AI drifting and converting emergency policies: an institutional theory perspective.

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Submitted: 31 January 2025, Revised: 26 March 2025, Accepted: 21 April 2025, Published: 19 May 2025

Abstract. The impact of Artificial Intelligence (AI) on emergency policies has been widely examined in digital government literature, focusing primarily on AI's role in policy design and delivery and on its effects on policy outcomes. However, limited attention has been given to how AI directly impacts emergency policies' change, that is, in which ways AI reshapes and steers the policies it mediates. Drawing on Hacker et al. (2015) framework of institutional change, particularly the concepts of drift and conversion, this research provides a novel lens to understand policy change in emergency contexts. Drift occurs when policies remain formally unchanged but fail to adapt to evolving contexts, altering their effects. Conversion refers to the redirection of policies towards new purposes without modifying their formal structure. By applying this framework, the paper investigates AI's dual role in changing emergency policies, both as a source of resistance to formal policy change and a catalyst for policy redirection. The research adopts an explanatory case study of Peru's welfare policies during the COVID-19 pandemic, focusing on the use of the SISFOH AI system to allocate emergency subsidies. Findings demonstrate how AI changes the policies it mediates by drifting formal policy modification and enabling conversion by reshaping policy ends. This paper contributes to the digital government literature by highlighting AI's ambivalent role in emergency policy change and offering fresh insights into the intersection of AI and emergency policies.

Keywords. Artificial Intelligence, emergency policies, policy change, COVID-19 pandemic, drift, conversion.
Research paper, DOI: https://doi.org/10.59490/dgo.2025.949

1. Introduction

Artificial Intelligence (AI) is increasingly recognized as a pivotal tool in shaping public policies, particularly in emergency contexts where time-sensitive, data-driven decisions are crucial (Scholl, 2023). The integration of AI into public administration has transformed how governments respond to emergencies, enabling more efficient resource allocation, enhanced impact assessments, and targeted interventions (Nasseef et al., 2022). In the domain of emergency policies, AI's role has been predominantly examined through its contributions to policy design and delivery, as well as its influence on policy outcomes (Agarwal et al., 2024; Yu et al., 2024). However, a critical dimension remains underexplored: how AI actively reshapes and steers the evolution of the policies it mediates. Very limited knowledge is offered on what happens between the ex-ante policy design and the post-facto assessment of the outcomes: indeed, policies are not fixed, they evolve and mutate over time (Pierson, 2006). Understanding the impact of AI on policy change is crucial because often emergency policies relying on AI evolve, which requires additional policymaking efforts to ensure expected goals are achieved without distortions (Milan et al., 2021). This paper addresses this gap by investigating how AI impacts emergency policy change, advancing our understanding of the intricate ways in which AI drives different forms of policy evolution.

To unravel how AI impacts emergency policy change, the paper adopts an institutional theory perspective, and it builds on the theoretical framework of institutional hidden change as outlined by Hacker et al. (2015). This framework introduces the concepts of "drift" and "conversion" to explain hidden forms of policy change. This research applies the drift and conversion framework to the context of AI-driven emergency policies, positing that AI can act as both a source of resistance to formal policy change (drift) and as a catalyst for policy redirection (conversion).

To shed light on this phenomenon, this paper addresses the following Research Question: *How does AI act as a source of drift and conversion affecting emergency policy change?*

To empirically explore these dynamics, the paper examines the case of the Peruvian government's AI-based Households Targeting System (*Sistema de Focalización de Hogares*, herein SISFOH), which played a central role in allocating emergency subsidies during the COVID-19 pandemic. Qualitative data from interviews with key policymakers provide evidence to illustrate how AI can simultaneously constrain and enable policy evolution, reflecting the dual processes of drift and conversion.

Building on the findings of the case study, the paper provides two main contributions. First, it extends the theoretical application of institutional change frameworks to the study of AI in governments' emergency policies, offering a nuanced perspective on how AI interacts with those policies. Second, it theorizes the ambivalent nature of AI's impact on policy change, illustrating its capacity to both resist and facilitate change. In doing so, this paper bridges a critical gap in the literature, addressing the underexplored intersection of AI and policy change in emergency contexts. It underscores the importance of understanding AI not merely as a tool for policy implementation but as an active agent that influences the trajectory of policy development.

