

LLMs for AI policies evaluation: discussing data sharing at *supra* national level

Abstract

Large Language Models (LLMs) possess remarkable capabilities in both analysing vast amount of data and generating coherent human-readable output. This makes LLMs invaluable tools for various applications, and in different sectors, including policymaking.

One notable application is in sentiment analysis, where LLMs can assess the effectiveness of policies from different perspectives. By analyzing sentiment, these models can identify which policies are effective and which are not, helping policymakers make informed decisions. Additionally, LLMs can evaluate the efficacy of policies by considering trade-offs and costs, providing a comprehensive understanding of their impact.

Such an analysis of different jurisdictional experiences on specifically AI policies has great potential, given the fact that different countries are adopting different approaches. However, challenges exist. Among others, data sharing among countries is limited, hindering comprehensive analysis. To address this, an international platform such as the United Nations could facilitate data sharing and analysis.

This paper addresses the relevance of *supra* national data sharing in relation to the deployment of LLMs for AI policies evaluation.

29 1 Introduction

The potential of LLMs in policymaking has attracted a lot of attention from stakeholders, including scholars. This potential can be harnessed to propel notable progress in environmental policy development, for example, as suggested by (Gao 2023), encompassing tasks like analysing policies, mining public opinion data, synthesising and extracting data, communicating findings, conducting literature reviews, drafting policy documents, monitoring legal compliance, and adapting policies to local contexts. Moreover, (Cao, Zhuang, and He 2024) discussed how conventional methods of managing extensive and intricate climate data typically present hurdles, requiring specialized expertise, but with LLMs, it is possible to address this

43 obstacle by allowing individuals without technical expertise 44 to readily access and comprehend climate datasets and 45 simulations. By facilitating natural language interaction, 46 stakeholders can effectively engage with the data and explore 47 different policy scenarios.

48 Nonetheless, there are risks linked to employing LLMs, 49 such as generating inaccurate or outdated information, 50 potential political bias, and the inability to access confidential 51 or restricted data during training (Gao 2023). Moreover, 52 (Ziegler et al. 2024) underline the risks of using LLMs in 53 marine policymaking, as they may exhibit biases favoring 54 Western economic perspectives over those of developing 55 nations. These biases can stem from foundational language 56 models, connections to UN documents, and application 57 design, and the authors call for more research on equity 58 implications.

59 At the same time, the topic of AI governance is also on the 60 spotlight, given the different approaches that countries are 61 adopting (Perry and Uuk 2019).

62 This paper focuses specifically on the employment of LLM 63 for the analysis of AI policies. First, it provides a granular 64 overview of the potential use of LLMs for AI policies 65 evaluation, identifying potential challenges and 66 opportunities. Then, it addresses data sharing, identifying 67 what data might be needed and how it could be analysed at 68 *supra* national level.

69 2 The case for employing LLMs in AI policies 70 evaluation

71 Various nations worldwide have adopted diverse 72 approaches to regulating AI. For instance, the European 73 Union (EU) is in the process of formulating draft legislation, 74 while the United Kingdom (UK) has adopted a more pro- 75 innovation and liberal stance. Given that AI is a rapidly 76 evolving technology, it remains uncertain which approach 77 yields greater benefits and what types of benefits are 78 generated, whether economic or social. To assess the impact 79 of different national and regional AI policies, leveraging 80 LLMs could prove beneficial.

81 LLMs can analyse the effects of various AI policies by 82 cross-examining different data sources. Additionally, 83 considering complementary policies such as employment 84 law, liability regulations, and intellectual property

85 frameworks is crucial to contextualise the implications of AI 40
86 approaches comprehensively. LLMs' ability to synthesised 41
87 diverse datasets makes them well-suited for this multifaceted 42
88 analysis. 143
89 However, realising this idea presents challenges and 44
90 opportunities. Challenges include ensuring a high degree of 45
91 structured data sharing among different jurisdictions 46
92 (Tedersoo et al. 2021), overcoming potential data privacy 47
93 concerns (Janssen et al. 2020), and maintaining the neutrality 48
94 and accuracy of LLM-generated analyses. Furthermore, 49
95 interpreting and integrating the vast amount of data generated 50
96 by LLMs require sophisticated analytical tools and
97 methodologies.

