Technological trajectories as an outcome of the structure-agency interplay at the national level: insights from emerging varieties of AI

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Abstract

Development studies have paid less attention to the role of technological innovations and we are yet to understand how, but more importantly why, technological trajectories differ across countries. This gap becomes sharper as emerging technologies such as artificial intelligence (AI) are becoming increasingly important in addressing many world development challenges. Drawing on insights from institutional work literature, this paper develops a structure-agency interplay framework to unravel the various trajectories of emerging technologies at the national level and examines the development and diffusion of AI in Canada and China. The findings show that Canada's stable institutional environment, reinforced through institutional work by various actors, generated a national AI trajectory driven by technology development through a strong focus on scientific research and ethics, with slower organic commercialisation of AI. In China, a dynamic and loose institutional structure characterised by lax regulations, low entry barriers, and high openness to novelties has resulted in a market-driven AI trajectory focused on technology commercialisation, with domestic digital giants and the government as dominant players. National-level dynamics in formal institutions, informal institutions, technologies, and actor strategies determine heterogeneous approaches to technology development and diffusion, giving rise to varieties of technological trajectories. The levels of institutionalisation exert different structural powers and create different spaces for institutional work across different geographical contexts.

Keywords: Structure-agency, institutions, institutional work, emerging technologies, artificial intelligence.

1. Introduction

To address the major development challenges facing the contemporary world (e.g., climate change, pandemics, water and food, poverty), it is imperative to understand the interplay between social, economic, political, technological, ecological, cultural and gendered aspects of societal change at the local, national, regional and global levels (EADI, 2017). Among these factors, practitioners and scholars have increasingly recognised that technological innovation is not only essential in promoting economic development but also pivotal to overcoming social and environmental challenges (Omri, 2020; Gates, 2021). In particular, digital technologies and green technologies are widely believed to be the key drivers of future transformations of human society toward more sustainable modes of production and consumption (Lenz, 2021; Sareen and Haarstad; 2021; Köhler et al., 2019).

However, technological innovation has hitherto received much less attention in development studies, which put more emphasis on traditional issues such as poverty, gender, environment, and inequality (Madrueño and Tezanos, 2018). For instance, in the journal of World Development, only a small number of papers examined technology change at the aggregate level or in specific sectors (e.g., IT and nanotechnology), usually with a strong geographical focus on developing/industrializing/latecomer countries (e.g., Fu and Gong, 2011; Dantas and Bell, 2011; Huang and Wu, 2012; Lee et al., 2021). These studies show that technological innovations do not develop, diffuse, and have the same impact uniformly across the world (e.g., Soete, 1985; Granville and Leonard, 2010; Casabonne and Kenny, 2012), highlighting the role of international technology transfer, indigenous learning, public support, and context-specific institutions (e.g., Fu et al., 2011; Kodama and Suzuki, 2007; Busom and Ve´ Lez-ospina, 2017). Still, there is a strong core-periphery narrative assuming developing countries are a passive part in technology development. This is increasingly challenged as the rise of emerging technologies, which are characterized by radical novelty, fast growth, prominent impact, uncertainty and ambiguity (Rotolo, Hicks, and Martin, 2015), are enabling latecomer countries to have the same starting line and even lower thresholds in technology development and diffusion (Lema et al., 2021; Pegels and Altenburg, 2020). On the other hand, the international management literature concerned with understanding industry-level dynamics, points to differences in industry architectures across countries (Jacobides, 2008), highlighting the context-dependent nature of technological trajectories in that “every industry has a potentially country-specific mode of organization” (Jacobides and Kudina, 2013, p.150). For example, studies on industry architectures (e.g., Jacobides, Knudsen, and Augier, 2006; Pisano and Teece, 2007; Jacobides and Winter, 2012), which are concerned with the rules and roles that govern how labour is divided among firms, showed that these differ across countries and that this creating country-specific challenges that influence firm success in global expansion (Jacobides and Kudina, 2013). More recently, Jacobides, Brusoni, and Candelon (2021) focus specifically on the industry architecture of AI, specifically the production, enablement, and consumption of AI, and show how this differs across the US, China, and Europe. While they point to the role of the interplay of structure and agency in shaping these differences, the focus is largely on how AI differs across the studied contexts as a result of the agency of different actors. Therefore, we still miss an in-depth understanding of why technological trajectories vary across countries and of what shapes the different trajectories of emerging technologies.

Building on previous work, this paper aims to contribute to development studies by unravelling the trajectory of emerging technologies at the national level from a structure-agency perspective through a case study of artificial intelligence (AI), drawing broader lessons and implications for the development and diffusion of emerging technologies around the world. Scholars have shown the influence of both institutions as structures and agency on socio-economic activities (Bergek et al., 2008;

Bathelt and Glückler, 2014; Gherhes et al., 2022), but the two have often been examined in isolation. Steen (2016, p.1608) argues that understanding the emergence of particular paths instead of others "requires more attention to agency and how actors respond to changes in (but also influence) the contexts in which they operate". Therefore, we draw on insights from institutional theory and recent institutional work literature and develop a structure-agency analytical framework to examine 'why does the development and diffusion of emerging technologies vary across national contexts?'.

The framework is illustrated by a comparison of the AI trajectories of Canada and China as two distinct empirical contexts. Widely believed as the cornerstone of the Fourth Industry Revolution, AI is likely to generate seismic socio-political, economic, and technological changes (Chalmers et al., 2021), and also shows great potential in addressing grand challenges such as climate change (Rolnick et al., 2022). However, there are numerous ethical concerns and potentially devastating consequences, e.g., inequality, privacy violation, algorithmic bias, and the displacement of workers (e.g. Korinek, 2019; Butcher and Beridze, 2019; Acemoglu and Restrepo, 2020). National economies worldwide have recognised AI's strategic importance, spurring a proliferation of domestic AI strategies (Erdélyi and Goldsmith, 2018; Cihon et al., 2020). Nevertheless, the approaches vary significantly, from national AI strategies with detailed objectives to no formal AI policy or strategy (Bell, 2018). Scholars also find the distinct roles of big tech in shaping AI industry architectures or sectoral innovation systems in leading AI players (Jacobides et al., 2021; Yu, Liang and Wu, 2021). Thus, as Korinek (2019, p.2) emphasises, "there is perhaps no single question more important than what direction future progress in AI will take". To begin to address the question of what future AI progress might look like, it is critical to first understand what shapes the development and diffusion of AI as a novel technology.

Drawing on 125 in-depth interviews, we compare AI development and diffusion trajectories between Canada as a developed economy and AI research pioneer and China as an emerging economy with global AI leadership ambitions. Our findings demonstrate how the national-level structure-agency interplay has resulted in nationally-specific AI trajectories in the two countries. We argue that these national-level dynamics in formal institutions, informal institutions, technologies, and actor strategies determine heterogeneous approaches to technology development and diffusion, giving rise to varieties of technological trajectories. The paper yields key lessons for emerging economies, highlighting the importance of understanding such national-level dynamics that bear developmental consequences.

The remainder of the paper is organised as follows: Section 2 provides the theoretical background on technology development and diffusion and develops a structure-agency analytical framework; Section 3 presents the research contexts and methodology; Section 4 presents the AI trajectories in Canada and China; Section 5 presents the cross-case analysis and discussions; and Section 6 concludes.

2. Theoretical background and analytical framework

2.1 Technology development and diffusion

Since Schumpeter (1942), the essential role of technological innovation and its related entrepreneurial activities in economic development has been widely recognized. Technological innovation entails the tradable application of inventions into economic and social practices (Malerba and Orsenigo,1997), comprising combinations of new or significantly modified technological products and processes (OECD, 2002). In the early days, the linear model assumes that technological innovation consists of sequential stages, from knowledge development to translation of knowledge into artefacts, production, and diffusion. In recent decades, scholars began to advocate for an interactive perspective to highlight the dynamic and interdependent relationship between technology development and diffusion (Rothwell, 1994; Cantisani, 2006; Diaconu, 2011).