2. Background

Literature has addressed the impact of Artificial Intelligence (AI) on governments' emergency policies in the context of the COVID-19 pandemic looking at two main issues: the use of AI to design and deliver emergency policies (Hagen et al., 2021; Nasseef et al., 2022; Rodriguez-Hidalgo, 2020), and the effects of AI on the outcomes of the emergency policies (Agarwal et al., 2024; Mhlanga, 2022; Qureshi, 2021). The first stream of research has investigated how AI can be utilized in the public sector to support an enhanced emergency policy provision (Yu et al., 2024). Specifically, there is now increasing evidence about the impact of AI in assisting policymakers by maximising the data available and offering improved impact assessments and forecasts (Agostino et al., 2021; Anshari et al., 2023). The adoption of AI instruments in the early stages of the decision-making process, including policy formulation and design, has enabled the public sector to reach a more informed and data-driven awareness (Moser-Plautz & Schmidthuber, 2023) that could limit the mismatches between the purpose of the policies and the means available in the policymakers' hands, which is crucial in emergency circumstances (Kummitha, 2020).

The second stream of research has mainly focused on the effects of AI on the outcomes of the policies (Agarwal et al., 2024). Contributions to this research effort have shown a more mixed picture. AI adoption in the public sector has often triggered unexpected outcomes. For example, AI tools to streamline service delivery have created misallocations that have unevenly impacted the population which is deeply problematic in countries already affected by social inequalities (Cerna Aragon, 2021). Moreover, AI adoption has been challenged by social groups due to discrimination and distortions (Milan et al., 2021; Naudé & Vinuesa, 2021). To complicate even more the picture, increased attention on the ethical issues related to AI-driven public policies has requested scholars and policymakers to closely scrutinize the effects of AI on the policies it informed (Qureshi, 2021).

The relevance of these two streams of research is undeniable and it is likely to be enhanced as the adoption of AI instruments to address emergencies is increasing at a fast pace (Urueña, 2023). However, in the complex entanglement between AI and emergency policies, the study of how AI impacts policy change has not received adequate attention. The literature has widely addressed how AI can be utilized before the policy is designed (Agarwal et al., 2024; Agostino et al., 2021) and what are the effects of AI after the policy has been implemented (Naudé & Vinuesa, 2021), however, there is a scarcity of works that examine the impact of AI on the change of the policy. Regrettably, literature has overlooked policy change for a long time, focusing more on other aspects such as the design, implementation, and evaluation of policies (Kuziemski & Misuraca, 2020; Lundgren et al., 2020; Moser-Plautz & Schmidthuber, 2023). However, this approach has shown limits because the space between the design and the implementation offers many opportunities for AI to deploy its effects and shape the evolution of the policy. Indeed, scholars reflecting on emergency policy design have called for a more dynamic perspective on the impact of AI on the whole phases of policymaking (Meijer & Webster, 2020). Although valuable, this stream of research mostly focuses on the process as a unit of analysis. Despite its relevance, scarce and limited knowledge exists on the study of how emergency policy evolves and modifies when AI is used to inform it.

To address this gap, the paper aims to explore policy change through a more nuanced understanding of the impact of AI on policies. By unpacking the different ways in which AI affects policy change, the paper accounts for the effects of AI that reshapes and steers the evolution of the policies it mediates. This research aims to connect with the longstanding research stream that has discussed how digital technologies – including AI – entangle emergency policies (Scholl, 2023). Beyond that, the paper aims to add to the limited works on the impact of AI on emergency policy change, adding fresh knowledge and theorization to a crucial phenomenon.

3. Theoretical Framework

To shed light on how AI impacts emergency policy change, the paper relies on the theoretical framework used by Hacker et al. (2015) to explain institutional change. In this section, justifications are provided to explain (a) what the framework is about; (b) why this framework has been selected to investigate the phenomenon; and (c) how to operationalize the key dimensions of the framework in the analysis.

