information

Review

Governing with Intelligence: The Impact of Artificial Intelligence on Policy Development

Muhammad Asfand Yar [1], Mahani Hamdan [1], Muhammad Anshari [1,*], Norma Latif Fitriyani [2] and Muhammad Syafrudin [2,*]

1 Institute of Policy Studies, Universiti Brunei Darussalam, Bandar Seri Begawan BE1410, Brunei; 23h1511@ubd.edu.bn (M.A.Y.); mahani.hamdan@ubd.edu.bn (M.H.)
2 Department of Artificial Intelligence and Data Science, Sejong University, Seoul 05006, Republic of Korea; norma@sejong.ac.kr
* Correspondence: anshari.ali@ubd.edu.bn (M.A.); udin@sejong.ac.kr (M.S.)

Abstract: As the field of artificial intelligence (AI) continues to evolve, its potential applications in various domains, including public policy development, have garnered significant interest. This research aims to investigate the role of AI in shaping public policies through a qualitative examination of secondary data and an extensive bibliographic review. By analyzing the existing literature, government reports, and relevant case studies, this study seeks to uncover the opportunities, challenges, and ethical considerations associated with leveraging AI in the formulation and implementation of public policies. This research will delve into the potential benefits of AI-driven policy analysis, such as enhanced decision-making processes, data-driven insights, and improved policy outcomes. Additionally, it will explore the risks and concerns surrounding AI's influence on policy, including potential biases, privacy implications, and the need for transparency and accountability. The findings of this study will contribute to the ongoing discourse on the responsible and effective integration of AI in public policy development, fostering informed decision-making and promoting the ethical use of this transformative technology.

Keywords: artificial intelligence; public policy development; ethics; decision-making

Citation: Yar, M.A.; Hamdan, M.; Anshari, M.; Fitriyani, N.L.; Syafrudin, M. Governing with Intelligence: The Impact of Artificial Intelligence on Policy Development. *Information* **2024**, *15*, 556. https://doi.org/10.3390/info15090556

Academic Editor: Willy Susilo

Received: 20 August 2024
Revised: 5 September 2024
Accepted: 6 September 2024
Published: 10 September 2024

1. Introduction

Today's rapid pace demands that policymakers be equipped with decision-making, broad conceptual thinking, and data analytics skills. In fast-paced digitalized societies, policymakers, public administrators, and managers must introduce novel concepts to develop and design the policy cycle from problem identification in agenda setting to policy evaluation through data-driven and evidence-based decision-making. This drive involves leveraging information and computer technologies (ICTs), artificial intelligence (AI), and machine learning (ML) and citizens' participation with co-creation and multi-stakeholder approaches. These methods will enhance public policymaking and make the policy validation process more appealing and data-driven.

The era of the fourth industrial revolution and the influence of digital transformation compels governments to rein in the benefits of AI technology and leverage AI to enhance decision-making. Artificial intelligence and data-driven policymaking started in 2010 following evidence-based policymaking. Before data-driven inclusion, policy decisions merely relied on incomplete, poorly integrated, fabricated, and politically twisted evidence besides policy communication errors. Evidence-based policymaking developed in the late 1990s as a sub-domain of policy analysis and an important principle in policy decision-making [1]. Data-driven policymaking becomes a game changer by avoiding the loss of relevant datasets from public and government authorities and creating a modern public value impact system based on understanding and integrated data as hard evidence that delivers high-quality and low-cost public services efficiently and effectively.

Technology inclusion in the form of technocratic and e-governance decision-making models is being practiced in democratic systems to offer more accurate, improved, rapid, and scientific solutions to public policy problems. Solo (2011) proposed the engineering and computational public policy to formulate, design, optimize, forecast, model, simulate, and analyze public policy with the help of mathematical models and computer programs [2].

AI tools and systems have gained the ability to analyze gigantic and vast patterns of data sets, give critical visions, forecast future outcomes and trends of different policy options, comprehend the consequences of policy decisions, and provide recommendations to policymakers. AI is achieving significant and successful acceptance in operative data-driven public policy crafting and drafting in many developed regions around the globe. European Union climate policies are being shaped and developed after analyzing the impact of emissions of greenhouse gases by different AI tools [3].

Governments across the globe have fully swung on AI to deliver public services and improve operations, recognizing AI's potential to redesign the policymaking and development process for efficient and faster decision-making. Although AI's reasonable aspirations open a new spectrum for public policymakers, the potential and planning vistas like predictive analytics, design of data-driven programs, and pattern detection adeptness to extend full-scale inclusion of AI in the policy development process are still in the early stages. In his empirical study, Daan Kolkman (2020) revealed that governments use algorithms to improve policymaking and find the benefits of different algorithms for public [4].

AI's role is not to replace but to ease policymakers by equipping them with a robust, rapid, comprehensive, and rigorous framework to develop, design, formulate, implement, and execute policy decisions with real-time improvements in a more responsive, effective, and fair manner. From the health sector to education and from agriculture to industry, governments are increasingly adopting and implementing AI and ML algorithms for optimal decision-making, low input costs, and high-quality services as outcomes. In a nutshell, the prospects of AI are changing the style, process, and approaches of governance and public service systems, allowing citizen inclusion in decision-making and policy formulation and adoption.

Policymakers are trying to drive the AI model like a bus that is fueled by data, and the algorithm works as the engine of the AI model in a cost-effective mechanism and has the objective of reaching the destination as a set target for the benefit of the public. Policymaking is a complex, extended, bureaucratic, and politically, economically, and socially motivated process consisting of various stages in a cycle, from a focusing exercise to narrow down the problem identification to evaluation of policy impacts using data. Rapid AI integration in policymaking offers policymakers the chance to improve the process and develop the policy landscape by making significant decisions that are based on reliable datasets and ample knowledge. Policy experts can also use analytical and predictive tools as well as real-time data dashboards to monitor and evaluate complex policy facts.

AI and ML algorithms, such as natural language processing (NLP) toolkits and Voyant tools, can be used to analyze the key patterns, themes, trends, and public opinion from the content consisting of social media posts, news articles, policy documents, and government reports based on public concerns and sentiments on policy problems. Zhijing Jin (2022) introduced NLP methods such as text classification, topic modelling, text scaling and event extraction for evidence-based policymaking, policy communications and policy effects [5]. These techniques and tools are bridging the gap between policymakers and the public in shaping policy problems and solutions, making the process more responsive and better communicated.

This practice enables policymakers to extract key information that will help them shape the policy agenda and frame the policy problem. In the traditional policy cycle, this is known as the agenda-setting or problem identification stage. However, in the dynamic policy cycle, this stage can be renamed as pattern detection or key information extraction with AI tools to analyze massive datasets rapidly, categorize persistent social problems of particular public concern without political influence and bureaucratic red tape, and make the policymaking process transparent and accountable.

The second stage in the traditional policy cycle is set for developing and designing different policy options as solutions using conventional cost–benefit analysis. In the dynamic policy cycle, this stage can be rephrased as forecasting policy options by training the ML models on historical datasets to predict the different policy options for various policy scenarios and suggest the optimal policy option to adopt the best policy decision. Public policymakers always make predictions while keeping causal inferences of cause and effect; ML provides a way to make data-driven and accurate predictions in strategic decision-making.