Technology development refers to the process of knowledge creation and translation into products, while technology diffusion is the gradual adoption of those products in a market segment or in a society (Ortt and Schoormans, 2004; Comin and Hobijn 2006). These two distinct processes can be both separated and interlinked in an economy. On the one hand, a country may have a strong capacity for specific technology development, but its diffusion may be hindered due to market failures (Stoneman and Diederen, 1994). Meanwhile, a country may lack the endogenous capacity for specific technology development but still can be beneficiaries of the technology (e.g., vaccine) through wide diffusion (Casabonne and Kenny, 2012). On the other hand, there is usually a positive feedback loop between the two processes, as technology development can facilitate diffusion through cost reduction and performance improvement, whereas technology diffusion can provide scale economy and new ideas to firms to advance technology development (Rogers, 1962; Cantisani, 2006). Therefore, the distinct relations between technology development and its diffusion as well as their resulting outcomes could lead to varieties of technological trajectories across countries. Extant development studies pay more attention to technology development in developing/emerging countries, highlighting its role in productivity improvement, economic growth, or industry catch-up (e.g., Fu et al., 2011; Choung et al.,2014), whereas the diffusion of technological innovation is much less studied. This could limit the social benefits of technologies in developing countries as it is only through wide applications that the societal functions of technologies (e.g., green technologies) can be fully fulfilled.

The focus of this paper is to understand why and how technological trajectories differ across countries. The national/regional/sectoral/technological innovation system approach (Freeman, 1987; Cooke et al., 2004; Malerba, 2002; Bergek et al., 2008) is one of the most influential approaches in understanding technology innovation. Innovation system studies advocate that territory- or sector-specific interactions between institutions, actors, and networks explain the various trajectories of technology development and diffusion over space (Weber and Truffer, 2017). However, the innovation system approach has a rather static view of institution-actor relations, making it less suited to understand 'bounded change' (Thelen, 2004), which occurs when some institutions or logics of action are created or restructured within a system while other elements continue to operate as before (Hart, 2009). Therefore, we need a more flexible framework to understand the dynamic relations between institutions and actors in technology development and diffusion, especially in the context where emerging technologies are driving more and more bounded changes.

2.2 Institutions and technology development and diffusion

Institutions play a critical role in the development and diffusion of technologies (Bergek et al., 2015; Musiolik et al., 2018). The pervasive influence of institutions as "structures that shape and direct action" (Bathelt and Glückler, 2014, p.2) makes them an appropriate theoretical lens for examining technological development and diffusion. There are various mechanisms whereby institutions shape technological development and diffusion. North (1990) distinguishes between formal institutions, namely the written down or formally accepted rules and regulations that constitute the economic and legal framework of a society, and informal institutions which refer to unwritten rules such as attitudes, customs, norms, values, and conventions. On the formal institutional side, governments can use a range of instruments to stimulate technological innovations. As Milner (2006, p.195) notes, governments can shape technologies "by making policies that shape the costs and benefits of its use, thus affecting both demand and supply for the technology". Specifically, science, technology and innovation (STI) policies, which focused on the development, diffusion, and use of scientific and technical knowledge from funding basic and applied research, play a critical role in promoting specific technologies (Lundvall and Borrás, 2005; Doern and Stoney, 2009; Martin, 2016).

Borrás and Edquist (2013) further disaggregate innovation policy instruments into regulatory, economic, and 'soft' instruments. The first refers to regulating aspects such as intellectual property rights, research, competition, and ethics, collectively setting the 'rules of the game' for knowledge and innovation processes; the second refers to supply-side instruments providing positive incentives, such as competitive research funding, tax incentives and exemptions, and seed capital; the last complements the first two and includes voluntary standardisation, codes of conduct, campaigns, and public communication (ibid.). These can be used in various mixes to shape the development and diffusion of technologies. Indeed, studies have shown the positive influence of national R&D expenditure, subsidies, and tax credits in driving technological innovations and entrepreneurial experimentation, and hence economic development (Koh and Wang, 2005; Wu, 2005; Feldman and Kelley, 2006).

While formal institutions have hitherto received widespread attention, the role of informal institutions in shaping technology development and diffusion, and their interplay with formal institutions, remains less studied (Granville Leonard, 2010; Wirth et al., 2013). Informal institutions form what is known as culture, namely "the enduring set of values of a nation" (George and Zahra, 2002, p.5), and are geographically specific. Technology policies differ across countries, reflecting national values and being shaped by national institutional contexts that influence the extent of involvement of the government vis-à-vis corporations (Vasudeva, 2009). Differences relate to aspects such as the allocation of public resources, the nature of collaboration between different types of actors, influencing firm behaviours and technology commercialisation strategies and leading to substantially different innovation outcomes across countries (ibid.). Therefore, understanding how formal and informal institutions interact at national levels and in different contexts to shape technological development and diffusion is critical.

Overall, previous research has shown how pre-existing institutions support, guide, or constrain technological development and diffusion. However, some sharp research gaps remain. First, little is understood about how institutions interact with the development of novel or emerging technologies (Wirth et al., 2013). Emerging technologies are characterized by radical novelty, fast growth, prominent impact, and involve many uncertainties and ambiguities (Rotolo, 2015). While some institutional structures pre-date emerging technologies, others co-develop with them, such as technology-specific standards, regulations and funding schemes (Musiolik and Markard, 2011). Previous research had tended to emphasise the role of institutions as a stable structural force and has merely taken technology development and diffusion as a passive outcome. However, in the case of emerging technologies, there are usually institutional voids to be filled, especially in developing countries (Miller et al., 2013; Castellacci, 2015).

Second, the role of agency in the formation or change of institutions remains largely overlooked (Binz et al., 2016; Fuenfschilling and Truffer, 2016). Methodologically, there is limited research on the role and scope of agency between different countries, and most empirical studies tend to adopt a single-case study approach, failing to reveal how different geographical contexts result in diverse outcomes (Bakir and Gunduz, 2017). Fuenfschilling and Truffer (2016, p.300) highlight that the extent and outcome of agency is shaped by actors' institutional context, meaning that "[n]ot all actions are equally possible, legitimate and probable" in all contexts. Therefore, we argue that a comprehensive understanding of technology development and diffusion trajectory in a country should be achieved through a focus on the interplay between institutions, actors, and technologies (Fuenfschilling and Truffer, 2016).

2.3 A structure-agency analytical framework

Based on the above rationales, we propose a structure-agency framework to understand different trajectories of technology development and diffusion across countries. The structure is the broader material and cultural context within which actors are embedded (Bakir, 2017). As a key form of social structure, institutions provide "the legal, administrative, and customary arrangements for repeated human interaction" (Pejovich, 1999, p.165). Agency refers to the individual and collective activities and strategies of firm and non-firm actors such as organisations, universities, public research organisations, and state and policy actors (Gherhes et al., 2022; Steen, 2016; MacKinnon et al. 2019). It can be interpreted as broadening the "empirical margins of what can happen within a given 'structural' constraint" (Storper 1997, p. 30). A longstanding issue that has attracted academic focus is the 'paradox of embedded agency', that is, "how actors can change institutions if their actions, intentions, and rationality are all conditioned by the very institution they wish to change" (Holm 1995, p.398).

For a long time, structure has been merely viewed as a constraining force upon actors, who can only passively react to it. Since Giddens' (1984) work on 'structuration', many scholars have advocated for a mutually constitutive relationship between structure and agency (Sewell, 1992), arguing that institutional structures do not necessarily constrain agency but can provide a platform or serve as the fabric to be used for entrepreneurial practices (Garud et al. 2007). Thus, actors can also influence the environment to which they adapt rather than adapting to a ready-made environment (Yu, 2001). At the sectoral level, industry architecture scholars have highlighted the role of dominant participants in shaping the rules of a sector to capture more value (Jacobides and Winter, 2012; Pisano and Teece, 2007). Jacobides et al. (2021) show how key actors shaping the AI industry architecture in three contexts and point to the importance of focusing on evolutionary dynamics and the interplay of structure and agency in shaping technological trajectories. Focusing on the structure-agency interplay could enable us to understand "who initiated change, and which structural features caused their change efforts to be modified, and partly abandoned" (Jacobides, Macduffie, and Tae, 2016, p.1943).