The work by Hacker et al. (2015) is rooted in the discipline of public policies and aims to investigate how policies evolve and change without formal revision (Hacker et al., 2015). Challenging the predominant stream of research of institutional theory that focuses on major changes in a long-term timeframe (March & Olsen, 1983; Powell & DiMaggio, 2012), public policies scholars have advanced the idea of "hidden forms of institutional change" (Hacker et al., 2015, p. 181). Hidden change refers to the modification of the policies that happens without a formal revision of the rules. Hidden change happens through two forms: drift and conversion (Hacker et al., 2015).

The concept of drift is explained as the failure of policymakers to update policies to reflect mutated social circumstances (Hacker et al., 2015). In other words, the change of the policy is resisted despite significant pressures to adapt the policy to a new context. It is worth noting that the concept of drift here is presented slightly differently from the one portrayed in other disciplines that have studied change related to technology, e.g. Information Systems, where drift is referred to as the deviation from planned purposes due to reasons beyond the control of actors (Ciborra & Hanseth, 2000). While the origin is similar – drift occurs when there is a modification of the surrounding context that triggers change – the emphasis on drift as presented by Hacker and colleagues lies on the attempts to maintain the status quo ante by not adapting policies despite the context transformations, which results in altered effects of the policies.

Conversion is a form of change occurring when a policy is redirected towards new ends (Hacker et al., 2015). In a similar fashion to drift, conversion happens without modifying formal aspects of the policy. However, the key difference is that while drift explains how a change in the policy is resisted despite context modifications, conversion accounts for how policy change is enabled by redirecting the policy to different purposes than those originally engineered. In other words, conversion occurs when policies designed and deployed to achieve specific sets of goals are harnessed by actors to execute different tasks within the same formal (legal-institutional) framework (Hacker et al., 2015). Similarities and differences between drift and conversion are presented in Table 1 below.

Tab. 1 – Key characteristics of drift and conversion. Source: authors' elaboration building on Hacker et al. (2015)

	Source of change	Substantial impact on policy	Formal impact on policy	Driving force
Drift	Context discontinuity	Policy's effects altered because of modified circumstances	Left unchanged	Resistance
Conversion	Actors' initiative	Policy's purposes shifted towards different ends	Left unchanged	Redirection

The above-presented framework has been selected for several reasons. First, it enables an investigation of the impact of AI on emergency policy change using a lens that focuses on the policy as the unity of analysis. In this light, the representation of policies as formal institutions (Pierson, 2006) is crucial because it accounts for how policies "set rules for social interactions that are enforced through the exercise of public authority" (Hacker et al., 2015, p. 183). The paper aligns with this conceptualization that enables a more specific investigation at the policy level. Second, it offers a new angle on an emerging phenomenon. The institutionalist perspective has widely been used to investigate the effects of technology on organizational change (Avgerou, 2004; Fountain, 2001; Luna-Reyes & Gil-Garcia, 2011). However, very limited works have utilized institutionalism to understand the impact of AI (Caplan & boyd, 2018; Rudko et al., 2024) and, specifically, the impact of AI on policy change. Third, the theorization advanced by Hacker et al. (2015) provides adequate granularity to unpack how AI influences emergency policy change. The identification of drift and conversion as key forms of change offers analytical tools to shed light on how the policy change happens.

The framework by Hacker et al. (2015) is a powerful analytical tool to appreciate the impact of AI on policy change. Indeed, the original framework is outlined by the authors to study public policies, that is, to understand which political actors drive drift and conversion in policy change. Utilizing the framework in the field of digital government requires a retuning of the focus, which includes not only the activity of political actors but also the role of digital technology, and in this case AI, as a factor that impacts policy change. Specifically, this research posits that AI triggers both drift and conversion, acting as an ambivalent catalyst for policy change. To validate this assumption, the paper outlines two propositions that are going to be tested in the following sections.

