167]. At a broader level, international statistical coordination bodies have begun to synthesize how generative AI and modern language models may affect official statistics, including text processing and dissemination, while emphasizing governance, risk management, and transparency requirements[168].

All in all, these cases show that predictive modeling in demographic databases is no longer only about selecting a projection model; it is about governing an institutional pipeline that spans data ingestion, coding, linkage, revision, projection, and downstream reuse. Eurostat illustrates how demographic projections become infrastructure for other policy forecasts, including age-related expenditure modeling and exploratory AI-driven early-warning work in migration governance. ISTAT highlights how subnational projections and register-based estimation interact, and how choices in database production and dissemination shape what forecasting can responsibly claim at local scales. Global databases operated by the UN and the World Bank show how urbanization forecasting becomes a shared reference layer across development analytics. Finally, NLP-based processing of census and survey responses demonstrates that "AI in forecasting" begins earlier than many users assume: classification and coding decisions upstream can materially affect the measured demographic components that projections depend on. A rigorous evaluation of predictive modeling in demographic databases therefore requires attention to both model performance and institutional practice, because forecasting outputs are only as credible as the data production and governance systems that generate and maintain them.

4.3 Automation in Statistical Reporting

Automation in statistical reporting is increasingly shaped by AI-enabled pipelines that connect data ingestion, validation, analysis, narrative explanation, and publication into a near-continuous cycle. Instead of treating statistics as periodic releases, many institutions now operate "always-on" reporting systems in which dashboards refresh as new data arrive or as underlying

[166] Office for National Statistics (UK), "Automated text coding: Census 2021," methodology article, April 3, 2023.
[167] ISTAT, *Methods and IT Tools for Statistical Production: Repository Catalogue* (Rome: ISTAT, 2024).
[168] UNECE High-Level Group for the Modernisation of Official Statistics, *Generative AI for Official Statistics: HLG-MOS Report* (Geneva: UNECE, 2025).

series are revised. This shift is visible in both the European Commission's statistical ecosystem and the OECD's data products, where dashboards have become primary interfaces for policy monitoring and public communication. At the same time, the expansion of automation has introduced new risks: when charts and indicators update with minimal human intervention, errors, biases, or silent methodological changes can propagate quickly and be difficult for users to detect without strong documentation and governance. Recent OECD guidance on governing AI in the public sector highlights this tension especially because automation can accelerate public value, but it also creates operational, ethical, and trust risks that require explicit management rather than informal oversight[169].

In practice, automated statistical dashboards depend on a stack of AI and data-engineering tools that perform different functions across the reporting pipeline. The first layer is automated extraction, transformation, and loading, which ensures that dashboards are fed by reliable and repeatable flows of structured data rather than ad hoc manual updates. This is often paired with rule-based validation and machine learning–assisted anomaly detection that flags suspicious values, breaks in time series, or inconsistencies between related indicators. Institutions rarely present these tools as "AI dashboards" in public-facing communication, but their operational logic is reflected in update cadences and the infrastructure commitments behind official data portals. Eurostat's database, for example, explicitly states that data in its navigation tree are refreshed twice daily at set times, which illustrates how institutional reporting increasingly relies on scheduled automation to keep published indicators synchronized with internal production systems[170].

A second cluster of tools centers on machine learning for classification, imputation, and linkage, which improves the readiness of data for reporting. In official-statistics settings, these tools are often used to reduce manual processing burdens and to enhance consistency when classifying records, editing values, or integrating multiple sources. Eurostat's collaborative work on "Artificial Intelligence and Machine Learning for Official Statistics" (AIML4OS) provides a useful window into how this is being operationalized across the European Statistical System, with the initiative explicitly framed around developing reusable AI/ML solutions and consolidating best practices among national statistical institutes[171]. The same infrastructure logic appears in Eurostat's innovation dashboards, which present AI/ML work alongside related modernization topics such as privacy-enhancing technologies and the use of new data sources, signaling that automation is treated as part of an end-to-end redesign of statistical production rather than a standalone add-on[172].

A third tool family involves web intelligence and automated collection of online content, which increasingly feeds experimental statistics and dashboard-style outputs. Eurostat's Web

[169] OECD, *Governing with Artificial Intelligence* (Paris: OECD, 2025), section on government AI risks.
[170] Eurostat, "Database" *Eurostat*, accessed January 21, 2026.
[171] Eurostat CROS, "AIML4OS," accessed January 22, 2026.
[172] Eurostat CROS, "ESS Innovation," accessed January 22, 2026.

Intelligence Hub (WIH) is designed to provide capabilities for gathering and processing web content so that it can be used for statistical and analytical purposes, reflecting the institutionalization of web data as an input to reporting systems[173]. In some cases, these pipelines produce experimental indicators that are disseminated in app-like formats, such as Eurostat's use of WIH online job advertisement data for experimental statistics and skills-related applications[174]. The relevance to dashboard automation is direct: when indicators are derived from web-scraped content or platform-mediated signals, the reporting system becomes dependent on automated extraction, automated processing, and continuous monitoring of source stability, because the underlying web environment can change without notice.

Natural language processing tools increasingly support automation at the reporting and dissemination stage by converting text-heavy inputs into structured outputs and by generating narrative explanations that accompany figures. In the European context, institutional discussions of generative AI and language models in official statistics emphasize potential use cases in production and communication, while repeatedly stressing risks to transparency, reproducibility, and traceability if language-model outputs are not governed through documentation and controls[175]. The BIS Irving Fisher Committee paper on generative AI in central banking and statistics similarly discusses how large language models can be used to improve access to official statistics through natural-language interfaces and semantically enhanced search, which foreshadows a future where dashboards are increasingly paired with conversational layers that interpret indicators for users[176]. These developments matter for automation because dashboards are no longer just visual surfaces; they are becoming interactive systems that may explain, summarize, or even recommend indicators, raising the stakes for accuracy and provenance.

The European Commission offers several concrete examples of how automated or semi-automated reporting infrastructures are used to support policy monitoring through dashboards. Eurostat's "European Statistical Monitor" is explicitly described as a dashboard updated monthly, designed to track developments across the EU and associated countries while combining indicator updates with commentary on trends[177]. This illustrates a hybrid form of automation: data updates are systematized, while editorial interpretation remains a structured human task layered onto an automated pipeline. Other Commission dashboards show different update rhythms and governance arrangements. The Recovery and Resilience Scoreboard, for instance, is designed as a transparency tool for tracking implementation of the Recovery and Resilience Facility and is used to support the Commission's reporting to EU institutions[178]. Its

[173] Eurostat CROS, "About WIH," accessed January 22, 2026.
[174] Eurostat CROS, "WIH OJA data," accessed January 22, 2026.
[175] UNECE High-Level Group for the Modernisation of Official Statistics, *Generative AI for Official Statistics: HLG-MOS Report* (Geneva: UNECE, 2025).
[176] Bank for International Settlements Irving Fisher Committee, "Challenges and opportunities presented by generative AI for central banks and statistical agencies," IFC Bulletin (Basel: BIS, 2024).
[177] Eurostat, "European Statistical Monitor: January edition," *Eurostat News*, January 24, 2026.
[178] European Commission, "Recovery and Resilience Scoreboard," accessed January 24, 2026.

"common indicators" documentation clarifies that member states report values on a fixed schedule twice per year, illustrating a model where dashboard refresh is tied to regulated reporting cycles rather than continuous streaming[179]. In parallel, the Commission's Joint Research Centre resilience dashboards describe periodic updates and explicitly note alignment of indicator sets with European Semester reporting, highlighting the role of institutional coordination and revision management in dashboard maintenance[180].

The OECD provides a different but complementary model of automated statistical reporting through its AI Policy Observatory and related dashboards. The OECD.AI dashboards are presented as a live, regularly updated resource, with the Policy Navigator described as a database updated by official contact points, contributors, and OECD experts, including visibility into who submitted or updated entries and when[181]. This "living database" approach makes update provenance part of the interface logic, which is significant because it addresses one of the central problems of automated reporting: users need to know what changed, when, and why. OECD.AI also publishes methodological documentation for certain visualizations, reflecting an institutional commitment to describing data sources and construction choices for dashboard outputs[182]. That kind of embedded documentation is an important governance mechanism when automation increases the rate of change in publicly visible statistics.

Across these settings, dashboards update through a handful of recurring operational patterns. One pattern is scheduled refresh from curated databases, where data are updated at defined intervals and dashboards pull from stable, versioned series; Eurostat's stated twice-daily database updates reflect this approach[183]. A second pattern is event- or cycle-based refresh, where new data are released on reporting deadlines and dashboards update when validated submissions are received, as in the Recovery and Resilience Scoreboard's semiannual reporting cycle[184]. A third pattern is contributor-driven refresh in which new entries or changes trigger immediate dashboard updates, visible in OECD.AI's live database model[185]. A fourth pattern is experimental-statistics refresh, common in web-intelligence systems, where pipelines depend on ongoing collection and processing of web content and therefore must treat source change as a normal operational condition rather than an exception[186].

A critical assessment of automated statistical dashboards begins with a simple observation: automation changes the failure modes of statistical reporting. Traditional statistical products can be wrong or misleading, but the cadence of publication and review tends to slow the spread of errors. Automated dashboards can disseminate errors faster, and because they often present

[179] European Commission, "Common indicators," *Recovery and Resilience Scoreboard*, accessed January 25, 2026.
[180] European Commission Joint Research Centre, "Resilience dashboards," last updated Spring 2024.
[181] OECD, "Policies—OECD.AI dashboards (overview)," accessed January 25, 2026.
[182] OECD, "OECD.AI data from partners: a methodological note," accessed January 25, 2026.
[183] Eurostat, "Database," 2026.
[184] European Commission, "Common indicators," accessed January 26, 2026.
[185] OECD, "Policies," 2026.
[186] Eurostat CROS, "About WIH," 2026.

results as smoothly updating visuals, users may overestimate stability and underestimate uncertainty. In fields where dashboards are used to guide operational decisions—public health, crisis response, or macroeconomic monitoring—systematic reviews show that dashboard design and implementation choices affect usability, comprehension, and the quality of decisions supported by the interface[187]. Research on interactive dashboards also finds that specific visualization features can influence user confidence and performance in ways that are not always aligned with correct interpretation, which becomes a governance concern when dashboards are framed as authoritative statistical products[188]. This is not merely an interface problem; it is an epistemic risk that grows when dashboards refresh frequently and when users cannot easily reconstruct the exact data state that produced a past view.

A second major risk is silent change arising from revisions, redefinitions, or pipeline updates that alter what a dashboard is "really" showing without a clear signal to users. Even in highly regulated statistical systems, revisions are common, and they can meaningfully affect trends and comparisons. The Joint Research Centre's resilience dashboards, for example, explicitly mention updates and refinements aligned with European Semester indicator sets and note that revisions in official statistics are considered within reference datasets, reflecting institutional awareness that dashboards must incorporate revision management rather than pretending that published values are immutable[189]. When automation is layered on top of revision-prone series, good governance requires visible versioning, change logs, and stable identifiers so users can cite and reproduce prior states. Practical frameworks for computational reproducibility emphasize that transparency depends on making data, code, and computational context re-runnable; this principle becomes harder, not easier, when dashboards update continuously[190].

A third risk is model drift and data drift in AI-enabled components of the pipeline, particularly where dashboards rely on machine learning to classify, impute, or detect anomalies. Drift can emerge from changing populations, evolving reporting practices, or shifts in how web content is generated, and it can degrade performance even when the dashboard continues to "look normal." Institutional guidance on generative AI in official statistics emphasizes traceability and ongoing control because automated systems can otherwise erode the reproducibility and reliability of outputs over time[191]. In web intelligence contexts, source instability is especially acute: platforms change page structure, content policies evolve, and automated extraction can break or subtly shift coverage, which can translate into indicator drift that is difficult to diagnose after the fact without robust monitoring and audit trails[192].

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[187] Annika Schulze et al., "Digital dashboards visualizing public health data: a systematic review," *Frontiers in Public Health* (2023).
[188] Sarah Hoffenson et al., "Graphical features of interactive dashboards have little consistent effect on decision making," *International Journal of Human-Computer Studies* (2023).
[189] Joint Research Centre, "Resilience dashboards," (2024).
[190] A. H. C. van Kampen et al., "ENCORE: a practical implementation to improve computational reproducibility," *PLOS Computational Biology* (2024).
[191] UNECE, *Generative AI for Official Statistics,* (2025).
[192] Eurostat, "About WIH," 2026.

A fourth risk concerns transparency and accountability when NLP or generative AI is used to create narrative summaries for dashboards. Narrative layers can improve accessibility, but they also introduce the possibility of confident-sounding errors, ambiguous sourcing, or loss of nuance about uncertainty and methodological limits. Both UNECE and BIS discussions of language models in official statistics stress the need for governance controls and careful operational design, particularly to protect trust in official outputs and to ensure that human oversight remains meaningful rather than symbolic[193] [194]. In statistical reporting, a misleading textual summary can be as damaging as a wrong number, because it shapes interpretation and downstream use especially for non-specialist audiences.

A fifth risk is security and integrity. Automated statistical dashboards are cyber-physical in the sense that they are connected to live data flows, APIs, and processing infrastructure. That connectivity can expand the attack surface for data poisoning, unauthorized alteration, or disruption of publication pipelines. While statistical agencies often treat security as an IT concern separate from methodology, the two increasingly overlap: if an automated pipeline is compromised, the dashboard may continue to publish plausible-looking results. OECD's emphasis on operational risk and public trust in government AI underscores that institutional adoption must include safeguards that match the sensitivity and public impact of automated reporting systems[195].

These risks do not imply that automated statistical dashboards should be avoided. Rather, they clarify what responsible automation looks like in practice. At minimum, trustworthy dashboards require strong provenance signals, including visible update timestamps, clear statements of refresh cadence, and user-facing explanations of revision policy. They benefit from publication of methodological notes and data construction documentation, as OECD.AI does for selected visualizations, because documentation is one of the few scalable tools for preserving interpretability under frequent change[196]. They also require internal governance: monitoring for drift, controlled rollouts for pipeline changes, audit logs that tie outputs to specific data and code versions, and explicit accountability for when automation fails. Eurostat's ecosystem of collaborative AI/ML work and web intelligence infrastructure illustrates that European institutions are actively building the technical capacities for automation; the critical challenge is ensuring that these capacities are matched by equally mature transparency, reproducibility, and risk-management practices so that rapidly updating dashboards remain credible statistical instruments rather than persuasive interfaces that outpace their own controls[197] [198].

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[193] UNECE, *Generative AI for Official Statistics,* (2025).
[194] Bank for International Settlements, "Challenges and opportunities," (2024).
[195] OECD, *Governing with Artificial Intelligence* (2025).
[196] OECD, "OECD.AI data from partners," (2026).
[197] Eurostat, "AIML4OS," (2026).
[198] Eurostat, "About WIH,"(2026).

5. Case Study of AI Performing Demographic Calculations

The experimental procedure begins with the AI condition, in which demographic computation tasks are completed using ChatGPT as the analytical interface. This approach enables systematic documentation of AI-generated outputs, intermediate reasoning steps, and interaction patterns, providing transparency into how the system navigates statistical data and applies demographic methods. To ensure reproducibility and consistent data access, the demographic datasets are first downloaded manually from the official statistical portals of Eurostat and ISTAT, where they are publicly available in bulk formats such as TSV or CSV files. These files are then uploaded directly into ChatGPT, allowing the AI system to operate within a controlled "database environment" that reflects realistic research practice while maintaining a clear provenance trail for all calculations and derived indicators.

What you uploaded (Eurostat "database environments")

These are Eurostat dissemination extracts in bulk TSV format, identified by **online data code**:

- estat_tps00019.tsv → **Population change – crude rates of total change, natural change and net migration plus adjustment** (tps00019). (European Commission)
- estat_tps00029.tsv.gz → **Deaths and crude death rate** (tps00029). (European Commission)
- estat_tps00199.tsv.gz → **Total fertility rate** (tps00199). (European Commission)
- estat_tgs00100.tsv.gz → **Total fertility rate by NUTS 2 region** (tgs00100). (European Commission)

Time coverage in the files**:** 2013–2024 (annual), but some indicators (notably fertility) have latest non-missing values only up to **2023** in these extracts.

Artificial intelligence experiment (quantitative phase)

I treated each TSV as a "table," then performed **fixed tasks** across two geographies:

- **IT** (Italy)
- **EU27_2020** (EU aggregate)

Core population calculations (Eurostat)

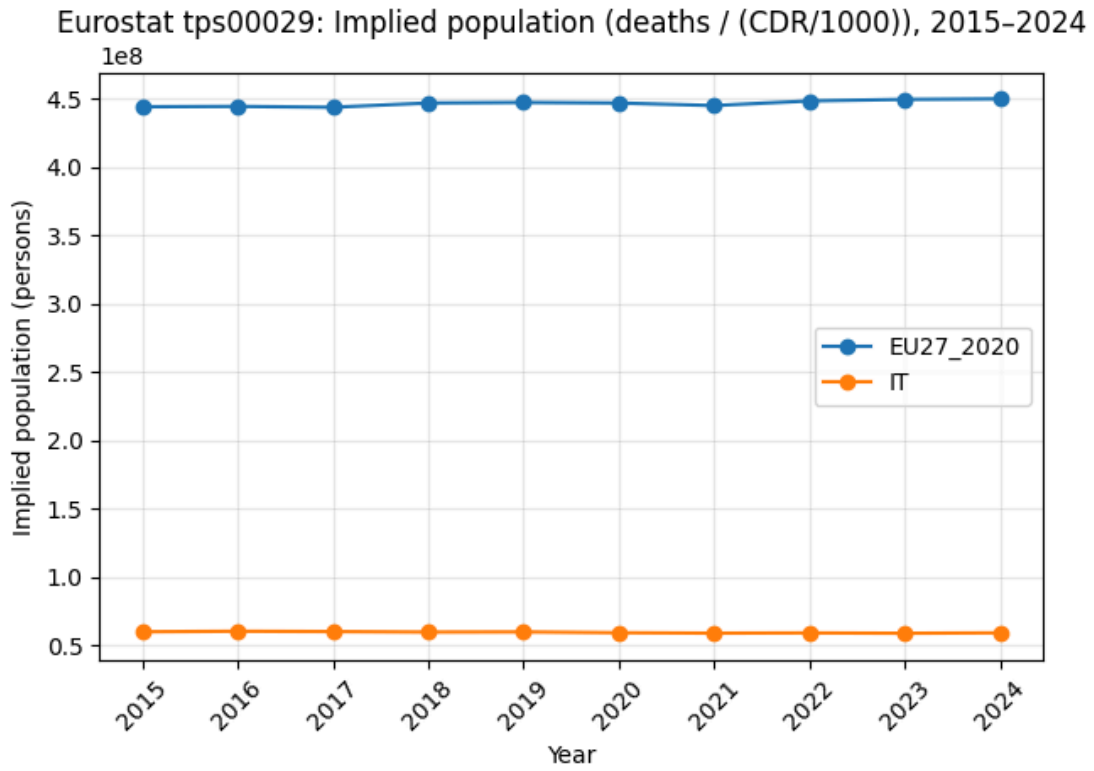
"Implied population" (derived, not directly reported)

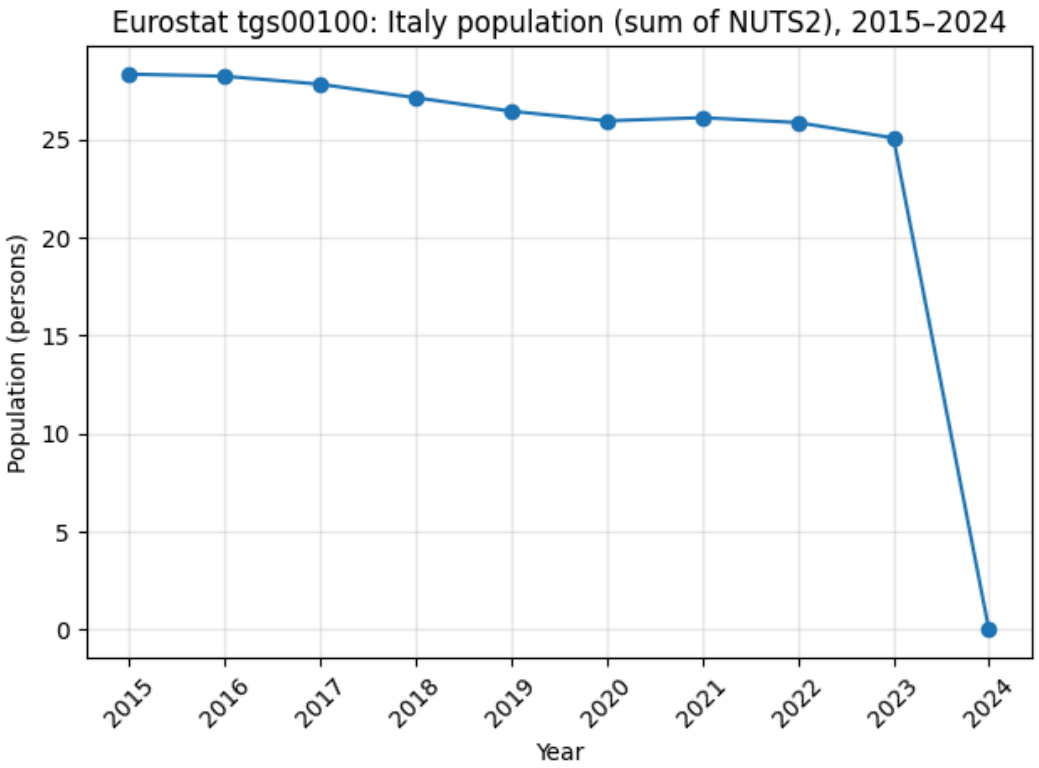
Because you didn't upload a direct population stock table (e.g., tps00001), I computed population via a standard demographic identity using **deaths and crude death rate** from tps00029:

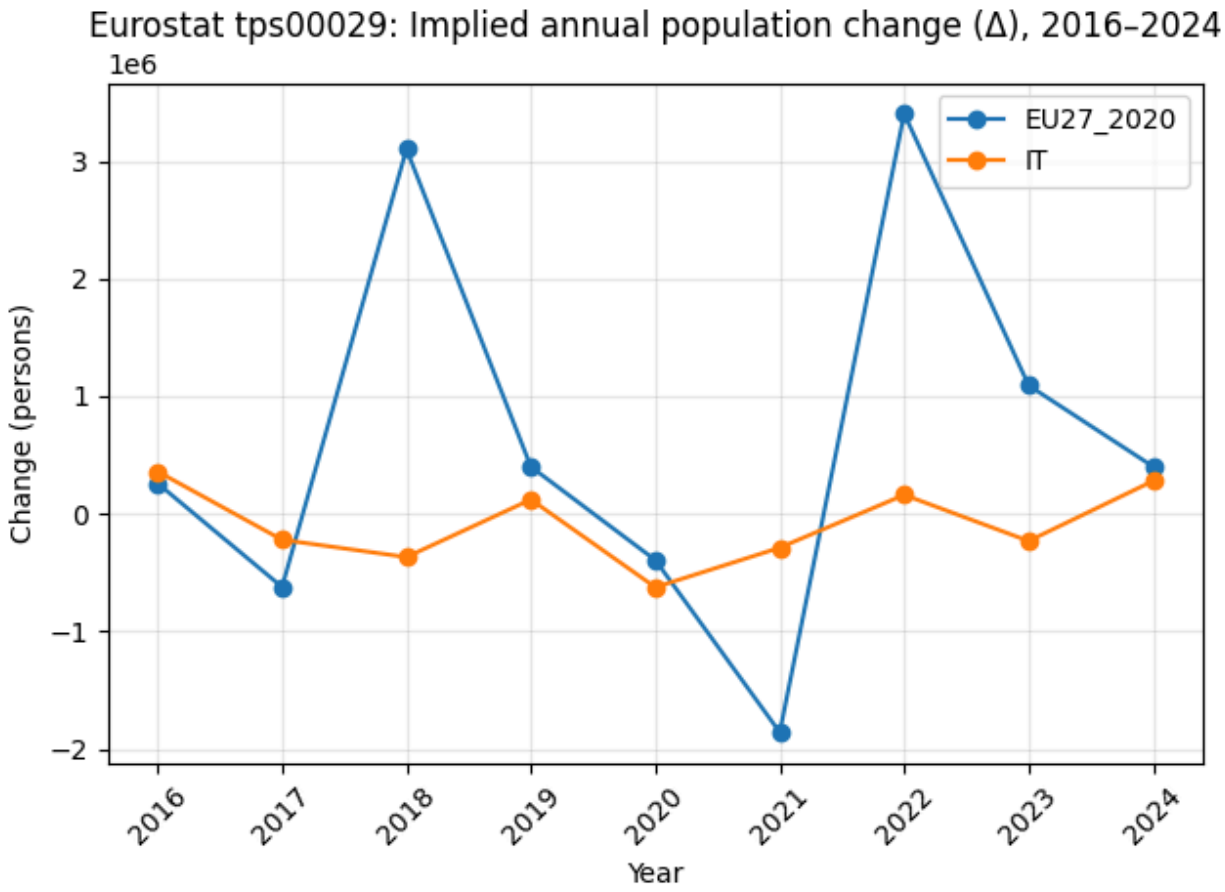
[\text{Population}*{t} \approx \frac{\text{Deaths}}{t}}{\text{CDR}_{t}/1000}]

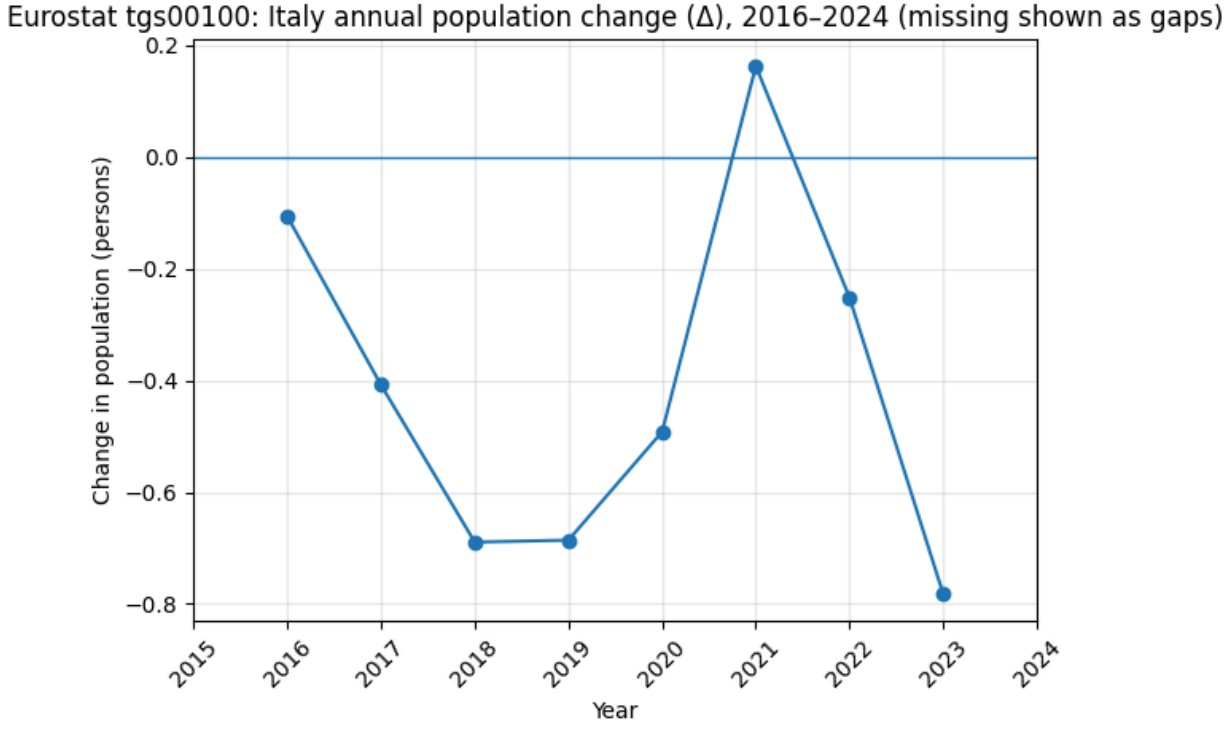
- Inputs:
  - DEATH_NR = deaths (number)
  - GDEATHRT_THSP = crude death rate (per 1,000)

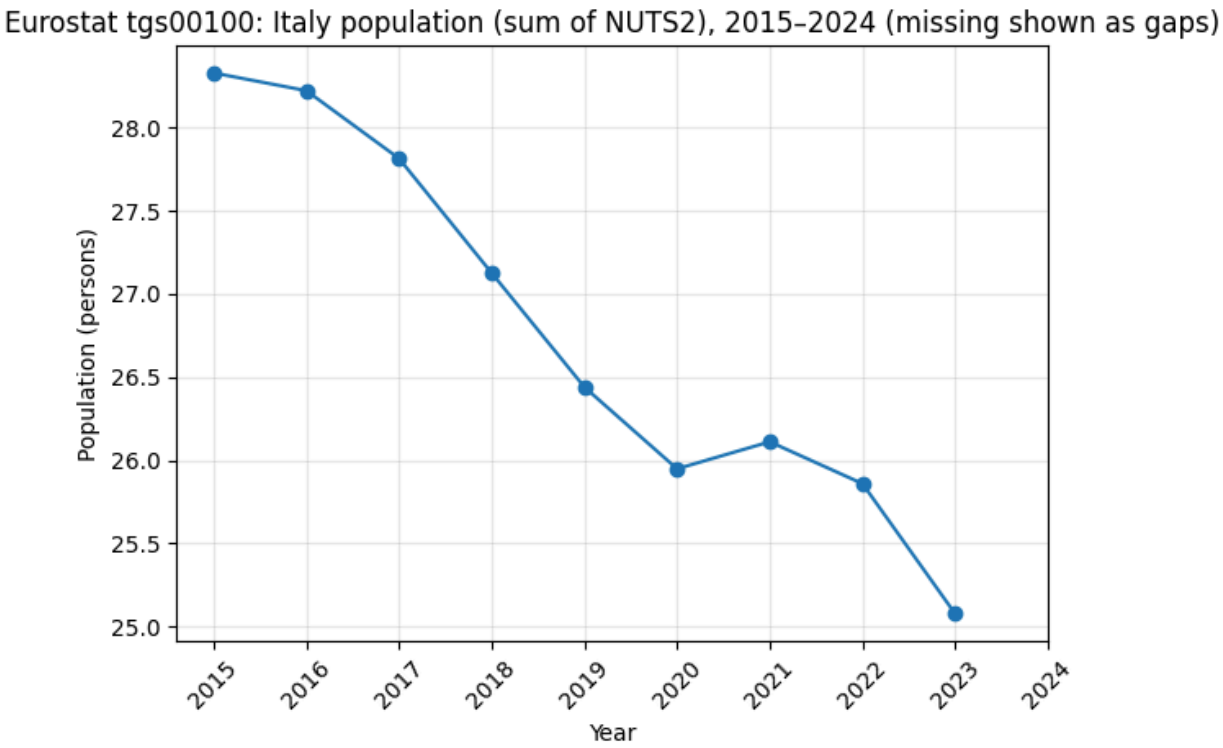
Graphs generated (Eurostat):




Eurostat tgs00100: Italy population (sum of NUTS2), 2015–2024
Population (persons)
0
5
10
15
20
25
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Year


Eurostat tps00029: Implied annual population change (Δ), 2016–2024
1e6
EU27_2020
IT
Change (persons)
Year
2016
2017
2018
2019
2020
2021
2022
2023
2024


Eurostat tgs00100: Italy annual population change (Δ), 2016–2024 (missing shown as gaps)
Change in population (persons)
Year
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024



Key 2024 results (from your TSVs):

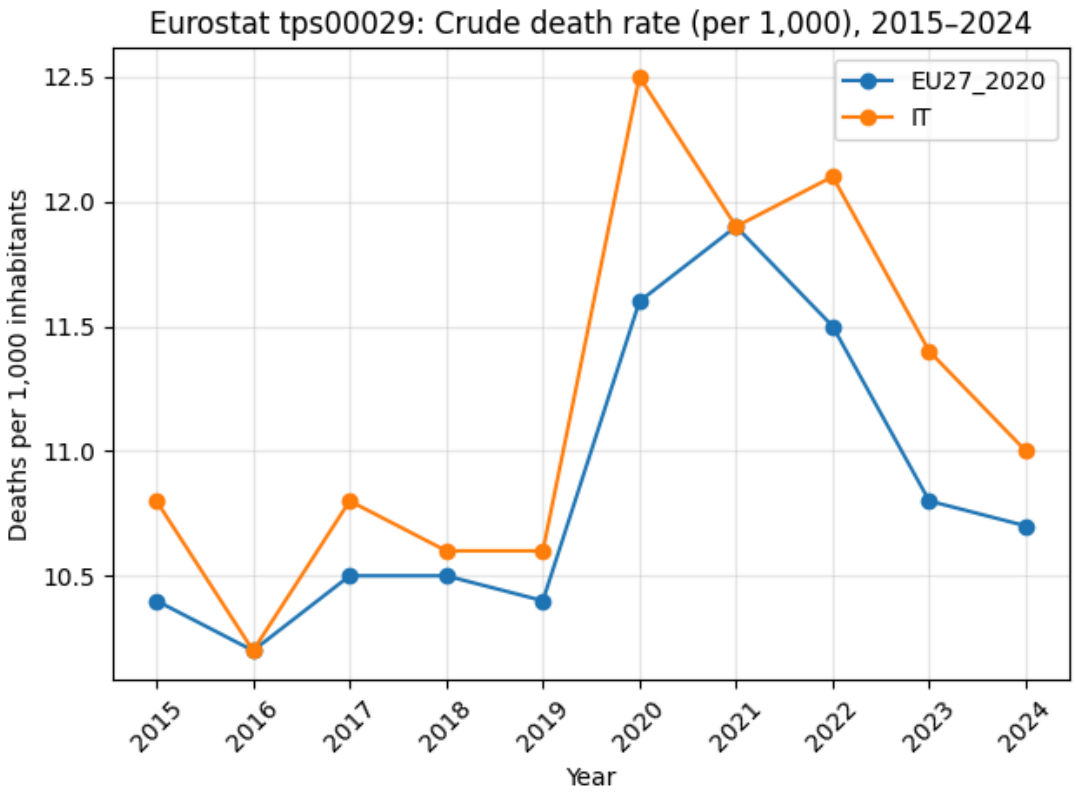
- **Italy (IT)**: deaths ≈ **650,587**, CDR **11.0‰**, implied population ≈ **59.14M**
- **EU27_2020**: deaths ≈ **4,815,526**, CDR **10.7‰**, implied population ≈ **450.05M**

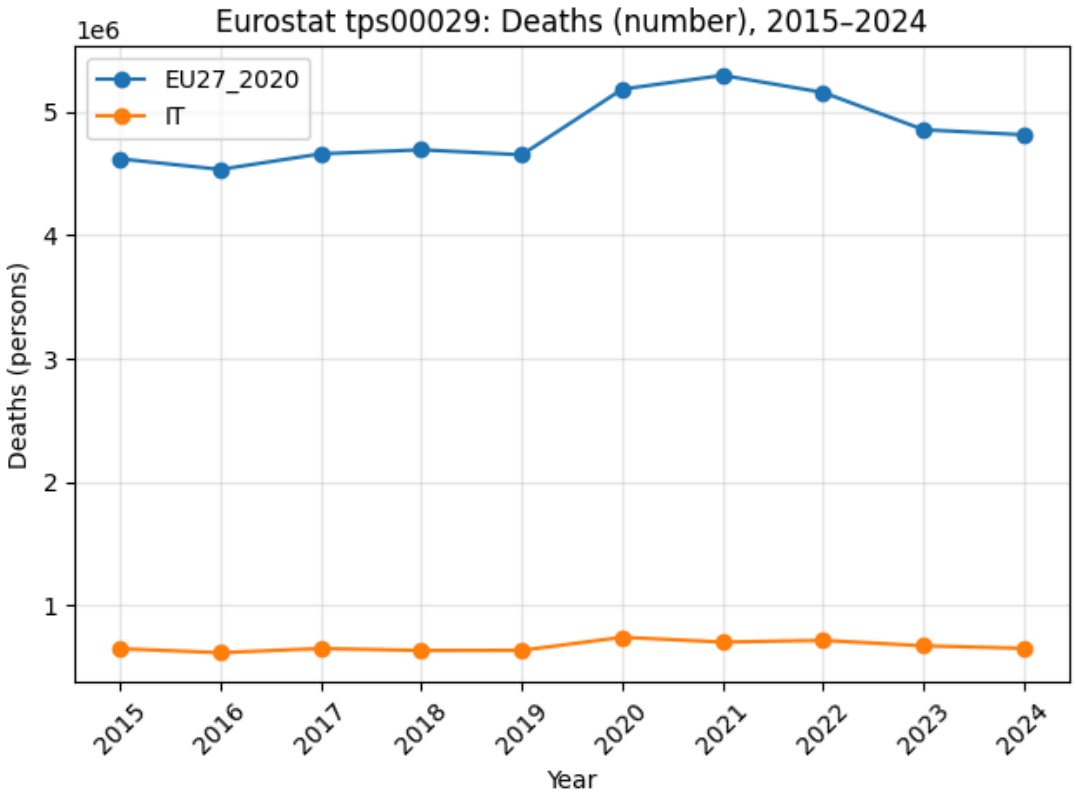
(These are computed directly from the TSV values; they're "implied mid-year population" style estimates, not official stock counts.)

Death rates (Eurostat)

From tps00029 I plotted:

Crude death rate (per 1,000)


Eurostat tps00029: Crude death rate (per 1,000), 2015–2024
EU27_2020
IT
Deaths per 1,000 inhabitants
12.5
12.0
11.5
11.0
10.5
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Year

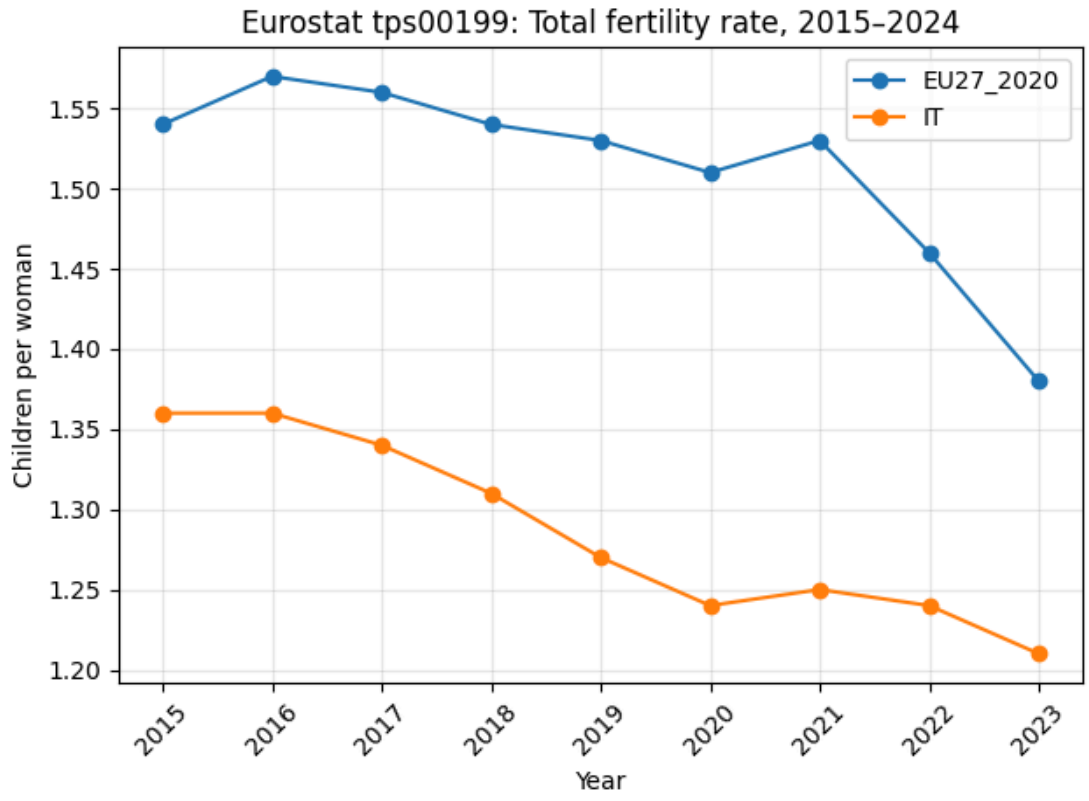

Eurostat tps00029: Deaths (number), 2015–2024
1e6
EU27_2020
IT
Deaths (persons)
5
4
3
2
1
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Year

- Visible pandemic-era peak around 2020–2021, then decline afterward (in both series).