Recent literature on institutional work and institutional entrepreneurship provides many insights into the role of agency in structural change (e.g. Lawrence and Suddaby, 2006; Battilana et al., 2009; Bakir and Gunduz, 2017). The institutional entrepreneurship concept pays more attention to the importance of those individuals and organizations "who leverage resources to create new institutions or to transform existing ones" (Maguire et al. 2004, p.657). However, the concept is often criticised for being too heroic and for depending on a "hyper-muscular entrepreneur" (Fuenfschilling and Truffer, 2016). Institutional work, instead, focuses on the interplay between institutions and actors, allowing for a mutually constitutive relationship between structure and agency. Focusing on the diverse and purposive practices and activities of a wide range of actors, it accommodates both visible and dramatic action such as institutional entrepreneurship and the more invisible and mundane agency of actors in the creation, maintenance, and destruction of institutions (Lawrence et al., 2009).

Institutional work is particularly relevant in emerging technologies such as AI where the key challenge is legitimacy and societal acceptance (Gherhes et al., 2022). This is due to emerging technologies' transformative nature and higher reconfiguration capacity to change underlying socio-technical structures (Fuenfschilling and Truffer, 2016). Institutional work enables actors to increase the legitimacy of new technology, which depends on the extent to which this aligns with pre-existing institutional structures (Bergek et al., 2008). Current fears that the development and diffusion of emerging technologies may have profound and negative socio-economic implications mean that they are unlikely to 'fit and conform' with prevailing institutional structures but requires significant change (Smith and Raven, 2012), and therefore more intense institutional work to diffuse.

Fuenfschilling and Truffer (2016) identify two types of institutional work, namely practices aimed at the mobilisation of resources and work that (de-)constructs rationales. The former relies on the employment of resources such as political power, money, knowledge, and social capital. The latter relates to influencing (de-)institutionalisation processes through the communication of narratives of what is morally right or wrong, exemplified by education and awareness campaigns. Where more dramatic action is taken, actors usually need to be able to discover political opportunities, frame problems, theorise new practices, bridge diverse stakeholders, and connect these practices to stakeholders' routines and values (Rao et al. 2000; Levy and Scully, 2007). This process inevitably entails many forms of power, such as discursive power, interpretive power, institutional power, and instrumental power (Geels, 2014; Grillitsch, 2019). This structure-agency interplay during the development and diffusion of technology can change its design, function, user practices, and associated values over time (Fuenfschilling and Truffer, 2016).

We hitherto argued that the outcome of the structure-agency interplay is context-dependent, as the causal powers of structure may operate as tendencies and in different contexts generate different events (Leca and Naccache, 2006). Bathelt and Glückler (2014, p.351–352) emphasise that "we can expect more fundamental differences to exist between different countries, as the various rules, norms, conventions, habits, and technology attitudes that affect economic practices – and, thus, institutions – are often shaped by the settings negotiated at the level of the national state". Similarly, Vasudeva (2009, p.1257) argues that "technological progress and globalization have not resulted in the convergence of institutional boundaries and national governments continue to matter for innovation". Thus, we focus on how the national-level structure-agency interplay shapes technology development and diffusion.

[Figure 1 here]

Figure 1 presents an analytical framework that depicts the interrelationships between institutions, actors, and technology trajectories. Here, formal institutions are the written rules created and enforced by generally accepted official organizations, while informal institutions are unwritten, socially shared rules that are usually created and enforced outside of official channels. Actors refer to the players involved in the development and diffusion of technologies (e.g., government, entrepreneurs, researchers, and users). Technological trajectories of a country are the patterns or outcomes of the interrelationship between technology development and technology diffusion. We argue that national-level formal and informal institutions interact to shape the focus, scope, and outcome of actors' actions in relation to technology development and diffusion at the national level. While institutions exhibit high stability and strong inertia, they are not definitive. At the structure level, national-level institutions *per se* are subject to changes of external environment and interactions between formal and informal institutions. Formal and informal institutions may align to reinforce the existing institutional structure, but they may also conflict to destabilise the existing institutional structure. Institutions exert structural power to shape actors' intentions and actions regarding technology development and diffusion. They also directly influence technology development and diffusion through incentives and deterrents, with outcomes feeding back into actors' future actions. At the agency level, actors may conform to existing institutions and even reinforce them in their daily practice regarding technology development and diffusion. If the technology trajectory matches initial intentions and aligns with the institutional structure, the approach to technology development and diffusion can cement into formal and informal institutions and reinforce the current trajectory. However, it is also the case that actors may resist existing institutional logics and alter institutional settings such as policies setting new standards and regulations. In particular, with the development and diffusion of technologies, certain actors could be empowered to do institutional work, either transforming existing institutions or maintaining them. Thus, the structure-agency interplay crystallises into a specific technological trajectory. We use this framework to examine how the structure-agency interplay shapes the development and diffusion of AI in two empirical contexts.

3. Research contexts and methodology

The paper focuses on AI development and diffusion in Canada and China as two distinct case studies. AI represents our case of emerging technology in this study. In its history, AI has gone through a series of 'AI winters' and advances oscillated with progress in computer science, increases in computational power, and the availability of huge datasets. Currently, a broad spectrum of specific policies (e.g., privacy, trade, liability) is employed to regulate its development and diffusion (Agrawal et al., 2018), which is also significantly shaped by country-specific ecosystems and active industrial participants (Arenal et al., 2020; Jacobides, et al., 2021).

Home to the "godfathers of deep learning", Canada is one of the leaders in AI development. The Canadian AI ecosystem notably includes the international AI hubs of Montreal and Toronto alongside regional and specialised hubs (Fox et al., 2018). Canada was the first country in the world to develop a national AI strategy and, with a strong AI research and talent profile (CIFAR, 2020), and has become a key player on the global AI scene. For example, Montréal is home to the world's largest concentration of AI researchers, with more than 80 AI start-ups and established firms, while Toronto has the largest concentration of AI firms in Canada, with more than 150 AI start-ups and established firms, both cities being recognised as major international AI hubs (Fox et al., 2018). A foundation of Canada's AI ecosystem is industry-academia collaboration, yet the fear of brain drain and difficulty acquiring late-stage venture capital remain important challenges to the future development of AI in the country (Fox et al., 2018). Contrastingly, despite lacking world-leading research breakthroughs, China developed a vibrant AI ecosystem with giant digital platforms, active entrepreneurship, and pervasive applications (Xue et al., 2018; Jacobides et al., 2021; Yu, Liang and Xue, 2022). In 2017, China released the 'Development Plan for the Next Generation Artificial Intelligence' (hereafter, DPNGAI), aiming to build China into the world centre of AI innovation by 2030. However, as Roberts et al. (2021, p.59) note, "a more comprehensive and critical analysis of the driving forces behind China's AI strategy, its political economy, cultural specificities, and the current relevant policy debates, is required to understand China's AI strategy".

Furthermore, the WIPO (2019) report provides some interesting contrasting statistics on the two case study countries. For example, while China dominates patents for AI functional applications along with the US, ranking second worldwide with regard the number of patent applications filed, Canada only ranks 8^{th}. Moreover, China leads in terms of share of scientific publications on AI techniques globally while Canada ranks among the last. Nevertheless, as Frank Chen observed, "A lot of AI is very nationalized" (WIPO, 2019, p.125). Indeed, while both countries aspire to become global AI leaders, they are governed by different laws, rules, regulations and cultures, which can enable or constrain actors to shape the AI narrative in specific ways. Importantly, their different histories and cultural backgrounds and specificities can be critical to the shape that AI will take in the two national contexts. As such, the same emerging technology, namely AI in this instance, can end up being developed and used in vastly different ways. It is therefore critical to unpack the dynamics between structure and agency and to understand how their interplay has hitherto shaped the development and diffusion of AI in the two contexts. Such a comparison is also helpful to illustrate why and how developed economies and emerging economies may respond differently to the opportunities brought by emerging technologies.