Proposition 1: AI is a source of drift because it reinforces resistance to policy change despite evolving contextual circumstances.

Proposition 2: AI is a source of conversion because it shapes the redirection of the policy to achieve distinct outcomes.

4. Methodology

4.1 Research settings

To shed light on the way by which AI impacts policy change, the research adopts an explanatory case study method which is suitable to illustrate how "conditions came to be" (Yin, 2018, p. 238) in specific settings over which the researchers have no control or influence. Explanatory research requires precise methodological choices. First, a review of the relevant literature that enables a thorough definition of the research question (Yin, 2018). Second, the outline of a theoretical foundation that drives the formulation of initial propositions in advance of the data collection (Yin, 2018). To study the impact of AI on policy change, we focus on the provision of emergency welfare measures by the Peruvian public administration, following the occurrence of the COVID-19 pandemic. This case is particularly suitable for the research because the government decided to rely on the SISFOH AI system that was driving the provision of welfare policies in ordinary time to deliver pandemic-related policies. The study of the impact of AI on Peruvian policies provides critical findings to understand how AI generates drift and conversion that underpin policy change.

4.2 Case study

The Peruvian government's welfare provision builds on a "targeting logic", that is, identifying the citizens in need to correctly provide services, avoiding unnecessary expenditures, and streamlining the delivery of measures such as pensions, subsidies, and loans (Silva Huerta & Stampini, 2018). Specifically, SISFOH's main task was to release a Socio-Economic Classification (SEC) of citizens, clustering users as "not poor", "poor", or "very poor", based on their level of poverty. The AI algorithm relied on a combination of criteria, variables and filters: for instance, possessing a vehicle and/or private health insurance, pre-determined levels of salary, and electricity consumption are the critical factors used to determine citizens' levels of poverty (Cerna Aragon, 2021).

In response to the COVID-19 pandemic, the Peruvian government took immediate action to sustain the citizens in need after the imposition of extraordinary decisions like lockdowns and restrictions on movement and business. Therefore, the government designed and released an emergency welfare policy named "Bono YoMeQuedoEnCasa" (I'm Staying at Home), a one-off subsidy of 380 soles (approximately USD 110) per household to support citizens who had lost their job or saw their activity disrupted due to the lockdown. Eligibility for the subsidy was determined prioritizing households (a) classified as "poor" or "very poor", (b) residing in urban areas, (c) that included other adults and not only minors, and (d) where nobody had a job in the public sector. To correctly target those eligible for the emergency subsidy, the government relied on the SISFOH AI, which was used to elaborate a database of the households.

However, implementation challenges arose: the resulting databases provided by SISFOH AI reflected errors in inclusion and exclusion: with citizens not entitled who nevertheless received the subsidy, and citizens in need who were excluded. In aggregate, misallocations concerned nearly 10% of the policy recipients (Contraloria General de la Republica del Perù, 2020). Acknowledging these shortcomings, the government introduced additional subsidies to expand coverage (e.g., self-employed workers, rural households, families). Peruvian policymakers relentlessly transitioned from the targeting approach utilized in the initial phase to the universal approach of the later stage, addressing gaps in the initial program.

4.3 Data collection and analysis

After an initial phase in which the researchers consulted secondary sources to get a background understanding of the issues at stake, the main data collection focused on interviews with high-level policymakers who played a critical role in the design and delivery of emergency policies. As the focus of this research is to understand how the policy changes, we privileged quality over quantity in the number of interviews: therefore, we limited our sample to pivotal policymakers who took the key decisions in the emergency policymaking process (Hansen et al., 2025). In aggregate, we reached out to six key policymakers: three former ministers of the Minister for Development and Social Inclusion (herein MIDIS) who took key decisions in the design and application of the SISFOH system; one former MIDIS deputy minister, and two senior civil servants who designed and delivered the emergency policy. Each interview lasted between 50 to 80 minutes. Interviews were effectuated in late 2022. Four interviews out of six were conducted in English, and two in Spanish (the latter were transcribed and translated to English before beginning the data analysis).

