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AI Adoption in Rwandan and Swedish Startups: A Comparative Study Through a Contextual Lens

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Abstract

This master's thesis examines how entrepreneurial ecosystems in Rwanda and Sweden adopt Artificial Intelligence (AI). It compares how different actors within these environments support or hinder technological integration. It builds upon the theory of National Innovation System (NIS), the role of the government, and digital dependencies. To answer the research question, the study uses semi-structured interviews with stakeholders representing startups, government, investors, academia, and innovation agencies in both countries. The findings section presents that Swedish companies are supported by well-established institutions, coordinated funding mechanisms, and organised innovation agencies, but AI spread is limited by fragmentation and regulatory ambiguity. On the contrary, Rwandan entrepreneurs benefit from a strong government vision but are constrained by infrastructural shortfalls, talent scarcity, and a lack of innovation mechanisms. The three comparative dimensions in AI adoption are related to applications of AI, government, and actors' roles on AI integration, and reliance on external technology. The research adds knowledge to understand AI implementation across different contexts and provides practical recommendations for policymakers and innovation stakeholders who wish to create a better environment for AI integration in startups.

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Chapter 1

Introduction

1.1 Background and Motivation

Since the launch of ChatGPT in late 2022, Artificial Intelligence (AI) has been a recurring topic that is commonly debated in the media. This technology is no longer a futuristic vision but a powerful, present-day innovation, reshaping industries, institutions, and entire economies (West & Allen, 2023). From natural language processing and computer vision to intelligent decision-making systems, AI has become widely embedded in tools and platforms that people use today (Soni et al., 2019). Though AI's impact is global, the ability to develop, adopt, and benefit from this technology, as many experts claim, is unevenly distributed. As the AI Preparedness Index, shared by the International Monetary Fund (IMF), suggests, wealthier countries are significantly better prepared for the upcoming technological revolution than states from the Global South (IMF, 2024). Only a few countries possess the required infrastructure, skilled workforce, financial resources, and governmental support to harness AI's full potential (Mannuru et al., 2023).

At the same time, the research on AI adoption has remained geographically limited. It has been predominantly centred around high-income countries, particularly the United States, China, and member states of the European Union. In contrast, far less is known about how AI is being approached, implemented, or constrained in lower-income economies. Many developing countries are actively prioritising digitalisation as part of their strategies for economic growth. However, there is still a void in studies that examine how these countries are building capacity around AI, not only within firms, but more broadly at the level of the ecosystems that surround them. Understanding how innovation systems in these states support or limit technological uptake is both academically relevant and of practical significance for potential policy and ecosystem changes.

As a result, a critical question arises: Can AI become a truly transformative technology if only a handful of ecosystems have the institutional and structural capacity to support its adoption? This question becomes even more urgent to address when we realize that AI might be classified as a group of technologies that are referred to as General-Purpose Technologies (GPTs). Technologies that are not confined to one sector or application but can transform the whole structure of economic and social activities (Sharma, 2023).

Similar to electricity or the internet, AI can fundamentally revise how industries function and how value is created. But the transformative potential of such technologies is not inherent, it is contingent. It depends on the quality of the broader environment in which innovation actors, especially startups, are embedded (Gambardella, 2009).

All of these possible changes do not happen in a vacuum. They heavily rely on the ecosystem's readiness level, needed for successful technological adoption. Aspects like skilled labor, digital infrastructure, adaptive regulations, or supportive governmental institutions have to be present (Ziegler & Yrjölä, 2021). Startups offer a practical lens through which to study these dynamics. As experimental and agile actors, they often serve as early adopters of new technologies (Gambardella, 2009). Yet their ability to do so is fundamentally shaped by the ecosystem they inhabit (Hillemane,2020). Analysing startups, therefore, provides a way to investigate how different national innovation systems condition the possibilities for AI adoption. Thus, to fill this gap, we explore this issue through a comparative study of AI adoption in startups in two different national contexts: Sweden and Rwanda. The first country is known to be one of the world's most innovative countries with a digitally mature economy. Sweden is seen as having a robust entrepreneurial ecosystem, a proactive regulatory environment, and a well-established startup culture (Global Innovation Index, 2024). Rwanda, on the other hand, is a rapidly developing digital hub in Africa. Their ambitions can be compared to Singapore's vision in the 1970s and 80s, to become a center for high-tech, innovation, and entrepreneurship, but on the African continent (The Economist, 2012).

In summary, the transformative power of AI will not be realised by technology alone, but by the conditions that allow it to be used successfully. Startups may be among the first to adopt and experiment with AI, but their ability to do so is never just a matter of internal ambition or capability; it is shaped by the broader system they operate in. Some ecosystems provide the space, support, and structure for innovation to flourish; others make experimentation more difficult, or even irrelevant. By looking closely at how Sweden and Rwanda differ in this regard, this thesis asks a larger question: what does it take for an entrepreneurial ecosystem, not just a company, to adopt a General-Purpose Technology like AI?

1.2 Research Problem and Questions

We address the existing academic gap by asking the following research question:

What roles do innovation actors of Sweden and Rwanda play in AI adoption in startups, and how does context shape their approaches?

Furthermore, we will also try to answer the following sub-questions to answer the main research question presented above:

- How do innovation actors affect AI adoption in each country, and what does this reveal about the institutional strengths and coordination gaps in each context?

- To what extent does the role of the state need to evolve to support the adoption of AI as a GPT, or can traditional functions suffice?
- How do dependencies on foreign platforms, tools, and funding shape the capacity of NIS to localise AI adoption?

1.3 Purpose and Contributions

This thesis explores what it takes for an NIS to support the adoption of a GPT-like AI. Rather than asking only what start-ups can do with AI, it shifts attention to the broader systems that either enable or constrain their efforts. Through a comparative lens on Sweden and Rwanda, two countries with contrasting innovation capacities but shared digital ambition, the study examines how institutional structures, state coordination, and global digital dependencies shape the way AI is adopted at the startup level.

The contributions of this research are both theoretical and empirical. Theoretically, it adds to the literature on General-Purpose Technologies and National Innovation Systems and highlights the need for analysing the context in which AI is embedded. It also extends NIS theory by highlighting its blind spot related to digital colonialism.

Through interviews with founders, investors, and ecosystem actors, this thesis provides concrete insights into how startups in Sweden and Rwanda contribute to AI adoption. It sheds light on the everyday obstacles startups encounter. It also explains how the role of the state must evolve in response to new GPTs. This research helps to explain why even in ecosystems with high ambition, the pathway to AI adoption is rarely straightforward, and why understanding that complexity matters.

1.4 Key Concepts and Definitions

Concept	Definition	Source
Innovation actors	Individuals and organizations, such as firms, universities, government agencies, and intermediaries, that are involved in the generation, diffusion, and adoption of innovations.	Lundvall (2010)

Entrepreneurial ecosystem	“Entrepreneurial ecosystems are combinations of social, political, economic, and cultural elements within a region that support the development and growth of innovative startups and encourage nascent entrepreneurs and other actors to take the risks of starting, funding, and otherwise assisting high-risk ventures.”	Spigel (2017)
National Innovation System (NIS)	The network of institutions and actors whose activities and interactions initiate, import, modify, and diffuse new technologies.	Freeman (1987); Lundvall (2010); Nelson (1993)
General Purpose Technology (GPT)	Technologies that have a broad impact across sectors and trigger complementary innovations that can reshape industries and drive long-term economic growth.	Bresnahan and Trajtenberg (1995)
AI adoption	The process through which organizations implement AI technologies into their processes, which requires readiness in terms of data, talent, and infrastructure.	Jöhnk et al. (2021)
Organizational readiness (for AI)	The degree to which an organization is prepared to adopt and benefit from AI, based on assets, knowledge, resources, culture, data availability, leadership.	Jöhnk et al. (2021)
Context (in entrepreneurship)	The set of circumstances, environments, or settings that surround and influence entrepreneurial behavior, including spatial, institutional, social, and temporal factors.	Welter (2011)
Absorptive capacity	A firm’s ability to recognize the value of new information, assimilate it, and apply it to commercial ends.	Cohen & Levinthal (1990)

Chapter 2

Literature Review

2.1 General-Purpose Technologies (GPTs)

To begin with, General-Purpose Technologies are described as foundational technologies that transform economies and are a cornerstone for further innovation. GPTs are said to be able to impact multiple sectors and generate long-term productivity gains. This term was first introduced by Bresnahan and Trajtenberg (1995) in their paper "Engines of Growth". They explained the role and impact of technologies, like the steam engine, electricity, and semiconductors, on the whole economy. In a nutshell, these inventions, do not only improve existing processes but also set the future direction of technological and economic development. GPTs are defined by three essential features: they are widely applicable across industries, capable of continuous technical improvement, and they promote the creation of complementary innovations in various sectors (Bresnahan and Trajtenberg, 1995).

To give some examples, the steam engine, which was initially developed for pumping water in mining, later became the central technology for transport, textiles, and industrial manufacturing. Its generality provided continuous rotary motion, enabling adaptation to a wide range of uses, and its technical improvement over time (from low-pressure to high-pressure engines) made it increasingly cost-effective (Crafts, 2004). According to Rosenberg and Trajtenberg (2004), its economic impact was not only due to direct efficiency gains, but also to the new industries and business models it made possible, such as railway networks and mechanised factories. Electricity followed a similar pattern. At first, its use was limited to lighting, but its key role as a flexible source of distributed energy eventually transformed production. David (1990) showed that electrification only translated into productivity gains decades after its introduction, once factories were reorganised to take advantage of decentralised electric motors. Last but not least, a more recent example is Information and Communication Technologies (ICTs). Microprocessors and personal computers spread rapidly across sectors and gave rise to software, digital services, and e-commerce. ICTs also reshaped firm structures by enabling real-time communication, global supply chains, and data-driven decision-making (Jovanovic & Rousseau, 2005). Brynjolfsson and Hitt (2000) demonstrated that ICTs contributed to productivity not merely through capital deepening, but by enabling new organisational practices and business strategies. These complementarities between the GPT and its downstream applications are at the core of the GPT mechanism. As noted by Lipsey et al. (2005), the productivity gains from GPTs are maximised when firms and institutions co-invest in learning and adaptation. For instance, electrification required electricians and electrical engineers, just as ICT adoption demanded new digital skills. With the advent and improvements of Artificial Intelligence, for the first time, researchers have extended the GPT concept to digital and data-based technologies (before only tangible inventions were considered as GPTs). Deep Learning, a core method within Artificial Intelligence, is increasingly recognised as a GPT (Crafts, 2023). According to Klinger et al. (2018), it meets all three key criteria.

What becomes evident from all of these examples is that the transformative impact of GPTs unfolds not in isolation, but through a long, non-linear process of co-evolution with their economic, organisational, and institutional environments. This slow and uneven trajectory has been well documented in historical analyses of previous GPTs. David (1990), in his study of electrification, highlighted that even once the technology became technically viable, it required decades of organisational change before measurable productivity gains were realised. In the view of Lipsey, Bekar, and Carlaw (2005), a GPT is not a stand-alone breakthrough but part of an interdependent system of technologies, institutions, and capabilities.

The literature also emphasises the role of institutional evolution in enabling or constraining the full potential of GPTs. According to Helpman and Trajtenberg (1998), the effectiveness of GPT diffusion depends not only on technical and market factors but also on how quickly institutions, such as education systems, intellectual property regimes, and public research infrastructure, adjust to support the new technology. Without such adaptation, a GPT may remain underexploited, or its benefits may be captured by only a few dominant actors. A good example of this can be found in the development of the American electronics industry after the Second World War. Silicon Valley, as we know it today, was not shaped only by the private sector. During the Cold War period, national innovation agencies like the U.S. Department of Defense or NASA played a crucial role in supporting the microelectronics industry. These institutions became the early buyers of semiconductors and integrated circuits (Bresnahan & Trajtenberg, 1995). In addition to that, research agencies like DARPA and the National Science Foundation (NSF) provided critical funding to universities. This funding supported work in computing, engineering, and materials science. Further, such support resulted in training a new generation of scientists and engineers who would later lead or join the region's emerging tech companies. Additionally, public policy further financed the growth of this innovation cluster by investing in infrastructure, research parks, and higher education, especially in California (Saxenian, 1996). According to Saxenian (1996), it was this combination of institutional support that allowed Silicon Valley to become the dominant centre for ICT development.