To enable an in-depth understanding of technological trajectory in different national contexts from a longitudinal perspective, we employed a qualitative case study. The focus of case study research on questions of 'how' and 'why' enables a rich and holistic understanding of phenomena and helps generates valuable analytical insights (Yin, 2014), being especially suitable for examining context-embedded phenomena. Moreover, case studies facilitate the advancement of theory (Andrade, 2009). The aim of case study research is analytical generalisation as opposed to empirical generalisation (Hyde, 2000). For data collection, we conducted a total of 125 in-depth semi-structured interviews in Canada and China between April 2018 and October 2020, during extended field trips. The interviewees included a broad range of stakeholders, from AI-focused companies, digital platforms, government agencies, and universities, to business support organisations, non-governmental organisations (NGOs), industry associations, and venture capital firms (VCs). In Canada, a total of 58 interviews were conducted in the AI hubs of Montreal (35) and Toronto (23). In China, a total of 67 interviews were conducted in the AI hubs of Beijing (16), Shenzhen (14), Hangzhou (10), Shanghai (6), Suzhou (12) and others (9). These interviews focused on understanding what shaped the development and diffusion of AI in the two contexts throughout the past decades as well as on current trajectories (for example interview questions, see Appendix 1 and 2). For instance, in China's fieldwork, the interviews focused on a) What are the facilitating and obstructing factors of AI development and diffusion in China? b) How are innovation resources (e.g., knowledge, investment and data) distributed and flow within the AI innovation system? c) How do different actors respond to the emergence of AI and its consequent changes? Additionally, we reviewed key policy and industry documents on AI strategies in the two countries to identify key initiatives and policies and to triangulate the interview data.

The interviews were recorded and subsequently transcribed and analysed. In analysing the interview data, we employed the Framework Method, largely following the steps described by Gale et al. (2013). As such, upon transcribing and familiarising with the interviews, we began coding the interview transcripts. The coding and data analysis processes were theory-guided, which helped increase the internal validity of the emergent theory (Kohlbacher, 2006). However, while we based the analysis on pre-existing theory, therefore employing a largely deductive approach to identify elements of structure and agency throughout the interview data, we also remained open to new concepts. Such a combined approach is appropriate when the research focuses on exploring specific issues but also intends to allow for the discovery of other unexpected aspects, and ensure that important aspects are not missed (Gale et al., 2013). By applying the analytical framework described in the previous section, we identified different aspects of structure, agency, and technology that uniquely configure the structure-agency interplay in the two empirical contexts (see Appendix 3 for examples). With the structure-agency interplay at the core of the analysis, we structured the presentation of the findings into temporal segments to tell the story of AI development and diffusion in each of the two cases. The distinct AI development phases are based on interviewees' accounts and were confirmed through document analysis. Quotes from the interviews are included to give voice to the study and illustrate key aspects. Participants remained anonymous and therefore we abbreviate Canadian stakeholders to CA-INT and the number assigned to the interviewee, and similarly CH-INT for the Chinese stakeholders.

4. Case analysis: AI trajectories in Canada and China

4.1 AI development and diffusion in Canada

4.1.1 1982–2015: early AI days

The Canadian AI story begins in the early 1980s with a core group of AI researchers supported by the Canadian Institute for Advanced Research (CIFAR), a government-funded organisation promoting the advancement of scientific knowledge through interdisciplinary and globally impactful research. Founded in 1982, CIFAR paved the way for AI development in Canada by creating a favourable institutional environment for research and innovation. Two critical aspects that underpin its approach to research funding are an ethos of curiosity and exploration that promotes long-term fundamental research, and not tying research to commercial objectives. This approach enables researchers 'to tackle really big scientific questions facing humanity … giving [them] the space to share ideas and work together over a 5, 10, even 15-year period' (CA-INT54) and represents a distinct feature of the Canadian institutional environment that has governed research and innovation over the past decades, spurring major breakthroughs.

Importantly, this approach to research funding enabled a handful of AI researchers to continue their work on artificial neural networks at a time when this lacked informal institutional support globally, namely during the second AI winter that spanned the late 1980s and early 1990s. The small research group was formed around three scientists renowned today as the "godfathers of deep learning"—Yoshua Bengio, Geoffrey Hinton, and Yann LeCun—who were supported by two CIFAR-funded programmes: AI, Robotics & Society (founded in 1983)—one of the world's first AI research programmes—and Neural Computation & Adaptive Perception (NCAP), founded in 2004. Institutional support from the state when AI "wasn't a very promising line of research" (CA-INT3) was critical:

> 'Geoffrey Hinton, 30 years ago, nobody thought he would be where he is now, and without CIFAR and the [Government] keeping his research alive we would not have the explosion we have today … [It was] that investment and that "playing the long game" [approach].' (CA-INT46)

This yielded numerous scientific breakthroughs, starting with the introduction of deep learning in 2006, which enabled new AI applications in areas such as speech recognition, followed by curriculum learning in 2009 and generative adversarial networks in 2014, making fundamental contributions to knowledge in the field. These not only led to the formation of a strong academic pillar but revived global interest in AI, enabling the researchers to garner greater institutional support for further funding.

4.1.2 After 2016: developing and diffusing AI

Around 2016, Canada began to 'wake up' to AI's potential and the whole ecosystem 'activated' (CA-INT6) to support its further development and diffusion. An AI hype built up through consecutive research breakthroughs, spurring AI start-ups, of which the most prominent is Element AI. Launched in 2016, it quickly became one of the fastest-growing AI start-ups in the world, drawing attention to Canada's potential in the field and attracting significant interest from domestic and private investors and VCs. Importantly, while AI did not even feature in Canada's Science, Technology and Innovation strategy prior to 2016, it rapidly climbed to the top of the national agenda.

Realising that 'AI would be the driver for economic prosperity' (CA-INT52), the government seized the momentum and appointed CIFAR in 2017 to develop and lead the CAD$125m Pan-Canadian Artificial Intelligence Strategy (PCAIS)—the world's first national AI strategy. This focuses prominently on supporting AI research and talent development and on developing thought leadership on the economic, ethical, policy and legal implications of AI advances (CIFAR, 2018). As an interviewee explained, 'the rationale here is that everything else in the AI ecosystem is going to flow from talent and this starts by having the best researchers in the world' (CA-INT19). PCAIS funded three AI centres of excellence in Canada's national AI hubs: Mila - Quebec AI Institute in Montreal, Vector Institute in Toronto, and Alberta Machine Intelligence Institute (AMII) in Edmonton. Importantly, the three "godfathers of deep learning" also received global recognition in 2018 when they received the Turing Award for their critical work that advanced AI in its early days. Formally recognising the importance of AI research and talent, this served to reinforce the PCAIS objectives.

Moreover, to support the development of applications, the government offers a series of incentives for businesses to establish and operate in Canada. These include the Scientific Research and Experimental Development (SR&ED) tax incentive programme (dating back to the 1980s), and the Industrial Research Assistance Program (IRAP) (dating back to the 1960s), which promote knowledge creation and technological innovation. These are particularly relevant to AI as 'when you're talking about AI, it's a lot of R&D … we can have massive credit reimbursement from the government' (CA-INT13). However, such federal-level programmes provide 'a clear incentive to do research' (CA-INT47). To stimulate commercial applications, the Canadian Government launched the Innovation Superclusters Initiative in 2017, a CAD$950m investment promoting innovation-led economic growth. This founded Scale AI, the only AI supercluster, to accelerate the application, adoption and commercialisation of AI in supply chains. The confluence of these incentives and the academia-fuelled hype led to a proliferation of AI start-ups from 2016 onwards while also attracting new actors, with a significant number of MNEs, predominantly US tech giants such as Microsoft, Google and Facebook, opening research labs in Canada's AI hubs.

However, Canada's AI strengths remain rooted in research and talent development, with the country lagging behind in commercialising AI. Interviewees highlighted that 'we underperform in terms of commercialising that research' (CA-INT46), with the AI ecosystem being 'academia-focused' (CA-INT4).