Fertility rates (Eurostat)

National total fertility rate (TFR)

From tps00199 (TFR, children per woman):



Latest available in your extract: 2023

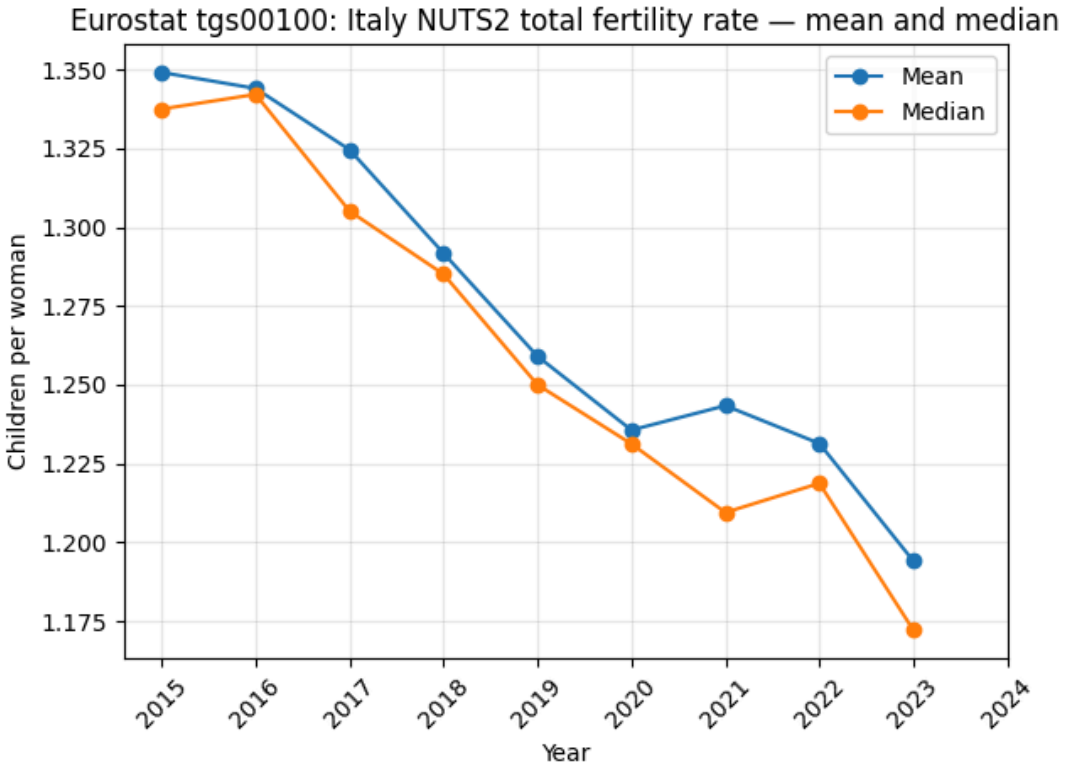
- **Italy (IT)**: **1.21** (2023)
- **EU27_2020**: **1.38** (2023)

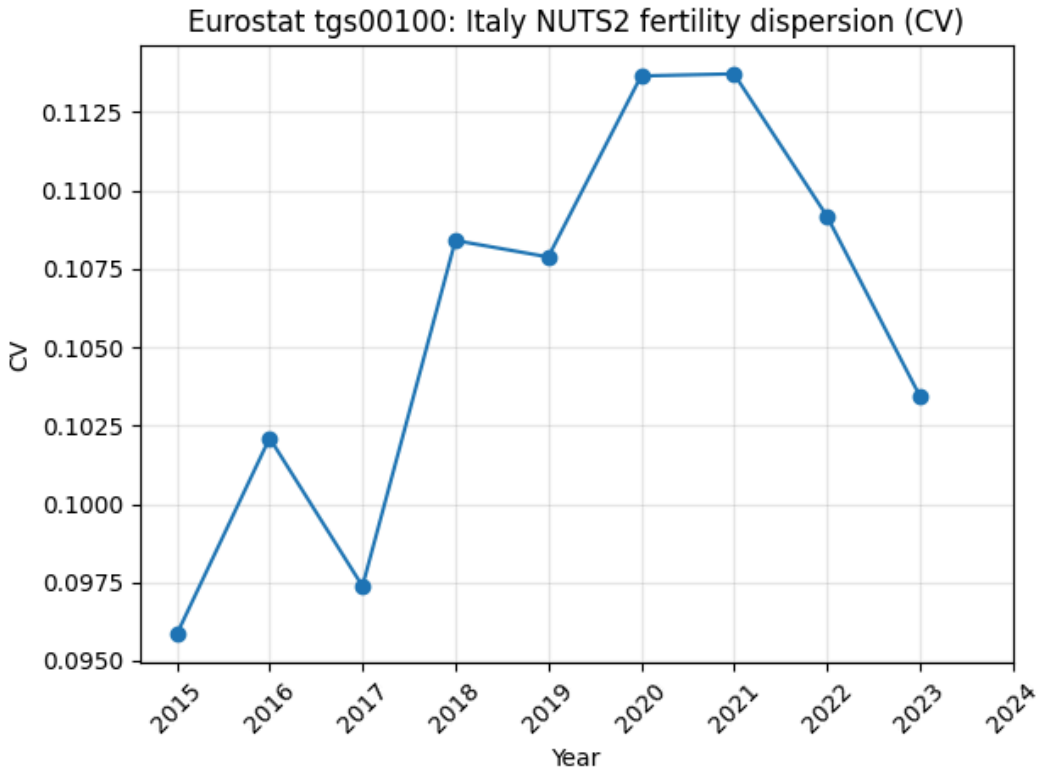
Regional fertility "structure ratios" (Italy, NUTS2)

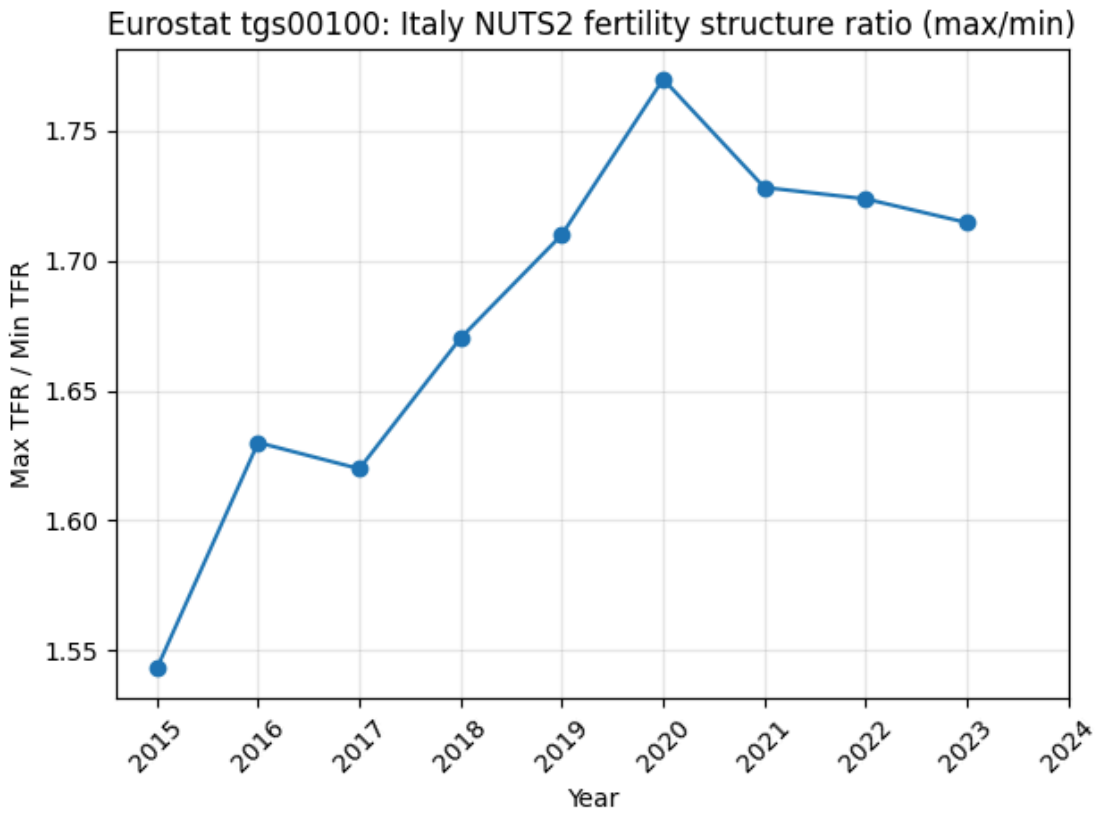
From tgs00100 (TFR by NUTS2 region), I computed **population-structure-style dispersion ratios** across Italian regions each year:

- Mean and median TFR across IT NUTS2
- **Coefficient of variation (CV = std/mean)** as an inequality/dispersion measure
- **Max/Min ratio** as a "structure ratio" for regional fertility inequality

Graphs generated (Italy NUTS2):







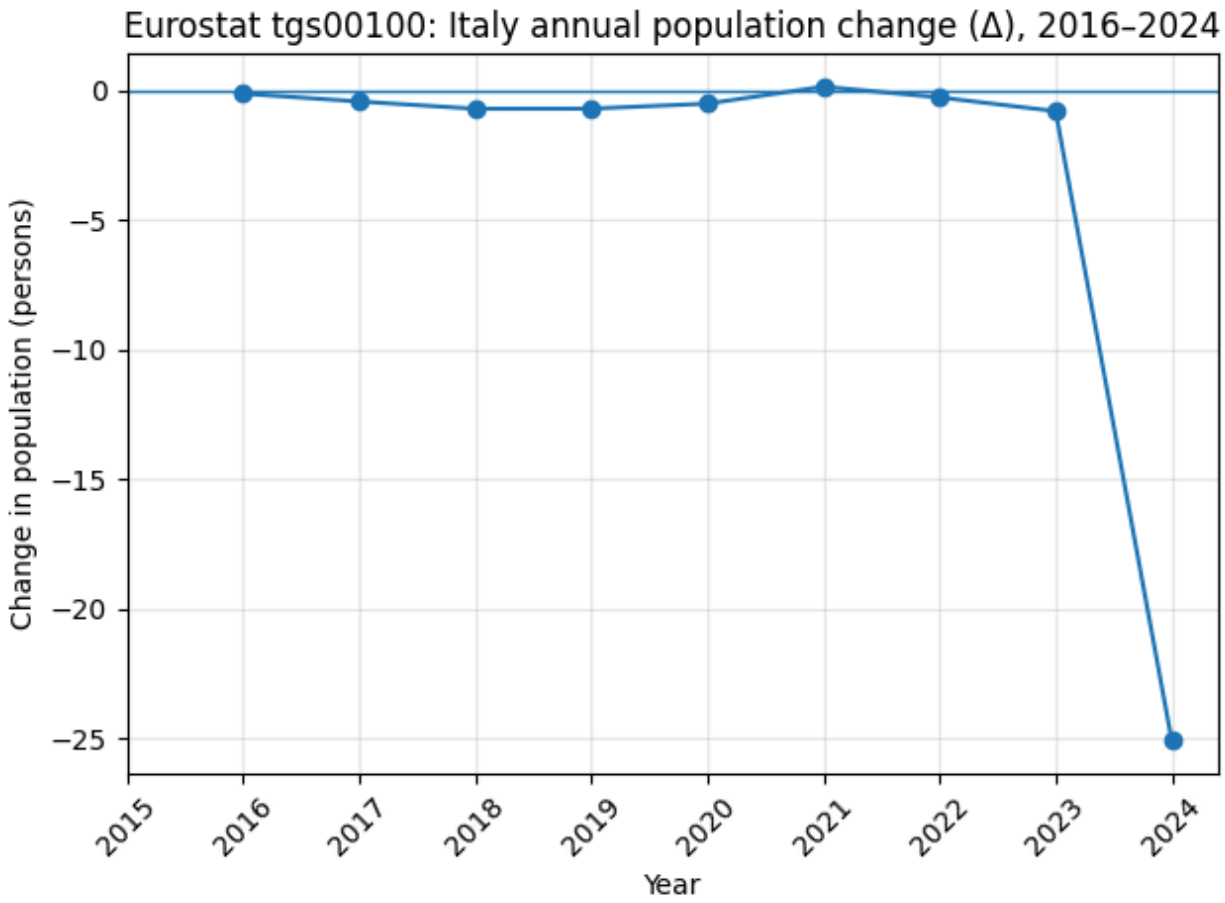
This gives you a defensible "structure ratio" family from a dataset you actually provided (since age-structure tables weren't included).

Population change decomposition (Eurostat)

From tps00019 I used:

- GROWRT = total population change rate (per 1,000)
- NATGROWRT = natural change rate (per 1,000)
- CNMIGRATRT = net migration + adjustment rate (per 1,000)

Rate-based decomposition (graphs)



“Contribution shares” (ratios)

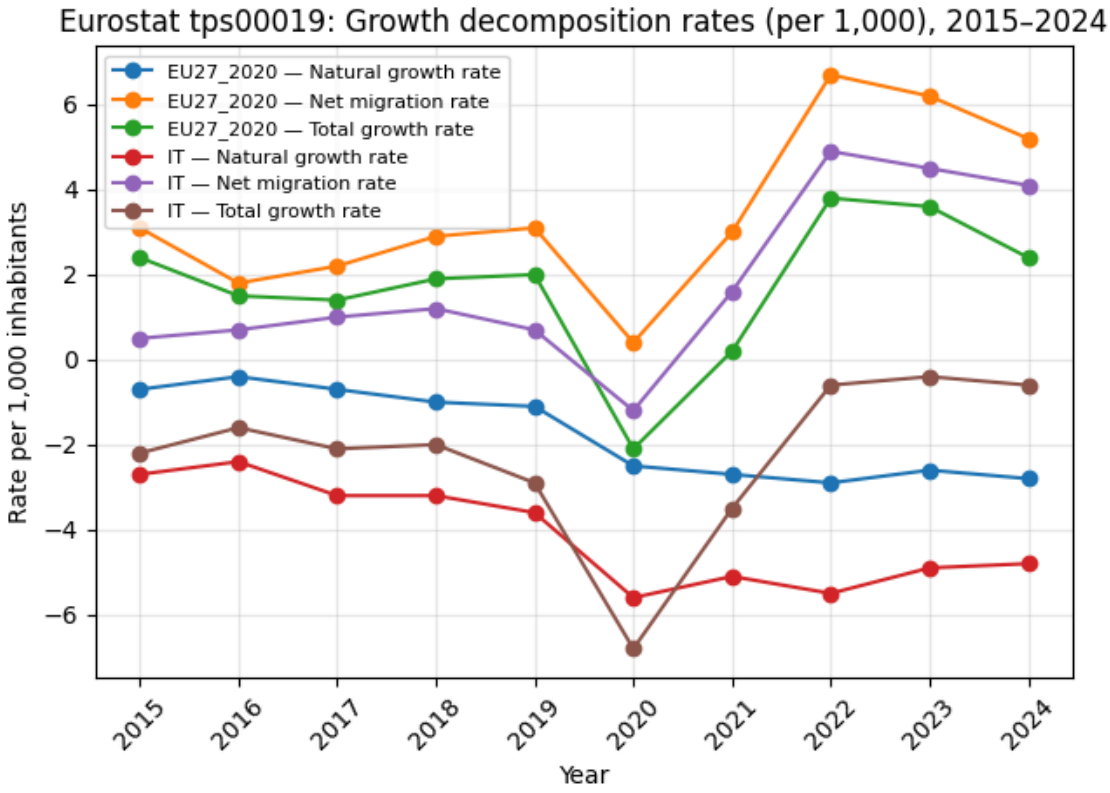
I also computed:
[\text{migration share}=\frac{\text{CNMIGRATRT}}{\text{GROWRT}},\quad\text{natural share}=\frac{\text{NATGROWRT}}{\text{GROWRT}}]

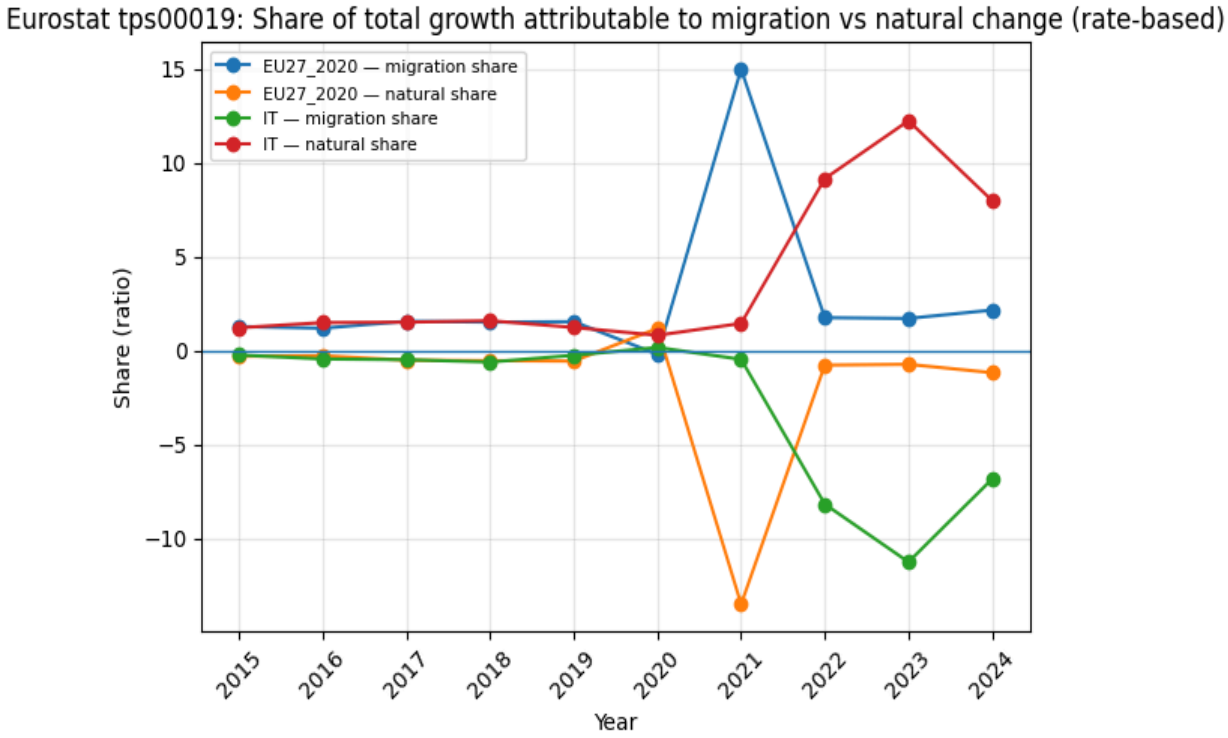
Convert rates → implied counts (multi-step task)

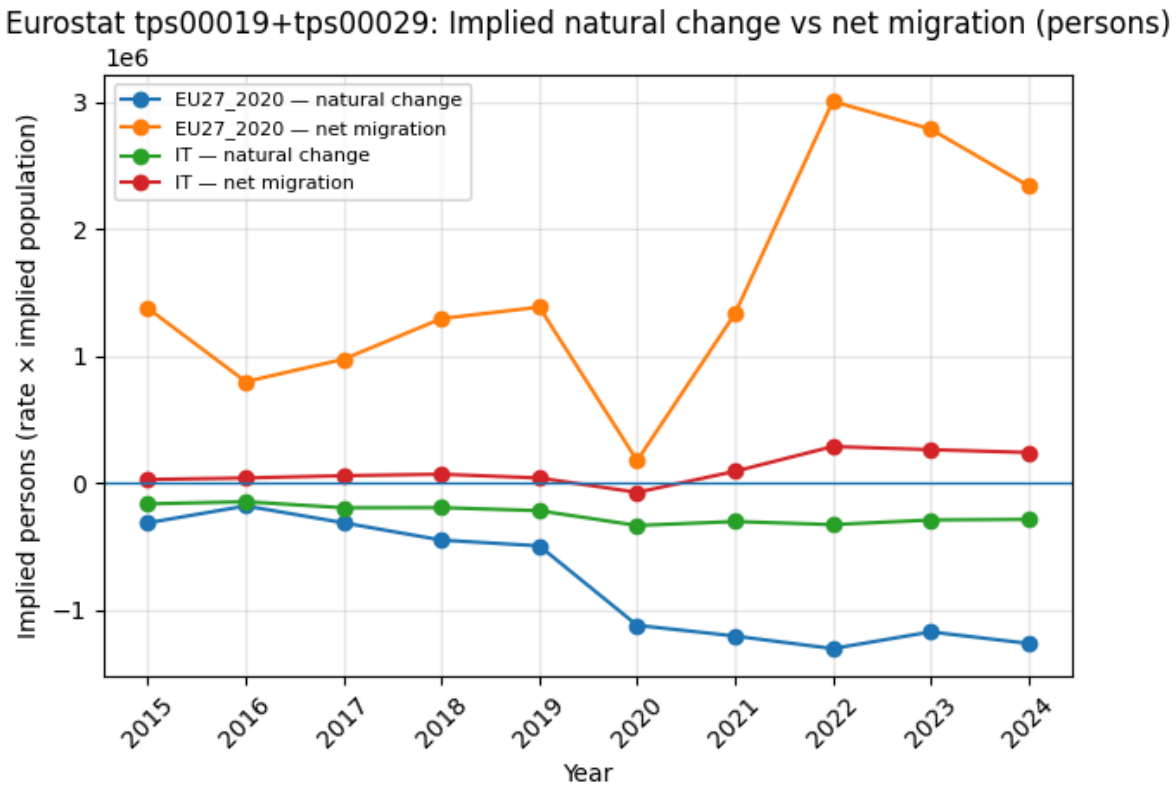
Using the implied population from tps00029, I converted rates into implied persons:

[\text{NaturalChangePersons}\approx \frac{\text{NATGROWRT}}{1000}\times \text{ImpliedPop}]

Graph generated:


Eurostat tps00019: Growth decomposition rates (per 1,000), 2015–2024
EU27_2020 — Natural growth rate
EU27_2020 — Net migration rate
EU27_2020 — Total growth rate
IT — Natural growth rate
IT — Net migration rate
IT — Total growth rate
Rate per 1,000 inhabitants
Year


Eurostat tps00019: Share of total growth attributable to migration vs natural change (rate-based)
EU27_2020 — migration share
EU27_2020 — natural share
IT — migration share
IT — natural share
Share (ratio)
Year



Key 2024 rate picture (from your TSVs):

- **Italy (IT)**: total growth rate **−0.6‰**, natural change **−4.8‰**, net migration **+4.1‰**
- **EU27_2020**: total growth rate **+2.4‰**, natural change **−2.8‰**, net migration **+5.2‰**

What went well (capability)

- **Schema inference succeeded** from Eurostat's encoded dimensions (freq/indicator/geo/year).
- **Multi-step derivations succeeded** (e.g., implied population and converting rates to implied persons).
- **Transparent logging:** I preserved intermediate tables (you saw them rendered as dataframes).

What was "messy schema / provenance risk"

- tgs00100 initially looks like a population table (freq, unit, age, geo), but it is **regional fertility**, not population stock. This is exactly the kind of **schema misunderstanding trap** your methodology anticipates.
- The dataset set you provided **does not include age-structure population**, so classic dependency ratios (0–14 / 65+ / 15–64) cannot be computed from these files alone.

- Failure to process missing or incomplete data and uploading **zero values** to fill in missing components rather than attempting to draw from different data sources.