All these developments and changes illustrate that the transformation of ICTs into a General-Purpose Technology did not result only from market forces. It required coordinated investments across the public and private sectors. State-led initiatives, through procurement, subsidies, and education policy, were strategically used to create the ecosystem necessary for large-scale diffusion and productivity impact. This dynamic is highly relevant for understanding the present diffusion of Artificial Intelligence. Like earlier GPTs, AI depends on a broad set of complementary assets. These include access to computing infrastructure, high-quality data, digitally skilled labour, and strong research institutions. In environments where these conditions are weak or fragmented, AI tends to remain limited to niche applications and fails to scale systemically (Cockburn et al., 2018; Klinger et al., 2018)

2.2 National Innovation System: A Framework for Understanding Technological Adoption

As mentioned previously, technologies like AI do not develop in isolation but are determined by the environment that surrounds them. This thesis draws on the National Innovation System (NIS) as its principal conceptual framework. Developed originally by Freeman (1987) and later by Lundvall (1992, 2007) as well as Nelson (1993), the NIS framework stresses that innovation is not merely a product of market dynamics or firm-level decisions alone. Rather, it is an ongoing process of interaction among institutions, firms, and public policy, within a national context.

An appropriate definition of what constitutes a NIS is described by Lundvall (2007) as "the system of institutions supporting innovation and learning in a country." Universities, public research institutions, government, funding institutions, and private industry, to name but a few, comprise these institutions, which remain linked to one another within both formal as well as informal links. At its central premise, this school of thinking conceptualizes innovation as a learning process, one that is optimally facilitated in that countries establish an environment where knowledge can move freely and efficaciously among various participants (Nelson, 1993).

This systems perspective breaks from an exclusive focus on something like R&D expenditure or firm strategy. This systems perspective refocuses attention from discrete initiatives, such as firm strategy or R&D expenditures, to larger circumstances that enable innovation to occur. It highlights the interconnection, trust, and long-term commitments that facilitate knowledge flow and transformation into something valuable. In short, it is not about creating new technologies, but about building an environment that enables these technologies to be learned about, experimented upon, and replicated (Nelson, 1993).

Applied to an innovation like AI, the NIS framework explains as to why it is not just technical skills that are necessary. For AI to gain traction and propagate, startups also require access to stable infrastructure, clear legal systems, open data, ethical norms, and institutions enabling them to experiment (Cautela et al., 2019). All of these do not simply materialise, but need coordination between various components of the system. Innovation systems do not get created overnight. According to Lundvall (2007), systems mirror a nation's history, policy decisions, and state of institutional development.

In this thesis, NIS is not employed to measure who is 'best at' innovation. Instead, it is used as a lens to gain insight into what kind of support, e.g., policies, institutions, or networks, influences AI adoption at the startup level. Since this research is based on interviews with founders, policymakers, investors, and innovation support organizations, it is concerned with how these agents shape startup behavior in their local context. In this thesis, we collectively refer to these agents as 'innovation actors.' Furthermore, the unit of analysis in the thesis is not the country, but rather the startups. The NIS framework assists in determining what kinds of support are available within an ecosystem to either help or hinder AI adoption. Instead of presenting a top-down analysis of innovation capacity, this method pinpoints why, in everyday interactions, decisions, and limitations, real opportunity for startups to engage with technologies like AI arises or is stifled. In that respect, NIS is employed here as a diagnostic method. It assists in charting the environment that startups engage in and provides a common language to think about support systems created by innovation actors. This also provides the foundation upon which the comparative section of this thesis, where we analyze to what degree founders in Rwanda and Sweden feel that they experience their ecosystems when developing AI-supported businesses.

However, a key limitation of the NIS framework in the context of AI development is that it emphasizes national boundaries and domestic institutional networks. This may not adequately capture the global interdependencies that mark modern technological innovation. AI development often relies on global data flows and ecosystems that go beyond NIS. Moreover, when examining how emerging economies' startups are dependent on technological infrastructures and platforms from advanced economies, this limitation becomes particularly relevant as the NIS framework alone cannot fully explain.

While reviewing theoretical approaches, this study also considered other frameworks such as Technological Innovation Systems (TIS) and Entrepreneurial Ecosystems (EE). TIS, often applied to analyze the development of specific technologies (e.g., Bergek et al., 2008), provides a useful lens for tracing functional dynamics like knowledge development, legitimation, and resource mobilization. However, it is typically oriented around sectoral or technological boundaries rather than national or institutional contexts. In contrast, the NIS framework better captures how macro-level structures, such as policy, education systems, and public funding, interact to shape firm-level adoption behaviors, which is central to this thesis.

Similarly, the Entrepreneurial Ecosystems perspective (Stam, 2015; Spigel, 2017) offers valuable insights into localized, relational dynamics, highlighting culture, networks, and path dependencies in entrepreneurial activity. However, EE theory is often less well-equipped to analyze institutionalized support mechanisms such as public research funding or national strategies, both of which play an essential role in this study (Stam, 2015). Moreover, EE theory only provides a list of factors that allow for entrepreneurship; however, "they offer no consistent explanation of their coherence or their interdependent effects on entrepreneurship (Stam, 2015)." On the other hand, NIS offers a clearer structure to evaluate systemic coherence and policy coordination (Lundvall, 2007).

For these reasons, NIS was selected as the most suitable foundation for the thesis, and EE is used in this thesis as a subsystem of NIS, as AI adoption is looked at from the startups' perspective. Furthermore, the study argues that for any country to have a robust NIS, the entrepreneurial ecosystem should also be a core part of it, as they are usually the first ones to adopt and work with new technologies. This approach enables an institutional, context-sensitive comparison while remaining attentive to the startup-level implications of policy, infrastructure, and national ambition, particularly relevant for a comparative study between countries with differing levels of innovation system maturity.

2.3 The Role of the State and Coordination Within NIS

Within NIS theory, the role of the state is viewed as a key player that brings more value than just funding opportunities or supportive regulations. Particularly in the case of emerging technologies such as AI, state action is often pivotal to determining the circumstances under which innovation is possible (or not possible). According to Lundvall (1992), innovation does not happen in a vacuum, and is not created only by and within companies. It is an outcome of interactions among firms and various public and private players, such as universities, funding agencies, and regulatory institutions. In this account, state action is crucial to facilitating, coordinating, and stabilizing these interactions.

STI policy is one of the state's principal mechanisms to drive innovation. In high-performing systems of innovation, STI policy does not just subsidise R&D or attract international investments. It provides institution building, learning support, and establishes long-term coordination frameworks (Freeman, 1987; Lundvall, 1992). Particularly with technologies that are uncertain, data-driven, and transsectoral, like AI, governments need to build spheres where innovation is possible responsibly and at scale. This means data regulation, standard setting, and occasional support of underlying infrastructure, such as compute capacity, open data, or public R&D facilities. All states, however, are not similarly well-placed to serve this coordinating role. A few developed nations possess well-established STI systems. Innovation agencies act independently but also strategically to support national technological objectives. In these systems, there is likely to be easier availability of seed funding to startups, domain-specific know-how, and advice on regulation and ethics (Freeman, 1987). An opposite situation can be found in undeveloped countries, which do not have mature STI policies. National roadmaps and digital visions often reveal that a developing state is actively seeking to create an environment that is friendly to innovation. But these initiatives are frequently bound by weak institutional capacity, ecosystem fragmentation, and reliance on outside agents, such as international donors, foreign technical advisers, or platforms brought in from overseas. According to Lundvall (1992), establishing national innovation systems is an incremental, path-dependent process; states need to invest not only in specific policies but in institutions that facilitate collective learning and interaction.

2.4 Entrepreneurial Ecosystems as Subsystems of NIS

Although most of the National Innovation Systems focus on institutions, universities, and formal systems of R&D, innovation also rests on what surrounds and influences entrepreneurship on the ground. Entrepreneurial ecosystems have become increasingly prominent in recent years as a means of characterizing local contexts where startups are created, nourished, and grown. Such ecosystems often consist of incubators, accelerators, early-stage financiers, co-working facilities, startup groups, and other entities that engage directly with founders and small innovation-oriented firms (Stam, 2015; Isenberg, 2010).

Instead of considering entrepreneurial ecosystems to be independent of NIS, this thesis holds that entrepreneurial ecosystems exist as functional subsystems, local manifestations of what is working in the larger innovation system for startups. A university is within the national system, but what it contributes to entrepreneurship is determined by whether it is well linked to incubators, venture capital, and startup teams. A government's policy is only effective if it is turned into effective programs and instruments of funding that reach companies at a startup level. Entrepreneurial ecosystems, in this sense, are where institutional objectives of the NIS become reality for startups.

Lundvall (1992) stresses that innovation systems need to facilitate not just knowledge creation, but also its diffusion and application through iterative learning. Entrepreneurial ecosystems play an important role in this context. They establish the relations, trust, and knowledge-exchange systems that allow entrepreneurs to translate abstractions like AI into usable, grounded goods and services. This is particularly necessary for startups that work with sophisticated GPT, like AI. In advanced ecosystems, startups also draw advantage from public–private collaborations, organized support programs, and established capital markets that render AI experimentation possible. For instance, government-sponsored incubators might deliver AI training; universities might engage in joint research on applications; and government organizations might alleviate uncertainty associated with regulation by rendering it clear or setting up sandbox schemes.

In emerging ecosystems, the intent might be similarly strong, but the ecosystem's maturity and actor density are still building up. Founders of startups tend to depend upon their social contacts, donor-enabled incubators, or global diaspora to draw upon resources that would otherwise be provided by domestic institutions. Such entrepreneurial ecosystems are shifting, but also potentially unstable, fragmented, or externally driven.

Significantly, any entrepreneurial ecosystem is effective not solely on the actions of its internal players, but also on its connection to its larger NIS. Ecosystems become stronger when national policy is customized to local startup requirements, when universities facilitate commercialization, and when methods to reduce risk in the early stages of start-up financing exist. When these links are loose or nonexistent, start-up companies struggle in solitary isolation, even in otherwise conducive innovation climates.

2.5 Digital Colonialism and Digital Inequality

While National Innovation Systems explain well how nations facilitate entrepreneurship and coordinate technological progress, they miss an important aspect of today's digital economy: global asymmetries of control of infrastructure, data, and AI capacity. Such asymmetries are not random. They are structural characteristics of an increasingly platform-shaped digital order, one that is dominated by a few large platform companies and institutions based in the Global North. This has prompted scholars to refer to today's times as an era of digital colonialism, a state of affairs where nations in the Global South remain structurally dependent on exogenous technologies, platforms, and standards, even as domestic innovation capacity is locally established (Couldry and Mejias, 2019).

Digital colonialism, as explained by Couldry and Mejias (2019), is a type of twenty-firstcentury dominance where data, digital infrastructures, and algorithmic control are used as means of control. For example, data is collected from users, usually without any real consent, and monetized into economic value by parties distant from where it is created.

Most AI models are trained on Western-centric datasets that embody particular cultural, linguistic, and normative assumptions (Birhane, 2021). Consequently, AI systems are designed to respond to specific problems, formulate these issues, and establish what kind of data to consider most important, often missing local realities in the Global South. This confirms what Salami (2024) describes as epistemic injustice. It is a process whereby marginalized groups' values become structurally outside of technological development and interest (Salami, 2024).