> 'Canada is leading in AI when it comes to producing the R&D talent, producing concepts, the innovations, but at the academic level. When it comes to commercialisation, I don't think that Canada is leading in any way. I don't think it traditionally has been Canada's strength.' (CA-INT50)

Indeed, Canada has seen a slower AI commercialisation through start-ups and scale-ups. Despite Element AI's resounding growth and an increase in private capital flowing into AI, the country lacks more prominent examples of AI business success. Interviewees highlighted this as a pan-Canadian challenge stating that 'that [enterprise] culture hasn't evolved' (CA-INT15) and that ambition and risk-taking are somewhat 'un-Canadian' (CA-INT1), contrasting Canada with more entrepreneurial places in the US such as Silicon Valley and New York. Even when asked about AI leaders, interviewees overwhelmingly mentioned prominent AI researchers or leading research institutes:

> 'The Vector Institute is definitely the name that comes most often when you talk to people about AI development … It is definitely Geoffrey Hinton. He is probably the biggest player in [AI].' (CA-INT52)

Therefore, while 'trying to chase [AI's] economic potential' (CA-INT46), as an interviewee emphasised, 'the next phase of AI will be to productize AI. That's the very next challenge' (CA-INT44). While state-led initiatives increasingly promote commercialisation, this challenge will take time to address, which may serve to reinforce the country's focus on technology development, at least in the shorter term.

Furthermore, businesses in Canada face more restrictions in applying AI, needing to adhere to more stringent personal data and privacy laws and regulations, such as the Privacy Act (PA) (dating back to 1983) and the Personal Information Protection and Electronic Documents Act (PIPEDA) (dating back to 2004), which regulate the collection, use, and disclosure of personal information by government and private-sector organisations, and Canada's Digital Charter—a set of principles on personal data use in the private sector that aims to build trust and grow the digital economy (Government of Canada, 2020)—alongside other provincial and sector-specific privacy laws. AI in government is also carefully scrutinised, with the Directive on Automated Decision-Making ensuring 'the development of fair and transparent and explainable AI' (CA-INT48). This requires companies developing AI for government to undergo detailed algorithmic impact, transparency, and quality assurance assessments. Therefore, AI-focused companies operate in an institutional environment with 'a lot more controls and a lot more guards' (CA-INT35) compared to other countries:

> 'The rules about deploying AI models are still a bit strict. It needs time, like around six months before any AI model has to be approved by a third party … just to make sure there are no biases in the model, it's not discriminating, etc.' (CA-INT41)

Critically, however, these safeguards reflect a strong ethical AI component, with multiple stakeholders—from AI academics and industry experts to citizens—organising early-on to advocate for the ethical and socially responsible application of AI. This started with the Montreal Declaration for the Responsible Development of

Artificial Intelligence in 2017, a principle-based framework aiming to mitigate the potential negative impacts of AI. As an interviewee explained:

> 'Technology has the potential to be a great equaliser, but with AI, it also has the potential to increase the income gap and income disparity between the very rich and the poor … [and] we need to be looking at inclusivity and inclusive growth.' (CA-INT27)

Ever since, there has been a proliferation of publicly-funded and third-sector-led initiatives promoting ethical approaches and 'AI for social good' (CA-INT3). These include the government-funded International Observatory on the Societal Impacts of AI and Digital Technologies (OIISIAN), the AI & Society programme (part of PCAIS) focusing on 'the social implications of AI' (CA-INT54), the International Centre of Expertise in Montréal for the Advancement of Artificial Intelligence (ICEMAI), and Montreal AI Ethics Institute (MAIEI), a third sector initiative aiming to 'build public competence and understanding the side effects of AI … [to promote] an informed and engaged citizenry' (CA-INT33).

These reflect deeply embedded cultural values. Interviewees emphasised that this ethical and human-centric approach has 'come up through our history, culture, that we want to be ethical' (CA-INT20), that 'there's an interest in making things ethical … it's part of [our] culture' (CA-INT6). This is also reflected in the missions of the AI centres of excellence, with Edmonton-based AMII, for example, promoting 'AI for good and for all'. Industry reports also emphasise the need 'to build AI standards and practices that mirror our distinctly Canadian values, and develop AI that is open, safe, equitable, and used in ways that create prosperity for all' (Deloitte, 2019, p.2). These institutions have created a distinctly Canadian AI trajectory, one focused on excellence in technological development and the ethical application of AI. This means that 'AI will have a different face in Canada' (CA-INT35), with national-level institutions shaping 'how we build AI [and] how we sell AI' (CA-INT48).

4.1.3 An AI trajectory in flux?

The current trajectory is, however, not definitive. Over the past four years, Canada's talent-rich, research-active AI ecosystem has attracted numerous foreign tech giants, creating fears that these 'are all in it obviously for their own bottom line' (CA-INT46). Key concerns relate to the acquisition of Canada-born AI start-ups and to the demand for talent, which can lead to such actors accumulating significant power in the future, especially against a backdrop of weaker organic commercialisation:

> 'American companies are acquiring Canadian ones and taking IP out of the country.' (CA-INT37)

> ‘One thing that fuelled this [trajectory] was rooted in fundamental R&D, but … there’s a threat of the private sector almost suffocating academia and then taking the talent out of it and leaving very few leaders in to actually prepare the next generations.’ (CA-INT34)

The issue of scarce AI talent being used for the profit of multinationals is seen to limit AI development and applications in other areas and to weaken the research-active environment, fuelling fears that ‘the knowledge could potentially end up in the hands of two or three massive players’ (CA-INT3).

Moreover, some highlighted that current approaches to regulating AI may hamper commercialisation (CA-INT54). Thus, regulations around personal data use in the private sector may need to change in order to enable more AI-based commercial activity:

> ‘The Federal Government is turning to a broader AI strategy and what it needs to look at from an ethics point of view, thinking about all of the privacy questions and data and IP ownership … to help create the right policy conditions for fair play … for industry.’ (CA-INT44)

However, recent events also highlight an active citizenry and civil society. Interviewees distinguished Canada as a ‘participatory democracy’ (CA-INT35), highlighting institutional mechanisms that enable the public to influence critical debates and prevent unwanted outcomes. A prominent example is Google’s Sidewalk Labs project, which came to an abrupt end in early 2020 due to public opposition stemming from privacy concerns (CA-INT35). An interviewee explained that the project was stopped by:

> ‘a healthy dose of scepticism. The #blocksidewalk movement came out there and [asked] “What's Alphabet trying to do taking a prime, private real estate … turning it into this technology utopia? Who’s getting the information? Where’s information being stored? How is Google, Alphabet making money off of it? What rights do we have as citizens?”’ (CA-INT35)

The Canadian society pushback sent strong signals to private actors regarding the type of socially acceptable AI applications, making it less likely for tech giants to attempt to dominate the landscape. As an interviewee emphasised, ‘Canadians really care about these [ethical] values and are not afraid of speaking up’ (CA-INT34).

Furthermore, while ‘entrepreneurs will have to play by a different set of rules’ (CA-INT34), because ‘if you can’t access the data or cannot absolutely anonymize it, you will only be able to do certain things’ (CA-INT35), the current approach is seen to benefit Canada in the long-term:

‘because if people know that the companies that are producing the AI software are ethical and are playing by the rules of civil society … [they] are going to buy from those.’ (CA-INT35)

‘Adhering to these [ethical] principles will actually be a market differentiator as public awareness rises, so it will be to your advantage to build solutions that are privacy-preserving, that do respect ethical principles.’ (CA-INT34)

4.2 AI development and diffusion in China

4.2.1 Before 2012: stumbling in AI research

Before 1978, while AI research began to gain increasing attention in western countries after the birth of the AI concept in Dartmouth in 1956, China barely started any AI research mainly due to ideological factors. Throughout this period, the American-born AI concept was deemed ‘a reactionary pseudoscience of the bourgeoisie’ in China (Cai, 2016). Besides, the concept of AI at that time was frequently mixed with human superperformance by Chinese society, including many researchers. These ideological and superstitious beliefs considerably impeded China’s AI research.

After a decade’s cultural revolution, China began to shift the country’s strategic focus from ideological struggle to economic development. In 1978, at the national science conference, the then political leader Deng Xiaoping made a historical speech that science and technology are productive forces, which significantly legitimized the role of scientists and freed their mind. The establishment of Sino-US diplomatic relations and the start of China’s Reforming and Opening began to facilitate China’s scientific communication with western countries. In the early 1980s, leading returnee scientists (e.g., Qian Xueseng) advocated for carrying out AI research in China. Several AI-related research projects were listed in national scientific research programs. China sent a large number of students to study modern S&T in developed countries, including AI. In 1981, China’s Association of AI (CAAI) was established, which also initiated the first academic AI journal in China. CAAI made many efforts to promote AI as an emerging field of science and decouple its linkage with superstitious beliefs.