In the AI phase of the experiment, the uploaded Eurostat and ISTAT datasets were treated as structured database environments through which the system performed a sequence of navigation and computation tasks. This involved identifying relevant tables, parsing multidimensional schemas, cleaning statistical flags and missing values, and transforming the data into analyzable formats. Using these prepared tables, the AI calculated core demographic indicators including crude death rates, total fertility rates, population change measures, and rate-based decompositions of natural increase and net migration. Multi-step derivations were also conducted, such as converting crude rates into implied population counts and constructing regional dispersion and structure ratios from NUTS-level fertility data. Throughout this process, intermediate outputs, assumptions, and limitations (for example, missing population stock tables or incomplete time coverage) were logged to maintain transparency and support later error analysis. Regardless of the promise shown in these calculations the AI was unable to process missing or incomplete data and provided incorrect data as a result (see Italy population graphs in which the 2024 values have been input incorrectly). This result does not refute my argument that artificial intelligence should be implemented in quantitative calculations but proves that human oversight is required in implementation. As artificial intelligence develops further and becomes a sophisticated tool, it will inevitably be able to realize these failures and improve the results by drawing from different sources than what is provided.

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6. Stakeholder Perspectives

6.1 Demographer Perspectives: AI and the Data-Intensive Turn in Demography

The past five years have seen demographic research increasingly shaped by what scholars describe as a "data-intensive turn," characterized by expanding administrative data infrastructures, digital trace data, and computational modelling[199]. Artificial intelligence, especially machine learning, has become central to this transformation, enabling demographers to analyse population processes across unprecedented spatial and temporal scales.

Recent demographic literature positions AI not as a radical rupture but as a methodological extension of quantitative demographic traditions. Demographers Tomas Sobotka and Stuart Basten argue that machine learning methods represent "a complementary toolkit for demographic

[199] Tomáš Sobotka and Stuart Basten, "The Rise of Data-Intensive Demography," *Population Studies* 76, no. 1 (2022).

inference, particularly when traditional models struggle with high-dimensional data structures."[200] This framing reflects the discipline's historical openness to methodological innovation, from life table analysis to Bayesian demography.

At the same time, demographers emphasize that AI's integration into official statistics raises normative questions regarding data governance, transparency, and the epistemology of demographic knowledge production. UNECE guidance notes that statistical offices adopting machine learning must balance innovation with "core statistical values of quality, trustworthiness and interpretability."[201]

Opportunities Identified by Demographers

Transforming Population Measurement and Statistical Production

Recent demographic and statistical scholarship highlights AI's potential to reshape population measurement by enabling integrated data ecosystems. National statistical offices increasingly rely on administrative data and digital sources, with AI supporting automated linkage, classification, and validation.

Eurostat's 2023 methodological report observes that machine learning is already used in European statistical production for tasks such as data editing, record linkage, and classification, noting that these applications "can reduce processing time and increase consistency while preserving statistical quality standards."[202] Demographers studying the modernization of official statistics, such as Emilio Zagheni, argue that the integration of machine learning and administrative data infrastructures is especially significant for the transition toward register-based censuses and the improvement of migration measurement[203].

Similarly, UNECE emphasizes that machine learning allows statistical agencies to process "high-volume, high-velocity and heterogeneous data sources that were previously infeasible to exploit."[204] Demographers working in digital and computational population research, including Ingmar Weber, emphasize that the integration of digital trace data and machine learning enables near-real-time observation of population change, urban dynamics, and labour mobility patterns[205].

[200] Ibid
[201] UNECE, *Machine Learning for Official Statistics: Recent Developments and Guidance* (Geneva, 2023).
[202] Eurostat, *AI and Machine Learning in European Statistical Production* (Luxembourg, 2023).
[203] Emilio Zagheni et al., "Digital and Computational Demography," *Population Studies* 76, no. S1 (2022): 3–18.
[204] UNECE, *Machine Learning for Official Statistics* (2023).
[205] Ingmar Weber, Emilio Zagheni, and Lisa P. State, "The Promise and Pitfalls of Using Digital Traces for Demographic Research," *Demographic Research* 46 (2022): 123–150.

The demographic literature therefore frames AI as enabling a transition from periodic measurement toward continuous population monitoring, a development with significant implications for policy responsiveness and demographic forecasting.

Advancing Demographic Forecasting and Modelling

Forecasting represents one of the most extensively studied intersections between demography and AI. Recent comparative studies demonstrate that machine learning approaches can complement traditional cohort-component and Bayesian models, particularly in short-term forecasting contexts.

A 2022 demographic analysis finds that machine learning models can "capture complex nonlinear relationships in fertility and migration data that may not be adequately represented in conventional demographic frameworks."[206] Wisniowski and other researchers highlight improved predictive performance for migration flows, mortality risks, and small-area population projections.

Importantly, Zagheni and Weber stress that predictive gains do not imply methodological replacement. Instead, hybrid modelling approaches combining demographic theory with machine learning are increasingly advocated. A computational demography review concludes that integrating ML with theory-driven models allows researchers to leverage predictive accuracy while retaining explanatory coherence[207]. This hybrid perspective reflects demographers' commitment to balancing methodological innovation with theoretical continuity.

Expanding Data Coverage and Inclusion through Alternative Data Sources

Demographers engaged in spatial and humanitarian population research, including Andrew J. Tatem, highlight that AI-enabled analysis of satellite imagery, mobile phone metadata, and online platform data offers new possibilities for estimating population distributions in settings where census systems are incomplete, outdated, or disrupted[208].

Studies using AI-assisted remote sensing demonstrate the ability to produce high-resolution settlement maps and population estimates, supporting humanitarian planning and migration research[209]. Such approaches can improve visibility for displaced or informal populations often undercounted in official statistics.

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[206] Arkadiusz Wiśniowski et al., "Combining Machine Learning and Demographic Models for Population Forecasting," *Demographic Research* (2022).
[207] Emilio Zagheni and Ingmar Weber, "Demographic Research with Nontraditional Data Sources," *Annual Review of Sociology* (2021).
[208] Andrew J. Tatem, "Mapping Populations at Risk: The Role of Spatial Data and Machine Learning in Population Estimation," *Philosophical Transactions of the Royal Society B* 376, no. 1817 (2021): 20190345.
[209] WorldPop, *AI-Based Population Mapping for Sustainable Development* (2022).

A 2023 review in *Population and Development Review* notes that digital trace data can "enhance demographic understanding of mobility and social behaviour at temporal and spatial scales unattainable with conventional surveys."[210] However, Zagheni cautions that inclusion benefits depend heavily on addressing bias and ensuring methodological transparency.

Critical Concerns among Demographers

Representativeness, Bias, and Data Quality

Representativeness remains a foundational concern in demographic research. Digital trace and administrative datasets frequently exhibit selective coverage, raising risks of biased population estimates when used in AI models.

Recent demographic scholarship highlights that big data sources "are not generated with statistical representativeness in mind," requiring careful methodological evaluation before integration into official statistics[211]. Demographers examining digital trace data and computational population methods, such as Zagheni, caution that algorithmic models can reproduce and even intensify demographic inequalities when underlying datasets systematically underrepresent marginalized or digitally excluded populations[212]. UNECE guidance similarly warns that quality assurance must remain central, emphasizing that machine learning outputs should be subject to the same validation standards as traditional statistical estimates[213].

Interpretability and Epistemological Tensions

The rise of AI has intensified debates about explanation versus prediction in demography. While machine learning offers strong predictive performance, its interpretability challenges the discipline's emphasis on causal explanation and theory development. Recent demographic commentary argues that black-box models risk producing insights that are difficult to contextualize within demographic theory, potentially limiting cumulative knowledge building[214]. This concern is particularly salient in official statistics, where transparency and reproducibility underpin public trust. Nevertheless, explainable AI methods and hybrid modelling approaches are increasingly explored as means of reconciling predictive accuracy with interpretability.

Privacy, Ethics, and Public Trust

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[210] Emilio Zagheni et al., "Digital Trace Data for Population Research," *Population and Development Review* (2023).
[211] UNECE, *Machine Learning for Official Statistics* (2023).
[212] Emilio Zagheni, Ingmar Weber, and Krishna Gummadi, "Leveraging Digital Trace Data for Demographic Research: Opportunities and Challenges," *Annual Review of Sociology* 48 (2022): 463–480.
[213] UNECE, *Machine Learning for Official Statistics* (2023).
[214] Jakub Bijak, "Forecasting in the Age of Big Data and Machine Learning," *Population Studies* 75, no. S1 (2021): 7–18.

AI-driven demographic analysis often relies on individual-level administrative and digital data, intensifying ethical concerns regarding privacy and surveillance. Demographers emphasize that public trust constitutes a prerequisite for data collection, especially in census contexts. The UN Committee of Experts on Big Data and Data Science for Official Statistics stresses that ethical governance frameworks are necessary to ensure that new data sources and AI methods "respect privacy, confidentiality and human rights while enabling statistical innovation."[215] Demographers studying data governance and public trust in official statistics, including Roberto Impicciatore, warn that the expanding use of administrative and digital data raises the risk of function creep, whereby information collected for statistical analysis may be repurposed for administrative control or surveillance, potentially eroding public confidence in demographic data systems.[216]

Counterarguments and Emerging Consensus

Explainable AI and Methodological Integration

Recent demographic research shows growing interest in explainable artificial intelligence as scholars seek to address concerns about the opacity of machine learning models. Demographers emphasize that interpretability is essential because population research often informs public policy and official statistics, contexts where transparency and accountability are central. As Jakub Bijak argues, the increasing use of machine learning in forecasting has prompted reflection on "the need to balance predictive performance with understanding of underlying demographic processes."[217] Explainable AI methods including feature importance analysis and interpretable model structures allow demographers to examine how variables such as age, migration status, or socioeconomic conditions shape predictions. Similarly, research on digital and computational demography notes that interpretability helps translate AI-generated outputs into substantively meaningful insights, strengthening their scientific and policy relevance[218].

Alongside explainability, demographic scholars increasingly advocate hybrid modelling approaches that combine machine learning with traditional demographic frameworks. This is one reason that the experiment in this study has pursued a hybrid approach. Rather than replacing cohort-component or Bayesian demographic models, machine learning is used to complement them by capturing nonlinear relationships while preserving theoretical grounding. A recent review in *Population Studies* highlights that integrating computational and demographic methods can "enhance demographic inference while maintaining the interpretability required for scientific explanation and policy use."[219] This emerging consensus suggests that hybrid and explainable

[215] UN Committee of Experts on Big Data and Data Science for Official Statistics, *Ethical Framework for Data Science in Official Statistics* (2022).
[216] Roberto Impicciatore, Jakub Bijak, and Arkadiusz Wiśniowski, "Administrative Data and the Future of Population Statistics: Opportunities, Risks and Public Trust," *Population Studies* 76, no. S1 (2022): 87–104.
[217] Jakub Bijak, "Forecasting in the Age of Big Data and Machine Learning,", (2021).
[218] Emilio Zagheni et al. "Digital and Computational Demography," (2022), 16.
[219] Sobotka and Basten, "The Rise of Data-Intensive Demography," (2022), 2.

approaches offer a pragmatic pathway for demographic research, allowing scholars to benefit from AI's predictive power while safeguarding transparency, theory-building, and public trust.

Institutional Safeguards and Statistical Governance

A key counterargument to skepticism surrounding AI adoption in demography emphasizes the strength of European statistical governance frameworks, which embed AI innovation within established norms of quality assurance, transparency, and professional accountability. Institutions within the European Statistical System (ESS) stress that AI-based methods must comply with the *European Statistics Code of Practice*, which requires methodological soundness, professional independence, and safeguards for statistical confidentiality. Recent Eurostat guidance on machine learning highlights that AI applications in official statistics remain subject to "existing quality frameworks, documentation requirements and human oversight," ensuring that automated outputs are validated and interpretable before dissemination.[220] Similarly, UNECE guidance on AI in official statistics underscores that human-in-the-loop validation and auditability are central to responsible adoption, noting that statistical organizations must maintain "transparency, reproducibility and explainability" when deploying machine learning tools[221]. These institutional safeguards are reinforced by broader EU regulatory developments, including risk-based AI governance and data protection requirements, which collectively limit unchecked automation and support public trust in demographic outputs. From this perspective, rather than undermining demographic statistics, AI operates within a dense governance architecture that mitigates algorithmic bias and enhances accountability, suggesting that concerns about opacity and automation can be addressed through established statistical standards and regulatory oversight.

AI as a Tool for Equity and Policy Responsiveness

Proponents within demographic and official statistics communities increasingly frame AI not only as a methodological innovation but also as a tool for identifying and addressing demographic inequalities. Machine learning applied to administrative and geospatial data enables high-resolution analysis of population dynamics, revealing spatial and social disparities that may remain obscured in aggregated statistics. Research in computational demography highlights that integrating digital trace and geospatial data allows scholars to "identify heterogeneity in population processes at fine spatial and temporal scales," improving understanding of inequality in mobility, access to services, and exposure to risk[222]. Similarly, work led by Emilio Zagheni emphasizes that novel data sources can uncover previously invisible demographic patterns, particularly among migrant and digitally mediated populations, thereby supporting more equitable measurement[223]. From this perspective, AI contributes to demographic equity by

[220] Eurostat, *AI and Machine Learning…*,(2023), 24.
[221] UNECE, *Machine Learning for Official Statistics…* (2023), 14.
[222] Ingmar Weber and Emilio Zagheni, "Methods and Measures for Using Digital Trace Data in Demographic Research," *Demographic Research* 47 (2022): 1210.
[223] Emilio Zagheni et al. "Digital and Computational Demography," (2022), 14.

improving visibility of marginalized groups and strengthening the empirical basis for inclusive policy design.

Beyond measurement, demographic and statistical scholarship underscores AI's capacity to enhance policy responsiveness through more timely and detailed evidence. High-resolution population mapping and predictive analytics support targeted interventions in urban planning, migration management, and ageing policy by enabling policymakers to anticipate demographic change and allocate resources more effectively. For example, geospatial population modelling research demonstrates that AI-driven estimates can inform infrastructure planning, humanitarian response, and service provision in rapidly changing urban and migration contexts[224]. International statistical guidance similarly notes that AI-enabled data integration can improve the responsiveness of official statistics, allowing governments to "adapt policies more quickly to emerging demographic trends."[225] Together, these perspectives offer a counterargument to skepticism about AI in demography: when embedded within robust governance frameworks, AI can enhance equity-oriented analysis and enable more adaptive and evidence-based demographic policymaking.

Synthesis: Contemporary Demographers' Position

Across recent demographic literature, the prevailing stance toward AI is characterized by cautious optimism grounded in methodological pragmatism. Demographers broadly acknowledge AI's transformative analytical potential while emphasizing the need for representativeness, interpretability, and ethical governance. The emerging consensus frames AI as a complementary methodological innovation embedded within demographic principles of transparency, quality assurance, and public trust particularly within official statistical systems.

6.2 AI Developers and the Population Data Opportunity

From the perspective of AI developers and data scientists, demographic research represents a particularly valuable application domain because of its rich data environment and policy relevance. Population datasets including censuses, administrative registers, geospatial data, and digital traces offer opportunities for developing and testing machine learning techniques capable of large-scale prediction, classification, and pattern detection. AI developers often characterize demographic applications as a "high-impact public interest use case" for AI, given their potential to inform policy in areas such as migration governance, urban planning, and public health[226]. Recent machine learning research emphasizes that demographic datasets provide complex, high-dimensional environments in which AI methods can demonstrate advantages over

[224] Andrew J. Tatem, "WorldPop, Open Data, and the Promise of High-Resolution Population Mapping for Policy," *Nature Communications* 12 (2021): 3.
[225] UNECE, *Machine Learning for Official Statistics,* (2023), 29.
[226] N. Tomašev et al., "AI for Social Good: Unlocking the Opportunity for Positive Impact," *Nature Communications* 11 (2020).

traditional statistical techniques, particularly in handling nonlinear relationships and large-scale data integration[227].

However, AI developers simultaneously recognize that demographic research poses methodological and governance challenges, including data quality constraints, interpretability requirements, and ethical considerations unique to official statistics contexts.

Opportunities Identified by AI Developers

Predictive Performance and Complex Pattern Detection

A central argument advanced by AI developers is that machine learning is particularly well suited to predictive tasks characterized by complex interactions, nonlinear dynamics, and large heterogeneous datasets. Demographic processes including migration flows, fertility behaviour, and mortality risk often emerge from multidimensional interactions among socioeconomic, environmental, and behavioural factors that are difficult to model using traditional linear or parametric approaches. AI researchers therefore emphasize the ability of machine learning to identify latent patterns and interactions across high-dimensional data environments. As Foster Provost and Tom Fawcett explain in their data science framework, machine learning techniques are designed to "automatically discover patterns in data and use them to make predictions," offering advantages when relationships are complex or poorly specified a priority[228]. Computational social science research similarly highlights that machine learning approaches can leverage large-scale digital and administrative datasets to produce more accurate predictions of mobility and population behaviour, demonstrating the value of AI for demographic forecasting contexts[229]. From a developer perspective, demographic datasets therefore provide an ideal testing ground for advanced modelling techniques capable of integrating diverse data streams and capturing nonlinear population dynamics.

Beyond methodological performance, AI developers also stress the practical policy implications of improved predictive capacity. Predictive modelling can support early warning systems for demographic change by identifying emerging migration trends, anticipating ageing-related service demand, or detecting patterns of urban expansion. Research on AI for social good underscores that predictive analytics can enhance policy responsiveness by enabling governments to anticipate societal shifts and allocate resources more effectively[230]. In mobility research, for instance, machine learning models applied to digital trace data have demonstrated the ability to forecast migration and mobility patterns in near real time, offering insights relevant to crisis preparedness and infrastructure planning[231]. From this perspective, AI developers view

[227] Foster Provost and Tom Fawcett, *Data Science for Business* (updated ed., 2022).
[228] Ibid.
[229] Sinan Aral, "The Promise of Computational Social Science," *Science* 371, no. 6524 (2021): 119–121.
[230] Tomašev et al., "AI for Social Good", (2020).
[231] Weber and Zagheni, "Methods and Measures for Using Digital Trace Data", (2022), 1217.

demographic forecasting not only as a methodological challenge but also as a high-impact application domain where predictive modelling can contribute directly to proactive governance and evidence-based policymaking.

Automation and Efficiency in Statistical Production

AI developers frequently emphasize the efficiency gains that machine learning can bring to statistical workflows, particularly in data-intensive domains such as demographic and official statistics production. Tasks traditionally requiring extensive manual effort including data cleaning, classification, anomaly detection, and record linkage can be automated using supervised and unsupervised learning techniques. Technical literature on data science highlights that automation of preprocessing and pattern recognition tasks allows organizations to manage large-scale datasets more efficiently and consistently, reducing human error while accelerating analytical pipelines. As Foster Provost and Tom Fawcett note, machine learning systems are especially effective in "automating decisions and processes that would otherwise require substantial human judgment and labour," making them valuable in large-scale data environments[232]. Within official statistics, these capabilities are increasingly applied to coding survey responses, linking administrative records, and detecting inconsistencies in demographic datasets.

Research focused on AI for official statistics reinforces this perspective, noting that automated classification and imputation models can enhance the timeliness and coherence of statistical outputs while freeing human experts to focus on methodological oversight and interpretation. UNECE guidance observes that machine learning applications in statistical production are typically deployed within human-in-the-loop frameworks, where automated outputs are reviewed and validated by statisticians to ensure quality and accountability[233]. Similarly, Eurostat's recent methodological work highlights that AI is primarily used to augment rather than replace statistical expertise, supporting scalable data processing while preserving professional judgment and quality assurance standards[234]. From an AI developer standpoint, demographic statistics therefore represent a particularly promising application domain: automation can reduce production costs and accelerate dissemination while enabling statistical agencies to respond more rapidly to emerging population trends and policy needs.

Integration of Nontraditional Data Sources

AI developers frequently emphasize the analytical value of alternative and nontraditional data sources including satellite imagery, mobile phone metadata, and social media content for expanding demographic insight beyond the constraints of conventional survey and census methods. Machine learning techniques enable the transformation of these unstructured or

[232] Provost and Fawcett, *Data Science for Business*, (2022).
[233] UNECE, *Machine Learning for Official Statistics,* (2023).
[234] Eurostat, *AI and Machine Learning,* (2023).

semi-structured data into usable demographic indicators through automated feature extraction, classification, and pattern recognition. In computer vision applications, for example, satellite imagery can be used to infer settlement patterns and population density, while natural language processing can identify migration intentions or labour market signals from online platforms. Research in computational social science highlights that the integration of digital trace and geospatial data allows AI systems to "extract behavioural and mobility patterns at scales previously unattainable with traditional data collection methods," demonstrating their relevance for population estimation and mobility analysis[235]. From an AI developer perspective, such capabilities illustrate how machine learning can augment demographic measurement by providing high-frequency and highly detailed insights into population dynamics.

A growing body of AI and interdisciplinary research further demonstrates the feasibility of deriving demographic indicators from unstructured data sources using advanced modelling techniques. Work on AI for social good and data-driven population mapping shows that computer vision models can generate high-resolution estimates of population distribution from remote sensing data, while mobile phone metadata and social media traces can inform models of migration and social behaviour[236]. These approaches are often presented by AI developers as complementary to traditional demographic data rather than replacements, helping to address data gaps and latency issues inherent in survey-based systems. As Stefano Ermon and colleagues argue, AI-driven analysis of unconventional data sources has the potential to "provide timely and actionable insights for societal challenges," including population monitoring and humanitarian planning[237]. Collectively, these perspectives reinforce the view among AI developers that machine learning-enabled alternative data sources can help overcome limitations of conventional demographic measurement, particularly in rapidly changing or data-scarce environments.