The collected data from the interviews were subsequentially coded using NVivo software. A combination of inductive and deductive approaches was chosen (Charmaz, 2014). Data were coded data relying on the key concepts of drift and conversion from the theoretical framework to assess whether alignment could be identified. Simultaneously, the coding process remained open to recognizing new codes emerging directly from the data. Researchers eventually discussed the codes and reviewed the outcomes, clearing discrepancies.

5. Findings

The findings from the case study mainly show three elements: (a) the relevance of the AI-based policy in defining the status quo ante; (b) how the AI impacted the drift of the policy; and (c) how the AI impacted the conversion of the policy. In this section, we are going to analyse each of these elements in detail with support of primary data.

5.1 Relevance of the AI policy in the Peruvian welfare

When asked about the provision of welfare in Peru, the policymakers interviewed remarked that, before the outbreak of the pandemic, the SISFOH AI was the backbone of the public services distribution. Over the years, increasing public agencies and ministries utilized SISFOH AI as a key information system to assess the eligibility of citizens for distinct social and welfare measures. A former Minister of the MIDIS points out: *"If people wanted to use welfare, they had to stick with SISFOH. Then, the need to have information was not only of a few sectors but was also shared by many actors within the Peruvian government: at that point, many other programs were aggregated to SISFOH, like SALUD, JUNTOS, PENSION65, CONTIGO"* (Interviewee-1). SISFOH AI centralized the information collection, processing, and management within the Peruvian welfare. As such, it established a standardized way to provide welfare services because it engrained the technological characteristics of the AI into the targeting logic of the Peruvian approach to welfare. In other words, the AI had been designed to fulfil a specific task – correctly target those eligible for welfare measures – and it became the standard for distributing welfare measures. Another former Minister explains the centrality of the SISFOH AI with respect not only to the whole welfare provision, but to the definition of the policy itself: *"The creation of SISFOH has provided to the social policy of Peru an instrument that it already had, but that was not an instrument within a policy"* (I-6). In other words, the AI became constitutive of the policy. The AI algorithms engrained into SISFOH provided the public administration with the information without which it would have been impossible to deliver services.

5.2 Challenges of the AI policy in the pandemic context

The outbreak of the pandemic was the contextual event that modified the status quo ante. The immediate response of Peruvian policymakers to the deteriorating living conditions of the citizens was to deliver a monetary subsidy. However, the external context altered the effects of the Peruvian welfare policy based on SISFOH AI. Before the pandemic, the AI-driven policy achieved targeting purposes: those clustered as "poor" and "very poor" received welfare measures, while those not in need didn't. After the pandemic, the effects of the policy generated further exclusion as many people classified by the AI as "not poor" found themselves left out of the database of eligible citizens despite being severely impacted by the pandemic. This aspect is emphasized by a former deputy Minister: *"We only can target people who are poor or extremely poor, but that was before the pandemic"* (I-4). This happened without any formal modification of the policy based on AI: what changed was the social environment. However, vis-à-vis these modified circumstances, the Peruvian policymakers resisted changing the policy, which would have required significant resources given the centrality of SISFOH and the AI engrained into it. Hence, the AI-calculated categories of "very poor", "poor", and "not poor" were applied in the emergency context in the same manner as they would have been during ordinary times. Resistances to change the policy emerged among civil servants and actors tasked to utilize the AI to deliver the first monetary subsidy, as noted by a senior civil servant: *"People* [in the Peruvian public sector] *were used to SISFOH, they had knowledge and expertise"* (I-5). At the time of the pandemic, the Peruvian public administration had relied on the SISFOH AI for several years with considerable success. However, in a situation of a modified environment, the targeting effects of the policy, embodied in the functioning of the AI, generated misallocations in the recipients of the subsidy, exposing the whole policy to *"challenges related to coverage and leakage"* (I-3). Eventually, the government realized that the attempts to leave the welfare policy formally unchanged could expose the emergency measures to significant flaws and weaknesses.