The institutional environment for AI research significantly improved when Deng Xiaoping indicated that ‘the popularization of computers should start with the childhood’ in 1984. The media began to have more positive reports on AI, and AI research stepped into a legitimate path in China. More AI-related research began to receive national S&T research grants (e.g. 863 programs). Universities, research institutes, and academic associations began to play important roles in promoting AI research. When it comes to the 21st century, China not only supported AI research with more government-funded research programs but also guided AI research to be more connected with China’s major economic development needs. During 2004–2010, the Ministry of Education officially approved the establishment of ‘Intelligent Science and Technology’ bachelor's degree program in 17 universities to cultivate more AI talent.

At this stage, though China did not achieve fundamental breakthroughs in AI research, it accumulated many technology capacities in areas such as pattern recognition, image processing, expert system, intelligent computing, and intelligent control (Cai, 2016).

4.2.2 After 2012: fast commercialization

By the 2010s, China has leapfrogged to one of the leading countries in the digital economy (UNCTAD, 2019). Particularly, the development in mobile internet has facilitated China to gain a dominant advantage in data volume globally (Ding, 2018). Chinese digital platforms, represented by Baidu, Alibaba, and Tencent (BAT), accumulated huge data volumes as well as computing capacities, and quickly grew to be listed as one of the world’s most valuable companies. After 2012, the progress in deep learning algorithms completed the last pillar of the current global AI paradigm. Chinese digital platforms actively adopted AI to profit from China’s massive data and huge markets. Baidu, for instance, was among the first group of companies that put forward an AI strategy globally. It established the world’s first research institute under the name of deep learning in 2013 (Li, 2017), and made huge efforts in attracting top deep learning talent from the United States. The joining of Andrew Ng, one of the world’s leading deep learning scientists, in 2014 was an eye-catching example. With these efforts, Baidu soon accumulated many world-leading technologies in voice recognition, image recognition, and autonomous driving, even before its global rival Google (CH-INT34). Similarly, other giant players (e.g., Tencent, Alibaba, JD, Didi, and Huawei) began to roll out their AI strategies and hugely invest in AI research, each with a different focus.

Meanwhile, AI start-ups mushroomed after 2014. Among them are many unicorns, such as Bytedance, Sense Time, iFlytek, and Megvii. However, most of the AI entrepreneurship occurred in the application domains. Many small start-ups rely on codes from global open-source communities (e.g., GitHub) and improve their technology by combining local data and application-specific knowledge. Many traditional sectors (e.g. finance, education, manufacturing) also actively adopted AI technologies to ‘empower their old business’ (CH-INT 61). Some even grew to be AI technology developers to make use of their data and build ecosystems (CH-INT 64).

AI entrepreneurship is considerably fertilized by China’s huge but diversified market demand, rich data, lower entry threshold, active venture capital, and lax regulations. Traditional sectors have a tremendous need to improve their efficiency to satisfy the growing but diversified demand of China’ huge population. AI, as an enabling technology, fulfils such a gap. For instance, in the scenario of healthcare, ‘China has much fewer regulations [in adoption], and hospitals are more willing to adopt new technologies’ (CN-INT05), despite current AI applications showing instability in accuracy. Similarly, in the scenario of security, there is significant demand from public security bureaus and residential communities for installing AI-based cameras to safeguard residents. Such applications are enabled by China’s lax regulations on privacy from the internet era (Li et al., forthcoming). As an interviewee of a face recognition company illustrated:

> '… China has lax regulations, resulting in huge demand. For instance, usually, a county-level city would need more than 10 thousand surveillance cameras, worth more than RMB 200 million, and a prefecture-city would need 100 thousand surveillance cameras, worth more than RMB1 billion' (CH-INT09).

In recent years, though concerns about privacy are rising with the expansion of information technology (Wang, 2011), privacy issues remain less considered when compared to efficiency, convenience, and safety by most Chinese citizens. For example, as the beneficiaries of many indigenous innovations such as e-payment and online shopping, the Chinese society, especially the young generation, has developed an optimistic attitude towards novelties (Arenal et al., 2020). According to a BCG/MIT Survey (see Jacobides et al., 2020), 86% of respondents in China generally trust the AI solution's decisions, whereas the figure is only 39% and 45% in North America and the EU respectively, highlighting key institutional differences at national levels that play a part in the development, application, and rates of diffusion of AI technologies across nations. Lastly, there is a high level of social trust in the technologies used by the public sector. As a researcher commented on face recognition technology: 'as a citizen, I do know that some of my information is being collected, but I don't worry at all that my data will be used maliciously' (CH-INT38).

This specific configuration of the institutional environment in China enabled heterogeneous actors to couple resources and to foster an AI innovation system (Arenal et al., 2020). Both domestic and foreign investors actively invested in Chinese AI companies, though most AI businesses have not made profits or even developed a clear business model (CH-INT05, 45, 54). From 2014 to 2018, China received the largest AI investment globally (Xue et al., 2018), with most investments in the fields of computer vision, speech recognition, and autonomous driving. Giant digital platforms were the main investors of many AI companies, especially in application domains. The primary rationale was to get into more scenarios and accumulate more data to expand their ecosystem (CH-INT58). These tech giants were also pioneers in developing domestic AI open-source frameworks (e.g., Paddle by Baidu, X-DeepLearning by Alibaba, and Mindspore by Huawei), showing ambitions to challenge the dominance of foreign frameworks (e.g., TensorFlow and PyTorch) in China. These AI frameworks, in turn, attracted talented developers and developed industry applications in various sectors (Jacobides et al., 2021).

Furthermore, the years after 2014 witnessed the implementation of several important AI-related national plans, particularly the DPNGAI, aiming to build China into a global AI powerhouse by 2030. As the primary implementor of DPNGAI, the Ministry of Science and Technology (MOST) not only allocated a large special fund for AI research—S&T Innovation 2030-Next Generation Artificial Intelligence—but also launched 15 National AI Open Innovation Platforms to advance industrialization in areas ranging from computing infrastructure to sectoral applications. Meanwhile, 13 AI pilot zones were initiated in dozens of cities for AI technology demonstrations, policy experiments, and social experiments (Arenal et al., 2020).

Governments at the provincial and municipal levels were also actively promoting AI industry development as they saw AI as the key lane for future regional competition. Measures such as tax reduction, R&D reimbursement, government procurement, and subsidies were the main policy tools. As a local industry association's executive observed: 'The government can either be a user through procurements or act as a bridge to connect the providers and users, sometimes use subsidies to encourage adoptions' (CH-INT03). Some local governments also collaborated with AI firms and universities to establish new-type AI research institutes to advance basic research (CH-INT14, 17).

4.2.3 What next: constraints and actor strategies

However, not all institutions are friendly to the infant AI industry, which *per se* is entwined with many legitimacy troubles. As AI applications transcend sectoral borders, the labour division between administration departments has been one of the most frequently mentioned issues (CH-INT34, 48, 49). In the case of the Internet of vehicles, for example, 'the vehicles and internet are administrated by Ministry of Industry and Information, while the road infrastructure is planned by Ministry of Transportation, who has a different roadmap for autonomous driving' (CH-INT26). A related obstacle is the segmentation of data among government departments. In projects such as Smart City, the major challenge is to aggregate relevant data that are scattered in various departments, such as the construction bureau, transportation bureau, environmental protection agency, and public safety bureau (CH-INT42, 50). A dilemma among the administration departments is that they want to support and regulate the emerging and complex AI industry at the same time, but many of them lack the expertise, personnel, data, and computing capacity to follow the industry development (CH-INT49).