Concerns and Critical Reflections among AI Developers

Data Quality and Domain Constraints

Despite methodological optimism, AI developers increasingly acknowledge that demographic applications present distinctive challenges related to data quality, representativeness, and standardization. Population datasets often originate from complex survey designs, administrative processes, or fragmented statistical infrastructures, leading to missing values, definitional inconsistencies, and sampling biases that complicate machine learning workflows. Technical literature in data science emphasizes that real-world datasets, particularly in public sector and social science domains, rarely exhibit the structured and balanced characteristics assumed in many commercial AI applications. As Foster Provost and Tom Fawcett observe, effective machine learning depends on careful data preparation because "the quality of the data and the

[235] Weber, Zagheni, and State, "Inferring Population and Mobility Patterns from Digital Trace Data,"(2022) 137..
[236] Tatem, "WorldPop, Open Data, and …," (2021): 3.
[237] Stefano Ermon et al., "AI for Social Good," *Communications of the ACM* 64, no. 6 (2021): 52–59.

appropriateness of preprocessing steps are critical determinants of predictive performance."[238] For AI developers working with demographic data, this reality underscores the need for rigorous preprocessing, harmonization, and domain-specific validation strategies.

Recent responsible AI research further stresses that model performance is inseparable from data quality and representativeness. Scholars examining fairness and bias in machine learning note that algorithmic systems inevitably reflect the limitations of their training data, highlighting that "machine learning models can encode and amplify existing biases present in data."[239] This recognition has prompted AI developers to emphasize interdisciplinary collaboration with demographers and statisticians, whose expertise in sampling design, weighting, and measurement error is essential for reliable modelling. Guidance on AI for official statistics similarly stresses the importance of joint methodological oversight, recommending collaborative validation processes to ensure that automated outputs meet statistical quality standards[240]. From this perspective, rather than undermining AI applications in demography, data challenges reinforce the necessity of cross-disciplinary cooperation as a foundation for trustworthy and scientifically robust population analysis.

Interpretability and Trust in Public Sector AI

AI developers increasingly recognize interpretability as a core requirement for AI deployment in public sector domains, including demographic research and official statistics. While complex models such as deep neural networks may deliver strong predictive performance, their opacity can limit trust and hinder adoption in policy contexts where transparency, accountability, and reproducibility are essential. Recent technical discussions on interpretable machine learning emphasize that public sector decision-making requires models whose reasoning can be communicated and scrutinized. As Finale Doshi-Velez and Been Kim argue, interpretability is particularly important in high-stakes domains because it enables stakeholders to "understand and trust a model's decisions" and to assess whether outputs align with policy objectives and ethical standards[241]. For AI developers working with demographic statistics, this requirement highlights the need to balance predictive accuracy with explainability to ensure that model outputs remain usable in governance and statistical communication.

Explainable AI (XAI) research therefore positions interpretability not as a limitation but as a key frontier of innovation. Techniques such as feature attribution methods, interpretable model architectures, and post-hoc explanation tools allow developers to reveal decision pathways and assess variable importance, supporting model validation and stakeholder engagement.

[238] Provost and Fawcett, *Data Science for Business*, (2022).
[239] Solon Barocas, Moritz Hardt, and Arvind Narayanan, *Fairness and Machine Learning* (Cambridge, MA: MIT Press draft, 2023).
[240] UNECE, *Machine Learning for Official Statistics,* (2023).
[241] Finale Doshi-Velez and Been Kim, "Towards a Rigorous Science of Interpretable Machine Learning," updated discussion paper (2022).

Responsible AI scholarship further underscores that explainability contributes to fairness assessment and bias detection, particularly when AI outputs inform policy interventions affecting populations[242]. Within official statistics contexts, international methodological guidance similarly stresses the importance of transparency and auditability in machine learning applications, recommending that AI systems provide clear documentation and interpretable outputs for expert review[243]. Collectively, these perspectives demonstrate that AI developers increasingly view interpretability as a catalyst for methodological advancement, driving the development of explainability techniques that enable responsible and policy-relevant demographic AI applications.

Ethical and Governance Challenges

AI developers increasingly engage with ethical concerns related to privacy, fairness, and responsible data use, particularly when working with population and administrative datasets that contain sensitive personal information. Unlike many commercial AI applications, demographic research often relies on individual-level data linked across registers or derived from digital traces, raising heightened risks of re-identification, surveillance, and discriminatory outcomes. Responsible AI literature emphasizes that ethical AI development must incorporate safeguards addressing data protection, algorithmic fairness, and accountability throughout the modelling lifecycle. As Solon Barocas, Moritz Hardt, and Arvind Narayanan note, fairness-aware machine learning requires explicit attention to how models may "encode and amplify existing social biases," highlighting the importance of bias detection and mitigation strategies in socially consequential domains[244]. Similarly, research on trustworthy AI underscores that ethical deployment depends on robust governance mechanisms ensuring transparency, fairness, and respect for fundamental rights when handling sensitive population data[245].

In response to these concerns, AI developers increasingly explore privacy-preserving and fairness-enhancing techniques tailored to demographic contexts. Differential privacy offers mathematical guarantees limiting disclosure risks in statistical outputs, while federated learning enables model training across decentralized datasets without requiring direct data sharing are approaches particularly relevant for official statistics and public health applications. Cynthia Dwork and colleagues describe differential privacy as a framework that allows analysts to extract population-level insights while "providing quantifiable privacy guarantees for individuals in the dataset," demonstrating its suitability for sensitive demographic data[246]. Parallel research on federated learning highlights its potential to support collaborative modelling across institutions

[242] Barocas, Hardt, and Narayanan, *Fairness and Machine Learning* (2023).
[243] UNECE, *Machine Learning for Official Statistics,* (2023).
[244] Barocas, Hardt, and Narayanan, *Fairness and Machine Learning* (2023).
[245] European Commission High-Level Expert Group on AI, *Ethics Guidelines for Trustworthy AI* (updated implementation context, 2021).
[246] Cynthia Dwork et al., "The Algorithmic Foundations of Differential Privacy Revisited," *Communications of the ACM* 65, no. 3 (2022): 98.

while maintaining data confidentiality[247]. International guidance on AI in official statistics further emphasizes that ethical safeguards and privacy-preserving technologies are essential for maintaining public trust, noting that statistical organizations must ensure that innovation does not compromise confidentiality or fundamental rights[248]. Collectively, these perspectives reinforce the view among AI developers that demographic applications demand particularly high ethical standards, motivating the integration of fairness-aware modelling, privacy-preserving techniques, and interdisciplinary oversight as core components of responsible population data science.

Counterarguments to AI Skepticism

Responsible AI Frameworks

AI developers increasingly promote responsible AI frameworks that integrate fairness metrics, bias mitigation strategies, and transparency tools as core design principles for socially consequential applications such as demographic research. These frameworks respond to growing recognition that algorithmic systems can reproduce structural inequalities if fairness considerations are not embedded in model development and evaluation. Technical scholarship on fairness-aware machine learning emphasizes that responsible AI requires systematic measurement of disparate impacts across demographic groups and the implementation of mitigation strategies throughout the modelling lifecycle. As Barocas, Hardt, and Narayanan argue, fairness in machine learning involves both "detecting and addressing unwanted bias in automated decision systems," underscoring the need for explicit fairness metrics and auditing procedures[249]. From an AI developer perspective, these tools enable practitioners to identify inequitable model behaviour and adjust training data, model architectures, or evaluation criteria to reduce discriminatory outcomes in demographic analysis.

Complementing fairness-aware modelling, responsible AI frameworks also stress transparency and accountability as mechanisms for managing ethical risks. Research on trustworthy AI highlights that explainability tools, documentation practices, and algorithmic audits can improve the interpretability and governance of AI systems, particularly when they inform public policy or official statistics[250]. Within statistical and public sector contexts, international guidance similarly recommends integrating bias detection and transparency measures into AI workflows to ensure that automated outputs meet quality and ethical standards[251]. Collectively, these approaches aim to operationalize responsible AI principles by embedding fairness evaluation, bias mitigation, and transparency throughout the model lifecycle, offering a counterargument to concerns that AI

[247] Qiang Yang et al., "Federated Learning: Concepts and Applications," *ACM Transactions on Intelligent Systems and Technology* 12, no. 3 (2021).
[248] UNECE, *Machine Learning for Official Statistics,* (2023).
[249] Barocas, Hardt, and Narayanan, *Fairness and Machine Learning* (2023).
[250] Virginia Dignum, *Responsible Artificial Intelligence: How to Develop and Use AI in a Responsible Way*. Updated ed. Cham: Springer, 2022.
[251] UNECE, *Machine Learning for Official Statistics,* (2023).

inevitably exacerbates inequality in demographic research. Instead, proponents argue that well-designed responsible AI frameworks can help detect structural disparities and support more equitable population analysis while maintaining public trust in data-driven policymaking.

Interdisciplinary Collaboration

AI developers increasingly emphasize that effective AI applications in demographic research depend on **interdisciplinary collaboration** with demographers and statisticians, whose expertise in sampling design, measurement error, and population theory helps ensure methodological rigor and policy relevance. While machine learning offers powerful predictive capabilities, developers recognize that domain expertise is essential for data preprocessing, variable selection, and interpretation of model outputs. Computational social science scholarship highlights that combining data science techniques with substantive social science knowledge enables researchers to generate insights that are both technically robust and theoretically meaningful. As Sinan Aral notes, interdisciplinary collaboration between computer scientists and social scientists is crucial for leveraging computational methods in ways that "advance understanding of social behaviour while addressing complex societal challenges."[252] From an AI developer perspective, demographic research exemplifies a domain where such collaboration enhances model validity and guards against misinterpretation of population patterns.

Recent literature on digital and computational demography further frames interdisciplinary integration as emerging best practice for population data science. Researchers working at the intersection of AI and demography argue that collaboration supports the development of hybrid modelling strategies that combine machine learning with demographic theory, improving both interpretability and predictive performance. Emilio Zagheni and colleagues emphasize that progress in digital demography depends on partnerships that bring together technical expertise in data science with substantive demographic knowledge, enabling responsible use of new data sources and modelling techniques[253]. This perspective positions interdisciplinary cooperation not merely as beneficial but as necessary for policy-relevant demographic AI applications, ensuring that model outputs are interpretable, ethically grounded, and aligned with the needs of statistical systems and decision-makers.

Privacy-Preserving Technologies

Privacy-preserving AI methods are frequently highlighted by developers as a means of reconciling the analytical potential of population data with strict confidentiality requirements. Techniques such as differential privacy, secure multiparty computation, and federated learning allow researchers to derive aggregate insights from sensitive datasets while limiting the risk of individual re-identification. In technical literature, differential privacy is described as providing

[252] Aral, "The Promise of Computational Social Science," (2021): 120.
[253] Zagheni, Bijak, Weber, "Digital and Computational Demography," (2022): 13.

"strong, mathematically provable privacy guarantees" by ensuring that statistical outputs do not reveal information about any single individual, even when datasets are linked or repeatedly queried[254]. This capability is particularly relevant for demographic and official statistics contexts, where confidentiality obligations are foundational to public trust and data access. From an AI developer perspective, privacy-preserving methods therefore offer a practical pathway for leveraging administrative and digital trace data without compromising individual rights.

Beyond differential privacy, federated and decentralized learning approaches further support confidentiality by enabling collaborative model training across institutions without centralizing raw data. Research on federated learning emphasizes its potential to support cross-organizational analysis of sensitive datasets while maintaining data sovereignty and security, making it suitable for public sector and health applications involving population information[255]. Scholars in responsible AI also argue that privacy-enhancing technologies can mitigate surveillance concerns by embedding confidentiality protections directly into model design and data processing workflows[256]. Collectively, these developments provide a counterargument to critiques that AI-driven demographic analysis inherently increases surveillance risks: when privacy-preserving techniques are properly implemented, AI systems can enable robust population research while maintaining strict safeguards for individual confidentiality and statistical disclosure control.

Synthesis: AI Developers' Overall Position

Overall, AI developers tend to approach demographic applications with a form of pragmatic optimism, grounded in both technical enthusiasm and awareness of domain-specific constraints. From a methodological perspective, developers emphasize that machine learning can substantially improve predictive modelling of population dynamics, automate labour-intensive statistical workflows, and enable the integration of diverse data sources such as administrative registers, geospatial imagery, and digital trace data. These capabilities position demographic research as a high-impact application domain for AI, particularly given its relevance to public policy and planning. At the same time, AI researchers increasingly acknowledge that demographic data present distinctive challenges, including measurement error, representativeness concerns, and complex ethical obligations tied to confidentiality and public trust. As Solon Barocas, Moritz Hardt, and Arvind Narayanan note in their work on fairness-aware machine learning, socially consequential applications require careful attention to bias and context because algorithmic systems can reproduce structural inequalities if deployed without safeguards[257]. This recognition contributes to a more nuanced developer perspective that balances innovation with methodological and ethical caution.

[254] Dwork et al., "The Algorithmic Foundations of …," (2022): 99.
[255] Yang et al., "Federated Learning: …," (2021).
[256] Dignum, *Responsible Artificial Intelligence…* (2022).
[257] Barocas, Hardt, and Narayanan, *Fairness and Machine Learning* (2023).

Consequently, an emerging consensus among AI developers centers on responsible innovation as the pathway for integrating AI into demographic research and statistical reporting. Responsible AI frameworks emphasize explainability, fairness auditing, and privacy-preserving techniques, while interdisciplinary collaboration with demographers and statisticians is increasingly viewed as essential for ensuring data quality and interpretability. Research on digital and computational demography similarly underscores that effective population data science depends on partnerships bridging technical expertise and demographic theory, enabling hybrid modelling approaches that combine predictive accuracy with substantive understanding[258]. Developers also frame explainability as a critical enabler of policy adoption, allowing stakeholders to understand model behaviour and trust AI-assisted demographic insights. Taken together, these perspectives suggest that AI developers do not view demographic applications as purely technical challenges but as socio-technical systems requiring governance, transparency, and cross-disciplinary engagement. Rather than undermining demographic research, AI is therefore conceptualized as a complementary analytical infrastructure whose benefits can be realized when embedded within responsible design principles and collaborative research practices.

6.3 EU Policymakers Perspective: Human-Centric Innovation and Statistical Modernisation

EU policymakers increasingly frame artificial intelligence within a governance paradigm centred on human-centric innovation, public trust, and regulatory oversight, reflecting the broader normative foundations of EU digital policy. The European Commission's strategic communications on AI repeatedly stress that technological development must remain aligned with democratic values, fundamental rights, and social welfare objectives. In this context, AI is positioned as a tool for strengthening public administration and enabling more responsive, evidence-based policymaking across domains including demographic analysis. The Commission's policy approach highlights that the EU seeks to "promote the uptake of human centric and trustworthy artificial intelligence" while ensuring a high level of protection of fundamental rights, illustrating the balancing act between innovation and safeguards that characterizes European AI governance[259]. This policy framing is reinforced by scholarly analyses of EU digital regulation, which argue that the EU's risk-based approach aims to embed AI innovation within a framework of accountability and transparency designed to sustain public confidence in automated decision-making[260]. Consequently, policymakers increasingly view AI as a potential driver of improved demographic insight, capable of supporting population

[258] Zagheni, Bijak, Weber, "Digital and Computational Demography," (2022): 15.
[259] European Commission, *Proposal for a Regulation Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act)*, COM(2021) 206 final; European Union, *Artificial Intelligence Act (Regulation (EU) 2024/1689)*.
[260] Raluca Csernatoni, "The EU's Artificial Intelligence Strategy: Between Geopolitics and Human Rights," *European View* 21, no. 1 (2022): 39–47.

forecasting, monitoring migration dynamics, and informing ageing and labour market policies, provided that its deployment remains subject to legal and institutional oversight.

Within demographic research and statistical reporting specifically, policymakers situate AI adoption within broader digital transformation agendas encompassing the European Data Strategy, sectoral European data spaces, and modernization of the European Statistical System (ESS). The European Data Strategy seeks to create a single market for data by enhancing data sharing, interoperability, and access for public interest purposes, thereby providing an enabling environment for AI-driven demographic analysis[261]. At the same time, Eurostat and ESS initiatives emphasize experimentation with machine learning and automation to improve statistical production, timeliness, and user engagement, while maintaining established quality frameworks and professional independence[262]. These developments reflect a policy vision in which AI is integrated into statistical systems as part of a wider socio-technical transformation of European governance. By linking AI innovation to data governance reforms and statistical modernization, EU policymakers aim to strengthen analytical capacity and cross-border comparability of demographic evidence while preserving methodological rigor and public trust in official statistics.

Opportunities Identified by EU Policymakers

Modernising Statistical Production and Evidence-Based Policymaking

EU policymakers increasingly highlight AI's capacity to enhance the efficiency, timeliness, and analytical depth of official statistics, positioning machine learning as a key component of statistical modernization within the European Statistical System (ESS). Eurostat's institutional reporting indicates that ESS actors are experimenting with AI tools to support statistical production processes such as data classification, editing, and dissemination, reflecting a broader commitment to innovation in the face of growing data volumes and user expectations. As Eurostat notes, the ESS is actively exploring artificial intelligence to support the development and production of official statistics, underscoring institutional recognition that advanced analytics can improve workflow automation and statistical responsiveness[263]. For demographic research specifically, policymakers emphasize that automated processing of administrative registers, geospatial data, and unstructured sources can facilitate more timely population indicators, enabling policymakers to respond more effectively to evolving demographic trends such as migration fluctuations or population ageing. Scholarly analyses of digital-era public

[261] European Commission, *A European Strategy for Data*, COM(2020).
[262] Eurostat, *Eurostat Report 2023* (Luxembourg: Publications Office of the European Union, 2023).
[263] Eurostat, *Sustainable Development in the European Union - Statistical Annex to the EU Voluntary Review - 2023,* 4.

administration similarly argue that AI-driven analytics can enhance governmental capacity for evidence-based policymaking by improving the speed and granularity of statistical insight[264].

This statistical modernization agenda is closely embedded within broader EU digital governance initiatives aimed at strengthening lawful data reuse and cross-border interoperability. The Data Governance Act represents a central pillar of this framework by establishing mechanisms to increase trust in data sharing and facilitate secure access to public sector data for research and policy purposes. The European Commission explains that the regulation seeks to "increase trust in data sharing, strengthen mechanisms to increase data availability and overcome technical obstacles to the reuse of data," thereby creating enabling conditions for AI-enabled analysis across sectors[265]. By linking data governance reform with AI experimentation in official statistics, policymakers conceptualize demographic AI as part of a wider ecosystem of interoperable data infrastructures and regulatory safeguards. In this vision, AI contributes to evidence-based governance not simply through technical innovation but by leveraging improved data accessibility and integration, ultimately enhancing the availability, comparability, and policy relevance of demographic information across the European Union.

Enhancing Policy Responsiveness and Equity

A second opportunity frequently emphasized in EU policy discourse concerns AI's capacity to enhance responsiveness to demographic change by enabling more in-depth monitoring and forward-looking analysis of population dynamics. Policymakers increasingly associate predictive analytics and high-resolution population modelling with improved anticipation of migration flows, ageing pressures, and spatial inequalities, thereby supporting more proactive policy interventions. The European Commission's work on demographic change highlights the importance of timely and disaggregated population data for addressing structural challenges such as labour shortages, population ageing, and regional disparities, underscoring the policy relevance of advanced analytical tools capable of capturing complex demographic patterns[266]. In this context, AI-enabled modelling is framed as a mechanism for strengthening evidence-based governance by improving targeting of public services, infrastructure planning, and social policy responses. Scholarly research on digital-era policymaking similarly argues that predictive analytics can enhance adaptive governance by allowing policymakers to anticipate social trends and allocate resources more efficiently[267].

Sectoral EU initiatives further illustrate this governance logic by linking AI adoption to the development of secure data ecosystems supporting research and policymaking. The proposed

[264] Christopher Ansell and Jacob Torfing, *Public Governance as Co-Creation: A Strategy for Revitalizing the Public Sector* (Oxford: Oxford University Press, 2021).
[265] European Commission, "Data Governance Act," Shaping Europe's Digital Future (2022).
[266] European Commission, *Report on the Impact of Demographic Change* (Brussels: European Commission, 2020.
[267] Christopher Ansell and Jacob Torfing, *Public Governance as Co-Creation: A Strategy for Revitalizing the Public Sector* (Oxford: Oxford University Press, 2021).

European Health Data Space (EHDS), for example, explicitly promotes the secondary use of sensitive health and population data for research, innovation, and policy analysis, enabling more timely and integrated understanding of demographic and health trends across member states[268]. Policymakers view such initiatives as foundational infrastructures that allow AI-driven analysis to operate within clearly defined legal and ethical safeguards, balancing innovation with data protection. More broadly, EU policy discourse suggests that AI-supported demographic analytics can contribute to identifying emerging inequalities and informing inclusive policy design, provided that data governance frameworks ensure confidentiality, interoperability, and trust. In this sense, AI is conceptualized not only as a technical tool but as part of a broader socio-technical strategy aimed at strengthening the responsiveness and equity of European public policy in the face of demographic transformation.

Risks and Critical Concerns among EU Policymakers

Fundamental Rights, Bias, and Accountability

Despite acknowledging the potential benefits of AI for statistical modernization and policy responsiveness, EU policymakers consistently express concern about the societal risks associated with AI deployment in demographic contexts. These concerns are rooted in the sensitivity of population data and the potential consequences of algorithmic outputs for public policy decisions. The EU's regulatory response, most notably the Artificial Intelligence Act, reflects this cautious stance by embedding AI innovation within a risk-based governance framework that prioritizes protection of fundamental rights, democratic values, and human oversight. The regulation explicitly seeks to ensure a "high level of protection of health, safety and fundamental rights" while supporting innovation, illustrating the EU's attempt to balance technological advancement with safeguards against harmful outcomes[269]. Policymakers therefore remain attentive to risks such as algorithmic bias, discriminatory impacts, and opaque decision-making processes, which could undermine public trust in AI-assisted demographic analysis and official statistics. Scholarly analysis of EU AI governance similarly highlights that the European approach emphasizes accountability and transparency as mechanisms for maintaining legitimacy in public-sector AI use[270].