The national climate change policy of Pakistan 2021 can be used as a case study of how AI integration can be possible in the policy development process. Although the original policy draft was not developed using AI tools, this vision can enhance decision-making and policy effectiveness through data-driven insights. The NLP-toolkit can access public opinions and concerns regarding climate change in Pakistan. Using the climate historic data, on the one hand, we can predict the future risks, and on the other hand, by introducing AI-based simulations of various policy scenarios such as increased forest cover, management of water, food, and energy security, we can provide evidence-based recommendations. Using AI can enable the development of a dynamic, real-time, data-driven and adaptive policy framework in case of emergencies like climate change challenges.

2. The Literature

Public policy should reflect public intentions, opinions, and sentiments, but a critical challenge afflicts the drift to give prevalence to simple policy solutions to complex public policy problems. Policymaking, being a complex process, requires a critical approach at each phase of the policy cycle equipped with a data bank for evidence-based solutions, decisions, and executions, and this study attempts to bridge this gap through the inclusion of AI and ML models and big data to provide an active agenda of algorithmic policymaking in policy discourse.

The literature on AI inclusion in policy sciences in general and in the development of public policy cycles in particular is very limited, as it is an emerging trend and needs more empirical research to uncover the potential opportunism and challenges of keeping ethical considerations of data-driven policy decisions and outcomes. AI is not a novel topic of research, but the knowledge and empirical gap in focusing AI inclusion on the development of the public policy cycle, transforming from traditional to dynamic (data-driven and computational) policy cycle, is a new area for policymakers, policy analysts, and researchers. There is a need for full-scale research on the application of AI and ML models throughout the entire policy cycle across various public policies, while addressing the ethical, legal, regulatory, and institutional frameworks in the development of public policy. The table below is the Thematic Synthesis Table, which will be explained in this section (see Table 1).

Table 1. Thematic Synthesis Table.

Authors	Key Theme	Findings
Newman, J. and M. Mintrom, 2023 [1]	Evidence-based policy using AI ethical practice of policy analysis.	Evidence-based policymaking developed as a sub-domain of policy analysis.
Solo, A.M., 2011 [2]	New fields of public policy engineering, computational public policy.	Proposed computational public policy to formulate, design, optimize, forecast, model, simulate, and analyze public policy with the help of mathematical models and computer programs.
Cowls, J., et al., 2023 [3]	AI gambit: leveraging artificial intelligence to combat climate change.	EU climate policies shaped and developed after analyzing the impact of emissions of GHG by different AI tools.
Kolkman, D., 2020 [4]	Usefulness of algorithmic models in policymaking.	Governments use algorithms to improve policymaking and finds the benefits of different algorithms for public services.

Table 1. *Cont.*

Authors	Key Theme	Findings
Jin, Z. and R. Mihalcea [5]	NLP for policymaking.	Introduced NLP methods (text classification, topic modelling, text scaling) on evidence-based policymaking.
Torjman, S., 2009 [6]	Community roles in policy.	Stakeholder engagement effectively to serve the large public interest.
Howlett, M., 2018 [7]	Effective policy design.	Effective policy design is a delicate process requires in-depth knowledge of policy context to formulate policy options and tools in policy implementation.
May, P.J., 2012 [8]	Policy design and implementation.	Emerging trends of technology resolving public problems by transforming policy design toward structured, analytical, and problem-solving modes.
Nam, T., 2020 [9]	Data-based policy.	Proposed the topology of data categorization based on the legitimacy of evidential data and analytical methods to avoid data biases, predesigned decisions, and uncontrolled outcomes.
Azzone, G., 2018 [10]	Big data and public policies.	Strategic potential opportunities of big data for effectively designing public policy based on quality public value system.
Christensen, J., 2021 [11]	Expert knowledge and policymaking.	Fragmented and scattered approaches across diverse academic and contemporary disciplines in forming an inclusive approach to design a well-informed and evidence-based public policy discourse.
Ibrahim, O. and A. Larsson, 2017 [12]	Tools for structuring public policy problems and design of policy options.	Proposed a new web-based tool called "public policy-oriented problem structuring method" known as "labelled causal mapping" to support scenario-based dynamic simulation and provide a graphical representation of policy actors, variables, and their dependency in policy modelling.
Valle-Cruz, D., 2020 [13]	Public policy-cycle framework in the age of AI: From agenda-setting to evaluation.	AI-powered simulations of policy outcome.
Steuer, F., 2018 [14]	Machine learning for public policymaking.	Application of machine learning predictive algorithms.
Thapa, B.E., 2019 [15]	Predictive Analytics and AI in Governance.	Real-time data dashboard for evaluation of HIV prevention program in Uganda through data analytics.
Dogaru, T.-C., 2018 [16]	Change and Public Policy.	Classical theory of policy change; when a policy fails to achieve the set objectives and goals, the policymakers must replace it with a new one.
Ehrentraut, C., O. Ibrahim, and H. Dalianis, 2014 [17]	Text Analysis to support structuring and modelling a public policy problem.	Application of NLP and extraction of information from qualitative textual data to automate the early stages of policy formulation.
de Fine Licht, K. and J. de Fine Licht, 2020 [18]	AI, transparency, and public decision-making.	AI should be used to justify decisions instead of relying on an absolute apparent system in utilizing AI tools.
Dwivedi, Y.K., et al., 2021 [19]	AI Multidisciplinary perspectives on initial challenges, opportunities, and policy.	Social, economic, political, data privacy, technological capacity, and ethical challenges are associated with AI decision making in government organizations.
Janssen, M., 2020 [20]	Data governance for trustworthy AI.	Proposed a framework built on 13 design rules comprising data and algorithmic stewardship to ensure a trusted data-driven AI algorithm.

2.1. Policy Development and Design as a Decision-Making Process?

Public policy development is a deliberate and vigilant process of decision-making aimed at addressing public sentiment, guiding the core public concerns, and selecting options to achieve set objectives. Policy development is a complex process involving making the best decisions that consider diverse stakeholder opinions from experts, officials, the public, the media, and other pressure and working groups, aiming to address social goals effectively and serve the broader public interest [6]. The policymaking process has political, administrative, and social contexts that influence the policy design and interventions. Howlett (2018), speaking on effective policy design, narrates that policy design is a delicate process and requires in-depth knowledge of policy context to formulate policy options and tools to intervene in policy implementation [7].

Policy development as a process/cycle is comprehensive and complex and has sub-cycles in the conventional policy cycle.

1. Agenda setting: find the core policy problem (research, discussion, information, data), stakeholders and targeted group, and beneficiary groups.
2. Policy formulation/design/directives/dialogue: set desired policy goals (value-based), define the vision and mission of policy (political, social, or economic context), establish policy goals and targets, and explore different possible policy options and alternatives as the best solution.
3. Adoption/decision making: determine and adopt the course of action and policy measures to reach the specified policy objective.
4. Implementation of policy: design the specific framework or tool to implement the policy and attain the policy goal.
5. Evaluation, monitoring and assessment: assess the impact(s) of policy outcome(s).

The policy cycle begins with setting an agenda to identify the problem(s) and then progresses to the stage of policy formulation, where a range of possible options, alternatives, and solutions are assessed and analyzed through frameworks of cost–benefit and predictive analysis, based on different factors like economic cost, social benefit, resource allocation, and political context, to select the best option for the identified problem(s). Several factors function as watchdogs throughout the entire decision-making process in policy development.

Effectiveness deals with how well the policy goals and targets have been met. Efficiency entails how well resource allocation and use are managed to achieve the set policy objectives. Consistency discusses the nexus between the broader policy goals and strategies of government. Implementation and evaluation are more complex and crucial phases in policy development. Public policy development is a process of making good decisions in the broader interest of the public on core issues.