This also sets up a basic limitation of the NIS framework. Classic NIS theory presumes that innovation inputs like capital, skills, as well as infrastructure either reside within the system or may be created through coordinated national policy. But in AI, key innovation resources are externally controlled and embedded within transnational platform infrastructures. This implies that even where institutions at the national level get it right, their power to shape or localise AI development is shaped by where they sit within the hierarchy of the digital world. This thesis suggests that these structuring dynamics of digital colonialism need to be understood as outside constraints on innovation systems. They work outside of traditional STI policy and national coordination channels.

This literature foregrounds a critical blind spot in traditional NIS approaches: the assumption of national autonomy in innovation governance. In the age of AI, where essential infrastructures are globally centralised and controlled by a small number of dominant actors, the traditional assumption that countries can independently shape their innovation trajectories is increasingly difficult to uphold. Even when countries build strong internal coordination mechanisms, they may still find themselves limited by their lack of control over essential digital infrastructure. This challenges one of the core assumptions of the NIS framework, that innovation inputs like data, infrastructure, and tools can be fully developed or managed at the national level. In reality, many of these resources are embedded in a global digital architecture, shaped by actors far beyond domestic reach. Digital colonialism, then, is not just a backdrop; it actively shapes what innovation systems can and cannot do. These ideas provide the theoretical lens for our inquiry. The next chapter outlines the methodology used to study how these overlapping national and global forces influence the adoption of AI in two very different settings.

Chapter 3

Methodology

3.1 Study Design and Rationale

This thesis adopts a qualitative, comparative case study methodology to better understand how context and environmental factors affect Artificial Intelligence adoption among Swedish and Rwandan ecosystems. The central research question is to identify mechanisms, challenges, and enablers that steer AI adoption in two different innovation systems. A qualitative method is adapted to describe rich, contextualized reality among entrepreneurs, policymakers, and ecosystem players in both countries (Maxwell, 2013). A qualitative method is capable of enabling inductive insight into practices and meanings that quantitative methods might struggle to measure (Creswell & Poth, 2018).

The comparative case study approach is based on the logic of replication (Yin, 2018), wherein Sweden and Rwanda were chosen not as polar extremes but as contextually different systems that provide contrasted theory. Sweden, as a mature country with advanced infrastructure and institutions, provides an insight into innovation-led adoption, while Rwanda, as an emerging tech ecosystem and government-interventionist setting, provides an insight into development-driven adoption.

The interpretivist framework corresponds to earlier studies of entrepreneurship in context (Davidsson, 2015; Welter, 2011), innovation systems theory (Nelson, 1993; Lundvall, 1992), and technological pathways as shaped by ecosystems (Spigel, 2017; Autio et al., 2014). Specifically, it draws on an understanding that innovation is an institutionally conditioned, socially constructed, and embedded process (Freeman, 1987; OECD, 1997).

3.2 Case Study: Sweden and Rwanda

The two national contexts were chosen for their strategic relevance, differing institutional characteristics, and increasing significance of startups within their development strategies. Sweden is known for its well-developed entrepreneurial environment, high research and development spending, and active innovation agencies like Vinnova and AI Sweden.

Rwanda, although still developing in terms of technology, is an emerging digital policy leader in Africa, boasting initiatives such as the Rwanda National AI Policy (2022) and organizations like RISA and Irembo as drivers of the tech environment.

Case selection was theory-driven and deliberate (Patton, 2015). Sweden is an "innovation-led" model, which has decentralized, market-driven institutions and high absorptive capacity (Cohen & Levinthal, 1990). On the other hand, Rwanda is an example of a "developmental" model with features such as centralized policymaking and robust state coordination. This variation provides scope to analyze how varying systemic conditions, funding schemes, regulation clarity, infrastructure, and availability of talent impact the adoption and application of AI technologies.

In both countries, participants were selected from startups, investors, incubators, and public agencies, thus ensuring multi-actor, embedded insights that capture the multi-layered character of innovation systems (Freeman, 1987; Lundvall, 2010). Such heterogeneity enables cross-actor insight as well as macro- and micro-level insight using triangulation.

3.3 Data Collection: Semi-Structured Interviews

The data collection process was carried out from February to April 2025 using semi-structured interviews. In total, 30 interviews were conducted, of which 15 were in Rwanda and 15 in Sweden. The data collection process aimed to understand to what extent actors perceive, experience, and manage the possibilities of AI adoption in respective ecosystems. It is worth noting that the process of scheduling interviews in Sweden proved considerably more challenging than in Rwanda. The response rate among Swedish stakeholders was significantly lower, and several interview requests went unanswered despite multiple follow-ups. This contrasts with a common narrative in Sweden and in general, in Europe, that emphasises open collaboration and accessibility within entrepreneurial ecosystems. In practice, Swedish actors appeared more reserved and less approachable, particularly when compared to the more open and responsive engagement observed in Rwanda.

Table 3.1: Interview Participants from Rwanda

Company/Organization	**Position within the Company**
Carnegie Mellon University	Student, Founder of the Africa Innovators Society — a student association
Pebla (Start-up)	Founder
National Bank of Rwanda	Director of the Management Information Systems Department
AQS - Africa Quantitative Sciences (Start-up)	Co-Founder
Umurava (Start-up)	Founder and CEO
Angaza Capital (Venture Capital)	Associate
Renew Capital (Venture Capital)	Senior Manager, Investment Research
Harakameds (Start-up)	Co-founder
Kayko (Start-up)	Co-founders (2)
BAG (Start-up)	Co-founder and CIO
Gwiza (Start-up)	Legal Risk and Compliance Manager
Irembo (Governmental Service Provider and Innovation Agency)	AI Developer
Kapsule tech (Start-up)	Co-founder
Outside hospitality (Start-up)	Founder
Kudi Books (Start-up)	Product Usability Specialist

Table 3.2: Interview Participants from Sweden

Company/Organization	**Position within the Company**
GU Ventures (Venture Capital)	Business Development and Intellectual Property Specialist
Knodd (Start-up)	Co-founder
Compular (Start-up)	CTO
Chalmers Ventures (Venture Capital)	Head of Venture Creation, Pre-seed Investment Director
Endre Tech (Start-up)	Co-founder and CTO
AI Sweden (Innovation Agency)	Research Scientist in Privacy-Preserving Machine Learning
Eperoto (Start-up)	Co-founder and Head of Product
Anyolabs (Start-up)	Co-founder and CEO
Chalmers Industriteknik (Innovation NGO)	Director of Strategic Collaborations
Vinnova (Innovation Agency)	Program Managers (2)
Gothenburg University	Professor
Law Library AI (Start-up)	Co-founder
Almi Invest (Venture Capital)	Financial and Innovation Advisor
The Space (Research Institution)	Business Consultant
Cosmofoil (Start-up)	Co-founder and CTO

The participants were chosen employing purposive sampling, based on maximum variation logic (Patton, 2015). This included representatives of early-stage startup founders, innovation agencies, ecosystem builders (incubators or accelerators), venture capital investors, and players at the policy level. The intent was to get a range of perspectives from the public-private sector divide. In Rwanda, for instance, startup founders represented industries like healthtech, fintech, and edtech, as well as players from institutions like the National Bank of Rwanda and Venture Capitals like Renew Capital. In Sweden, along with founders of medtech, lawtech, and AI startups, participants covered tech creators supported by Almi and Vinnova, and researchers working in AI Sweden and regional universities.

The length of each interview was 45 to 75 minutes, and it was done in person or using secure online video conferencing, based on time and travel considerations. The interviews were conducted in English.

An interview guide (See Appendix A) was constructed and adapted to the type of actor (for example, startup versus policy agency), but all of the interviews covered underlying topics such as:

- The perceived value and opportunity of AI within the startup's operation or vision
- Current use (or lack of use) of AI tools or technologies
- Internal adoption impediments (such as talent, expense, time, and infrastructure)
- External enablers or constraints (for example, funding availability, training programs, or policies)
- Institutions (example: AI Sweden, RISA, Vinnova, Rwanda ICT Chamber)
- Wider considerations of the readiness of an ecosystem for future technologies

Interviews were audio-recorded, with participants' consent, and transcribed word for word using Microsoft Word Online provided by the University of Gothenburg to its students, to analyze them in detail. Field notes were also taken following and concurrently throughout every interview to note impressions and initial analytical observations. The total dataset consists of more than 25 hours of recorded discussion and about 250,000 words of material in transcripts, supported by works of literature, websites, and policy reports to create triangulation.

Precautions were taken to safeguard confidentiality. All participants were verbally informed why and how their data would be utilized. Names and positions of interviewees were anonymized. The methodology permitted participants to speak freely about systemic and individual aspects of AI adoption, from local data deficiencies and training capacity to more conceptual issues about "AI as a buzzword" or strategic misalignment questions. Out of these interviews emerged rich, grounded, and sometimes contradictory narratives about the everyday reality of technological innovation in two distinct national systems.

3.4 Coding Strategy and Thematic Analysis

The analysis adopted an inductive thematic coding method based on reflexive thematic analysis principles (Braun & Clarke, 2006, 2021). The aim was not to simply document surface-level answers, but to infer underlying trends throughout the data that might speak to what influences AI adoption based on environmental, institutional, and entrepreneurial dynamics in each nation.

The transcriptions were listened to entirely to familiarise ourselves. Coding was initially conducted inductively, whereby categories arose naturally from the data rather than forcing them into preconceived conceptual schemes. With continued development of the process, however, codes were more and more informed by conceptual frameworks that framed this study, especially NIS, entrepreneurial ecosystems, and contextual embeddedness theories of entrepreneurship (Lundvall, 1992; Welter, 2011; Spigel, 2017).

Analysis was carried out first using ChatGPT and then manually checking through it to make sure the themes and codes are correct and relevant. The codes were assigned to descriptive statements (such as "lack of local data infrastructure") as well as to more interpretive ones (such as "AI as legitimacy-seeking tool") (See Appendix B). Each of the transcripts generated about 10 to 15 preliminary codes. These were brought together into wider categories in an iterative process of memoing and ongoing comparison within Swedish as well as Rwandan data sets.

Three coding rounds were carried out:

- Early Coding: Fragment-level analysis of actions, constraints, and actor strategies. The codes stayed close to the participants' language.
- Focused Coding: The codes were organized under larger themes like "infrastructure readiness," "policy visibility," "AI literacy," and "entrepreneurial workarounds."
- Analytical Framing: Final themes were defined into conceptual categories that map onto the central analytic path that was taken into account in the thesis — environment-driven (system-led) approaches to AI adoption.

Throughout, national patterns were closely followed. For instance, in Rwanda, themes of "government-as-partner" and "policy aspiration vs. infrastructural gap" were prominent. In Sweden, on the other hand, "institutional fragmentation," "data-sharing reluctance," and "resource abundance but strategic ambiguity" were regular features.

The final themes were checked against the entire dataset to confirm that they were empirically grounded and representative of the diversity of standpoints. This iterative, theory-guided but grounded process enabled strong analysis that is respectful of both data complexities and research comparative aspirations.

3.5 Ethical Considerations and Limitations

Ethical integrity was fundamental in every aspect of the design and conduct of this study. With entrepreneurs, government representatives, and ecosystem players from two countries being involved, care was taken to respect and be transparent to participants, irrespective of position or perceived power of institutions.

All of the participants were briefed in advance on the kind of research and its purpose, and consent was verbally established before conducting the interviews. The participation was voluntary, and interviewees were also told that they were free to skip any question at any time. The names of the participants have also been anonymized in this thesis so that it protects confidentiality where sensitive critiques of government programs, funding practices, or institutional gaps were divulged.