Complementing this regulatory framework, EU institutions and advisory bodies stress the importance of fundamental rights impact assessments as a governance tool for identifying and mitigating risks in high-stakes AI applications. The European Union Agency for Fundamental Rights (FRA) argues that systematic rights assessments can help ensure that AI systems operate in ways that respect equality, privacy, and non-discrimination, thereby contributing to

[268] European Commission, *Proposal for a Regulation on the European Health Data Space*, COM(2022), 197.
[269] European Union, *Artificial Intelligence Act (Regulation (EU) 2024/1689)*.
[270] Csernatoni, "The EU's Artificial Intelligence Strategy…" (2022), 42.

trustworthy and socially beneficial AI deployment[271]. In demographic applications, these concerns are particularly pronounced because population statistics often inform policy decisions affecting resource allocation, migration governance, and social welfare. The sensitivity of demographic indicators especially when derived from administrative or linked datasets heightens the potential societal implications of bias or error in AI-driven analysis. Consequently, EU policymakers frame risk assessment, transparency requirements, and ethical oversight as essential preconditions for integrating AI into demographic research and statistical reporting, reinforcing the view that innovation must proceed within a robust framework of rights protection and institutional accountability.

Public Trust and the Governance of Data Reuse

Another key concern in EU policy debates relates to public trust in data use and the preservation of statistical confidentiality, particularly as demographic research increasingly relies on linked administrative datasets and integrated data infrastructures. Policymakers acknowledge that while such data integration can improve analytical capacity, it may also generate perceptions of surveillance or "function creep," whereby data collected for statistical purposes are reused in ways that citizens did not anticipate. The European Statistics Code of Practice directly addresses this issue by emphasizing professional independence, data protection, and strict confidentiality safeguards as foundational principles of official statistics. It stresses that maintaining these standards is essential for ensuring credibility and preventing misuse of statistical information, noting that public trust depends on the assurance that data are used exclusively for statistical purposes[272]. Scholarly analyses of statistical governance similarly argue that trust in official statistics is closely linked to institutional guarantees of confidentiality and methodological independence, especially in contexts involving sensitive population data[273].

At the same time, EU digital policy debates reveal persistent tensions between innovation objectives and the protection of rights and trust. Discussions surrounding regulatory simplification and competitiveness have prompted concerns among policymakers and civil society actors that weakening safeguards could undermine the legitimacy of AI deployment in public sector domains. Recent policy commentary highlights that trust in digital governance depends on maintaining robust legal protections for data protection and fundamental rights, warning that regulatory rollbacks may erode confidence in data-driven policymaking[274]. In demographic research, where statistical outputs can influence migration policy, social welfare allocation, and regional development strategies, such legitimacy concerns are particularly salient. Consequently, EU policymakers often frame confidentiality safeguards and regulatory stability

[271] European Union Agency for Fundamental Rights, "Fundamental Rights Impact Assessments and AI," 2025.
[272] Eurostat, *European Statistics Code of Practice* (Luxembourg: Publications Office of the European Union, 2017.
[273] Andreas Georgiou, "Trust in Official Statistics: Challenges and Responses," *Statistical Journal of the IAOS* 37, no. 2 (2021): 303–312.
[274] Paul Nemitz, "Constitutional Democracy and Technology in the Age of Artificial Intelligence," *Philosophical Transactions of the Royal Society A* 379 (2021).

as prerequisites for responsible AI integration, reinforcing the notion that trust is both a normative goal and a functional requirement for effective demographic data governance.

Counterarguments to AI Skepticism

Risk-Based Governance and Institutional Safeguards

EU policymakers frequently respond to skepticism about AI in demographic research by emphasizing the robustness and layered nature of the European regulatory framework, which is designed to integrate technological innovation within a system of enforceable safeguards. Central to this counterargument is the AI Act's risk-based governance model, which categorizes AI systems according to their potential societal impact and imposes proportionate obligations on high-risk applications. In the public sector including statistical and demographic contexts this framework introduces requirements related to transparency, documentation, human oversight, and risk management, aiming to ensure that AI deployment remains aligned with fundamental rights and democratic values. The regulation explicitly seeks to establish a "high level of protection of health, safety and fundamental rights" while fostering innovation, illustrating the EU's commitment to balancing technological development with societal safeguards[275]. Scholars of EU digital governance note that this model represents a distinctive regulatory philosophy that embeds accountability and ex-ante risk mitigation into AI development processes rather than relying solely on post-hoc enforcement[276].

This risk-based approach is further reinforced by complementary legal and institutional safeguards, including the General Data Protection Regulation (GDPR) and the quality frameworks governing official statistics. GDPR provisions on purpose limitation, data minimization, and individual rights provide a legal backbone for responsible data use in AI-driven demographic analysis, helping to mitigate privacy risks and maintain public trust. At the same time, the European Statistics Code of Practice establishes professional independence, confidentiality, and methodological rigor as core principles guiding statistical production, ensuring that AI integration does not undermine established quality standards[277]. Together, these overlapping governance mechanisms form a multi-layered regulatory architecture that policymakers present as capable of addressing ethical concerns such as algorithmic bias, opacity, and misuse of sensitive population data. From this perspective, the EU's institutional safeguards do not merely constrain AI adoption but actively enable responsible innovation by providing a structured environment in which demographic AI applications can be developed, audited, and deployed with accountability and public legitimacy.

Statistical Independence and Quality Assurance

[275] European Union, *Artificial Intelligence Act (Regulation (EU) 2024/1689)*.
[276] Csernatoni, "The EU's Artificial Intelligence Strategy…" (2022), 42.
[277] Eurostat, *European Statistics Code of Practice,* 2017.

A related counterargument advanced by EU policymakers emphasizes that institutional safeguards within the European Statistical System provide a strong foundation for integrating AI without undermining statistical integrity. Central to this argument is the European Statistics Code of Practice, which establishes principles of professional independence, methodological soundness, quality assurance, and statistical confidentiality as core requirements for official statistics production. These principles apply irrespective of the analytical methods used, meaning that AI-based approaches must meet the same standards of transparency, reliability, and accuracy as traditional statistical techniques. The Code of Practice explicitly stresses that professional independence safeguards protect statistical processes from political or external interference, thereby ensuring that innovation in methods does not compromise objectivity or credibility[278]. Policymakers therefore present ESS governance structures as a stabilizing framework that anchors AI experimentation within established norms of statistical professionalism and accountability.

Beyond normative principles, the ESS quality framework operationalizes these safeguards through systematic evaluation, peer review, and documentation requirements that apply to new methodological approaches, including machine learning. Eurostat highlights that methodological innovation in official statistics is subject to quality assurance processes covering relevance, accuracy, timeliness, and coherence, reinforcing confidence in outputs regardless of underlying technology[279]. Scholarly research on trust in official statistics similarly argues that institutionalized quality assurance mechanisms are crucial for maintaining credibility during periods of methodological change, including the adoption of new data sources and analytical tools[280]. From this perspective, policymakers contend that AI integration does not represent a departure from statistical standards but rather a continuation of methodological evolution governed by robust oversight structures. Consequently, the ESS's institutional safeguards are frequently cited as evidence that AI can be adopted responsibly in demographic research and statistical reporting while preserving methodological rigor, public trust, and the independence of official statistics.

Human Oversight and Transparency Requirements

A further counterargument emphasized in EU policy debates concerns the role of human oversight and transparency requirements as safeguards against the risks of excessive automation in AI-assisted demographic analysis. The AI Act embeds human oversight as a core governance principle, particularly for high-risk AI systems deployed in public sector contexts. This requirement aims to ensure that automated outputs remain subject to professional judgment, enabling human operators to interpret, validate, and, where necessary, override algorithmic

[278] Eurostat, *European Statistics Code of Practice,* 2017.
[279] Eurostat, *Quality Assurance Framework of the European Statistical System* (Luxembourg: Publications Office of the European Union, 2020).
[280] Georgiou, "Trust in Official Statistics…" (2021), 307.

decisions. The regulation specifies that AI systems should be designed so that natural persons can "effectively oversee" their functioning and prevent or mitigate risks to fundamental rights, thereby reinforcing accountability in automated decision-making processes[281]. Scholars analyzing the AI Act argue that these oversight provisions reflect a deliberate attempt to maintain meaningful human control over AI applications in socially consequential domains, including official statistics and public administration[282]. From a policymaker perspective, human oversight thus serves as a mechanism for balancing efficiency gains with democratic accountability and professional responsibility.

Transparency requirements complement human oversight by enhancing the interpretability and auditability of AI systems used in demographic research and statistical production. EU governance frameworks emphasize documentation, traceability, and explainability as prerequisites for trustworthy AI, enabling experts and stakeholders to understand how algorithmic outputs are generated. Research on AI governance highlights that transparency facilitates both internal quality assurance and external accountability, supporting trust in automated systems and enabling scrutiny of potential biases or errors[283]. Within statistical contexts, these principles align with established norms of methodological transparency and reproducibility, reinforcing the view that AI adoption must remain consistent with professional standards. Together, human oversight and transparency are therefore presented by EU policymakers as mutually reinforcing safeguards that ensure AI-driven demographic insights remain interpretable, accountable, and aligned with public sector values, mitigating concerns about the erosion of professional judgment and statistical integrity.

Synthesis: EU Policymakers' Overall Position

Overall, EU policymakers exhibit what can be characterized as careful institutional optimism toward AI in demographic research and statistical reporting, reflecting a governance logic that seeks to reconcile innovation with legitimacy. Policy discourse consistently acknowledges that AI can strengthen statistical production by enabling faster processing of administrative and unstructured data, improving the accuracy of demographic indicators, and supporting more responsive policy interventions in areas such as migration governance, ageing, and regional development. At the same time, policymakers remain acutely aware that demographic data are socially sensitive and politically consequential, meaning that the credibility of AI-assisted analysis depends on maintaining public trust and adherence to fundamental rights. The EU's broader digital policy framework, including the Artificial Intelligence Act and the European Data Strategy, therefore positions AI as a public-sector capability that must operate within clear accountability and transparency requirements to ensure that technological innovation does not

[281] European Union, *Artificial Intelligence Act (Regulation (EU) 2024/1689)*.
[282] Lena Enqvist, "'Human Oversight' in the EU Artificial Intelligence Act: What, When and by Whom?" *Information & Communications Technology Law* 32, no. 3 (2023).
[283] Dignum, *Responsible Artificial Intelligence…* (2022).

undermine democratic values or statistical independence[284]. Scholarly assessments of EU AI governance similarly highlight that the European model is defined by its attempt to embed technological advancement within a normative framework of trustworthiness and rights protection, distinguishing it from more market-driven approaches to AI development[285].

Within this context, the emerging policy consensus frames AI as a policy instrument embedded in a structured governance ecosystem rather than as a disruptive force challenging existing statistical norms. Risk-based regulation under the AI Act establishes differentiated obligations for high-risk applications, while data protection law provides safeguards for confidentiality and lawful data use in demographic analysis. Complementary institutional mechanisms within the European Statistical System including the European Statistics Code of Practice and quality assurance frameworks reinforce methodological rigor, professional independence, and transparency, ensuring that AI adoption remains aligned with established statistical standards[286]. Policymakers thus conceptualize responsible AI integration as a socio-technical process combining regulatory oversight, institutional accountability, and interdisciplinary expertise. From this perspective, the benefits of AI for demographic research can be realized when innovation is embedded within governance structures that sustain public trust, support ethical data use, and maintain the legitimacy of official statistics. The EU policymaker stance therefore reflects a pragmatic middle ground: AI is neither uncritically embraced nor fundamentally resisted, but incorporated as a carefully governed instrument for enhancing evidence-based demographic policymaking in an increasingly data-driven European governance landscape.

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7. Discussion

Synthesis of Case Study and Stakeholder Findings

The findings of this study illustrate that artificial intelligence is increasingly embedded within the epistemic and institutional landscape of demographic research, yet its role remains fundamentally hybrid rather than substitutive[287]. The experimental case study demonstrated that AI systems are capable of navigating structured demographic databases, interpreting multidimensional statistical schemas, and producing a range of core demographic indicators through multi-step computational processes. These capabilities highlight the operational feasibility of AI-assisted workflows and confirm the growing viability of conversational and

[284] European Union, *Artificial Intelligence Act (Regulation (EU) 2024/1689)*; European Commission, *A European Strategy for Data*, COM(2020) 66.
[285] Csernatoni, "The EU's Artificial Intelligence Strategy…" (2022), 45.
[286] Eurostat, *Quality Assurance Framework…,* (2020).
[287] Roberta Kashyap, Emilio Zagheni, Jakub Bijak, and Ingmar Weber, "Leveraging Digital and Computational Demography for Policy Insights," in *Data Science and Public Policy* (2023)

retrieval-augmented systems as interfaces to complex statistical infrastructures[288]. However, the experiment also exposed persistent vulnerabilities, including schema misinterpretation, reliance on data completeness, and limitations in deriving indicators when underlying population variables were absent as seen in other studies on the capabilities of AI[289]. These limitations underscore that AI effectiveness is contingent upon metadata transparency, statistical literacy, and domain-aware validation mechanisms, reinforcing the notion that AI functions best as an augmentative analytical layer rather than an autonomous methodological replacement.

The stakeholder perspectives further contextualize these technical observations within disciplinary and governance debates. Demographers broadly interpret the integration of AI as part of a wider "data-intensive turn" in population studies, in which digital trace data, administrative registers, and computational modelling expand the temporal and spatial granularity of demographic analysis[290]. This perspective frames AI as a methodological extension of longstanding quantitative traditions rather than a rupture, suggesting continuity in the epistemological foundations of the discipline. At the same time, demographers emphasize that the increasing reliance on automated analytics introduces normative questions concerning interpretability, representativeness, and the preservation of statistical quality standards within official statistics systems[291].

AI developers offer a complementary yet distinct interpretation rooted in technical opportunity and system design considerations. Their perspectives highlight the suitability of demographic datasets for machine learning applications due to their scale, complexity, and policy relevance. From this vantage point, AI is positioned as an enabling technology capable of integrating heterogeneous data sources, uncovering nonlinear relationships, and automating labour-intensive analytical workflows. Nevertheless, developers also acknowledge that demographic applications present unique methodological and ethical challenges, particularly regarding data quality, fairness, and the interpretability demands associated with policy-relevant analysis[292]. This convergence of enthusiasm and caution reflects a broader shift within the AI community toward responsible innovation and interdisciplinary collaboration as prerequisites for impactful deployment.

Policymakers, particularly within the European context, articulate a governance-oriented perspective that situates AI within broader frameworks of human-centric digital transformation and statistical modernization[293]. AI is conceptualized not merely as a technical instrument but as part of a governance ecosystem in which data protection, transparency, and public trust are

[288] Martin Klesel, "Retrieval-Augmented Generation (RAG)," *Business & Information Systems Engineering* (2025).
[289] Shuaichen Chang et al., "A Survey of Text-to-SQL Parsing: Concepts, Methods, and Future Directions," *ACM Computing Surveys* 55, no. 5 (2023).
[290] UNFPA, *The Future of Population Data: ICPD30 Think Piece* (2024).
[291] UNECE, *Machine Learning for Official Statistics* (workshop materials and guidance, 2023).
[292] NIST, *AI RMF 1.0* (2023).
[293] European Commission, "AI Act: Shaping Europe's Digital Future" (2023).

foundational. This framing highlights the political and institutional dimensions of AI adoption, emphasizing that the legitimacy of AI-assisted demographic policymaking depends as much on regulatory alignment and accountability structures as on technical performance.

The synthesis of these findings reveals a shared but differentiated consensus across stakeholder groups. AI is broadly recognized as a transformative analytical resource capable of enhancing demographic knowledge production, yet its integration is mediated by disciplinary norms, institutional responsibilities, and governance constraints. Rather than representing a disruptive paradigm shift, AI emerges as a socio-technical infrastructure embedded within existing demographic and policy frameworks, reshaping practices while simultaneously reinforcing the continued necessity of expert oversight.

Evaluating AI's Transformative Potential in Demography

The transformative potential of artificial intelligence in demography can be understood across epistemic, methodological, and institutional dimensions that collectively redefine how population knowledge is produced and mobilized for policy purposes. At the epistemic level, AI enables the incorporation of novel data sources and analytical perspectives that expand the scope of demographic inquiry beyond traditional census and survey-based paradigms. The integration of digital traces, geospatial imagery, and linked administrative records facilitates more continuous and detailed monitoring of population dynamics, thereby enhancing the capacity to capture rapidly evolving phenomena such as migration flows, urbanization, and demographic responses to crises. This epistemic expansion contributes to the consolidation of digital demography as a distinct subfield characterized by data integration and computational modelling, positioning AI as a catalyst for more responsive and context-sensitive population research[294].

Methodologically, AI introduces modelling approaches capable of addressing the complexity inherent in demographic processes. Machine learning techniques are particularly suited to identifying nonlinear relationships and interactions across high-dimensional datasets, offering advantages in forecasting contexts where traditional parametric models may struggle[295]. The study's findings support this view by demonstrating AI's capacity to perform multi-step derivations and integrate heterogeneous data inputs, yet they also highlight that methodological gains are uneven and dependent on data quality, model transparency, and interpretability. Consequently, AI's methodological transformation is best conceptualized as hybridization, in which predictive analytics complement rather than supplant established demographic methods. This hybridization fosters an analytical environment that combines theoretical insight with computational efficiency, thereby enriching demographic research without undermining its conceptual foundations.

[294] Kashyap et al., "Leveraging Digital and Computational Demography for Policy Insights" (2023).
[295] Irina Grossman et al., "Can Machine Learning Improve Small Area Population Forecasts? A Forecast Combination Approach," *Computers, Environment and Urban Systems* 95 (2022).

Institutionally, AI contributes to the modernization of statistical systems and governance practices by enabling automation, real-time monitoring, and scenario-based policy analysis[296]. Statistical agencies and international organizations increasingly view AI-enabled data integration as a mechanism for enhancing the timeliness and relevance of official statistics, allowing governments to respond more rapidly to demographic change and policy challenges. Yet institutional transformation also introduces new governance demands, including regulatory compliance, ethical oversight, and capacity-building within public administrations. The transformative potential of AI in demography is therefore inseparable from broader digital governance frameworks that shape how analytical innovation is translated into legitimate policy action.

Taken together, these dimensions suggest that AI's transformative significance lies less in technological novelty than in its capacity to reconfigure relationships among data, analysis, and decision-making. AI reshapes the infrastructure of demographic knowledge production, enabling more adaptive and integrated policy analysis while simultaneously amplifying longstanding methodological and ethical debates within the discipline.

Opportunities and Risks in Real-World Policymaking

The integration of AI tools into demographic policymaking presents a range of opportunities that reflect the evolving nature of evidence-based governance. One of the most significant opportunities lies in the capacity of AI to enhance the accuracy and timeliness of demographic insights, thereby supporting more adaptive and context-sensitive policy design. By enabling the integration of administrative records, geospatial data, and digital traces, AI-assisted analytics can provide policymakers with near real-time indicators of population change and social dynamics[297]. This enhanced informational environment facilitates targeted interventions, more efficient resource allocation, and improved responsiveness to emerging demographic challenges such as migration surges or population aging. In this sense, AI contributes to anticipatory governance by expanding the analytical horizon of policymakers and enabling scenario-based decision support that was previously difficult to operationalize within traditional statistical frameworks.

Another opportunity emerges in the domain of efficiency and institutional capacity. Automation of data processing, classification, and reporting can reduce the administrative burden associated with demographic analysis, particularly within national statistical offices facing resource constraints and declining survey response rates[298]. AI-driven workflows can accelerate the production of indicators and support cross-agency data integration, thereby strengthening the operational capacity of public administrations. Moreover, the interdisciplinary collaboration

[296] OECD, *Digital Transformation of National Statistical Offices* (2022).
[297] World Bank, "Shaping the Future of Data Systems and Statistics: Key Insights," World Bank Open Data Blog, July 10, 2025.
[298] Daniel Fraisl et al., *Artificial Intelligence through the Lens of Official Statistics: Benefits and Risks* (Paris21, 2024).

fostered by AI adoption encourages knowledge exchange between demographers, data scientists, and policymakers, promoting methodological innovation and enhancing the relevance of demographic research to policy debates. These efficiency gains, however, extend beyond cost reduction to encompass the broader modernization of statistical infrastructures and the development of more agile policy processes.

Despite these opportunities, the integration of AI into policymaking also introduces significant risks that reflect the sociotechnical nature of population analytics. One of the most prominent concerns relates to data bias and representativeness limitations. AI systems trained on digital or administrative datasets may reproduce structural inequalities embedded within those data, potentially leading to skewed policy recommendations or uneven distribution of public services[299]. The reliance on incomplete or selective datasets can obscure marginalized populations and reinforce existing disparities, raising concerns about fairness and equity in AI-assisted decision-making. These representational challenges underscore the importance of hybrid data strategies and methodological transparency as safeguards against biased policy outcomes.

Transparency and accountability constitute another critical area of risk. The complexity of AI models can hinder interpretability and complicate efforts to justify policy decisions derived from automated analysis, particularly within democratic governance systems that require explainability and legal defensibility. In the European context, regulatory frameworks such as the GDPR and the EU AI Act impose transparency obligations that may be difficult to reconcile with proprietary models or highly complex algorithms[300]. This tension highlights the need for layered transparency mechanisms and institutional practices that enable meaningful oversight without compromising technical integrity or security.