Also, defining the ownership of data and the legal boundary of data use remains highly contested in China. Ambiguous data regulation is worrying many digital companies as to how to balance the trade-off between value creation and data protection legally (CH-INT67). Meanwhile, international data regulations (e.g., EU's GDPR) are triggering heated debates on data use in China, pushing China to improve its privacy standards. Ethics concerns on information leaks, information cocoons, algorithm discrimination, and job replacement are also spreading fast in Chinese society, especially in academia. In October 2019, a university professor in Hangzhou filed China's first lawsuit against face recognition use in a city zoo, leading to a widespread debate on the controversial technology.

Actions are being taken to respond to these challenges. At the central government level, to coordinate labour division between departments, a DPNGAI Promotion office consisting of 15 major ministries and commissions was established to implement DPNGAI and organize major AI research projects. Meanwhile, the government starts to pay much more attention to the ethical aspects of AI development. This is reflected in MOST's S&T Innovation 2030 project, which for the first time granted two social science research programs on the social impact of AI. In 2019, MOST issued 8 principles of AI governance, including fairness and justice, inclusiveness and sharing, respect for privacy, security and controllability.

China is also making efforts to balance data exploitation and data protection. In March 2020, the State Council issued an opinion to list data as the fifth market factor for the first time, parallel to the conventional factors: land, labour, capital and technology. In 2021, national laws on data security and personal information protection were released to strengthen data protection. Voluntary standards such as the Personal Information Security Specification have also been published and trialled by companies like Tencent and Alipay. At the local level, Beijing has released AI principles on R&D, use, and governance (BAAI, 2019). Also, local governments are striving to break department barriers and establish specialized data management bureaus to improve public service, as well as facilitate the development of digital industries (CH-INT50, 51).

Digital platforms and AI start-ups are active in shaping China's current and future AI institutions. At the planning level, digital giants actively lobby the central government to use AI to improve public service and boost economic development. At the 2017 National People's Congress, AI was written in the central government work report for the first time, indicating a consensus reached between government and industry in AI development (Li, 2017). Several industry players also sit on the board of the National AI Governance Committee and participate in formulating China's AI governance principles. At the industry policy level, digital platforms are deeply involved in forming regulations in areas such as autonomous driving, fintech, and smart cities due to their control of data and industry expertise. Many digital platforms have established specialized public policy or AI governance research institutes to study the frontier issues, such as data governance and privacy regulation (CH-INT26, 46, 48, 52). These platforms control a lot of data and thus can leverage this valuable resource to collaborate with influential universities to publish scientific papers and industry reports, and hence, influence policymakers. At the operational and technological level, the industry has more say in establishing standards. As a CEO from a face recognition company illustrated:

> 'When we first developed this technology, we were very aware of the ethical issue of privacy, that's why we voluntarily published our standard, which was adopted by the Shenzhen' Public Security Bureau and diffused to its 12 districts in 2017.' (CH-INT63)

Moreover, these tech corporations also develop many channels to influence public attitudes towards AI. Very often, they advertise the positive image of AI in e.g., finding missing people, reducing traffic pressure, and boosting economic development (CH-INT01, 37, 63). AI is also associated with global Sustainable Development Goals (SDG) to gain more legitimacy. Tencent, for example, launched an initiative of 'AI for FEW' (food, energy and water), and Megvii announced a public research project on AI governance and sustainable cities and communities. Together with academics, Chinese tech companies develop more ambitions in participating in international AI governance and using AI to address global challenges such as Covid-19 and climate change.

5. Cross-case analysis and discussion

The case presentation shows how the structure-agency interplay shaped AI development and diffusion in two case studies, resulting in nationally-specific AI trajectories: one focused on technology development and ethics in Canada and one driven by the market through commercial applications in China. Both countries have seen an intensification of agency in their second phases of AI development and diffusion, yet the key difference in institutional contexts and the type of actors involved at different stages have led to distinct AI trajectories.

In Canada, formal institutional support for long-term research and scientific innovation has generated a strong focus on AI research and talent development, underpinned by an ethical and human-centric approach rooted in culture. The strong role of formal institutions in supporting AI development and fostering a culture of scientific research and innovation is particularly evident in the initial phase of AI development through the provision of continued AI research talent funding by the government. On the other hand, stringent privacy laws and regulations coupled with an underdeveloped entrepreneurship culture have seen a slower organic commercialisation of AI technologies, prompting state-led initiatives aimed at stimulating AI applications. The interviews point in particular to broader informal institutional challenges, namely an underdeveloped entrepreneurship culture reflected in constrained start-up and growth ambitions, which consequently impact and hinder the scale of commercialisation. Entrepreneurial experimentation only started to take off around 2016, crystalizing in a proliferation of AI start-ups and the attraction of MNEs, with only a handful of prominent Canadian-born AI start-ups compared to the high number of Chinese-born tech giants. The Canadian institutional environment is therefore less developed in certain areas, with entrepreneurial culture lagging behind the strong culture of innovation driving AI research. However, these national-level institutional dynamics also reflect the choice for a 'different face of AI', one that may see slower commercialisation initially but one that is aligned to widely shared national values.

Moreover, awareness of the potential downsides of AI spurred significant institutional work through multi-stakeholder engagement to educate the public about the risks of AI. Institutional work by actors across academia, industry, government, and the Canadian public advocates for an ethical and human-centric approach to AI development, reflecting efforts to align the technology with Canadian values and thus the importance of national-level informal institutions. This has seen informal institutions in favour of ethical and socially responsible AI development more seamlessly translated into formal institutions through various policy instruments and public initiatives, reinforcing more stringent laws and regulations on privacy and personal data. Importantly, the focus on ethical AI reflects deeply embedded cultural values, highlighting the important role of informal institutions in shaping the development and diffusion trajectory of AI in Canada.

Conversely, though not a pioneer in AI research, China started to capitalise on AI's commercial potential early on. Formal and informal institutional support for AI basic research since the 1980s was gained by changes in political discourses and the influence of leading scientists and academic organisations. Nonetheless, the driving structural force of AI commercialisation is the result of a mix of laxer regulations, lower entry threshold, vast domestic market, and consumer openness towards novelties. As such, AI entrepreneurship in China became considerably fertilized by a combination of loose institutional soil and favourable growing conditions. Domestically-born digital platforms and the government are key actors that play a critical role in taking this institutional, market, and technological window of opportunity (Lee and Malerba, 2017), propelling AI to the top of the national agenda and prompting significant state support. A particularity of AI development in China is the ascent of digital giants and their accumulation of power, which enables them to not only mobilise important innovation resources to speed up AI commercialisation but also to act as institutional entrepreneurs in shaping formal and informal institutions (Yu et al., 2021). At the same time, informal institutions also play a key role in shaping the diffusion of AI within the country. In particular, Chinese traditional perceptions of privacy are more related to collectivism, 'saving face', and community-oriented values (Li et al., forthcoming), therefore leading to different societal preferences compared to the West. The structure-agency dynamics characterising AI development and diffusion in each case are presented in Figure 2 and Figure 3 below.

[Figure 2 here]

[Figure 3 here]

While Canada's institutional landscape remained relatively stable, China's formal and informal institutions have experienced more dynamic and fundamental changes during the past few decades. This was influenced by international political-economy changes, China's radical social transformation and rapid economic development, and influential political leaders, leading scientists, and powerful industry players. While a very rigid institutional structure constrained AI research before 1978, since the reform and opening, China's institutional structures were subject to frequent fluctuations, leaving significant space for heterogeneous actors to do substantial institutional work. It is reasonable that actors are more likely to fit and conform in a rigid institutional structure, while those in a changing institutional environment may be more able to stretch and transform (Smith and Raven, 2012). The difference in the stability of institutional structures is a key aspect that explains the different outcomes of the structure-agency interplays in China and Canada.

Moreover, while in Canada the diverse and purposive practices and activities of a wide range of actors is reflective of more mundane types of institutional work, in China, institutional changes by powerful actors are more resembling of institutional entrepreneurship, with little participation from the public. With citizens playing an active role in public debates and in shaping formal institutions, multi-stakeholder engagement and public participation are key features of the Canadian structure-agency interplay. This helps maintain the balance of power and prevents private actors from accumulating power to disproportionately shape the national institutions in relation to AI. In contrast, citizens in China are not active in shaping formal institutions.