The traditional rational cycle of public policymaking does not depict real-world problems, as policymakers consider deliberately limited policy options and alternatives instead of a wide-range exploration of all possible workable policy solutions. The analytical perspective of complex policy processes suggests that policy actors make policy decisions, as seen in Figure 1, with less information, limited resources, time constraints, and weak human intellectual skills rather than logical, comprehensive, and rigorous analysis.

The process of policy design with a narrow focus has led to failures on social, economic, and governance fronts because of a lack of extensive conceptualization of policy problems. The established policy design approach is either narrowing down the policy options or narrowing down the policy problem, ignoring the problem space frame and focusing on approximation rather than a problem-solving approach. The emerging trend of technological input and inclusion to resolve public problems is inducing a transformation of policy design toward structured, analytical, and problem-solving modes [8].

Several promising AI tools are being adapted to develop and design policy cycles based on foresight, analysis, and decision optimization. Voyant tools are web-based and offer text analytics of policy documents by extracting key themes, trends, and social outlooks from huge textual datasets. The Google Cloud-AI platform, Microsoft Azure machine learning (v1.48.0), Rapid-miner 10, Tableau 2023.3, Tensor-flow 2.13.0, and Civic analytics provide an inclusive set of tools and services for predictive policy analytics, decision-making support, and trend analysis in policy design and formulation.

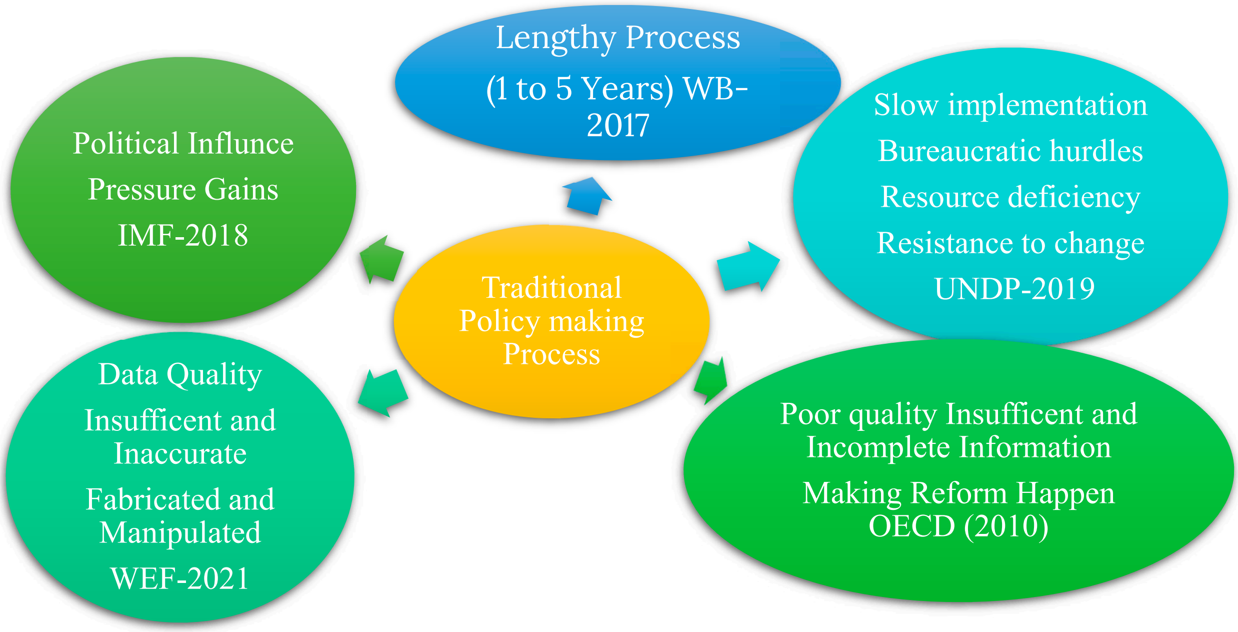

Figure 1. Problems associated with the development of the traditional policy cycle.

Data-driven policymaking frames evidence-based policymaking through the optimal use of ICT and the inclusion of big and open data sources to maximize the benefits of public value and the collaboration of citizens as relevant stakeholders. The existing literature shows that tough data-driven policymaking is complex with many challenges of data collection, sorting, integrating, reusing, and controlling. However, it justifies the significance of three kinds of evidence—systematic (scientific), management (practical), and political (judgmental)—in evidence-based policymaking for legitimate actions. Data-driven policymaking is a domain of evidence-based policymaking, where irregularities in evidence or political influences on evidence can impact decision-making. Data-driven policy is also susceptible to data manipulation and misinterpretation, raising questions about the legitimacy of the policy process. Nam (2020) proposed the topology of data categorization based on the legitimacy of evidential data and analytical methods to avoid data biases, predesigned decisions, and uncontrolled outcomes [9].

Big data operating in public policy development provides the opportunity to expand the capacity of the dynamic policy cycle while keeping public value; however, there are several key technical and ethical challenges regarding data overflow, data diversity, unstructured data, privacy, rights, biases, fairness, transparency, and algorithmic models. Azzone (2018), in a comparative study, highlights the strategic potential opportunities of big data for effectively designing quality public policy based on the quality public value system and underlines the interdisciplinary collaborative approaches to regulating the challenges of big data, such as organizational readiness for change, conceptual arrangements for developing new tools and methods of data, and AI governance [10].

Today, with a decentralized governance style and the power of big data, politicians and bureaucrats are losing control and the authority to shape, frame, and influence public policy and decision-making processes. The growing knowledge and technology-based economic, social, and political models have opened fostered collaboration among experts from diverse fields such as politics, administration, policy, data, and computers. This cohesion helps evolve, develop, and practice evidence-based public policymaking by lowering ambiguous and uncertain factors through expert knowledge. Christensen (2021), in a systematic empirical study, finds fragmentation and scattered approaches across diverse academic and contemporary disciplines in forming an inclusive approach to designing a well-informed evidence-based public policy discourse based on advanced specialist knowledge [11].

2.2. Can AI and ML Help Policymaking?

Algorithmic public policymaking is gaining potential due to the rapid increase in digital data and the development (creation and modification) of innovative machine-learning-based algorithms. The formation of AI and ML systems is mature enough to learn, predict, classify, and make decisions that can be useful for policymakers to design, develop, and implement a policy. AI can aid in each phase of the policymaking cycle, and the use of AI in the public sector has grown. AI tools can provide updated analytics of daily accessible public data to make policymakers eligible for identifying the core emerging public issues. During the COVID-19 pandemic, AI-based tools like Aarogya in India and data-driven applications such as GPS were being practiced in updating policy decisions by tracing, tracking, identifying, and managing the hotspots and circulating important health updates to improve public trust in the health system.

Emerging AI-driven policymaking enhances the public policy cycle, as in the agenda-setting phase. AI-powered tools such as text mining and natural language processing techniques help to identify, rank, and predict emergent public concerns and hot issues based on objective analysis of datasets such as social media trends, in a more quick and modified style. How can AI models help frame actual problem identification, shape the policy agenda, design and assess the policy alternatives, and develop the overall policy discourse while addressing challenges in the preliminary stages of policy formulation such as ill-defined problems, uncertainty, external factors, and the complex policymaking process? Ibrahim and Larsson (2017), in a scientific study, proposed a new web-based tool called the "public policy-oriented problem structuring method", known as "labelled causal mapping", to support scenario-based dynamic simulation and provide a graphical representation of policy actors, variables, and their dependency in policy modelling [12].