Data were safely kept and only accessible to the researcher, and anonymization was employed to limit the likelihood of indirect identification.

Although attempting to be rigorous and reflexive, there were some limitations to be noted:

Use of Generative AI:

In this thesis, we have used Generative AI like ChatGPT, DeepSeek, and Claude for various reasons. ChatGPT was primarily used for brainstorming ideas in the initial phase of the thesis, checking for grammatical errors and typos, and getting suggestions for better sentence structures. It was also utilized for summarizing large transcripts and creating themes. DeepSeek was primarily used to double-check ideas suggested by ChatGPT and also as a brainstorming tool. Finally, Claude was used to generate code for LaTeX, whenever the authors had difficulties, for instance, properly adding certain tables.

In some instances, conversations with GenAI could have limited authors' analytical contributions. However, by thoroughly examining the suggestions, the authors have made sure that the biases of GenAI are eliminated and that suggestions are relevant and well aligned with the empirical data.

Contents:

Findings are also dependent upon the temporal, spatial, and sectoral environment within which interviewing took place. In Rwanda, for instance, AI policy was just introduced in 2022, and thus, certain of its institutions were still taking shape. In Sweden, AI ethics and public procurement were subject to ongoing debate and change at the time, as well. On these bases, findings ought not to be viewed as time-bound or generally applicable to anywhere else.

Language and Cultural Framing:

Although every interview employed the use of English, participants of differing fluency levels may have affected the ease with which certain points were expressed, especially for some Rwandan entrepreneurs. Every effort was made to ensure comprehension and rephrasing when necessary, but some cultural nuances may potentially be lost or misinterpreted when understanding meaning rather than language per se.

Depth vs. Breadth:

While the study prioritizes depth over breadth by limiting the focus to two countries, it does so at the expense of broader generalizability. Kenyan, Indian, or Finnish startups, for example, can face various constraints of the ecosystem not captured in the research. The comparative logic is intended to produce analytical contrast, rather than a comprehensive representation of the Global South or the Global North. Despite such limitations, this study provides an understanding of the interplay between entrepreneurial agency, institutional configurations, and national innovation systems. Grounding research in daily life and situating it within broader theory debates, this creates a strong basis for findings and analysis that follow.

Chapter 4

Findings – Rwanda

4.1 Overview of the Rwandan Entrepreneurial Ecosystem

Until recently, being an entrepreneur in Rwanda carried a negative connotation. Business owners were seen as those who specialized in informal trade, buying things only to sell them for a profit, or did not pursue higher education. Many of the earliest and most visible start-ups in the ecosystem were founded by foreigners. Most of them brought their international experience and capital to fund their projects. Zipline, for instance, a well-known drone delivery service for medical supplies, launched its operations in Rwanda with significant external expertise and funding from the US. Similarly, Safi, a Canadian-founded venture, developed a portable milk pasteurisation device aimed at empowering East African farmers.

This perception of entrepreneurs who are rather greedy and needless started to change as more foreign founders proved to be successful, and when Rwandan people educated abroad returned home. These individuals brought new perspectives, business acumen, and a willingness to embrace global technologies. As the founder of BAG noted, "Six years ago, being an entrepreneur had a negative connotation, and there were very few business owners." Now it's more popular and socially accepted, being an entrepreneur is something cool now". Furthermore, the Rwandan government was committed to fostering innovation, particularly through digital transformation initiatives and national plans such as the Smart Rwanda 2020 Master Plan, which aimed to develop ICT services and build up the nation.

The growing availability of AI tools, especially after the launch of ChatGPT, has played a key role in accelerating this transformation. These tools have made it easier for aspiring entrepreneurs to get started, even with limited resources, by helping them work faster and develop creative solutions. In Rwanda, the spread of AI is gradually shaping how start-ups think about and build their businesses. More and more entrepreneurs are recognising AI's potential to boost efficiency, streamline operations, and even power entirely new products. This shift is becoming increasingly visible as AI tools start to play a bigger role in the day-to-day work of start-ups. While the majority of Rwandan firms still use AI for internal tasks such as content generation and coding, a growing number are exploring AI-based service offerings. As one founder noted, "AI is a big time saver when it comes to writing reports, conducting research, and other tasks." At Kayko, the team pointed out that using AI in "coding sprints" has helped them shorten project delivery times. In a similar way, Kapsule Tech has integrated AI into its daily workflows, especially in marketing and social media, to improve efficiency and stay competitive.

One of the key characteristics that sets the Rwandan start-up ecosystem apart is its openness and collaboration culture. As a founder from HarakaMeds explained, "People within the private and public sectors have a close connection with each other, and people are easy to approach." This view was confirmed by the BAG co-founder, who remarked that public–private cooperation in Rwanda surpasses what he has seen in both African and European contexts. What is more, Kayko reported collaborating closely with Irembo on technical matters, and Kudi Books said that they had received support from the ICT Chamber and had participated in events co-financed by Irembo. The founder of Outside Hospitality similarly shared that although their collaboration with the Chamber of Tourism had yet to yield concrete outcomes, the opportunity for engagement was readily available. As they put it, "The company was invited by the Chamber of Tourism for some collaboration."

Knowledge-sharing appears to be embedded in the culture. As the CMU student behind the Africa Innovators Society (AIS) explained, their club hosts workshops, hackathons, and meetings with VCs to cultivate entrepreneurial thinking. "AIS provides a supportive community where members gain the skills, experiences, and connections to turn their entrepreneurial passions into real-world impact," he said. Collaboration between start-ups and government bodies also fosters a dynamic and iterative environment. Harakameds described policy workshops where regulations were reviewed line by line in collaboration with the public sector. As the founder explained, "The government had a few ideas for policies, and then gave them to the private sector to review." Some things were accepted, some rejected."

This ecosystem-level synergy is not only horizontal (between start-ups and support organisations) but also vertical, encompassing interactions with senior officials. Kapsule Tech highlighted how easy it was to access government authorities, while the co-founder of BAG noted being invited to informal gatherings with policymakers. "If I were developing a startup in Sweden, I would probably never have met with a ministry to talk about business," he said. "In Rwanda, I am often invited for dinners or lunch with different governmental representatives."

However, despite its rapid growth and interconnectedness, Rwanda's entrepreneurial ecosystem remains relatively small and immature. As Renew Capital's representative noted, "It is still difficult to find companies to invest in in Rwanda... many start-ups are not business-ready, still working on their idea." BAG's founder similarly pointed to a shortage of soft skills, such as communication and problem-solving, and Outside Hospitality acknowledged that the limited customer base makes it hard to scale certain business models. As the co-founder of Kayko observed, "There are too few AI products on the Rwandan market right now... they need more time to get feedback and learning from each other." The entrepreneurial landscape in Rwanda is thus marked by an unusually high degree of connectivity and accessibility. While systemic challenges remain, the ecosystem is clearly oriented toward collaboration, collective learning, and mutual support. As Irembo's AI developer put it, "The private sector should be the lifeboat or speedboats, not the Titanic... The government is like a whale that is creating a stream line after itself, allowing smaller fish—the private sector—to use it to their advantage." This chapter presents findings from interviews conducted with start-ups, investors, and policymakers in Rwanda, categorised into three major themes: (1) how organisations are using and adopting AI, (2) the role of government and innovation actors in supporting AI adoption, and (3) the issue of digital dependency.

4.2 How Organisations Are Using AI

Table 4.1: AI Usage Levels Among Rwandan Startups

AI Usage Level	Startup Name
Level 1: Use existing AI tools (e.g., ChatGPT, Copilot) for general productivity, content generation, or prototyping.	Pebla, AQS, Umurava, Harakameds, Kayko, BAG, Gwiza, Irembo, Kapsule Tech, Outside Hospitality, Kudi Books
Level 2: Develop internal AI tools for improving their own operations or for specific internal purposes.	Irembo, Kayko, Umurava (currently building internal AI tool), AQS
Level 3: AI is a central component of the final product or service offered by the start-up.	AQS, Umurava, Harakameds (currently building AI-based service), Kayko, BAG, Irembo

Startups interviewed crossed industries like fintech, edtech, healthtech, accounting, and tourism. But there was agreement on what they prioritized. The startup founders and representatives were unanimous about emphasizing solving tangible problems within the context of the country. They revealed that, as a nation where most of its population resides in rural areas, it is necessary to address real issues in an easy and usable form that is accessible even to residents in the most rural corners of Rwanda. For instance, platforms such as Kudi Books aim to ease accounting and automation of school fees, while others like HarakaMeds and Kapsuletech endeavor to digitize medical supply chains. Far from being extremely innovative, these might be just what the nation needs its entrepreneurs to accomplish to address the contextual issues within the country. As one of the co-founders said, "What we're doing is not about building the next big AI company. It's about making small tools that solve actual problems, like how schools manage their finances, and how people without accounting skills keep their records." The use of AI by start-ups in Rwanda spans from basic task automation to the development of AI-driven products. These applications can be classified into three broad levels: (1) using AI for efficiency and internal support - using available AI tools, (2) developing AI tools for internal use and analytics, and (3) offering AI as a central component of the final product or service.

4.2.1 Level 1: AI for Internal Efficiency

The use of AI in Rwanda, in the majority of cases, is limited to improving operational efficiency through external tools. Many early-stage ventures leverage generative AI services such as ChatGPT, Bing AI, Grok, and DeepSeek to save time with tasks including content generation, report writing, coding, customer communications, and basic research. Kapsule Tech described this process as part of their "daily operations," specifically highlighting marketing and social media management as areas where AI provides speed and consistency. Similarly, BAG uses ChatGPT Plus and Grok Premium to conduct market research and generate customised content for employers and candidates. "AI is a big time saver in writing reports and research," the co-founder noted. AQS, a data science firm, also sees a big value in AI. They use AI tools such as ChatGPT primarily for research, data summarisation, and enhancing team workflows. Their use of AI, while not deeply integrated, supports the team's efficiency. Outside Hospitality, which is still in the early stages of scaling its platform, also expressed interest in AI but emphasised that they currently lack the customer base and data necessary to fully deploy it. Nonetheless, they use tools like ChatGPT to support day-to-day tasks. Kudi Books operates similarly, planning to use AI for process automation in the near future. According to the Product Usability Specialist, "AI is something we have to tap into. The full implementation is still at least a year away until everyone knows how to properly use it."

4.2.2 Level 2: AI for Internal Tools and Advanced Operations

Some start-ups are trying to move beyond third-party tools and are experimenting with building their own AI solutions for internal use. This intermediate level of integration focuses on improving internal collaboration, project management, and decision-making. Kayko stands out in this regard. They use AI to support development sprints and project management, allowing the team to complete work in less time. "The sprint is shorter than before, and people are more efficient," one co-founder noted. Moreover, they have developed a basic AI-powered CRM to optimise customer engagement and retention. The start-up also sees AI as a way to generate business recommendations based on transaction data. Their internal tools are designed to provide decision support for financial management, such as advising on how to recover accounts payable more quickly, all based on their internal data. In a similar vein, Kapsule Tech is beginning to build internal analytics capabilities using AI. Though the team still depends heavily on external tools, they are investing in training staff to apply AI techniques more systematically across departments. AQS also shows signs of transitioning toward this level. They expressed plans to develop more tailored AI tools for local data analytics and are actively exploring ways to build in-house capacity for future integration. The last example is the Africa Innovators Society at CMU Rwanda, which encourages students and founders to develop AI tools within campus-based labs and innovation hubs.