98 Despite these challenges, the opportunities are significant 152
99 A comprehensive analysis facilitated by LLMs could provide 153
100 insights into the real-world impacts of AI policies across 154
101 sectors and their influence on AI development, business 155
102 operations, and public services (Verma 2022). By identifying 156
103 best practices and lessons learned, policymakers can refine 157
104 and optimise AI policies to maximise benefits while 158
105 minimising risks and disparities. 159
106 Achieving this requires concerted efforts to address 160
107 technical, legal, and ethical considerations surrounding data 161
108 sharing and LLM usage. The next sessions will discuss data 162
109 sharing and human oversight.

110 3 Discussing data sharing: what data? To 111 whom?

112 A comprehensive analysis of the impact of AI policies using 168
113 LLMs would require a diverse array of data sources. 169
114

115 First, the regulatory Frameworks. Detailed information on 170
116 existing regulations and policies governing AI usage 171
117 including their scope, objectives, enforcement mechanisms, 172
118 and any amendments or updates over time. This data would 173
119 help assess the legal landscape and identify areas of 174
120 regulatory divergence or convergence. 175

121 Additionally, sector-specific regulations: specific 176
122 regulations and guidelines tailored to different industries or 177
123 sectors, such as healthcare, finance, transportation, and 178
124 education. Understanding sector-specific regulations is 179
125 essential for evaluating the sectoral impact of AI policies and 180
126 identifying sector-specific challenges or opportunities. 181

127 Policy implementation data, including compliance rates, 182
128 enforcement actions, and reported incidents, offers insights 183
129 into the effectiveness of AI regulations. Economic indicators 184
130 such as GDP growth and employment rates, help gauge the 185
131 economic impact of AI policies. Social impact data 186
132 encompassing societal attitudes and equity implications, is 187
133 crucial for addressing societal concerns. Lastly, technology 188
134 development data, such as research activities and patent 189
135 filings, is essential for assessing AI policies' effectiveness in 190
136 fostering innovation.

137 All the data should be structured to allow the comparative
138 type of analysis to be performed by the LLMs. International
139 comparisons would provide insights into global trends, best

practices, and potential policy benchmarks for guiding new
policy development.

42 In summary, a comprehensive analysis of AI policies using
143 LLMs would require a wide range of data sources, including
44 regulatory frameworks, sector-specific regulations, policy
45 implementation data, economic indicators, social impact
46 data, technology development data, and international
47 comparisons. Access to diverse and high-quality data is
48 essential for generating meaningful insights and informing
49 evidence-based policymaking in the rapidly evolving field of
50 AI governance.

151 3.1 The need for an international platform and the 152 potential role of the UN

153 From a data protection standpoint, challenges arise due to the
154 sensitive nature of the data required for analysing AI policies.
155 This includes personal data collected for compliance
156 monitoring, incident reporting, and impact assessments,
157 raising concerns about privacy, consent, and data
158 security (Topham, Boscolo, and Mulquin 2023). Ensuring
159 compliance with stringent data protection regulations, such
160 as the GDPR in the European Union, while accessing and
161 sharing such data across borders presents significant
162 hurdles (Finck and Pallas 2020).

163 Geopolitically, challenges emerge from divergent national
164 interests, regulatory frameworks, and geopolitical tensions
165 that may hinder international cooperation and data sharing
166 efforts (O'Hara and Hall 2021). Countries may be reluctant
167 to share sensitive information, fearing loss of sovereignty or
168 competitive disadvantage, particularly in strategic sectors
169 like AI and technology (Khan et al. 2022). Moreover,
170 geopolitical rivalries and power dynamics may complicate
171 efforts to establish common standards and norms for AI
172 governance on a global scale.

174 In light of these challenges, the United Nations (UN) can
175 play a pivotal role as an international platform to facilitate
176 dialogue and cooperation on AI governance. The UN's *supra*
177 national and inclusive nature makes it well-suited to foster
178 multilateral collaboration among nations with varying
179 interests and regulatory approaches. By providing a forum for
180 discussion, information exchange, and capacity-building, the
181 UN can promote transparency, trust, and consensus-building
182 in AI policymaking. Additionally, the UN can serve as a
183 forum for the development of common frameworks,
184 standards, and best practices for data sharing, privacy
185 protection, and ethical AI deployment, helping to address
186 concerns related to data protection and geopolitical tensions.
187 The UN has already demonstrated its commitment to
188 advancing global dialogue on AI governance, making it a
189 promising platform for addressing the complex challenges at
190 the intersection of AI, data protection, and geopolitics
191 ('General Assembly Adopts Landmark Resolution on
192 Artificial Intelligence | UN News' 2024). □

193 Ethical Statement

194 There are no ethical issues.

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