The AI and ML simulations and predictive models inform the impacts of different policy alternatives based on the training of past data in the policy formulation and design stages. The mature AI and ML decision support tools assist policymakers in adopting policy decisions. Automation tools monitor policy execution and suggest interventions and improvements in effectiveness and impact.

A theoretical and systematic study discussed the revolutionary effects of AI in public services, administration, and policy. It highlighted AI-powered simulations of policy outcomes for San Mateo County's seismic data algorithm, smart police stations in Dubai, USTAAD, the Indian railway safety system in the prediction of maintenance, machine learning tools employed in the FDA USA to detect cyber-attacks, facial recognition in China, and Dutch ICIA networks [13]. Another study discusses the application of machine learning predictive algorithms such as random forest, neural networks, Bayesian learning, gradient boosting, and support vector machines in predicting public policy outcomes such as the criminal justice system, cleanliness intrusions in restaurants, estimation of poverty levels, social services, health, resource allocations, economics, and crop yield production [14].

A report by the European Liberal Forum on predictive analytics and AI data-driven governance in free society illustrates the example of problem identification through a data-driven approach. It stated that UN Global Pulse projects in Africa and Indonesia are nowcasting food security using mobile phone airtime and Twitter data to identify the problem in price hikes of food commodities. Similarly, another example supports the use of data analytics for evidence-based policy formulation and highlights the case of Espoo, Finland, which identifies the need for child welfare services through predictive analysis and the formulation of policy alternatives.

The report describes that after designing policy options, the government chose one of the best policy options for implementation using simulations. The report discussed the case of tax and social benefit rules in the "French OpenFisa" simulation platform as data-driven analytical decision-making. In the next phase of policy implementation, the public administrators and managers are responsible for the adopted decision to implement. The report depicts the example of automation and rule-based algorithms in Finnish social insurance programs. Policy evaluation is important for assessing the impacts of a policy after a certain period and suggesting interventions for policy improvements. The report presents a real-time data dashboard for the evaluation of HIV prevention program in Uganda through data analytics [15].

3. Methodology

This study employs a qualitative examination of secondary research approaches, encompassing an extensive bibliographic review of peer-reviewed journals using the Scopus database from the past ten years focusing on the following key terms: public administration, public policy, big data, algorithmic policymaking, data-driven policymaking, artificial intelligence in public policy, machine learning and public policy, natural language processing in public policymaking, and computational public policy. Through this comprehensive literature review, government reports, and relevant case studies, a diverse array of scholarly sources is gathered, including articles and reports focusing on the domain of AI inclusion in the development of public policy, data-driven public policies, and the transformative influence of AI on the public policy cycle. The limited number of articles found indicates the scarcity of research on AI inclusion in the development of public policy. The majority of studies discussed AI in a broader context without considering AI and ML inclusion in the policy cycle. Data were handled by systematically extracting key information and combining results through meta-analysis for quantitative studies and thematic synthesis for qualitative studies. Variability among studies was addressed by conducting sensitivity analyses.

This study employed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to guide the systematic review of the literature on the role of artificial intelligence (AI) in policy development. The PRISMA process involved a comprehensive search and selection of relevant academic articles and reports, adhering to established criteria for inclusion and exclusion. The study protocol was pre-registered with the Open Science Framework [osf.io/q4j8b] to ensure methodological rigor and promote research transparency.

The PRISMA Statement of our study is presented in Figure 2 and is explained in the following paragraphs.

Identification: The initial search identified a total of 140 articles from academic databases that explored the role of artificial intelligence (AI) in policy development. Additionally, 8 government and international reports were identified as supplementary sources to provide further context and analysis.

Screening: After a preliminary review of titles and abstracts, the selection was narrowed down based on relevance to the study's objectives. Out of 140 articles, a significant portion was excluded for being unrelated to the intersection of AI and policy development. This screening process resulted in the inclusion of 39 articles and reports for further detailed examination.

Eligibility: Upon conducting full-text reviews of the remaining 39 sources, 20 articles were excluded due to low quality, lack of detailed analysis on AI's implications for policy, or being out of scope. Consequently, the final selection comprised 19 articles that met the quality and relevance criteria, alongside 1 report.

Included: The final analysis was based on 19 academic articles and 1 government or international report. These sources provided insights into AI's role in policy development, trends and gaps in current research, future research directions, and policy implications for AI integration in governance (see Figure 3).