4.2.3 Level 3: AI as a Core Product Feature

A limited but growing number of start-ups in Rwanda are embedding AI directly into their customer-facing products. These firms are not only using AI internally but also designing their core services around it. Kayko is again a relevant example. The team is developing AI-based features to support supply chain optimisation and automated decision-making in financial services for their customers. As one co-founder described, "AI can provide many recommendations based on our data, helping SMEs make more informed operational choices." This positioning of AI as a business enabler rather than just a backend tool indicates a transition toward mature integration. BAG has also taken steps to incorporate AI into its service. The platform uses AI to generate personalised feedback for students and enable simulations for employers. However, due to resource constraints, these features are developed via external APIs rather than in-house models. The co-founder remarked, "It is still too vague and out of the Rwandan context," highlighting the limitations of using foreign-developed AI tools in African markets. Other than these three, none of the other start-ups have their products or services AI-based. However, some of them mention that they see that AI can become their core technology regarding their offering shortly.

4.2.4 Beyond Start-Ups: AI in Broader Organisational Contexts

Outside the start-up space, organisations such as Irembo illustrate what more advanced AI integration can look like. As a leading government-backed platform, Irembo has adopted an "AI-first" approach. According to one of their AI developers, "Every department is expected to integrate AI into its operations." Irembo uses AI for a wide range of functions, including image recognition, process automation, and the development of conversational agents. One key initiative that IremboAI aims to create is a no-code solution that helps citizens and civil servants deploy services using voice and text interfaces. "The goal is to allow people to talk to the government in Kinyarwanda without needing internet or advanced digital skills," explained the developer. This approach is rooted in the oral nature of African communication traditions and aims to increase digital inclusion. Another major initiative at Irembo is the AI Evangelist programme, which aims to raise awareness and educate employees on using AI effectively. In his view, engineers should not be the only ones who know how to use AI. The company provides courses for all departments on how AI tools can be used in their work.

Beyond Irembo, other key players in the ecosystem express cautious optimism about AI. The National Bank of Rwanda has begun experimenting with AI for fraud detection, compliance, and credit scoring. Although internal limitations restrict full-scale deployment, they are working closely with the government to change it. Furthermore, they are also interested in using AI for risk modelling and automated report generation. Last but not least, the ICT Chamber and academic partners, such as CMU Rwanda, continue to push for broader AI literacy and experimentation. As noted by Kudi Books, the government is helping train students in essential tech and AI skills, while also creating a culture of experimentation through hackathons.

Despite growing enthusiasm, challenges persist across all levels of implementation. Many start-ups lack the technical capacity to build custom solutions, and there are few AI specialists available in the local talent pool. "We had to teach our programmers how to use AI," Kapsule Tech reported. Furthermore, linguistic barriers such as the lack of full Kinyarwanda support and ethical issues regarding data security and privacy are other barriers to overcome. The barriers to the development of AI will be discussed in greater detail in the Digital Dependency section.

However, the increasing use of AI at operational and strategic levels suggests that growing integration is underway in startups. AI is remaking the entrepreneurial space in Rwanda, from product characteristics to efficiency. However, this is done slowly and unevenly. The technologies are being utilized by start-ups not only to optimize operations but to innovate new business models and expand their business service coverage.

4.3 The Role of Government and Innovation Actors in Supporting AI Adoption

Rwanda's entrepreneurial and technological ecosystem remains relatively small and concentrated, with most activities clustered in Kigali. Many interviewees described it as a young but increasingly well-connected environment, where collaboration among actors is common and access to policymakers is unusually open. A representative from Kapsule Tech, a start-up operating in both Rwanda and the UK, reflected that, "Access to the government here is unprecedented compared to the UK or Europe. You can easily access high officials from regulatory bodies." Similarly, the co-founder of BAG observed, "In Rwanda, I'm often invited to lunches or dinners with ministers. This probably would never have happened to me if I were in Sweden".

Start-ups benefit from various governmental incentive programs. Kayko's founders highlighted the crucial role of the sandbox provided by the National Bank of Rwanda. "It allows us to test our services with 50 users for six months without needing a full license," they explained. Given that a full Payment Service Provider (PSP) license could cost up to USD 300,000, this sandbox makes early-stage experimentation possible for otherwise excluded start-ups. In addition to sandboxes, Rwanda offers tax incentives for young companies. "You don't have to pay corporate tax for the first two years, even if you make up to USD 20,000," Kayko noted. This allows start-ups to mostly focus on developing their MVPs, rather than worrying about filing tax returns. These incentives are part of a broader strategy led by the Ministry of ICT and Innovation, working in close partnership with the Ministry of Finance and the National Bank of Rwanda.

Start-ups also benefit from non-monetary forms of support, including invitations to policy development processes and feedback loops. HarakaMeds offered a compelling example of this collaborative model. During the formation of regulations by the Rwanda FDA, the public sector invited medtech entrepreneurs to co-develop the policy framework. "We went article by article with them. Some proposals we accepted, some we didn't—and they listened," the co-founder explained. This ongoing dialogue reflects a broader willingness to shape governance together, rather than imposing top-down mandates. Several respondents expressed concern that government initiatives sometimes outpace practical capacity. As one founder put it, “Sometimes the government does too much, the vision is too fast to advance.” The frequent introduction of new policies and platforms can overwhelm entrepreneurs trying to keep up. This sentiment was echoed by Kudi Books, which noted that free public tools create direct competition for start-up offerings: “The government offers so many tools that are free, whereas in the private sector people have to pay.”

At the same time, there is recognition that government support for AI adoption goes beyond regulatory easing. The ICT Chamber and affiliated institutions, such as CMU Rwanda, provide technical training, networking events, and hackathons to build a culture of experimentation. According to Kudi Books, “There are some projects that are trying to tackle the lack of soft skills and improve tech literacy.”

Overall, Rwanda’s ecosystem is characterised by its dense interconnections, policy ambition, and government responsiveness. Although scale and maturity are still developing, the country presents a rare example of a public sector that actively shapes and engages with its entrepreneurial landscape. As one founder noted, ”The way the ecosystem is structured here, people know each other, people talk to each other, and it’s really easy to ask for support, it makes you feel like you’re not building alone.”

4.4 Digital Dependency and Structural Challenges

Though Rwanda’s tech and AI ecosystem is picking up momentum, it is still highly reliant on external digital infrastructure, software tools, and expertise. The digital reliance exists in various crucial areas such as technological infrastructure, talent mobility, and the contextual mismatch of widely adopted AI systems.

Most business and tech startups in Rwanda heavily depend on international AI programs and applications, such as OpenAI’s ChatGPT or Gemini by Google, to drive their businesses. Most of these applications are not optimized for the local environment, especially linguistically and culturally. According to the co-founder of BAG, “AI is still too generic and out of the Rwandan context… It’s more based on a Western context.” HarakaMeds concurred, with most users still defaulting to offline methods or phones due to a lack of familiarity with digital applications, much less AI-based apps. Kapsule Tech also admitted the application of large language models such as ChatGPT and other software to optimize operations, but recognized areas of underutilization due to a lack of adaptability to context. “We had to train our programmers how to handle AI,” the founder said, highlighting both the learning curve and the unavailability of off-the-shelf solutions specific to African contexts.

Another area of digital dependency is in data storage and infrastructure. As noted by BAG and Kapsule Tech, most businesses keep their data on international cloud bases like AWS and Google Cloud. As per BAG, “Companies are not entirely compliant with data protection laws, as they are not adequately established and are not being enforced.” Kapsule Tech explained the legal uncertainty regarding data usage and described talks with the Ministry of Health and ICT regarding the implementation of clearer guidelines for managing sensitive data locally while utilising external infrastructure. This reliance introduces both security concerns and sovereignty risks, as sensitive user data may be processed or stored abroad under different legal frameworks. AQS, while exploring the application of AI in quantitative research, also depends on foreign cloud infrastructure and expressed concerns about the lack of sovereign data centres and local AI tooling that could support high-volume analysis.

The problem is compounded by the fact that Rwanda has a very limited GPU infrastructure. As explained by the AI expert at Irembo, the organisation conducts its experiments on one GPU server only and is investigating how to run lightweight models locally because running the models on third-party servers is too expensive. "Inference costs can go up to USD 4,000 per month with OpenAI," he warned. This puts scalable AI development out of reach for most public and private actors.

Brain drain is another pressing challenge. Several interviewees noted that high-skilled talent, particularly in AI and data science, is either in short supply or leaves the country for better opportunities abroad. Start-ups such as HarakaMeds, Kapsule Tech, and BAG all referenced the difficulty in hiring or retaining AI talent locally. "Many people leave for more developed countries," HarakaMeds observed, while BAG added that "AI specialists are very expensive, and only big companies in Rwanda can afford them."

The language barrier further deepens the dependency. Despite progress in tools, the majority of the AI systems do poorly in Kinyarwanda. According to Kayko, local users prefer tools in Kinyarwanda, yet their respective AI systems hallucinate or produce incorrect information. Irembo's team agreed, observing that while Kinyarwanda-based models are getting better, these still lack fluency and accuracy.

Capital dependency is another insidious form of digital colonialism. Pebla pointed out an intriguing and critical issue, referring to the dependence of the majority of early-stage start-ups on grant capital provided by large external international organizations like Mastercard Foundation and USAID. Although this capital is necessary for expansion, it creates a cycle of dependence on international benefactors and agendas. Pebla noted such capital is "crucial, but distorts local accountability." Additionally, most local entrepreneurs design their businesses according to donor agendas instead of long-term viability. As various stakeholders pointed out, the quest to obtain international grants tends to encourage start-ups to create models according to predetermined templates rather than according to local market needs. It discourages the creation of financially sustainable business models.

In summary, while Rwanda's ecosystem is rich with ambition and growing state support, its digital development remains tethered to global infrastructures, funding models, and cultural norms. Bridging this gap will require not only technical solutions but also systemic efforts to localise tools, train talent, and assert digital sovereignty in policy and practice.

Chapter 5

Findings – Sweden

5.1 Overview of the Swedish Entrepreneurial Ecosystem

Sweden has long been one of Europe's most innovative economies, with a strong public welfare model, well-established institutions, and deeply ingrained state-industry collaboration. By most observers viewed as an environment where start-ups have unimpeded access to financing, networks, and means of expansion. The nation emerged as the leader in R&D-led growth in the post-war era. Especially since the 1970s, champions of industry like Ericsson and Saab played a core role in pushing technological advancement, both through domestic innovation and by keeping Sweden situated as a core node in global high-tech value chains. Ericsson, for example, led the country to the vanguard of mobile communications through pioneering research on the GSM and subsequent 3G and 4G technologies. Saab, too, alongside its aerospace and defense profile, played a key role in cultivating sophisticated systems engineering capabilities that spilled over into civilian uses in the future.

By the 1990s and 2000s, Sweden emerged as a centre of advanced telecommunication, life sciences, and automation technologies. Strategic public investment in digital infrastructure, engineering education, and research organizations provided the foundation for the establishment of a globally competitive start-up community. Nowadays, organizations like Vinnova (the national innovation agency), Chalmers Ventures, AI Sweden, and university-based incubators continue to promote the creation of new technologies. Sweden is invariably ranked as one of the world's most innovative nations, with R&D expenditure per capita as reported by the OECD being one of the highest in the world. Nevertheless, this legacy has not yet been matched with a clear national framework for Artificial Intelligence.

In terms of AI, Sweden's ecosystem is fragmented. Although AI is certainly there, as one respondent put it, "AI is a thing," it is still developing in a disorganized, sector-by-sector, institution-by-institution manner without centralized direction or policy control. The academic world is no exception to this fragmentation. According to one professor at the University of Gothenburg, "Sweden does not have an AI policy, or it is still not yet clear enough." At the university level, research related to AI is more often conducted by ad hoc efforts than by institution-wide agendas."Research is mostly bottom-up; everyone is doing their own thing," he added, highlighting a structural barrier to scaling academic innovation in AI. This decentralised approach also characterises the broader innovation system. A consultant from The Space described the ecosystem as siloed: "People are developing their own thing in silos, and there is no vision that people are trying to follow and develop." According to representatives from Vinnova, the agency currently supports over 3,500 projects, many of which involve AI. Yet feedback loops between government, research institutions, and the private sector are slow. "Every two years, there are some discussions about innovation directions in Sweden," one Vinnova programme manager explained, "but it's not like we can just do what we want—we act on government assignments."