5.3 Adopting the AI policy

The misallocations of the first monetary subsidy urged Peruvian policymakers to pursue an adaptation of the

SISFOH AI policy to achieve different ends. The modification of the formal aspects of the policy was excluded as it would have required dismantling not only the policy architecture but also the technological infrastructure of the AI engrained at the core of SISFOH. A former Minister emphasizes this point, reinforcing the boundary conditions within which Peruvian policymakers had to operate: "*Without SISFOH, we would not have been able to design the emergency policy at all. SISFOH did impact, it has radically changed the social policy in Peru*" (I-6). Hence, Peruvian policymakers began efforts to redirect the purpose of the policy leveraging on the potentiality of the SISFOH. The strategy of Peruvian policymakers focused on utilizing the data produced by SISFOH AI with a distinct purpose. While in ordinary time the database of citizens eligible for a specific welfare service was the landing point of SISFOH, in emergency time it became the basis for further subsidies provided by other ministries and agencies building on the information provided by SISFOH AI. The first monetary subsidy was designed and delivered to citizens in less than two weeks: however, due to the prolonged restrictions, several other subsidies were provided to other categories and social groups. Further measures were released to expand the number of people eligible beyond the "poor" and "very poor" citizens classified by SISFOH AI, as explained by a former deputy Minister who accounts for the many queries received about SISFOH data*: "People who lost their jobs, artists, informal workers… All these categories needed Bonos [subsidies], but they weren't poor! We also needed to reach people who weren't poor, but not all of them. So, we used SISFOH data to identify the non-poor"* (I-4). Therefore, building on AI classifications, the Peruvian public administration began to provide subsidies to those who were initially excluded from the recipients of the first monetary measure. This ultimately led to a situation in which the SISFOH AI, designed to increase efficiency and effectiveness in targeting, was the instrument that enabled the Peruvian government to effectuate reverse targeting. Policymakers pursued reverse targeting until the recipients of the subsidies reached almost universal coverage. This is confirmed by a former Minister who explains how the provision of a subsequent subsidy to informal workers occurred: "*They had the national ID registry; they took out from that registry all the people that remained with a formal job. And that's it: everybody else should receive a Bono, that was the reverse targeting*" (I-2).

6. Discussion

The purpose of the research is to understand the impact of AI on emergency policy change. To achieve this goal, findings from the case study of the Peruvian government's emergency measures are discussed through the analytical lens of drift and conversion framework as portrayed by Hacker et al. (2015) to validate Propositions 1 and 2 above presented.

6.1 AI as a source of drift

Proposition 1 upholds that AI can be a source of drift underpinning resistance to policy change when the contextual circumstances modify. Key characteristics of drift, as summarized in Table 1, are (a) context discontinuity; (b) alteration of policy's effects due to evolved context; (c) formal policy unchanged; and (d) resistance as a driving force.

Concerning context discontinuity, findings from the case study indicate that the outbreak of the COVID-19 pandemic represents the transformation of the social circumstances altering the status quo ante. Specifically, the context discontinuity observed in the case takes the shape of a major disruption that overturns the social order. An event like the pandemic – without the reasonable control of any of the actors – embodies a more than sufficient modification of the context to trigger the policy change in the form of drift.

The context discontinuity impacts the effects of the policy: the AI was originally designed to target citizens eligible for welfare services and to exclude those not eligible. The engrained technology at the core of the policy – SISFOH's AI – produced altered effects in the pandemic context generating additional leakages and distortions in the subsidy administration. The SISFOH AI had been designed to provide only a static understanding of poverty, based on data that did not capture the modified poverty circumstances.

In these settings, Peruvian policymakers decided to avoid the formal modification of the policy, which would have requested an alteration of the technological infrastructure of the AI at the core of SISFOH. The formal scaffolding of the Peruvian welfare system relying on SISFOH remained in place without modifications. Two motivations can explain this choice. First, civil servants tasked with administering the policy were accustomed to the use of SISFOH, and an abrupt discontinuation such as a policy formal change would have impacted the chances of the monetary subsidy being delivered effectively. However, there is a second element that deserves to be unravelled: the specific role of AI in the formal constitution (Pierson, 2006) of the policy. The centrality of the AI algorithm within SISFOH, and the pervasiveness of SISFOH within the Peruvian welfare system, generated an additional source of resistance towards a formal modification of the policy.