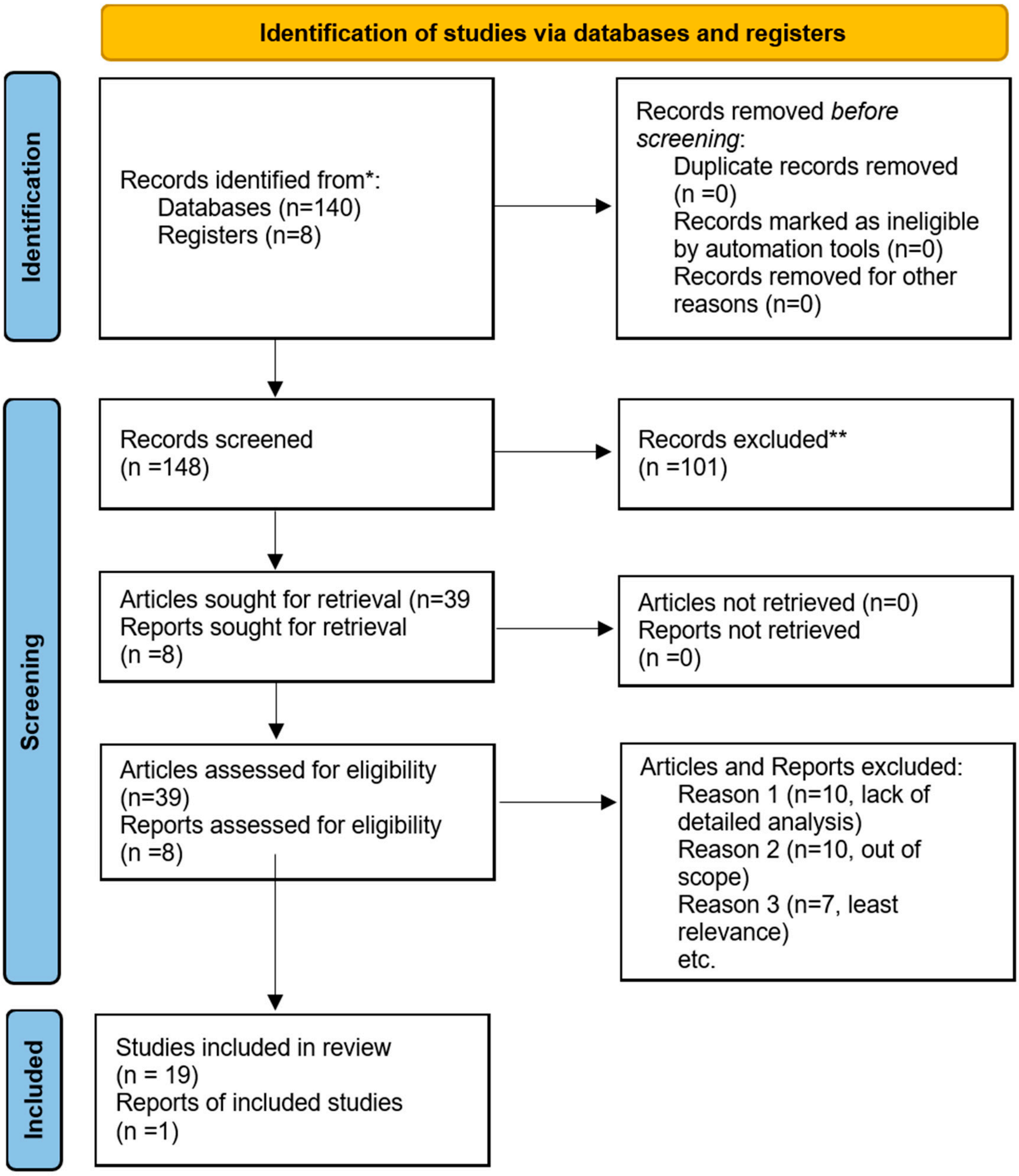

Figure 2. PRISMA 2020 flow diagram of the current study on AI in policy development. * Records identified from Scoups database. ** Records excluded due to reasons mentioned in the text.

The main source of these articles and report is Scopus, and all available data collection is in the English language. Subsequently, a rigorous thematic data analysis is undertaken to distill key themes and patterns from this wealth of peer-reviewed content. By leveraging insights from this curated collection of reputable sources, the study aims to uncover the opportunities, challenges, and ethical considerations associated with leveraging AI in the formulation and implementation of public policies. This methodological framework not only ensures a robust foundation for understanding the dynamic interplay between AI and public policy but also provides a holistic view of their collective impact on the enhancement of public decision making, thus enriching the scholarly discourse with current and relevant insights. The study assessed the risk of bias in each included study using the Cochrane Risk of Bias Tool. This evaluation focused on potential biases such as selection, performance, detection, attrition, and reporting biases. Studies were categorized as having a low, high, or unclear risk of bias. Thematic synthesis was used to summarize key themes and patterns.

These measures were selected to provide a comprehensive overview of the impact of AI on policy development.

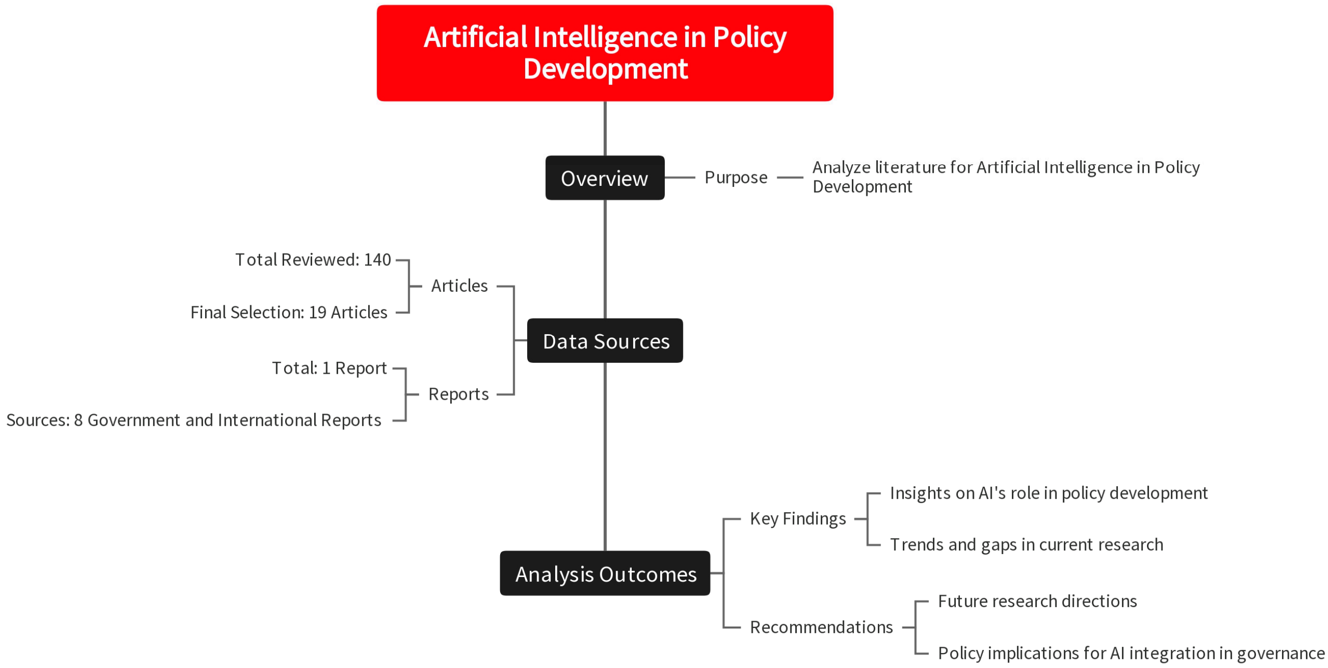

Figure 3. Flow diagram of the current study on AI in policy development.

4. Analysis

The policy process develops as time evolves, which leads to the merit of public policy, and time is a dynamic factor in policymaking that requires action and authority at distinct levels. However, policymakers prefer policy design to keep certain conditions along with other external factors like social constraints, institutional resistance, and environmental concerns. The dynamic and evolving nature of the policymaking process requires adaptation to changing conditions. However, the classical lens of evidence-based policymaking lacks policy adaptiveness that responds to change and fosters challenges to policy cycle stages such as agenda setting, formulation, and adoption.

Dogaru (2018), in his study on policy adaptiveness and change, explained different policy change models such as path dependence, policy windows, punctured equilibrium, and policy advocacy frameworks. He highlighted that the classical theory of policy change states that policies follow problems. When a policy fails to achieve the set objectives and goals, the policymakers must replace it with a new one [16].

The core problems associated with the policymaking process are the nature, scope, and gravity of policy problems; unclear motives, preferences, and behaviors of policymakers; inaccurate evaluation of policy outcomes; invalidated analysis of policy impacts; uncritical acceptance of policy statements based on assumptions and speculations; a lack of ground facts and information; unskilled public policy executors; and a lack of reliable data, representing a key barrier in the e-policymaking process. There should be some certainty factor in why, how, and according to what criteria some public issues gain attention and others do not. Quantitative empirical data are important for establishing cause-and-effect relationships and selecting the best policy measures. Like business, public policymaking is a complex domain that makes decisions in a constant struggle of prediction.

The first stage is agenda-setting to identify and define the policy problem. The policy problem affects every stage of the policymaking cycle and drives the policy in an explicit direction. An inclusive approach and inductive technique to policy problems involves identifying the causes of problems, evaluating diverse subjective arguments, and structuring well-defined problem statements. The policy agenda is assigned as the first and fundamental step in the policymaking cycle to fix policy problems as public issues. The importance of public agenda-setting is at the core of public policy development; it reflects the broader nature and view of public problems, issues, concerns, sentiments, opinions, and values that need attention and preferences shaped by the community, highlighted by the media, discussed in academia, influenced by socially active groups, modelled by politicians, and framed by policy experts.

The public policy cycle consists of different activities, drivers, tools, and actors to decide on the development of a public policy. Machine learning, a subarea of AI, has improved remarkably in predictive analytics, learning and training historical data, analyzing trends and patterns, predicting outcomes, and providing key assessments for strategic decision-making. The performance of machine learning models depends on the quality and reliability of the data, the training of the data, the best prediction, and the model parameters that seek to select and optimize the model wisely.