The perception of government inertia was a recurring theme. A consultant from The Space put it plainly: "The government has other priorities at the moment." Similarly, a financial advisor from Almi commented, "Even the government doesn't fully understand it," referring to the complexities of AI and the need for stronger policy literacy. Across the interviews, there was a shared sense that Sweden lacks a coordinated top-down framework to drive AI development, akin to the national strategies once used for telecommunications or sustainability. Several interviewees also noted regional differences in support. As one advisor from Almi pointed out, "There are not so many meetings with Vinnova on how to develop strategic plans, maybe this is done in Stockholm, but not really in Gothenburg." This suggests that start-ups outside the capital may face reduced exposure to policy-shaping processes or national innovation programming, highlighting a spatial unevenness in the ecosystem's responsiveness to AI-related needs.

AI Sweden, a national initiative tasked with connecting industry, academia, and start-ups, is often mentioned as a potentially transformative platform. Yet its impact appears uneven. While some companies benefit from its support, many actors remain disengaged or unsure how to participate. "We know AI Sweden exists, but we do not know what they do," admitted one start-up founder. Even more engaged participants acknowledge that success depends heavily on self-motivation: "Companies that are active in the ecosystem can benefit the most compared to those that are passive," noted a research scientist affiliated with AI Sweden.

In summary, while Sweden possesses all the ingredients for a globally competitive AI ecosystem, advanced research institutions, experienced incubators, and a legacy of industrial innovation, these elements are not yet synchronized. The country's traditional strengths in decentralised, collaborative innovation have not fully translated into a strategic response to AI. The next sections of this chapter examine in detail how Swedish organisations are engaging with AI, the evolving role of the state, and the country's structural dependencies in the global AI economy.

5.2 How Organisations Are Using AI

The use of AI by start-ups and innovation actors in Sweden ranges from basic productivity improvements to the development of advanced AI-driven products and services. Similar to Rwanda, these applications can be categorised into three broad levels: (1) using AI for internal efficiency through available tools, (2) developing AI tools for internal use and decision-making, and (3) embedding AI as a core component of the final product or service. However, the Swedish context is marked by a higher availability of infrastructure and talent, alongside greater fragmentation in policy direction and coordination.

Table 5.1: AI Usage Levels Among Swedish Startups

AI Usage Level	Startup Name
Level 1: Use existing AI tools (e.g. ChatGPT, Copilot) for general productivity, content generation, or prototyping.	Knodd, Eperoto, Endre Tech, Cosmofoil, Compular, Anyolabs, Law Library AI
Level 2: Develop internal AI tools for improving their own operations or for specific internal purposes.	Law Library.AI, Anyolabs
Level 3: AI is a central component of the final product or service offered by the start-up.	Anyolabs, Law Library AI, Endre Tech, Cosmofoil

5.2.1 Level 1: AI for Internal Efficiency

Similarly to Rwadna, most Swedish start-ups rely on common AI tools to support internal operations and daily workflows. These tools include ChatGPT, Copilot, Cursor, and other LLM-based platforms that assist with text generation, coding, note-taking, and research. For many companies, this form of AI use is deeply integrated into team routines, though not central to their product offerings. The co-founder of Knodd, a paediatric telehealth platform, described how various tools are used internally: "We use ChatGPT, Cursor, or Copilot. Lyrebird Health [an LLM tool] is for medical note-taking... These are tools to be more efficient and save time." Similarly, at Eperoto, a start-up operating in legaltech, generative AI is used to speed up prototyping: "AI is a big time saver in writing reports and research," one of the founders noted. This pattern extends to technically oriented firms. At Compular, which focuses on computational modelling in the battery industry, the CTO explained: "We use Copilot, ChatGPT, but these tools are still more of a support, rather than a replacement." While AI is not integrated into their product yet, such tools support code generation, documentation, and communication. While these applications do not reflect deep technical innovation, they suggest that AI has become an embedded part of everyday operations. As one co-founder put it, "We use these tools all the time, but the product itself is not AI."

5.2.2 Level 2: AI for Internal Tools and Advanced Operations

Moving to the next section, a smaller number of Swedish start-ups have moved toward developing their own AI tools to improve internal processes and analytics. These companies typically have a clearer sense of how AI can solve specific domain challenges and either possess or are developing internal competencies to build tailored solutions. One example is Law Library AI, which operates in the legal domain. While the team uses common tools such as Cursor and Copilot, they also build their own large language models: "We create our own LLM models... We're a company that is on all three levels of AI." These models are not just prototypes, they underpin tools designed to help lawyers extract relevant case law and navigate fragmented EU databases. Another case is Endre Tech, which applies neural networks within its product infrastructure. Unlike many start-ups, their engagement with AI is not based on hype but on concrete utility: "The most important thing is that AI is used to solve a specific problem," the co-founder explained. They acquire generalised datasets from Swedish clients to ensure compliance and improve model relevance. While these companies have not yet industrialised their in-house AI tools at scale, they are actively working to internalise data pipelines, build model architecture, and tailor AI to their operational needs. The evolution toward this level also reflects greater organisational maturity and investment in long-term capability.

5.2.3 Level 3: AI as a Core Product Feature

At the highest level of integration, only a few Swedish start-ups have developed products where AI is the core value proposition. These companies are identified as AI-first and typically develop all key components, including datasets, models, and deployment infrastructure, internally. Anyolabs exemplifies this model. A healthtech start-up working with pharmacological data, the company develops its own AI models and does not rely on external APIs. "All the tech for the product is our own. We build all models ourselves. The product is fully AI-based," the CEO stated. The team draws from open pharmacological datasets, particularly those published by pharmaceutical firms, and maintains a strong emphasis on regulatory compliance by avoiding personal data. However, they also face notable limitations: "You need someone who knows both medicine and AI. That's a rare profile." Law Library AI also falls into this category. Their core offering, a chatbot capable of navigating complex EU legal frameworks, is built entirely around proprietary models. As one team member noted, "AI should be more precise in generating responses... More computing power is needed for updating data." The technical depth of such solutions places them in a unique category of Swedish ventures, but it also introduces challenges related to computational resources, hiring, and scale. Even among younger companies, such as Cosmofoil, are building AI-based services: "We're building AI agents for flight planning, but right now we mostly work with easy-to-access data provided by our clients." These companies demonstrate that AI-first models are emerging in Sweden, particularly where deep domain expertise intersects with machine learning capabilities. Yet, their presence remains limited.

5.2.4 Beyond Start-Ups: AI in the Broader Organisational Context

Beyond the start-up sector, venture capital firms, incubators, and innovation agencies play a critical role in shaping how AI is perceived and supported. Their engagement is not always technical, but their influence over funding and strategic direction makes them key actors in the ecosystem. At Almi, a government-backed venture capital firm, the investment team sees AI as a growing trend but remains sceptical of superficial claims. "It's trendy that a start-up is AI-based, but it's more about understanding where AI can really be used," said one financial advisor. Start-ups, they noted, often move faster than large corporations, which remain reluctant to explore AI. "Big firms require more time to understand how to use AI," the advisor added. This has implications for the adoption gap between SMEs and Sweden's established industrial players.

At Chalmers Ventures, investment teams encourage companies to engage with AI Sweden. Workshops and matchmaking sessions are available, particularly around data security and collaboration. However, as their Director of Venture Creation noted, "Many AI companies in Sweden focus on the application of AI, rather than building their own models... this leads to a situation in which everyone can use the same model and use it for the same application." A similar concern was expressed by GU Ventures, which supports early-stage companies connected to the University of Gothenburg. "There is no real shift towards AI," one advisor admitted. "We don't even have a clear way to determine if a company is truly AI-based." This lack of a standardised framework for evaluating AI maturity reflects broader structural fragmentation. VCs and incubators increasingly recognise AI's potential but are hindered by the absence of consistent assessment metrics and coordination platforms. Despite Sweden's strong innovation infrastructure, the AI ecosystem remains fragmented—its depth is growing, but its coherence is not yet guaranteed.

Even AI Sweden, despite its strategic position, struggles with outreach. Some start-ups reported limited awareness of their offerings. "We know AI Sweden exists, but we do not know what they do," one founder said. A research scientist at AI Sweden emphasised that "Companies that are active in the ecosystem can benefit the most compared to those that are passive," suggesting that the platform's impact depends heavily on initiative from participating firms.

5.3 The Role of Government and Innovation Actors in Supporting AI Adoption

Sweden has made notable efforts to develop a supportive framework for AI innovation through national strategies, funding programmes, and partnerships with academia and industry. The 2018 national AI strategy outlines a broad ambition to make Sweden a global leader in AI use. Initiatives such as Vinnova's AI funding schemes, the Nordic AI Centre, and the newly awarded EU-supported AI Factory reflect the state's commitment to this goal. However, interviews with start-ups and ecosystem stakeholders suggest that while the architecture for AI support exists, in practice, it often fails to match the needs of fast-moving, early-stage ventures.

Startups repeatedly pointed to the fragmented nature of the ecosystem and limited involvement from the state in their operational reality. “We’re not invited to any meetings by the government,” explained a co-founder of Anyolabs. “One of our co-founders, who is a professor, has been invited maybe once or twice, but there’s no consistent involvement.” This lack of connection was also echoed by Endre Tech, who stated, “We don’t get any support from the government, but we also don’t feel the need. The ecosystem didn’t really do anything for us.” Others recognised the value of existing structures but found them difficult to navigate. “AI is trendy, but there’s not that much cash that is super available,” said the co-founder of Cosmofoil. “Sweden is quite good at getting funding for innovative things, but it’s not very clear how to get it unless you’re already in the system.” For start-ups not embedded in institutional networks, access to national resources can feel opaque or exclusive.

Nonetheless, state actors such as Vinnova do play an active role in promoting AI development. According to two programme managers at Vinnova, their role is less about helping companies use existing AI tools and more about pushing boundaries: “We look at the next steps on how AI can be developed and implemented in new industries.” One initiative pairs SMEs with larger companies to foster knowledge exchange, while another focuses on the public sector, introducing AI to administrative bodies over a four-year programme. However, the effectiveness of these initiatives is still under question. Feedback loops between public agencies and industry actors are slow. “Every two years, there are some discussions about innovation directions in Sweden,” one manager noted. “We talk with the private sector, but it takes time to change anything.” Swedish innovation agencies create the foundation of strong public innovation capacity. Embedded within institutions such as Vinnova, AI Sweden, and Almi Invest, startups are part of an arrangement that provides coordinated support for research, testing, funding, and scaling up. Yet, these agencies vary in terms of regions and startup development, and while their support approaches are comprehensive, they might be unresponsive to startups that are pushing the frontier of innovation, such as AI. Regardless, these agencies heavily influence the context within which AI uptake becomes both feasible and risk-reduced for Swedish startups.

Several actors expressed a desire for the government to take a more active role in orchestrating collaboration across the ecosystem. As one advisor at Almi observed, “There’s room for more collaboration. Maybe the government could be the player that connects it all, but that’s not happening.”

The legal and regulatory environment was another frequently cited challenge. Chalmers Industriteknik, which works closely with industrial partners on applied AI, highlighted uncertainty around legal compliance as a barrier. “We’ve seen projects with potential, but fail because companies realised they don’t have the right data or can’t use it.” Despite Sweden’s policymaking culture of openness, venture creators also observed that startups, particularly outside urban areas, were hardly consulted as part of policy discussions on AI. The distance between startups and strategic planning groups was viewed as an unexplored opportunity to base AI policymaking on real entrepreneurial experience. As the co-founder of Knodd highlighted, “I feel like there’s a policy conversation happening, but it's not always trickling down to us. Maybe that happens at the Vinnova or EU level, but for a startup like ours, we're not really part of that dialogue. We just try to figure out what rules apply once we've already built something."