Drift elucidates a substantial change in the effects of the policy without formal modifications, as a consequence of an evolved context (Hacker et al., 2015). In this respect, policy change is supported not only by actors' behaviour but also, and more significantly, by the impact of AI. When the context shifts the effects of the policy, the AI shapes the policy change by creating resistance to any formal modification, drifting the policy towards unexplored territory. In other words, the policy changes not only because the context has altered its effects, but also because the AI has prevented any formal modifications to the policy itself. Accordingly, proposition 1 can be considered validated.

6.2 AI as a source of conversion

Proposition 2 upholds that AI can be a source of conversion, shaping the redirection of the policy to achieve different outcomes. Key characteristics of conversion, as summarized in Table 1, are (a) actors' initiative; (b) adaptation of policy's purposes towards different ends; (c) formal policy unchanged; (d) redirection as driving force.

Actors' initiatives refer to the proactive decisions taken by relevant policymakers to modify the circumstances (Hacker et al., 2015). In contrast to drift, the source that triggers policy change is not the context – although the context is not irrelevant – but rather the behaviours of policymakers. Findings from the case study show that Peruvian policymakers reacted to the misallocations and disruptions generated by the delivery of the first monetary subsidy. Policymakers acted under the pressure of providing immediate relief to those impacted by the pandemic and excluded by the AI classification of "poor" and "very poor".

Similarly to the drift form of change, conversion occurs when the actors leave unchanged the formal constitution of the policy. The modification of the SISFOH infrastructure at the core of the welfare provision encounters the same challenges characterizing drift: it is impossible to disentangle the AI engrained in SISFOH from the policy architecture, which is diffused across several branches of the government. Further, despite its limitation, the AI had released enough information to deliver an initial subsidy provision, even if incomplete. The design and delivery of the first monetary subsidy constituted a benchmark for policymakers who aimed to rely on AI to provide further measures. Indeed, the SISFOH AI turns out to be a necessary condition for implementing other policies, not only because the rigidity of the AI-driven policy limits the options available to policymakers, but also because without the use of AI, delivering further policies becomes impossible.

This specific nature of the AI leaves the policymakers with the only option to adapt to the purposes of the policy without changing its formal constitution. Furthermore, the actors engage in a redirection of the policy towards completely different purposes than those that drove its design: from targeting, aimed to exclude those not eligible, to reverse targeting, to include those not yet covered by any measure. Concerning the adaptation of the policy, the role of AI deserves further discussion. The findings of the case study account for the policymakers' decisions and acts, however, the impact of AI in constraining the options available cannot be neglected. The AI, setting boundaries between what is possible to achieve and what is not, has a critical role in substantially adapting the policy towards new and distinct purposes. It is the SISFOH AI installed base that orientates the redirection of the policy.

Conversion happens because policymakers aim to adapt the ends of the policies vis-à-vis the unfeasibility of formally changing the policy (Hacker et al., 2015). In this context, policy change occurs because the redirection of the policy is steered by an entanglement made of policymakers' actions and AI-defined boundaries of the redirection. Accordingly, proposition 2 can be considered validated.

6.3 The ambivalence of AI in drifting and converting policies

The validation of the propositions outlined building on the framework by Hacker et al. (2015) accounts for the role of AI impacting policy change: when AI is engrained at the core of the policy, it acts as a source for drift and conversion. However, the analysis emphasizes an additional element: AI possesses the capacity to drive both drift and conversion forms of policy change.