As seen in Table 2, the inclusion of AI in the entire policy cycle, from agenda setting to the evaluation stage, requires different analyses and models to achieve the requirements of each stage. In the agenda-setting phase, policymakers and analysts try to list, frame, classify, and identify the problem(s) that concern them most and need attention. In the traditional policy cycle, political interests and power centers can influence this key stage to shape and manipulate the problem framing. The AI and ML models have a vital impact on the agenda-setting and problem-identification phases of performing sentiment, situational, and critical analysis of large datasets of public discussions on digital media and social platforms using the tools of NLP.

Table 2. Analyses and models are required for integrating AI across different stages of the policy cycle, from agenda setting to evaluation.

Policy Stages	Passive	Dynamic	Tools	Significances	Applications
Agenda-Setting and Problem Identification	Lengthy and slow process Political influence and interest Poor exchange of information Absence of quality data	Available real-time data to classify, rank, and select	NLP-toolkit, Gensim LDA, BERT Data and Text Mining Voyant Tools	Speedy Analysis Accuracy, Inclusivity, Public Trust	Themes, trends, patterns, topics, content modelling, tracking, recording and mapping
Formulation and design	Cost–benefit analysis Stakeholder analysis	ML predictive models and real-time simulations	Random Forest, Linear Regression SVM, KNN, Naïve Bayes	Reinforcement, self-learning, automated decision making	Prediction, optimal solutions
Adoption	Power-centered, vertical flow	Citizen-centered, horizontal flow	Game theory models	Resource efficient	Strategic decision sciences
Implementation	Bureaucratic hurdles, Budget constraints, unskilled implementing staff	Rapid improvements and interventions	Robotics, drones	Cost effective, responsive	SMART approach executes policy
Evaluation	End-line analysis to evaluate the policy impact for short, medium and long term	Continue real-time evaluation and monitoring of each policy stage	Big-data analytics, artificial neural network, intelligent system	Effective, efficient	Adoption, correction, improvement, termination

The updated and innovative techniques of topic modelling using LDR, an NLP toolkit, can be used to analyze key themes, identify emerging trends, detect patterns, facilitate diverse discussions, and promote agendas. A study articulates the application of the algorithm of NLP, extracting information from qualitative textual data to automate the early stages of policy formulation [17]. This AI inclusion at the key stage of the public policy cycle helps policymakers and analysts foster the process of problem identification and definition with high accuracy and low error. The government's role is also important in the provision of legal and regulatory frameworks to avoid the negative implications of data privacy and combat digital bias.

The policy formulation and design for alternate policy options is the second foremost stage of the policy cycle, and the traditional practice of cost–benefit analysis is used to evaluate the effectiveness of each policy option. Predictive models of AI and ML like random forest classifiers and regressors, Naïve Bayes, support vector machines, K-nearest neighbors, and artificial neural networks can be used at this phase of the policy cycle to save time and resources. The models are trained on the available historical data set consisting of different policy scenarios and simulate future predictions. For diverse policy options, NLP toolkit data mining, data scouting, and text analysis can also be performed at this stage to convert unstructured descriptive data into structured data. The utilization of AI tools enhances the inclusivity and policy response in the presence of real-time data in a dynamic policy environment.

The implementation of policy-adopted decisions is a key stage where maximum policies may lead to failure due to several key factors such as bureaucratic hurdles, resource scarcity, an unskilled workforce, poor communication, and change resistance. The AI tools and reinforcement techniques of ML are being utilized by the revenue department to control tax frauds, in the police department for crime surveillance and traffic control, and in the health sector for diagnosis, detection, and operation. The last and most important stage of the policy cycle is evaluation, which determines the continuity by suggesting policy interventions for improvements or termination of any policy based on monitoring and evaluation criteria. AI analytical tools can facilitate policy evaluation at specific stages and the end of the policy cycle process using real-time data simulations.

Technological power is most beneficial only when it is integrated with humans' shared values for humankind's common good. As AI systems develop more ability in strategy and decision-making, the prospect of AI demands responsible use to navigate the ethical implications to balance between technology and morality. AI can answer specialized and designed questions and discover options with built-in programmed rules, but it cannot imagine, feel, critically think, and inquire in war-like scenarios; its over-reliance overshadows human intelligence and adaptive capabilities. AI could intensify already established social, political, and economic disparities if access to AI technologies is asymmetrically distributed among the masses. A balanced approach to AI learning and human intelligence is vital to address complicated human security problems such as war, military sciences, surveillance, and security studies.

5. Discussion

The application of AI to develop public policy provides a strategic option to enhance the decision-making process. AI tools and ML models are evolving the public policy cycle, improving and innovating the public policy development process. A comparison between conventional and the exciting advent of AI with a data-driven approach to more informed steps shows a paradigm swing in e-policymaking, as seen in Table 3, and public policy analytics as policy informatics evolve traditional policy approaches.

AI can accelerate and enhance the accuracy of the public policy cycle based on real-time data input and analysis and track the public policy cycle over time for policy readjustments. The AI inclusion allows interventions and increments at each phase of the dynamic public policy cycle based on data-driven analytical tools, techniques, and intelligent algorithms. The techniques of data and text mining are generating significant evidence and information for innovative solutions with strategic decisions in uncertain policy scenarios and low public spending. AI-based public policy development improves public participation and makes an intelligent and automated public sphere. A study advocates explainable AI systems to achieve transparency mechanisms, legitimacy, and public acceptability of AI technological inclusion in high-quality and more informed social decision-making in public affairs. These systems offer justifications for decisions instead of an apparent system in processing AI techniques [18].

Table 3. Policy Development Discourse: A Move from Classical to Dynamic.

Policy Cycle	Passive Approach in Policymaking	AI-Based Dynamic Mode of Policymaking
Agenda Settings (Detection, Identification, Choice)	Political monopoly, complexity (social, political, economic)	Automation, simulation, big data, algorithms (NLP, text mining)
Formulation (Development and Design)	Objectives, vision, mission, goals, alternatives, options, using cost–benefit Analysis	Data analysis, simulation models, AI predictive tools
Adoption (Decision making)	Decision-makers are government officials	Decision-makers are AI systems
Implementation (Tools, Instruments)	Financial and human hindrances	AI sequential, cost-effective, inflexible
Evaluation (Interventions, Improvements)	End of policy (slow, delayed)	Reinforcement at each stage of the policy cycle (better execution, improves policy outcomes)

The increasing maturity and advancement of AI technologies such as machine and deep learning will soon open new and innovative prospects for policy development, design, and decision-making. The rapidly increasing AI practice in the decision-making of public affairs (policy and administration) has raised serious questions about the socio-techno transition and sparked concerns about transparent processes, legitimate justifications, and accountable systems to ensure fairness, equity, and reliability, fostering public perception and trust, and enhancing AI public value decision-making. Applying an explainable AI system can rectify the crucial challenges of ethics, transparency, fairness, quality, reliability, validation, accuracy, and unbiased data.

5.1. Opportunities

Government delivery services can improve their capacity mission by exercising modern, integrated, and efficient AI tools. Data analytic tools are helpful for policymakers to develop thought-provoking policies enriched with smart cost and resource accuracy and grasp social and environmental outcomes. Law enforcement departments can analyze crime data by using predictive tools of machine learning techniques to counter crimes. Policymakers in shaping public health policy can predict the outbreak of disease and suggest preventative measures after analyzing data, patterns, and trends.