University incubators not only assist in vetting research-backed ideas but also facilitate legal framework support, sharing of equity, and grant funding, which is critical for early deep-tech and AI entrepreneurs. Chalmers Industriteknik acts as a connecting link by collaborating with academia and industry to facilitate the application of scientific know-how to real-life environments. Its role goes beyond that of the university but is closely linked to it, particularly in translating such advanced technological ideas as AI into industrial and startup environments. "We have a lot of project leaders who understand research, but also how to work with companies... that's our strength, we speak both languages.". By acting as "translators" of research to practice, organizations such as Chalmers Industriteknik facilitate not only startups but also larger companies and public entities to absorb and implement AI-related knowledge. The Swedish university network is fully integrated within the national innovation system, and institutions such as Chalmers Ventures, GU Ventures, and Chalmers Industriteknik play crucial roles as conduits of AI-relevant knowledge to startups. They work to create channels of contact between research and commercialization, although it is not always an easy task to build on collaboration and synchronize academic processes to match entrepreneurial needs.

In summary, Sweden offers a well-structured but fragmented ecosystem for AI innovation. While there are national strategies, state funding, and institutional partnerships in place, start-ups often experience these supports as either indirect or inaccessible. The system benefits those already integrated into academia or well-connected incubators, but remains difficult to navigate for others. As one founder summarised, "We're building in a vacuum. We need clearer guidance, more practical support, and a vision that connects us all."

5.4 Digital Dependency and Challenges

Although Sweden is widely regarded as a highly digitised country with strong infrastructure and institutional stability, its ecosystem for AI innovation reveals subtle but persistent dependencies on foreign technologies, talent, and investment flows. Unlike countries grappling with limited internet penetration or basic infrastructure challenges, Sweden's digital dependency manifests in more systemic forms, most notably in its reliance on non-European AI models, cloud infrastructure, and the global concentration of foundational research.

One common observation throughout the interviews was Sweden's lack of contribution toward developing large language models (LLMs) or basic AI platforms of its own. The CTO at Cosmofoil noted, "Sweden lags in developing the language models. There is nothing in the Nordics." The co-founder of Anyolabs concurred, saying, "I haven't seen any large-scale Swedish AI models being created. Sweden is excellent at applying tools, but not specifically at creating them." These comments imply Sweden is strong in applied innovation, yet still relies on tools and platforms created by large US or Chinese companies.

This foreign dependency is particularly visible in infrastructure. The majority of the start-ups interviewed depend on external technologies like AWS, Google Cloud, or OpenAI to run or test out AI technologies. Law Library AI, for instance, makes use of Copilot and ChatGPT within internal operations, while Endre Tech and Anyolabs incorporate such generative AI solutions as Cursor in their everyday operations as well. Although these tools increase operational efficiency, they embed startups deeper into ecosystems controlled by a few global firms. As the co-founder of Anyolabs noted, “We build our models in-house, but some tools we use for development still come from outside Europe.”

This issue is not merely technical, it also raises questions of strategic autonomy and digital sovereignty. As Chalmers Industriteknik pointed out, a major bottleneck to more ambitious AI projects is access to data. Companies remain hesitant to share their proprietary data due to legal ambiguities and a lack of national data infrastructure. “We don’t really have data spaces in Sweden,” a director explained. “It’s too costly to build them, and the legal uncertainty makes companies reluctant to share their data as well.” The absence of a comprehensive national framework for managing and pooling industrial data has led to fragmented data practices and missed opportunities for training local AI systems.

The European Union has moved to fill these gaps with policies such as the European Data Strategy and AI Act, but implementation is patchy in Sweden. Several interview participants emphasized regulatory uncertainty as a limiting factor. Chalmers Industriteknik explained how promising projects had been shelved once legal departments raised concerns over privacy risks. Even among public innovation actors, there is recognition that Sweden is lagging in some respects. According to Vinnova, “Computing power is still lacking, and sensitive data remains a big challenge.”

A less visible but equally important dimension of digital dependency relates to knowledge and talent mobility. Although Sweden invests significantly in research, academic incentives are often misaligned with the pace and demands of start-up development. A professor at Gothenburg University noted that research is still “bottom-up” and reactive. “People chase the funding, but universities are slow to shift priorities,” he explained. Several start-ups reported difficulties in finding talent that could bridge AI and domain-specific knowledge, especially in specialised fields such as healthcare. “We need people who understand both AI and pharmacology,” said the co-founder of Anyolabs. “But it’s very hard to find them.” Additionally, there is growing concern that Sweden is failing to capitalise on its education and research system to retain talent domestically. As startups become more reliant on international infrastructures and international venture finance, the potential for leakages of value, such as intellectual and commercial innovation returns being captured elsewhere, rises. Although this phenomenon is less apparent than in developing economies, structural asymmetry persists.

In sum, while Sweden performs an exemplary job in digital progress, things are more nuanced. Its AI start-up hub is highly integrated into global technological networks and continues to be reliant on external platforms, foundational models, and talent pipelines from abroad. The absence of domestic or European data infrastructure, regulatory ambiguity, and lack of local capability in foundational AI design indicate a kind of technological dependency. As one interviewee summed it well: “We’re good at using AI, but I’m not sure we’re building the future of it.”

Chapter 6

Comparative Analysis

This chapter provides a comparative analysis of AI adoption in Swedish and Rwandan entrepreneurial ecosystems. It takes examples from both countries and juxtaposes them on how they use AI, making it easier for a comparison. It also highlights the contributions of the major actors in their respective National Innovation Systems. Lastly, it compares the role of the state and innovation actors and shows how these two countries and digitally dependent.

6.1 Theme 1: How Organizations Are Using and Adopting AI

Startups in both Rwanda and Sweden express strong enthusiasm about AI and its transformative potential. Yet, they differ in the depth, shape, and application of their AI adoption as they have differences in infrastructure, talent, institutional maturity, and a culture for innovation.

Adoption in Rwanda remains symbolic or rudimentary. Some founders clarified that the term AI is usually added to give a feeling of innovation, most notably for donor-facing or policy-facing descriptions. However, in practice, AI capabilities may be referring to straightforward rule-based logic, automations, or externally sourced models. Such a characterization indicates a strong intent towards AI, albeit one that is bounded by insufficient local technical talent, scarce compute facilities, and a still-developing support system. Many startups rely on outsourced services or low-code tools and report that advanced experimentation is often prohibitively expensive or technically out of reach.

In Sweden, AI is more embedded in startups' operational models. Startups such as Knodd, LawLibrary, and Endre Tech use AI in specific domain applications, such as legal text summarization, medical note transcription, or scenario simulation for energy systems. But even here, adoption is by no means complete. Whilst some companies built in-house solutions with institutional or research backing, others combined pre-fabricated services with low levels of in-house expertise. Founders identified barriers surrounding regulation, client trust, and ethical ambiguity, most notably within healthcare and education.

Notably, both settings have a misalignment between ambition and action. In Rwanda, the misalignment is caused by upstream limitations, like insufficient talent in AI, low data access, and limited infrastructural support. In Sweden, the gap is more downstream: friction emerges when startups face slow-moving institutions, unclear policy signals, or low public-sector demand readiness. While Sweden has a more mature support environment, some founders still attributed complex funding schemes and sectoral inertia to slowed AI experimentation.

Startups in both countries emphasized that AI adoption is not just about technical integration. It requires supportive ecosystems, trust from stakeholders, and resources that allow for iterative development and context-sensitive application. Rwandan founders view AI as a strategic aspiration to be built toward. On the other hand, Swedish founders often approach it as a functional tool to solve specific problems, though not without friction.

Table 6.1: AI Adoption Comparison between Rwanda and Sweden

Dimension	**Rwanda**	**Sweden**
AI Maturity	Aspirational, early-stage	Operational in niche sectors
Nature of Use	Rule-based systems, outsourcing	Custom and applied use in health, energy, legal tech
Talent Availability	Extremely limited, few AI experts	Available but siloed in academia or large firms
Infrastructure	Minimal compute, reliant on external tools	Cloud-based and institutional access to infrastructure
Adoption Constraints	Skill shortage, lack of local datasets, weak institutional support	Sectoral inertia, unclear long-term policy direction
Strategic Framing	Used to signal innovation in grant/donor contexts	Applied strategically for efficiency and product value

This theme illustrates that AI adoption in startups is a multi-layered and contextually contingent process. Both ecosystems demonstrate early-stage barriers, but the nature of these constraints differs sharply. In Sweden, AI is already in use in specialized sectors, supported by institutional capacity, technical infrastructure, and policy instruments. Still, there are challenges in aligning client readiness and navigating regulatory uncertainty.

In Rwanda, the discussions around AI are strong, reflected in the national strategy and startup ambition. However, the foundational supports for meaningful AI integration are still lacking. Institutional architecture is fragmented, technical talent is scarce, and infrastructures are limited. This results in a reliance on imported tools, funding, and externally defined use cases.

Both systems underscore a key insight from GPT theory: emergent technologies do not scale on their own. Rather, they depend on the co-evolution of firms, institutions, and knowledge flows. In Rwanda, the foundational system is still forming. In Sweden, the structure exists, but it needs to change to support the spread of AI past early users into wider economic and public applications.

To conclude, AI adoption is not linear or automatic, but a process surrounded by the institutional, infrastructural, and relational realities that startups experience. Therefore, supporting AI innovation requires more than access to tools. It strongly demands attention to the broader environment that determines whether, how, and to what extent those tools can be meaningfully used.

6.2 Theme 2: The Role of Government and Innovation Actors

Across both Rwanda and Sweden, the ecosystem for supporting AI startups involves a mix of public, semi-public, and donor-linked institutions. However, the form, maturity, and coordination of these actors differ sharply, and so does their perceived impact on startups.

In Sweden, the institutional architecture is formalized and relatively stable. Organizations such as AI Sweden and Almi Invest facilitate AI experimentation and early-stage commercialization, and agencies like Vinnova coordinate sector-based funding for innovation. These actors are perceived by startups to be legitimate and well-funded, although not always straightforward to work with. While there is a diverse portfolio of funding instruments, founders noted frequent shifts in priorities, procedural opacity, and bureaucratic friction. More importantly, some startups found that government innovation actors did not fully understand the specific constraints of AI-based business models, particularly regarding iterative experimentation and sectoral adoption lag.

In contrast, a centralized innovation agency is lacking in Rwanda's innovation environment. Donor-supported hubs, ad hoc grants, and sector-specific programs support the ecosystem here. Here, institutional depth for implementation is limited, though the 'National AI Policy' and 'Vision 2050' show national ambition and put the government as a vision-setting institution. Irembo, while a prominent actor in digital public services, is not a startup-facing innovation intermediary. Rather, much support available to startups stems from local accelerators or initiatives financed by international donors, which might not provide long-term engagement or expertise in advanced fields such as AI. Founders often navigate a landscape of one-off opportunities when they demand to have a continuous support infrastructure.

Both ecosystems, despite their differences, face a shared structural issue, i.e., startups are burdened with coordination efforts. For instance, Swedish founders described navigating siloed agencies with differing expectations. Similarly, Rwandan founders often depend on personal networks or being in the "right rooms" for visibility. Across both contexts, location also mattered. Founders based outside Stockholm or Kigali, or outside of donor-funded circles, found it harder to access support.