Institutional feedback loops represent a more subtle yet consequential risk. When administrative data inform predictive models that guide policy interventions, the resulting actions may generate additional data reinforcing existing classifications of risk or need. Over time, this recursive process can blur the distinction between social reality and institutional attention, potentially distorting policy priorities and amplifying surveillance concerns[301]. Such feedback dynamics illustrate how AI integration can reshape not only analytical processes but also the underlying data ecosystems that inform policymaking.

Finally, ethical and legitimacy concerns remain central to the governance of AI in demographic policymaking. Population-level analytics raise questions about privacy, collective harms, and the potential normalization of surveillance practices, particularly when sensitive data sources are

[299] Kinga Flaga-Gieruszyńska et al., "The Problem of Discrimination in AI-Supported Public Service Management," *Management* (2025).
[300] A. Lukács, "GDPR-Compliant AI-Based Automated Decision-Making," *Computer Law & Security Review* (2023).
[301] Jenna Burrell and Marion Fourcade, "The Society of Algorithms," *Annual Review of Sociology* 47 (2021): 217.

integrated across institutional boundaries. Public trust may be undermined if AI systems are perceived as opaque or inequitable, emphasizing that legitimacy is a critical determinant of sustainable AI adoption in governance contexts. The case study's demonstration of schema misinterpretation and data dependency further highlights the epistemic risk of overreliance on automated outputs, reinforcing the continued necessity of human expertise and institutional accountability in policy analysis.

Integration of Risks and Opportunities

The integration of artificial intelligence into demographic policymaking can ultimately be understood as a balancing act between analytical innovation and institutional legitimacy. Opportunities primarily relate to enhanced knowledge production, efficiency gains, and the emergence of anticipatory governance models capable of addressing complex demographic challenges in a timely manner. At the same time, risks arise from biases embedded in data infrastructures, transparency constraints, feedback effects, and ethical concerns that may undermine public trust. Crucially, these risks are not inherent properties of AI technologies but rather outcomes of sociotechnical configurations involving data governance, institutional practices, and policy frameworks.

The study's findings suggest that responsible integration requires governance approaches that extend beyond technical performance evaluation to encompass lifecycle oversight, participatory engagement, and hybrid data strategies. By embedding AI within transparent, accountable, and ethically grounded institutional frameworks, policymakers can harness its analytical potential while mitigating risks associated with bias, opacity, and legitimacy erosion. In this sense, the future of AI in demographic policymaking depends not only on technological advancement but also on the evolution of governance practices capable of aligning innovation with democratic values and statistical integrity.

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8. Recommendations

Recommendations for governments and statistical agencies: adopting the NIST AI RMF 1.0

Governments and national statistical agencies should adopt the *Artificial Intelligence Risk Management Framework (AI RMF 1.0)* as an organizing structure for the responsible design, procurement, and use of AI-enabled demographic tools. The AI RMF is particularly well-suited to official-statistics environments because it is designed as a lifecycle framework that operationalizes trustworthy AI through four practical functions govern, map, measure, and

manage which translate well into statistical production chains where risk identification, documentation, and iterative quality assurance are already core institutional practices[302].

To make adoption concrete, agencies should embed AI RMF practices into routine statistical governance: mandating risk registers and model documentation for AI-supported estimation or classification workflows; requiring pre-deployment "mapping" of stakeholder impacts and intended use; validating outputs through measurable performance and error metrics aligned with official statistics quality principles; and instituting incident response and monitoring procedures for model drift, data pipeline changes, and downstream misuse[303]. This approach is consistent with the direction of international statistical guidance that emphasizes the need for rigorous governance when integrating alternative data sources and automated methods, especially where representativeness and privacy risks rise as data become more granular and linkable[304].

Because much demographic policymaking in Europe operates under strong legal and legitimacy constraints, AI RMF adoption should be paired with "fit-to-context" public-sector guardrails that stress transparency, accountability, and stakeholder engagement. In practice, that means agencies should treat AI RMF implementation not only as a technical checklist but as an institutional capacity-building programme by investing in staff training, establishing cross-disciplinary review boards that focus on statistics, law, ethics, domain demography, and publishing layered transparency materials calibrated for different audiences like technical peers, auditors, policymakers, and the public[305]. This aligns with wider OECD guidance on trustworthy AI in government, which frames trustworthy deployment as a combination of enabling capabilities, governance guardrails, and meaningful engagement with affected stakeholders[306].

Finally, where governments rely on external vendors, agencies should use the AI RMF to harden procurement: requiring suppliers to provide auditable documentation data provenance, evaluation protocols, limitations, specifying redress and accountability arrangements, and insisting on monitoring support through the system lifecycle. Recent OECD due diligence guidance for responsible AI reinforces the importance of continuous monitoring and stakeholder engagement as part of practical risk management across the AI value chain which is useful for structuring contractual obligations and accountability when systems are procured rather than built in-house[307].

Recommendations for AI developers: open-source, social-science-tailored tools for demographic research

[302] NIST, *AI RMF 1.0,* (2023).
[303] UNECE, *Framework on Responsible AI…,*(2025).
[304] UNSD, *Handbook on the Use of Big Data…,* (2023).
[305] NIST, *AI RMF 1.0,* (2023).
[306] OECD, *Governing with Artificial Intelligence: Enablers, Guardrails and Engagement for Unlocking Trustworthy AI* (Paris: OECD, 2025).
[307] OECD, *OECD Due Diligence Guidance for Responsible AI* (Paris: OECD, 2026).

AI developers seeking to advance demographic research should prioritize open-source tools tailored to social science workflows, with an emphasis on transparency, reproducibility, and domain-appropriate evaluation. Demographic analysis often depends on complex operational definitions (e.g., denominators, exposure periods, cohort logic), nuanced measurement assumptions, and sensitivity to coverage and representativeness. Open-source tooling can make these assumptions inspectable and contestable, enabling demographers and statistical agencies to validate methods, adapt pipelines to local data realities, and comply with governance expectations for explainability and auditability[308] [309].

Concretely, developers should build and maintain open-source components that align with how social scientists actually work: curated data connectors for common administrative and statistical formats; reproducible processing pipelines with transparent provenance tracking; and modular evaluation harnesses that compare AI-assisted estimates against conventional baselines and known-quality benchmarks. Developers should also publish "social-science-first" documentation in the form plain-language model cards and data documentation that specify intended uses, limitations, subgroup performance behavior, and known failure modes especially because these artifacts are often as important as model accuracy in policy-facing demographic contexts. Tooling should support privacy-respecting research like local execution, secure enclaves compatibility and should avoid design patterns that require sending sensitive population microdata to external services by default[310].

Developers should additionally provide open-source resources that help researchers use language models responsibly for demographic-relevant tasks, such as coding open-ended survey responses, extracting information from policy documents, and assisting with literature synthesis. Work in behavioral and computational social science increasingly emphasizes that open-source ecosystems can improve reproducibility and transparency for research uses of large language models, particularly when code and evaluation procedures are made directly executable[311]. At the same time, developers should incorporate emerging best practices for reliability in LLM-based annotation and classification workflows such as prompt stability checks, validation against human-coded samples, and careful reporting of uncertainty because these safeguards directly address the kinds of validity concerns that arise when outputs are used to inform policy narratives[312].

Taken together, these recommendations position open-source social-science tooling not as an ideological preference but as a practical strategy for aligning AI innovation with the

[308] Zak Hussain, Moritz Binz, Rui Mata, and Dirk U. Wulff, "A Tutorial on Open-Source Large Language Models for Behavioral Science," *Behavior Research Methods* (2024)
[309] Wouter van Atteveldt, Damian Trilling, and Carlos Arcíla, *Computational Analysis of Communication: A Practical Introduction to the Analysis of Texts, Networks, and Images with Code Examples in Python and R* (Hoboken, NJ: Wiley, 2021).
[310] UNSD, *Handbook on the Use of Big Data…,* (2023).
[311] Hussain, Binz, Mata, and Wulff, "A Tutorial on Open-Source…," (2024).
[312] Petter Törnberg, "Best Practices for Text Annotation with Large Language Models," *Sociologica* 18, no. 2 (2024).

methodological norms of demography and the accountability requirements of real-world policymaking. The highest-impact contributions will be those that reduce barriers to rigorous use making it easy for researchers and agencies to reproduce results, inspect assumptions, audit bias and error, and document uncertainty while remaining flexible enough to support heterogeneous administrative systems and population data infrastructures.

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9. Conclusion

Results of the experiment and overall findings

This study set out to examine the evolving role of artificial intelligence in demographic research and policymaking, focusing specifically on its ability to interact with demographic databases, produce statistical outputs, and support evidence-based policy analysis. The experimental component demonstrated that AI systems can successfully navigate structured demographic datasets, infer multidimensional schemas, and compute a range of indicators central to demographic analysis. These findings align with emerging scholarship in computational demography showing that machine learning and data science methods can extend the analytical reach of demographic research by enabling the integration of heterogeneous data sources and facilitating more flexible modelling approaches[313]. At the same time, the experiment revealed that AI performance remains contingent upon data quality, schema clarity, and domain expertise, with misinterpretations and incomplete datasets posing persistent challenges. Such limitations reinforce the view that AI currently functions most effectively as an augmentative tool embedded within human-led analytical workflows rather than as a substitute for demographic expertise. Therefore, my argument that artificial intelligence should not replace demographic expertise but serve as a tool to be used in the course of research with human oversight is proven correct.

Beyond technical capability, the broader findings of this research underscore the sociotechnical nature of AI integration in demographic contexts. Stakeholder perspectives indicated a shared recognition of AI's analytical promise coupled with concerns regarding interpretability, representativeness, and ethical governance. Demographers emphasized the continuity between AI and traditional demographic methods, framing computational approaches as an extension of established statistical practices rather than a disruptive paradigm shift[314]. AI developers, meanwhile, highlighted predictive advantages and automation benefits but acknowledged the challenges of bias, data governance, and transparency. Policymakers approached AI primarily through the lens of legitimacy and public trust, emphasizing the importance of regulatory

[313] Emilio Zagheni et al. "Digital and Computational Demography," (2022), 16.
[314] Tomas Sobotka and Stuart Basten, "Understanding Fertility Trends through New Data Sources and Computational Methods," *Population Studies* 76, no. 3 (2022): 13.

alignment and accountability mechanisms. Collectively, these perspectives suggest that the integration of AI into demographic research and policymaking is not solely a technical process but one that is mediated by institutional norms, professional epistemologies, and governance frameworks. This supports my argument that AI should be properly regulated in its use within demographic research to avoid the misuse or miscalculation of demographic statistics and subsequent spread of misinformation.

The findings also contribute to a growing body of evidence demonstrating that AI-assisted demographic analysis can enhance the timeliness and granularity of population insights. Research on digital trace data, geospatial population modelling, and administrative data integration similarly highlights AI's potential to improve the responsiveness of demographic monitoring and policy planning[315]. However, the study's results caution against uncritical adoption, as methodological gains may be offset by risks related to bias, data gaps, and opaque decision-making processes. The experiment therefore reinforces a central conclusion of contemporary population data science: AI's value lies not in automation alone but in its capacity to support hybrid analytical approaches that combine computational efficiency with theoretical and contextual understanding.

Contributions to academic and policy discussions

This thesis contributes to academic debates by empirically illustrating how AI systems operate within the practical realities of demographic data environments. While much existing literature has examined AI applications in demographic forecasting or digital demography conceptually, fewer studies have explored the operational dynamics of AI interacting directly with statistical databases and producing demographic indicators. By combining experimental evaluation with stakeholder analysis, this research bridges methodological and governance-oriented scholarship, offering a more holistic understanding of AI's role in demographic knowledge production. The study thus extends computational demography literature by demonstrating the practical challenges associated with schema interpretation, data provenance, and error propagation in AI-assisted demographic workflows.

The findings also contribute to theoretical discussions surrounding the "data-intensive turn" in the social sciences, reinforcing arguments that digital and administrative data are reshaping the epistemic foundations of demographic research. Scholars have argued that digital demography represents a paradigm characterized by continuous data flows, interdisciplinary collaboration, and computational modelling, enabling new forms of population analysis and policy engagement[316]. This research supports that characterization while emphasizing that methodological innovation must be accompanied by robust governance mechanisms to preserve

[315] Tatem, "WorldPop, Open Data, and …," (2021): 3.
[316] Kashyap et al., "Digital Demography: New Data Sources for Population Research," *Demographic Research* 45 (2021): 32.

statistical quality and public trust. By foregrounding stakeholder perspectives, my thesis highlights how AI adoption is shaped by disciplinary values and institutional constraints, thereby contributing to sociotechnical analyses of algorithmic governance and data-driven policymaking.

From a policy perspective, the study provides insights into the opportunities and risks associated with integrating AI into demographic decision-making processes. The experiment demonstrates that AI can support anticipatory governance by enabling scenario analysis and more adaptive policy responses to demographic change, echoing international policy guidance that advocates the use of alternative data sources and computational tools to modernize official statistics[317]. At the same time, the research underscores the importance of transparency, accountability, and participatory governance in maintaining the legitimacy of AI-assisted policymaking. This aligns with emerging regulatory frameworks such as the EU AI Act and broader global efforts to operationalize trustworthy AI through risk-based governance models[318]. By situating empirical findings within these policy debates, my thesis contributes to ongoing discussions about how AI can be responsibly integrated into public sector decision-making without undermining democratic values or statistical integrity.

Future research directions: explainable AI and the future of demographic analysis

The findings of this study point toward several promising avenues for future research, particularly in relation to explainable artificial intelligence and its implications for demographic analysis. As AI systems become increasingly embedded in policy-relevant domains, the need for interpretability and transparency will intensify, especially in contexts where demographic outputs inform resource allocation, social policy design, or population forecasting. Explainable AI offers a pathway for addressing these challenges by providing methods that make model behaviour more understandable to researchers, policymakers, and the public. Recent scholarship highlights the importance of explainability for building trust, facilitating accountability, and enabling meaningful human oversight in high-stakes decision environments[319].

Future research could explore how explainable AI techniques can be adapted to demographic workflows, including the development of tools that clarify the contribution of specific variables to model predictions, visualize uncertainty in population forecasts, and document the assumptions underlying data integration processes. Such work would be particularly valuable for official statistics, where interpretability is closely linked to quality assurance and public legitimacy. Moreover, integrating explainable AI with privacy-preserving methods represents a promising area of inquiry, as demographic data often involve sensitive personal information requiring careful governance. Investigating how explainability and privacy can be jointly

[317] UNSD, *Handbook on the Use of Big Data…,* (2023).
[318] European Union, Regulation (EU) 2024/1689 of the European Parliament and of the Council (Artificial Intelligence Act), 2024 O.J.
[319] Adadi Amina and Mohammed Berrada, "Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence," *IEEE Access* 8 (2020).

operationalized could contribute to the development of trustworthy population data infrastructures capable of balancing analytical innovation with ethical safeguards.

Another direction for future research concerns the sociotechnical dimensions of AI adoption in demography, including the role of institutional capacity, professional training, and interdisciplinary collaboration in shaping outcomes. As demographic research becomes increasingly computational, there is a need to examine how educational programmes, organizational practices, and collaborative networks evolve to support responsible AI integration. Additionally, comparative research across national statistical systems could provide valuable insights into how governance frameworks and institutional cultures influence AI adoption trajectories, thereby informing policy strategies for digital transformation in official statistics.

Ultimately, the future of AI in demography will depend on the continued development of methods that are not only technically sophisticated but also transparent, equitable, and responsive to societal needs. Explainable AI represents a critical component of this trajectory, offering tools that can bridge the gap between computational complexity and democratic accountability. By advancing research in this area, scholars and practitioners can help ensure that AI-driven demographic analysis contributes to more informed, inclusive, and legitimate policymaking.

Bibliography

Ada Lovelace Institute. *Participatory Approaches to AI Governance*. London: Ada Lovelace Institute, 2023.

Adadi, Amina, and Mohammed Berrada. "Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence." *IEEE Access* 8 (2020).

Ahmad-Yar. "Anatomy of a Misfit: International Migration Statistics." *Sustainability* 13, no. 7 (2021).

Aral, Sinan. "The Promise of Computational Social Science." *Science* (2021).

Baeza-Yates, Ricardo, and Berthier Ribeiro-Neto. *Modern Information Retrieval: The Concepts and Technology behind Search*. Updated ed. 2020.

Bank for International Settlements Irving Fisher Committee. "Challenges and opportunities presented by generative AI for central banks and statistical agencies." *IFC Bulletin*. Basel: BIS, 2024. https://www.bis.org/ifc/publ/ifcb62_25.pdf

Barocas, Solon, Moritz Hardt, and Arvind Narayanan. *Fairness and Machine Learning*. 2023.

Bassolas, Lucile, et al. “Mobility Patterns in the COVID-19 Pandemic: Implications for Data-Driven Policy.” *PNAS Nexus* 2, no. 1 (2023).

Bijak, Jakub. “Forecasting in the Age of Big Data and Machine Learning.” *Population Studies* (2021).

Billari, F. C. (2022). Demography: Fast and slow. Population and Development Review, 48(1), 9-30. DOl: 10.1111/padr.12464

Blasi Casagran, Cristina. “Developing AI Predictive Migration Tools to Enhance Humanitarian Support: The Case of EUMigraTool.” *Data & Policy* (2024).

Bo, Hongbo, et al. “Failing on Bias Mitigation: Investigating Why Predictive Models Struggle with Government Data.” arXiv preprint, 2026.

Braun, Virginia, and Victoria Clarke. *Thematic Analysis: A Practical Guide*. London: SAGE, 2021.

Breen, C. F. “New Data Sources for Demographic Research.” *Population and Development Review* (2025). https://doi.org/10.1111/padr.12671

Carammia, Marcello, Stefano Maria Iacus, and Teddy Wilkin. “Forecasting Asylum-Related Migration Flows with Machine Learning and Data at Scale.” *Scientific Reports* 12 (2022): 1457. https://doi.org/10.1038/s41598-022-05241-8

Chang, Shuaichen, et al. “A Survey of Text-to-SQL Parsing: Concepts, Methods, and Future Directions.” *ACM Computing Surveys* 55, no. 5 (2023).

Connor, Henry. “John Graunt F.R.S. (1620–1674): The Founding Father of Human Demography, Epidemiology and Vital Statistics.” *Journal of Medical Biography* 32, no. 1 (2022): 57–69. https://doi.org/10.1177/09677720221079826

Conrado, Francesco, et al. “Forecasting Impact of Demographic Changes on the Expenditures of Healthcare and Social Security in Italy from 2022 to 2060.” *Health Economics Review* 15 (2025). https://link.springer.com/article/10.1186/s13690-025-01719-9

Council of Europe. *Artificial Intelligence and Migration*. 2025.

Crawford, Kate. *Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence*. New Haven, CT: Yale University Press, 2021.

Creswell, John W., and Vicki L. Plano Clark. *Designing and Conducting Mixed Methods Research*. 3rd ed. Thousand Oaks, CA: SAGE, 2021.

Duckmanton, Callum. “Automated Decision Making: The Impact of the Data (Use and Access) Act 2025 and a Recent CJEU Judgment.” Burges Salmon (Passle), June 25, 2025.

Doshi-Velez, Finale, and Been Kim. “Towards a Rigorous Science of Interpretable Machine Learning.” arXiv preprint, 2017.

Duan, Haorui, et al. “High-Resolution Population Mapping Based on SDGSAT-1 Night-Time Light Images and Built-Up Area Extraction.” *International Journal of Remote Sensing* (2024).

Dwork, Cynthia, et al. “Differential Privacy: A Primer for Public Policy.” *Communications of the ACM* (2022).

Enqvist, Lena. “‘Human Oversight’ in the EU Artificial Intelligence Act.” *Information & Communications Technology Law* (2023).

Ermon, Stefano, et al. “AI for Social Good.” *Communications of the ACM* (2021).

Eubanks, Virginia. *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*. New York: St. Martin’s Press, 2018.

European Commission. *Ethics Guidelines for Trustworthy AI: Assessment List for Trustworthy AI (ALTAI) – 2022 Update*. Brussels: European Commission, 2022.

European Commission. “European Data Governance Act.” Digital Strategy policy page, 2022.

European Commission. *European Health Data Space Regulation Proposal*. Brussels, 2022.

European Commission. *Feasibility Study on a Forecasting and Early Warning Tool for Migration Based on Artificial Intelligence Technology*. Luxembourg: Publications Office of the European Union, 2021. https://publications.europa.eu/resource/genpub/PUB_DR0221131ENN.1.1

European Commission. *The 2024 Ageing Report: Economic and Budgetary Projections for the EU Member States (2022–2070)*. Luxembourg: Publications Office of the European Union, 2024. https://economy-finance.ec.europa.eu/publications/2024-ageing-report-economic-and-budgetary-projections-eu-member-states-2022-2070_en

European Commission. “Recovery and Resilience Scoreboard.” Accessed January 24, 2026. https://ec.europa.eu/economy_finance/recovery-and-resilience-scoreboard/index.html

European Commission. “Common indicators.” *Recovery and Resilience Scoreboard*. Accessed January 25, 2026.

https://ec.europa.eu/economy_finance/recovery-and-resilience-scoreboard/common_indicators.html

European Commission Joint Research Centre. "Resilience dashboards." Updated Spring 2024. https://joint-research-centre.ec.europa.eu/projects-and-activities/resilience/resilience-dashboards_en

European Commission. "Anticipating and Managing Migration Flows towards the EU." 2024.