AI and ML models can forecast climate change effects and scenarios and help in developing mitigating and adapting policy measures to combat climate threats. IMF has developed an AI-based resilient tool named the Climate Policy Assessment Tool (CPAT) to assist in executing policy measures like carbon credits and taxation. Similarly, the World Bank also utilized a machine learning algorithm named Causal Inference for Policy Making to connect causal links between diverse policy interventions and policy outcomes.

The inclusion of NLP in the agenda-setting phase of the policy cycle improves the accuracy in framing and shaping the policy problem, making the agenda-setting process more efficient and adaptive and increasing citizen trust in participation and expert collaboration. Similarly, the alternative formulation and design stage enhances the information and communication process based on available real-time data and makes the decision process more inclusive, responsive, accountable, and cost-effective. AI tools are resource-efficient in offering better services, crime control, fraud detection, and disease diagnostics in cost-effective implementation of policy decisions. AI tools are providing remarkable improvements in monitoring and analyzing real-time data, increasing the overall effectiveness of the public policy development process with innovative and simulative analytical models.

5.2. Challenges

Legal (regulations, legitimacy, accountability, and responsibility), ethical (model biases, fairness, data privacy, and transparency) and technical (data quality, data management, mathematical modelling and computational skills) challenges are the prime challenges that AI and ML may have in policy and technology infusion science along with digital divide, AI obedience, dominance, and dependence. The accessibility and availability of quality data, handling and managing capacity of data, and computational power of data are the serious risks that public policymakers and policy analysts may have to face during AI and ML models employed in policy cycles from agenda-setting to evaluation. Social, economic, political, organizational resistance, data privacy, technological capacity, and ethical challenges are associated with AI decision-making in government organizations [19].

Public policies based on algorithms face unaddressed challenges related to legal coverage, moral standings, ethical principles, legitimate footings, transparency concerns, accountability problems, public trust in automation decisions, and expert collaborations. A communication gap exists among experts in policy, machine learning, and subject matter. Who is held responsible and accountable for both ethical and legal aspects in case of incorrect ML predictions? How can ML predictions gain the trust of citizens in shaping public policies in case of wrong predictions? The algorithm and model designers, computer programmers, data provider authorities, and policy analysts need more clear communication and collaboration.

The integration of big and open data with AI and ML has led to the development of big data algorithms, which need data governance to guarantee algorithmic reliability and fairness and counter the risks of data and algorithmic biases that may lead to unplanned outcomes. A study argued for rigorous data governance to ensure a trusted data-driven AI algorithm and proposed a framework built on 13 design rules comprising data and algorithmic stewardship [20].

AI inclusion in policymaking demands a skilled workforce, infrastructure costs to establish data centers, and developed computation technologies to set up AI-based policymaking systems. The testing of model accuracy is a technical as well as human challenge for public policy experts who require expert knowledge of machine learning models. The policy-technology infusion demands a regulatory, legal, and ethical strategy for security, privacy, and ethics, more critical than the use of machine learning algorithms for optimization purposes. AI also has perils and risks of biased algorithmic results that fortify unfair practices due to prevailing social biases and the digital divide, which are merely reflected in AI-generated intelligence decisions and outcomes during the development of an algorithm fed by built-in raw data.

Algorithms are a set of mathematical rules that start and end with human interaction for performing a logical and specific set of operations with reliable outcomes. Machine learning, a narrow version of AI, is a kind of algorithm with a set of techniques and the ability of computer systems to learn without openly being automated. The sensitivity of the context matter demands the vigilance of policy, data, legal, and ethical experts to carefully examine and monitor all categories of biases, risks, ethics, privacy, and rights under ethical, legal, institutional, and regulatory frameworks during the construction of an algorithm. It should check the reliability and validity by piloting tests of the newly designed model before its final deployment and fully operationalizing.

Certain conditions and systems are unpredictable in real-world cases, where ML models cannot predict entirely or accurately, such as who will win the Russia–Ukraine war. This uncertain scenario is beyond the predictive capacity of any AI and ML model. Machine and intelligent systems cannot make perfect predictions of random and complex behavior because of the diversity and dynamic conditions of technological, social, and environmental factors. When policymakers and analysts meddle with the data and alter variables continuously, the risk of inaccurate prediction rises, as forecasting a weather pattern is easier than predicting the behavior of the dynamic system.

Policymakers should adopt the value-based principle that stands on the parameters of transparency, accountability, equity, fairness, and inclusivity in the application of data-driven AI policies that can have a significant impact on the public and avoid the ethical misuse of AI tools. The panel of experts should maintain a balance between technological innovation and regulatory framework by "responsible use of AI" in terms of accountability, transparency, fairness, and equity.

5.3. Ethical

The resonant integration of policy and technology ensures the reliable use of AI to streamline the policymaking process. However, the ethical implications, transparency risks, data privacy, algorithmic biases, and fairness are the prime concerns, and the sensitivity of policy context requires legal covering and regulations. This will ease AI use in the development of policymaking for large benefits such as quality of life, improvement in social impact, and economic efficiency. The conditions of critical insights, future predictions, and proposals are based on feed data and training of AI models. Thus, the risks of data security, model performance, anomalies, inaccuracies, and AI ethics demand serious legal frameworks and ethical regulations to evaluate AI tools before business for responsible use, instead of designing data and operating algorithms on machine learning. The bias comes into the machine through self-learning algorithms, the choice of incorrect prediction objectives, and biased data. These can be overcome and checked by measuring the performance metrics (accuracy, precision, recall, FI-score, scalability, and robustness) of the chosen predictive AI or ML model.

Besides the ethical concerns, AI also contributes to issues such as unemployment, economic inequality, fake news, computational propaganda, disinformation, hate speech, cyber harassment, social media bots, and the digital divide. These are key challenges that demand careful and thoughtful policy interventions.

Table 4 provides guidance for policymakers and can be applied to different stages of the policy cycle. Human, social, and environmental impacts are significant in the agenda and identification stage as the stakeholders' interests, roles, and influences are directly connected with nature, roots, causes, shaping, and framing the policy problem. A hybrid mode of policymaking, i.e., humans' input in a loop at every stage of the policy cycle along with data sets in the AI model, can boost the quality of a policy, evolve the policy process, and improve social value, ensuring fairness and equity in the implementation process.

Table 4. Framework Parameters for Ethical, Legal, Institutional, and Regulatory Frameworks.

Parameters
Companies (public and private) must be held responsible for informing the public about the aim, target, and need of AI systems, ensuring transparency and being accountable for biased outcomes under an institutional framework.
The design and deployment of the AI systems should focus on fairness and equity in results, eliminate biases, and promote values focusing on the ethical framework.
Resilient, robust, and reliable AI systems reduce the risk of privacy breaches and comply with data governance and cyber laws by adhering to the legal framework.
AI systems should be designed to permit, promote, and preserve progressive sovereignty and sustainability for the well-being of individuals, society, and the environment, ensuring regulatory compliance.

6. Limitations

Recognizing limitations is important to ensure the accuracy and future direction of the study. The key limitation is the choice of AI tool and ML model and its validity with the quality of available dataset at each stage of policy cycle for different policies. The rapid changes and technological evolution in AI and ML models pose the limitation, with quick replacement of outdated models discussed in the literature. The integration of AI and

ML models with traditional approaches of policymaking cycle is also a limitation of this study. Ethical considerations such as model bias, data transparency, and result fairness are prominent concerns in academia regarding the potential of AI and ML in public policy. A greater focus on technology-based policy development may overshadow the broader policy process, and the absence of human input can lead to new challenges in the practical use of AI and ML tools within the policy cycle.