The case analysis also highlights recent developments and implications for the evolution of current AI trajectories in the two contexts. In Canada, there are concerns that the presence of foreign tech giants, especially in the context of weaker organic commercialisation, and potential regulatory changes required to enable better AI commercialisation, may steer the current trajectory in new directions. However, a strong national culture supporting ethics and social responsibility, and democratic mechanisms that promote public participation, support an active citizenry and civil society advocating for an ethical approach to AI development and diffusion and are likely to reinforce the current trajectory. On the other hand, while domestic tech giants have come to dominate China's AI landscape, the country has more recently turned to AI governance considerations, aiming to lead on AI standards and code of ethics. The trialling of new, albeit voluntary, AI standards and regulations, as well as emerging public debates on the ethics of AI, may lead AI development and diffusion into new directions.

Furthermore, as pointed by others previously (Jacobides et al., 2021), we cannot ignore global dynamics and how these influence the development of AI across the world. Indeed, the AI trajectories of the two countries are not isolated but are also subject to influence by international institutions and actors. For example, at the institutional level, the EU's GPDR, is particularly relevant for international trade. This affects AI products and services of both Canada-based and China-based AI companies doing business with EU countries. Canada has recently updated PIPEDA, which mirrors GDPR to a great extent, while China is using the GDPR as an inspiration source in drafting its laws and standards. At the industry level, while Canada's AI industry is somewhat threatened by US tech giants, China has largely benefitted from the inflow of knowledge, talent, and capital from the US. China's giant digital platforms and AI unicorns play a critical role in mobilizing these innovation resources. Therefore, commercialisation is a pivotal process that anchors and couples innovation resources from both domestic and foreign territories.

Therefore, trajectories of emerging technologies are not definitive but in a constant flux whereby the structure is continually reinforced, contested, created, or changed by actors. This relates to a key issue in technology studies that concerns human agency, namely the extent to which actors can shape the development of a technology (Dafoe, 2015). Our findings challenge the acceptance of technological determinism and the imminence of potentially negative consequences. By showing how actors can resist and oppose unwanted technological outcomes in Canada's case and how they can create new structures in China's case, we highlight that it is also within our power to influence the trajectories of emerging technologies. Thus, the future progress of emerging technologies can be influenced by the choices made by societies and nations around the world.

6. Conclusions

Prior development studies have paid less attention to the role of technological innovations and barely investigated how, but more importantly why, technological trajectories differ across countries. This gap becomes sharper as the development and diffusion of emerging technologies (e.g., digital technologies, biotech, renewable energy technologies) are becoming increasingly important in addressing many development challenges in current world, e.g., economic growth, public health, and ecological environment. This paper examined the development and diffusion of AI in Canada and China, demonstrating how the structure-agency interplay in each country resulted in nationally-specific trajectories of emerging technologies. We show that Canada's AI trajectory is shaped by a rather stable institutional structure that stimulates scientific research, encourages multi-stakeholder participation, and promotes the ethical application of AI. However, a weaker entrepreneurship culture alongside stringent privacy laws and regulations has led to slower organic commercialisation of AI. Meanwhile, institutional work by various actors largely reinforces existing institutions, acting to solidify the current AI trajectory. In contrast, China's AI industry emerges in a dynamic and loose institutional structure with huge markets, lax regulations, low entry barriers, and high openness to novelties. Moreover, tech giants and the government are dominant players in mobilising innovation resources and commercialising AI but also playing the role of institutional entrepreneurs to legitimise AI development and diffusion.

While it is not new in other fields to study social-economic phenomena from a structure-agency perspective (e.g., Jacobides et al., 2016), this paper adapts this perspective with more enriched conceptual elements (e.g., institutional work) and dynamic relationships to understand trajectories of emerging technologies at the national level. We extend previous work on industry architectures and technological innovation through a focus on why technological trajectories differ across national contexts and on the structure-agency interplay. Tracing the development and diffusion of AI from its inception point, we provide an in-depth account of its different trajectories across the two geographical contexts studied, highlighting the varieties of AI as the result of the national-level structure-agency interplay across the decades. We go beyond institutional structures of production to show how the national-level formal and informal institutions at play have shaped technological development and diffusion more broadly. Importantly, we argue that institutions condition actor strategies in different geographical contexts but, as the technology develops, actors can act through institutional work to induce and initiate institutional changes, hence directing the technology's trajectory.

On the structure side, though some development scholars have highlighted the mutual influence between institutions and development process (e.g., Casson, Giusta and Kambhampati, 2010), there is little research addressing how formal institutions and informal institutions interact to impact the stability of institutional structures. In this paper, we show that formal institutions and informal institutions may align or conflict, reinforcing each other in Canada's case but reshaping existing structures in China's case. This analysis shows that institutions are not an 'unmoved' explanatory variable (Weber and Truffer, 2017) but are subject to changes from the international landscape, political economy, and actor strategies, especially in the context of developing countries. The levels of institutionalisation or stability of institutions exert different structural powers and create different spaces for institutional work. Developing countries may take advantage of institutional voids to facilitate fast development of emerging innovations (Castellacci, 2015). For development studies, when examining the impact of institutions on development issues, it is not sufficient to focus only on what institutions exist, but more attention should be paid to how stable they are and what accounts for their stability.

On the agency side, this paper articulates how institutional contexts condition the nature and outcome of institutional work. Facing the same opportunities brought by emerging technologies, actors in different institutional contexts exhibits different values, have different power relations and resources, and adopt different approaches to influence institutions. In AI's case, the emphasis on participatory democracy and lack of dominant players in Canada's AI ecosystem allows the civil society to maintain a stable institutional environment that matches their ethical values. In contrast, China is often characterized as a 'statist triple-helix' where the national state directs the government-industry-university relations (Ranga and Etzkowitz, 2013). China's government played a key role in directing the development and diffusion of AI through research support and industrial policies at the central and local level. Meanwhile, as AI commercialization progresses, tech giants gain an increasingly pivotal position in China's AI ecosystem (Arenal et al., 2020; Jacobides et al., 2021) and develop more resources and power to influence institutional changes (Yu et al., 2021). Therefore, we argue that institutional work literature should better recognise the role of the institutional contexts where the actors are embedded and pay more attention to the role of power relations between actors.

Therefore, the causal power of structure has different forms and strengths in different institutional contexts, and actors have different agencies, resulting in various spatial outcomes. Despite many technological innovation systems becoming increasingly global, and while regions may draw innovation resources from distant places (Binz and Truffer, 2017), the impact of technological innovation will be mediated by national institutional contexts and actor strategies. An institutionally-grounded and context-sensitive approach can help explain why certain technologies develop and/or diffuse more rapidly in some contexts than in others but also differences in how technologies are applied across different institutional contexts. This can provide practical insights for developing/emerging countries in terms of how to address the trade-off between the opportunities and risks brought by emerging technologies and leverage their institutional characteristics to pursue not only industry catch-up but also the social benefits of emerging technologies.

Admittedly, by focusing on the national-level structure-agency interplay, our analytical framework may overlook other elements such as value chain structures and the production and consumption blocks which are specific to individual technologies and which have been highlighted in previous industry-level studies (e.g., Jacobides and Kudina, 2013; Jacobides et al., 2021). Future studies can examine other national contexts to further unpack the dynamics between structure and agency, specifically how trajectories of emerging technologies unfold in other institutional contexts. Other aspects include power dynamics and the ability of specific actor groups to influence the rules of the emerging technologies, and the political-economic implications of varieties of technological trajectories. We need to better understand the impacts and implications for entrepreneurs, businesses, policymakers, and global governance initiatives. At the same time, future studies could focus on global influences and investigate the extent to which global dynamics permeate national-level boundaries to influence technological trajectories at the country level—this will be especially interesting in the case of AI given its strategic importance to countries and recent efforts towards the development of global AI governance frameworks and standards. Moreover, while this study focused on AI as a case study of an emerging technology, future studies can explore the development and diffusion of other emerging technologies across national contexts and untangle the complexities of their specific structure-agency dynamics. While AI is a general-purpose technology with wide applicability, it would be interesting to explore the influence of the structure-agency interplay in the case of other emerging technologies which may not lend themselves to the same degree of outcome variability.

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