On the one hand, AI drifts the policy change by creating resistance to formal policy modifications which overshadows the need to adjust the mutated effects of the policy. On the other hand, AI enables a substantial redirection of the policy ends that enable policymakers to achieve significant outcomes without formally altering the policy. The embedding of the AI within the policy and the diffusion of the policy within the welfare system confers the AI a critical relevance in the whole public administration scaffolding, up to the point that a formal modification of the AI-driven policy encounters several challenges. However, the same factors that make the formal modifications unfeasible – the centrality of AI engrained in the policy and the centrality of the policy within the system – drive the adaptation of the policy towards other ends which ultimately serves the interests of the policymakers. In other words, the AI possesses an ambivalent capacity to impact policy change because it is both a source of drift and conversion.

7. Conclusions

This research has explored the transformative role of Artificial Intelligence (AI) in emergency policy change, focusing on its dual capacity to resist and enable policy change through the theoretical lens of drift and conversion (Hacker et al., 2015). By analysing the case of Peru's SISFOH AI system during the COVID-19 pandemic, the research has illustrated how AI reshapes policies in ways that extend beyond their original design, highlighting its ambivalent role in both stabilising and adapting policy frameworks.

The findings demonstrate that AI systems when embedded into policy processes, act as powerful institutional actors (Avgerou, 2004; Rudko et al., 2024). On one hand, the SISFOH system triggered drift, resisting formal policy changes even as the pandemic dramatically altered the socio-economic context. This resistance stemmed not only from the public administrators' inertia but also from the structural centrality of the AI itself, which constrained policymakers' capacity for formal reform. On the other hand, the same system enabled significant policy redirection through conversion, as policymakers leveraged SISFOH's capabilities to expand welfare coverage and address emergent challenges. By facilitating reverse targeting and reorienting policy goals, AI proved instrumental in adapting to the demands of a rapidly evolving crisis.

These findings contribute to the digital government literature in several ways. First, they underscore the importance of studying AI not merely as a technical tool but as a dynamic force that interacts with institutional structures to shape policy change (Agostino et al., 2021; Luna-Reyes & Gil-Garcia, 2011). Second, they offer empirical insights into the complexities of AI-driven policy change in emergency contexts, where resource constraints and socio-economic inequalities amplify the stakes of emergency response (Firmino & Evangelista, 2023; Meijer & Webster, 2020).

However, this research also raises important questions about the governance of AI in public administration. The dual capacity of AI to resist and facilitate change suggests that its integration into policy processes must be carefully managed to balance stability and adaptability (Valle-Cruz & Sandoval-Almazán, 2024). This implies the need for a more robust, modular approach to AI design, that facilitates reprogramming and re-tailoring to achieve desirable outcomes. Moreover, policymakers must consider the ethical and operational implications of AI-driven systems, particularly in contexts where technological limitations may exacerbate social inequities (Milan et al., 2021). Furthermore, the findings point to the need for ongoing scrutiny of how AI shapes policy outcomes over time, calling for future research into its long-term institutional effects (Cordella & Gualdi, 2024).

In conclusion, this research highlights the ambivalent role of AI as both a source of drift and conversion forms of policy change. As governments increasingly turn to AI to address complex challenges (Scholl, 2023), it is crucial to recognise and navigate its dual nature, ensuring that the integration of AI into policymaking serves not only to optimise outcomes but also to uphold principles of equity and inclusivity. By advancing the understanding of how AI drives hidden forms of policy change, this research contributes to a deeper appreciation of the transformative potential of digital technologies.

Acknowledgement

- **Funding or Grant:** This project has received the support of the Regent's University London Vice-Chancellor Fund.
- **Data/Software Access Statement**: The data that support the findings of this study are available from the corresponding author upon reasonable request.
- **Contributor Statement***: Francesco Gualdi: Conceptualisation, Writing-Original Draft, Methodology, Writing-Editing, Validation, Funding Acquisition. Vincent Ong: Conceptualisation, Writing-Editing, Validation, Funding Acquisition.
- **Use of AI***: During the preparation of this work, the authors used Grammarly to check the appropriateness of language, and ChatGPT to check the correctness of the translation from Spanish to English. After using these tools, the authors reviewed, edited, made the content their own and validated the outcome as needed, and take full responsibility for the content of the publication.
- **Conflict Of Interest (COI)***: There is no conflict of interest.

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