7. Conclusions

In this study, we analyzed AI inclusion in the development of the public policy cycle from the agenda-setting to the evaluation stage. This research aims to assess the opportunities and challenges along with the ethical implications of AI on public policy development. The literature explored in this study shows that AI tools such as machine learning, big data analytics, robotics, and intelligent systems are applied to diverse policy scenarios from the health sector to the police, and from the banking sector to the environment. There is an increase in the flux of AI and data-driven governance and administration for smooth deliveries of citizen services. and the development of public policy is another aspect.

This study proposes a research agenda to apply the ML model(s) on the entire policy cycle along with the measurement of the performance (accuracy and precision) of different models fit for specific policy data. This study promotes the adoption of innovative AI and ML models in the policy development process, addressing socio-economic challenges and enhancing policy capacity in the policymaking landscape. AI inclusion in the form of data in the agenda-setting stage has the potential to transform the extracted data into knowledge for policy formulation and decision adoption. Public policy development will be revamped and measured equally by a panel of experts including policy, data, legal, political, ethical, technological, and computer programmers to shape the policy measures, actions, and programs based on principles and purpose. Soon, data-driven public policy development, planning, and execution systems will be adaptative to real-time policy versions and discretions by equipping policy implementation actors with experimental techniques of data handling and algorithmic use that will make them more effective and strengthen the problem-solving role of policy. AI inclusion in the development of the public policy cycle is an evolving step towards e-policymaking that can provide innovation, prediction, efficiency, and citizen-inclusive features in the process of decision-making. AI technologies in public policy development that transform the public policy process have the potential to bridge the information and communication gaps between policymakers, analysts, experts, and stakeholders from problem identification to evaluation.

This research distinguishes between policy on AI and policy with AI with different roots and solutions. This study provides a general overview of AI application in the development of e-policymaking; in the future, this research will be extended to a particular case study of a policy with the application of different AI tools and ML techniques from the agenda-setting to policy evaluation. The extended study will also cover the potential outcomes of different AI and ML models based on their accuracy, precision, scalability, recall, robustness and F1 score. Ethical challenges such as transparency, fairness, and biases of AI inclusion in the development of public policy for enhancing decision-making represent an area that requires more research.

Author Contributions: Conceptualization, M.A.Y., M.H., M.A., N.L.F. and M.S.; methodology, M.A.Y., M.H., M.A., N.L.F. and M.S.; formal analysis, M.A.Y., M.H. and M.A.; investigation, N.L.F. and M.S.; writing—original draft preparation, M.A.Y., M.H. and M.A.; writing—review and editing, N.L.F. and M.S.; supervision, M.H. and M.A.; funding acquisition, M.A. and M.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in the study are included in the article; further inquiries can be directed to the first/corresponding author/s.

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

References

1. Newman, J.; Mintrom, M. Mapping the discourse on evidence-based policy, artificial intelligence, and the ethical practice of policy analysis. *J. Eur. Public Policy* **2023**, *30*, 1839–1859. [CrossRef]
2. Solo, A.M. The new fields of public policy engineering, political engineering, computational public policy, and computational politics. In Proceedings of the International Conference on e-Learning, e-Business, Enterprise Information Systems, and e-Government (EEE), Las Vegas, NV, USA, 18–21 July 2011.
3. Cowls, J.; Tsamados, A.; Taddeo, M.; Floridi, L. The AI gambit: Leveraging artificial intelligence to combat climate change—Opportunities, challenges, and recommendations. *AI Soc.* **2023**, *38*, 283–307. [CrossRef] [PubMed]
4. Kolkman, D. The usefulness of algorithmic models in policy making. *Gov. Inf. Q.* **2020**, *37*, 101488. [CrossRef]
5. Jin, Z.; Mihalcea, R. *Natural language processing for policymaking, in Handbook of Computational Social Science for Policy*; Springer International Publishing: Cham, Switzerland, 2022; pp. 141–162.
6. Torjman, S. *Community Roles in Policy*; Caledon Institute of Social Policy: Ottawa, ON, Canada, 2009.
7. Howlett, M. The criteria for effective policy design: Character and context in policy instrument choice. *J. Asian Public Policy* **2018**, *11*, 245–266. [CrossRef]
8. May, P.J. Policy design and implementation. In *The Sage Handbook of Public Administration*; SAGE: Newcastle upon Tyne, UK, 2012; pp. 279–291.
9. Nam, T. Do the right thing right! Understanding the hopes and hypes of data-based policy. *Gov. Inf. Q.* **2020**, *37*, 101491. [CrossRef]
10. Azzone, G. Big data and public policies: Opportunities and challenges. *Stat. Probab. Lett.* **2018**, *136*, 116–120. [CrossRef]
11. Christensen, J. Expert knowledge and policymaking: A multi-disciplinary research agenda. *Policy Politics* **2021**, *49*, 455–471. [CrossRef]
12. Ibrahim, O.; Larsson, A. A systems tool for structuring public policy problems and design of policy options. *Int. J. Electron. Gov.* **2017**, *9*, 4–26. [CrossRef]
13. Valle-Cruz, D.; Criado, J.I.; Sandoval-Almazán, R.; Ruvalcaba-Gomez, E.A. Assessing the public policy-cycle framework in the age of artificial intelligence: From agenda-setting to policy evaluation. *Gov. Inf. Q.* **2020**, *37*, 101509. [CrossRef]
14. Steuer, F. Machine Learning for Public Policy Making: How to Use Data-Driven Predictive Modeling for the Social Good. 2018. Available online: https://www.ibei.org/ibei_studentpaper46_162056.pdf (accessed on 5 February 2020).
15. Thapa, B.E. Predictive Analytics and AI in Governance: Data-Driven Government in a Free Society. 2019. Available online: https://liberalforum.eu/wp-content/uploads/2021/07/PUBLICATION_AI-in-e-governance.pdf (accessed on 22 November 2019).
16. Dogaru, T.-C. Change and public policy: A mutual dependency relationship. *J. Public Adm. Financ. Law* **2018**, *14*, 168–177.
17. Ehrentraut, C.; Ibrahim, O.; Dalianis, H. Text Analysis to support structuring and modelling a public policy problem: Outline of an algorithm to extract inferences from textual data. In *DSV Writers Hut 2014, Åkersberga, Sweden, 21–22 August 2014*; Department of Computer and Systems Sciences, Stockholm University: Stockholm, Sweden, 2014.
18. de Fine Licht, K.; de Fine Licht, J. Artificial intelligence, transparency, and public decision-making: Why explanations are key when trying to produce perceived legitimacy. *AI Soc.* **2020**, *35*, 917–926. [CrossRef]
19. Dwivedi, Y.K.; Hughes, L.; Ismagilova, E.; Aarts, G.; Coombs, C.; Crick, T.; Duan, Y.; Dwivedi, R.; Edwards, J.; Eirug, A.; et al. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int. J. Inf. Manag.* **2021**, *57*, 101994. [CrossRef]
20. Janssen, M.; Brous, P.; Estevez, E.; Barbosa, L.S.; Janowski, T. Data governance: Organizing data for trustworthy Artificial Intelligence. *Gov. Inf. Q.* **2020**, *37*, 101493. [CrossRef]