European Data Protection Board. *Guidelines on Automated Decision-Making and Profiling – Updated Interpretation*. Brussels: EDPB, 2022.

European Statistical System. *Data Science Strategy for Official Statistics*. Luxembourg: ESS, 2023.

European Statistical System. *Quality Assurance Framework for Official Statistics*. 2022.

Eurostat. *AI and Machine Learning in European Statistical Production*. Luxembourg, 2023.

Eurostat. "AI and Machine Learning in European Statistical Production." Luxembourg, 2023.

Eurostat. "Database." Accessed January 21, 2026. https://ec.europa.eu/eurostat/

Eurostat. *Demography of Europe—2024 Edition*. Luxembourg: Publications Office of the European Union, 2024.

Eurostat. "Digitalisation and Data Science in Official Statistics." 2023.

Eurostat. "European Statistical Monitor: January edition." *Eurostat News*. January 24, 2026. https://ec.europa.eu/eurostat/web/products-eurostat-news/w/wdn-20260219-1

Eurostat. "European Statistics Code of Practice and Independence." *Eurostat News*, 2025.

Eurostat. *Eurostat Report 2023*. Luxembourg, 2023.

Eurostat. *Methodological Guidelines for the Use of Non-Traditional Data Sources in Official Statistics*. Luxembourg: Publications Office of the European Union, 2022.

Eurostat. *Mobile Network Data for Official Statistics: ESSnet Big Data II Results*. Luxembourg: Publications Office of the European Union, 2021. https://ec.europa.eu/eurostat/web/essnet-big-data

Eurostat. "Population projections in the EU." *Statistics Explained*. March 30, 2023. https://ec.europa.eu/eurostat/statistics-explained/index.php/Population_projections_in_the_EU

Eurostat. “Population projections in the EU – methodology.” *Statistics Explained*. Accessed February 4, 2026. https://ec.europa.eu/eurostat/statistics-explained/index.php/Population_projections_in_the_EU_-_methodology

Eurostat. “Population structure and ageing.” *Statistics Explained*. Last updated February 2, 2026. https://ec.europa.eu/eurostat/statistics-explained/index.php/Population_structure_and_ageing

Eurostat. *Feasibility Study on the Use of Mobile Positioning Data for Tourism Statistics*. Luxembourg: Publications Office of the European Union, 2019. https://ec.europa.eu/eurostat/documents/3888793/10051488/KS-FT-19-004-EN-N.pdf

Eurostat CROS. “AIML4OS.” Accessed January 22, 2026. https://cros.ec.europa.eu/dashboard/aiml4os

Eurostat CROS. “ESS Innovation.” Accessed January 22, 2026. https://cros.ec.europa.eu/dashboard/innovation-statistics

Eurostat CROS. “About WIH.” Accessed January 22, 2026. https://cros.ec.europa.eu/dashboard/wih-about-wih

Eurostat CROS. “WIH OJA data.” Accessed January 22, 2026. https://cros.ec.europa.eu/dashboard/wih-oja-data

Federal Communications Commission (FCC). “FCC Declares AI-Generated Voices in Robocalls Illegal under the Telephone Consumer Protection Act.” Declaratory Ruling. February 8, 2024. https://www.fcc.gov/document/fcc-declares-ai-generated-voices-robocalls-illegal

Gebru, Timnit, et al. “Datasheets for Datasets Revisited.” *Communications of the ACM* 64, no. 12 (2021).

Gillespie, Tarleton. *Custodians of the Internet*. Updated ed., 2022.

Gornet, Max. “Regulating AI through Technical Standards: The EU AI Act and Fundamental Rights.” *Internet Policy Review* (2024).

Green, Ben. *The Smart Enough City: Putting Technology in Its Place to Reclaim Our Urban Future*. Updated ed. Cambridge, MA: MIT Press, 2022.

Grossman, Irina, Kasun Bandara, Tom Wilson, and Michael Kirley. “Can Machine Learning Improve Small Area Population Forecasts? A Forecast Combination Approach.” *Computers, Environment and Urban Systems* 95 (July 2022): 101806. https://doi.org/10.1016/j.compenvurbsys.2022.101806

Hancock, Peter, et al. “Meta-analysis of NASA-TLX Workload Scores in Human–AI Interaction.” *Human Factors* 65, no. 2 (2023).

Hargittai, Eszter. “Potential Biases in Big Data: Omitted Voices on Social Media.” *Social Science Computer Review* 38, no. 1 (2020): 10–24.

Hart, Sandra G., and Lowell E. Staveland. “NASA Task Load Index Revisited in Human–AI Interaction Research.” *Human Factors* (2021).

Haorui Duan et al. “High-Resolution Population Mapping Based on SDGSAT-1 Night-Time Light Images and Built-Up Area Extraction.” *International Journal of Remote Sensing* (2024).

Heaton, Jonathan L., Nicholas G. Polson, and Jan Hendrik Witte. “Deep Learning for Finance: Deep Portfolios.” *Applied Stochastic Models in Business and Industry* 37, no. 3 (2021).

Hoffenson, Sarah, et al. “Graphical features of interactive dashboards have little consistent effect on decision making.” *International Journal of Human-Computer Studies* (2023). https://www.sciencedirect.com/science/article/pii/S1071581923001301

Hosner, Roland, Zachary Strain-Fajth, and Veronique Lefebvre. *Bias Estimates for Mobile Phone Data (MPD)-Derived Mobility Statistics in Low- and Middle-Income Countries*. Flowminder Foundation, 2025.

Hussain, Zak, Moritz Binz, Rui Mata, and Dirk U. Wulff. “A Tutorial on Open-Source Large Language Models for Behavioral Science.” *Behavior Research Methods* (2024).

Hyndman, Rob J., and George Athanasopoulos. *Forecasting: Principles and Practice*. 3rd ed. Melbourne: OTexts, 2021.

IBM. *watsonx.governance: Govern AI Models for Trust and Transparency*. Armonk, NY: IBM, 2023. https://www.ibm.com/products/watsonx-governance

IBM. *watsonx on AWS: Secure and Compliant Deployment Options*. Armonk, NY: IBM, 2024. https://www.ibm.com/cloud/watsonx

Ineli Ciger, Meltem. “Rethinking Mass Influx and Derogation in the Age of AI.” *Refugee Survey Quarterly* (2025).

Intahchomphoo, Channarong, Jason Millar, Odd Erik Gundersen, Christian Tschirhart, Kris Meawasige, and Hojjat Salemi. “Effects of Artificial Intelligence and Robotics on Human Labour: A Systematic Review.” *Legal Information Management* 24, no. 2 (2024): 109–124. https://doi.org/10.1017/S1472669624000264

International Organization for Migration. *Harnessing Data Innovation for Migration Policy*. 2023.

Istituto Nazionale di Statistica (ISTAT). *Censimento permanente della popolazione e delle abitazioni – Settima edizione*. Rome: ISTAT, 1 October 2024. https://www.istat.it/statistiche/per-temi/censimenti/popolazione-e-abitazioni

Istituto Nazionale di Statistica (ISTAT). *Uso dei Big Data nella statistica ufficiale*. Rome: ISTAT, 2021. https://www.istat.it/it/archivio/big-data

ISTAT. *Machine Learning and Data Integration in Official Statistics*. Rome: ISTAT, 2022.

ISTAT. *Machine Learning Methods for Record Linkage in Official Statistics*. Rome: ISTAT, 2022.

ISTAT. *Small Area Estimation Using Machine Learning Techniques*. Rome: ISTAT, 2023.

ISTAT. *Methods and IT Tools for Statistical Production: Repository Catalogue*. Rome: ISTAT, 2024. https://www.istat.it/wp-content/uploads/2024/02/Repository_Catalogue_16_02_2024.pdf

ISTAT. *Methodological Note: Municipal Population Projections, 1st January 2024–2050*. Rome: ISTAT, 2025. https://www.istat.it/wp-content/uploads/2025/07/NotaMet_previsioni_pop_comunale_2025_english.pdf

ISTAT. "Population and household projections – Base 1/1/2024." Press release. July 28, 2025. https://www.istat.it/en/press-release/population-and-household-projections-base-1-1-2024/

Keilman, Nico. "Uncertainty in Demographic Forecasts." *Population Studies* (2021).

Kashyap, Roberta, et al. "Digital Demography: New Data Sources for Population Research." *Demographic Research* 45 (2021): 1–40.

Keilman, Nico. "Uncertainty in Demographic Forecasts." *Population Studies* (2021).

Kitajima, T., et al. "Analysis of the Factors Related to the Total Fertility Rate and Its Changes across Japanese Municipalities Using Machine Learning." *Procedia Computer Science* (2025). https://www.sciencedirect.com/science/article/pii/S1877050925033095

Malo, Shireen Fathi, and Adel Al-zebari. "Intelligent Semantic Search for Academic Journals Using AI and NLP Techniques." *Journal of Information Systems Engineering and Management* 10, no. 41s (2025). https://www.jisem-journal.com/index.php/journal/article/download/7884/3594/21464

Mitra, Bhaskar, and Nick Craswell. “An Introduction to Neural Information Retrieval.” *Foundations and Trends in Information Retrieval* (2022).

National Academies of Sciences, Engineering, and Medicine. *Social Media and Democracy: The State of the Field, Prospects for Reform*. Washington, DC: National Academies Press, 2020.

National Institute of Standards and Technology (NIST). *Artificial Intelligence Risk Management Framework (AI RMF 1.0)*. Gaithersburg, MD: NIST, 2023. https://nvlpubs.nist.gov/nistpubs/ai/NIST.AI.100-1.pdf

National Institute of Standards and Technology. *Artificial Intelligence Risk Management Framework (AI RMF 1.0)*. Gaithersburg, MD: NIST, 2024.

National Institute of Standards and Technology. *Artificial Intelligence Risk Management Framework (AI RMF 1.0)*. NIST AI 600-1. Gaithersburg, MD: National Institute of Standards and Technology, 2024.

Nikiforova, Anastasija, et al. “Responsible AI Adoption in the Public Sector: A Data-Centric Taxonomy of AI Adoption Challenges.” arXiv preprint, 2025.

“NPR.” “A political consultant faces charges and fines for Biden deepfake robocalls.” *NPR*. May 23, 2024. https://www.npr.org/2024/05/23/nx-s1-4977582/fcc-ai-deepfake-robocall-biden-new-hampshire-political-operative

Office for National Statistics (UK). “Automated text coding: Census 2021.” Methodology article. April 3, 2023. https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/methodologies/automatedtextcodingcensus2021

OneTrust. *OneTrust AI Governance: Manage Risk and Build Trust in AI Systems*. Atlanta, GA: OneTrust, 2023. https://www.onetrust.com/products/ai-governance/

Organisation for Economic Co-operation and Development (OECD). *Good Practice Principles for Data Ethics in the Public Sector*. Paris: OECD Publishing, 2021. https://www.oecd.org/gov/digital-government/good-practice-principles-for-data-ethics-in-the-public-sector.htm

Organisation for Economic Co-operation and Development (OECD). *Governing with Artificial Intelligence: Enablers, Guardrails and Engagement for Unlocking Trustworthy AI*. Paris: OECD, 2025.

Organisation for Economic Co-operation and Development (OECD). *OECD Due Diligence Guidance for Responsible AI*. Paris: OECD, 2026.

Organisation for Economic Co-operation and Development (OECD). *OECD Framework for the Classification of AI Systems*. Paris: OECD Publishing, 2022.

Organisation for Economic Co-operation and Development (OECD). *OECD Framework for the Classification of AI Systems and Trustworthy AI Lifecycle Management*. Paris: OECD, 2022.

Organisation for Economic Co-operation and Development (OECD). "OECD.Statistics and Data Directorate – About." Paris: OECD, 2025. https://www.oecd.org/about/directorates/statistics-and-data-directorate.html

OECD. "Policies—OECD.AI dashboards (overview)." Accessed January 25, 2026. https://oecd.ai/en/

OECD. "OECD.AI data from partners: a methodological note." Accessed January 25, 2026. https://oecd.ai/en/partner-data-methodological-note/

OECD. *Using Non-Traditional Data Sources for Official Statistics: Framework and Case Studies*. Paris: OECD, 2023.

Pappalardo, Luca, et al. "Using Digital Trace Data to Study Migration and Mobility." *EPJ Data Science* 10 (2021).

Pegasystems. *The Pega AI Manifesto: Nine Principles for Responsible AI*. Cambridge, MA: Pegasystems, 2023. https://www.pega.com/ai-manifest

Pentland, Alex, et al. "Data for Good: Toward Trustworthy Population Data Science." *Nature Human Behaviour* 6, no. 7 (2022).

Preston, Samuel H., Patrick Heuveline, and Michel Guillot. *Demography: Measuring and Modeling Population Processes*. Updated ed. Wiley, 2023.

Pratschke, J., et al. "Population Change and Residential Segregation in Italian Cities." *City, Territory and Architecture* 11 (2024). https://link.springer.com/article/10.1007/s40980-024-00124-0

Provost, Foster, and Tom Fawcett. *Data Science for Business*. Updated ed., 2022.

Raji, Inioluwa Deborah, et al. "Auditing Algorithms: Research Methods for Detecting Bias and Harm in AI Systems." *Communications of the ACM* 65, no. 12 (2022).

Rampazzo, Francesco, Emilio Zagheni, Ingmar Weber, and Maria C. Testa. “Mater Certa Est, Pater Numquam: What Can Facebook Advertising Data Tell Us about Male Fertility Rates?” *Proceedings of the International AAAI Conference on Web and Social Media* 12 (2018).

REGULATION (EU) 2024/1689 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL, Laying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act), 2024 O.J. (L 1689).

Sani, Jamilu, Salad Halane, Abdiwali Mohamed Ahmed, and Mohamed Mustaf Ahmed. “Application of Machine Learning Algorithms and SHAP Explanations to Predict Fertility Preference among Reproductive-Age Women in Somalia.” *Scientific Reports* (2025). https://doi.org/10.1038/s41598-025-04704-y

Samartzidis, Lasare, Marco Quatrosi, and Angelika von Dulong. “Gender and Age Matter! Identifying Important Predictors for Subjective Well-being Using Machine Learning Methods.” *Social Indicators Research* 179 (2025): 955–978. https://doi.org/10.1007/s11205-025-03643-5

Schulze, Annika, et al. “Digital dashboards visualizing public health data: a systematic review.” *Frontiers in Public Health* (2023). https://pmc.ncbi.nlm.nih.gov/articles/PMC10192578/

Sebastian, Meryl. “AI and deepfakes blur reality in India elections.” *BBC Asia*, May 16, 2024. https://www.bbc.com/news/world-asia-india-68918330

Semantic Scholar. “About Semantic Scholar.” https://www.semanticscholar.org/about

Short, John Rennie. *Demography and the Making of the Modern World: Public Policies and Demographic Forces*. Cambridge: Agenda Publishing, 2024. https://doi.org/10.1017/9781788217057.001

Singh, Shalvi. “Artificial Intelligence Models for Predicting Fertility Transitions: A Systematic Review.” *Asian Journal of Research in Computer Science*, May 20, 2025. https://journalajrcos.com/index.php/AJRCOS/article/view/684

Sobotka, Tomáš, and Stuart Basten. “The Rise of Data-Intensive Demography.” *Population Studies* (2022).

Sobotka, Tomas, and Stuart Basten. “Understanding Fertility Trends through New Data Sources and Computational Methods.” *Population Studies* 76, no. 3 (2022): 1–18.

Sokol, K. “Artificial Intelligence Should Support Clinical Decision-Making and Not Replace Clinicians.” PMC Article, 2025.

Suresh, Harini, and John V. Guttag. “A Framework for Understanding Sources of Harm throughout the Machine Learning Life Cycle.” *Communications of the ACM* 65, no. 12 (2022).

Tatem, Andrew J. “WorldPop, Open Data, and the Promise of High-Resolution Population Mapping for Policy.” *Nature Communications* 12 (2021).

Törnberg, Petter. “Best Practices for Text Annotation with Large Language Models.” *Sociologica* 18, no. 2 (2024).

Tschalaer. *Human Rights Risks of Migration Flow Predictions*. 2025.

Tzitiridou-Chatzopoulou, Maria, et al. “Predicting Future Birth Rates with the Use of an Adaptive Time-Series Forecasting Strategy.” *International Journal of Environmental Research and Public Health* 21, no. 7 (2024). https://www.mdpi.com/1660-4601/21/7/841

UN Committee of Experts on Big Data and Data Science for Official Statistics. *Ethical Framework for Data Science in Official Statistics*. New York, 2022.

UN ESCAP. *Using Big Data for Official Statistics*. United Nations Economic and Social Commission for Asia and the Pacific, 2022.

UNESCO. *Guidelines for the Governance of Digital Platforms and Elections*. Paris: UNESCO, 2023. https://www.unesco.org/en/internet-conference/guidelines-digital-platforms-elections

UNECE High-Level Group for the Modernisation of Official Statistics. *Generative AI for Official Statistics: HLG-MOS Report*. Geneva: UNECE, 2025. https://unece.org/sites/default/files/2025-09/Generative%20AI%20for%20Official%20Statistics%20HLG-MOS%20Report.pdf

UNECE High-Level Group for the Modernisation of Official Statistics. *Framework on Responsible AI for Official Statistics*. Geneva: UNECE, 2025.

UNECE High-Level Group for the Modernisation of Official Statistics. *Guidelines on the Use of Big Data for Official Statistics*. Geneva: United Nations Economic Commission for Europe, 2023.

UNECE High-Level Group for the Modernisation of Official Statistics. *Guidelines on the Use of Machine Learning in Official Statistics*. Geneva: UNECE, 2021.

UNECE. *Machine Learning for Official Statistics: Recent Developments and Guidance*. Geneva, 2023.

United Nations. *Data Science for Sustainable Development*. New York: United Nations Global Pulse, 2022.

United Nations, Department of Economic and Social Affairs, Statistics Division. *Handbook on Registers-based Population and Housing Censuses*. New York: United Nations, 2022. https://unstats.un.org/unsd/demographic-social/publication/handbook-registers-phc.pdf

United Nations, Department of Economic and Social Affairs, Statistics Division. *Handbook on the Use of Big Data for Official Statistics*. New York: United Nations, 2023. https://unstats.un.org/bigdata/task-teams/big-data-handbook/

United Nations Statistics Division. *Data Quality Framework for Big Data in Official Statistics*. New York: United Nations, 2023.

United Nations Statistics Division. *Handbook on the Use of Big Data for Official Statistics*. New York: United Nations, 2023.

United Nations Statistics Division. *Privacy-Enhancing Technologies and Their Use in Official Statistics*. New York: United Nations, 2023.

United Nations Department of Economic and Social Affairs, Population Division. "World Urbanization Prospects: The 2025 Revision." 2025. https://population.un.org/wup/

United Nations Population Fund (UNFPA). *State of World Population 2021: My Body Is My Own*. New York: UNFPA, 2021. https://www.unfpa.org/swp2021

United Nations Population Fund (UNFPA). *State of World Population 2023: 8 Billion Lives, Infinite Possibilities*. New York: UNFPA, 2023. https://www.unfpa.org/swp2023

United Nations Population Fund (UNFPA). *The Future of Population Data: ICPD30 Think Piece*. New York: UNFPA, 2024.

van Atteveldt, Wouter, Damian Trilling, and Carlos Arcíla. *Computational Analysis of Communication: A Practical Introduction to the Analysis of Texts, Networks, and Images with Code Examples in Python and R*. Hoboken, NJ: Wiley, 2021.

van Kampen, A. H. C., et al. "ENCORE: a practical implementation to improve computational reproducibility." *PLOS Computational Biology* (2024). https://pmc.ncbi.nlm.nih.gov/articles/PMC11405857/

Viel, Shira, Maria Tackett, Sarwari Das, and Joseph Choo. "Classroom Community amid Covid-19: A Mixed-Methods Study." arXiv, 2023.

Wiśniowski, Arkadiusz, et al. "Combining Machine Learning and Demographic Models for Population Forecasting." *Demographic Research* (2022).

World Bank. *Poverty and Shared Prosperity 2022: Correcting Course*. Washington, DC: World Bank, 2022. https://www.worldbank.org/en/publication/poverty-and-shared-prosperity

World Bank. "Urban population (% of total population)." *World Development Indicators*. Accessed February 2, 2026. https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS

WorldPop. *AI-Based Population Mapping for Sustainable Development*. Southampton, 2022.

Yabe, Takahiro, Nicholas K. W. Jones, P. Suresh C. Rao, Marta C. González, and Satish V. Ukkusuri. "Mobile Phone Location Data for Disasters: A Review from Natural Hazards and Epidemics." *EPJ Data Science* (2022).

Yildiz, Dilek, Arkadiusz Wiśniowski, Guy J. Abel, Ingmar Weber, Emilio Zagheni, Cloé Gendronneau, and Stijn Hoorens. "Integrating Traditional and Social Media Data to Predict Bilateral Migrant Stocks in the European Union." *International Migration Review* (2024). https://doi.org/10.1177/01979183241249969

Yeung, Karen. *Algorithmic Regulation and Public Administration*. 2022.

Yu, Tao, et al. "Spider 2.0: Benchmarking Text-to-SQL Systems in Realistic Settings." arXiv, 2023.

Zagheni, Emilio, and Ingmar Weber. "Demographic Research with Nontraditional Data Sources." *Annual Review of Sociology* (2021).

Zagheni, Emilio, et al. "Digital Trace Data for Population Research." *Population and Development Review* (2023).

Zagheni, Emilio, Jakub Bijak, and Ingmar Weber. "Digital and Computational Demography." *Annual Review of Sociology* 48 (2022): 1–24.