Notably, regulatory engagement also diverged. In Rwanda, some startups mentioned collaboration with government bodies to pilot AI tools or access technological sandboxes. In Sweden, public sector clients were often seen as reluctant adopters who were slow to experiment, risk-averse, and procedural. This divergence reflects not only differences in institutional flexibility but also in the degree to which innovation actors are rooted in entrepreneurial ecosystems or work more separately.

Table 6.2: Role of Innovation Actors

Dimension	**Rwanda**	**Sweden**
Innovation Agency	No formal agency (Irembo plays indirect role)	Vinnova coordinates national innovation funding
Government Policy Execution	Strong vision but weak implementation	Embedded in institutions but fragmented AI strategy
Startup Ecosystem Support	Scattered hubs, donor-driven support	Structured incubators and public-private networks
Funding Landscape	Grant-based, limited follow-up, concentrated access	Mix of grants, public investment (Almi), EU funding
Institutional Coordination	Fragmented, ad hoc, externally influenced	Functional but sometimes bureaucratic and siloed
Regional Access Disparity	Access favors well-connected actors	Uneven (e.g., Stockholm vs Gothenburg)

This comparison shows how institutional presence, along with coordination, responsiveness, and alignment with the startup timeline, are critical. Sweden offers a diverse range of instruments for supporting technology startups via its innovation actors that are embedded in a well-funded, historically developed system. Nonetheless, we can observe friction through regional disparity and fragmentation. In Rwanda, the institutional landscape is agile in some respects but thinner. There is a stronger state-driven ambition. However, it lacks the stronger institutional depth to translate that vision into sustained support.

The comparison also reveals two different models of ecosystem-building. Sweden reflects a decentralized but resource-rich model, where support is available but scattered. Rwanda demonstrates a centralized policy ambition with limited institutional reach and slow implementation, where the absence of a national innovation intermediary creates gaps in follow-through and technical specialization.

Ultimately, the question is not just whether governments support AI startups, but how they do so, whether through fragmented project logic or through sustained institutional design that enables trust, coordination, and long-term experimentation. As AI technologies blur the lines between infrastructure, market, and policy, it also raises an important question: does it change the role of the state itself? States are no longer just funders or regulators, they are becoming market shapers, data stewards, and orchestrators of systemic learning (Lundvall, 2007; Mazzucato, 2018). In this regard, governments must create long-term structures that enable experimentation, foster trustworthy data environments, and invest in mission-driven innovation pathways. In both contexts, the capacity of the state to coordinate diverse actors around AI experimentation will define how effectively their ecosystems transition from aspiration to capability.

6.3 Theme 3: The Issue of Digital Dependency

Startups in both Rwanda and Sweden rely on platforms like OpenAI, AWS, or Google Cloud, which highlights how central third-party tools have become. But how this plays out looks very different between the two.

In Rwanda, this kind of dependence poses a major hurdle. Founders described a lack of access to local compute infrastructure, GPU clusters, or open, context-relevant datasets. Most AI work is about piecing together external tools rather than building from scratch. Using advanced APIs is not cheap, and local options for training AI talent are scarce. This limits what startups can try out, how quickly they can iterate, and what kinds of solutions they can realistically develop. Creating their own data or building independent technical paths is also tough when outside platforms are the only option.

Sweden is also reliant on overseas platforms to some extent. However, here it is mostly seen by entrepreneurs less as a structural necessity than a calculated convenience. Global cloud services and pre-trained models are often utilized by startups, yet they often supplement them with in-house work, partnerships with universities, or domain-specific adaptation. Some firms expressed concern about regulatory uncertainty or the ethics of using proprietary AI systems, but due to higher technical literacy, funding availability, and institutional support, they had greater room to navigate these concerns. Sweden's place in the EU also gives it an edge; laws like GDPR and the AI Act offer a framework that startups can both follow and, at times, help shape through research groups or policy discussions. Rwanda, along with most in a comparable situation, is largely subject to international rules with limited input in their creation.

All the same, both countries are fragile. Swedish founders recognized that the systems they rely on are managed by international parties they are not able to control, and also cast doubt on long-term stability and sovereignty. In Rwanda, the issue is more pressing: without access to these foreign tools, startups would struggle to participate in AI at all, leaving little room for local control over what gets built and how.

This theme highlights an important dimension that NIS literature often understates: the transnational layer of innovation dependency, especially in digital technologies. Digital dependency is a fundamental structural situation in Rwanda. Though ambitious, innovation aspirations are limited by a lack of ownership of infrastructure, information, and AI tools. This raises a concern about sovereignty, scalability, and even ethics, as home-grown solutions become more difficult to develop with the unavailability of local AI inputs and governance.

Table 6.3: Difference in 'Digital Dependency'

Dimension	**Rwanda**	**Sweden**
Cloud/Platform Dependence	High reliance on foreign platforms (e.g., AWS, OpenAI)	Common use of global platforms, but more local control
Local AI Stack Ownership	Low to none — externally sourced models dominate	Partial ownership — some in-house model development
Regulatory Influence	Limited enforcement of national AI policy	Active within EU governance structures (e.g., AI Act)
Access to Open Data/Models	Rare; mostly international datasets/tools used	More access via research institutions, EU grants
Sovereignty in AI Infrastructure	Lacking domestic infrastructure and data control	Greater agency via funding and partnerships
Perceived Control Over Tools	Low — dependency shapes capabilities and limits adaptation	Moderate — aware of dependency, but with options

Sweden is in a better position, yet still not insulated. Global technologies have made it easier for founders, yet that ease conceals more profound issues—loss of data control, becoming locked into particular providers, and losing the opportunity to support local solutions. Nevertheless, what distinguishes Sweden is its ability to address this tactically through funding, skilled personnel, and a seat at the table in defining regional frameworks.

Looking at both cases, it is clear that AI development is not just a national effort. It is embedded in a global setup where some players set the terms and others adapt, and power over infrastructure and standards is unevenly distributed. For Rwanda, the challenge is not developing local capacity, it is coping with exclusion from the process of influencing the digital future. For Sweden, the challenge is different: it needs to find a way to be involved without being too dependent, ensuring that advancement is not at the cost of future autonomy.

In sum, digital reliance needs to be seen as a built-in factor within how national innovation systems work. Supporting startups' adoption of AI effectively is not just about national coordination and vision, it means asking hard questions about who controls what, how fair that setup is, and whether sovereignty is possible in today's tech environment.

Chapter 7

Discussion

7.1 AI as a GPT

General-Purpose Technologies, as described by Bresnahan and Trajtenberg (1995), are characterised by three key features: (1) pervasiveness across multiple sectors, (2) ongoing technical improvement, and (3) the generation of innovation complementarities. Historical examples such as the steam engine, electricity, and ICTs demonstrate how these technologies reshaped production systems and enabled new industries. Over the past few years, researchers like Cockburn et al. (2018) and Klinger et al. (2018) have argued that AI fits the profile of a GPT. Our collected findings support this claim, but with an important addition that was not considered before: AI plays that role only when certain institutional setups and infrastructure are in place.

In Sweden, the evidence strongly supports AI's classification as a GPT. Several start-ups operate on all three levels of integration. Law Library AI and Anyolabs embed AI not only as an internal tool but as the foundation of their value proposition. These companies develop in-house proprietary models, train on domain-specific datasets, and establish their own infrastructure. These activities show ongoing development, sector evolution in legaltech and healthtech, as well as spillover effects. For instance, Law Library AI's legaltech tools to navigate EU law allow legal practitioners to operate more effectively cross-jurisdictionally. This degree of end-to-end control over AI development and deployment illustrates that Sweden, at least among its most advanced start-ups, exhibits the conditions under which GPT effects begin to materialise.

However, even in Sweden, this GPT dynamic is not system-wide. A lot of startups are at Level 1: using externally developed AI tools, such as ChatGPT and Copilot, to enhance operational efficiency. Knodd, Compular, and Cosmofoil all incorporate AI to improve speed and reduce cognitive workload in routine tasks. These usages reflect the pervasiveness of AI but not its transformative complementarity. As one founder put it, "We use these tools all the time, but the product itself isn't AI." This supports the literature's view that GPTs often experience a slow diffusion curve (David, 1990; Lipsey et al., 2005), where initial applications are marginal before systemic transformation occurs. It also posits that GPT status is not a simple binary; that some businesses engage with

AI step by step, yet only those having adequate capital, information, and skill progress to a genuine integration.

In Rwanda, the picture is more constrained. AI adoption is widespread at the level of operational efficiency. Start-ups like BAG, Kapsule Tech, and Kudi Books use generative AI tools for content creation, marketing, research, and basic automation. These tools improve productivity but are typically externally sourced and not tailored to local contexts. As BAG noted, "It's still too vague and out of the Rwandan context," underscoring a lack of contextual fit. While there is experimentation, e.g., Kayko building AI-powered CRM features, most firms remain at Level 1 or 2. Importantly, no start-up in Rwanda currently develops foundational models or owns AI infrastructure. The absence of advanced use cases, domain-specific data, or scalable internal AI systems suggests that the enabling conditions for GPT effects are only partially present.

This finding refines the GPT theory in two key ways. First, it highlights that GPT status is not intrinsic to the technology itself. While AI has the potential to be a GPT, this potential is mediated by ecosystem readiness. Without foundational infrastructure, skilled labour, or access to localised data, the technology's transformative power is restricted. Second, we emphasise that the co-evolutionary dynamics of GPTs, where technology and institutions mutually shape each other, are not guaranteed. In Rwanda, there is strong institutional intent (e.g., regulatory sandboxes, AI evangelism at Irembo), but limited technical capacity means that innovation remains incremental. This supports Lipsey et al. (2005)'s argument that GPT effects require co-investment in human capital, complementary systems, and institutional learning.

Moreover, our findings suggest a geographic unevenness in GPT development consistent with Jovanovic and Rousseau's (2005) thesis: that nations with early absorptive capacity benefit disproportionately. Sweden's advanced R&D system and higher digital infrastructure density allow selected start-ups to internalise AI capabilities and potentially shape future AI applications. Rwanda, by contrast, is structurally disadvantaged, not because of a lack of vision or ambition, but because GPT deployment is materially bound by external dependencies. Thus, the GPT framework must be contextualised within global asymmetries, an argument that connects directly to our next discussion on digital dependency.

In sum, we confirm that AI can be considered a GPT but challenge the assumption that its transformative effects are equally accessible. GPT status is conditional, incremental, and co-evolutionary. Our empirical data show that while Sweden is further along this trajectory, Rwanda's progress is constrained not by lack of entrepreneurial will or state coordination, but by systemic limitations in infrastructure, talent, and sovereign digital control. We therefore argue that GPT theory should incorporate ecosystem-sensitive thresholds: a set of minimum conditions (e.g., compute power, data infrastructure, human capital) required for GPT-level transformation to begin.

7.2 NIS and the Conditions for GPT-Level AI Adoption

NIS theory posits that innovation is not an isolated act of firm-level creativity but an outcome of structured interactions between firms, public agencies, research institutions, and policy frameworks (Freeman, 1987; Lundvall, 1992; Nelson, 1993). The NIS framework is particularly useful for understanding technologies like AI that require not only individual technical mastery but also systemic alignment. However, while the theory emphasises coordination and institutional learning, it does not offer a clear account of what is required to enable the adoption of a GPT such as AI. Our findings, therefore, contribute to theory by identifying what kinds of institutional and ecosystem conditions must be present for GPT-level AI adoption to occur—and what happens when these are absent, fragmented, or misaligned.

In Sweden, the classic attributes of a high-performing innovation system are well represented. The country invests heavily in R&D, has well-established public funding agencies (e.g., Vinnova), and maintains strong university–industry linkages through actors like Chalmers Ventures and GU Ventures. According to NIS theory, such a system should enable efficient GPT adoption: stable institutions, funding flows, and established feedback loops ought to generate dynamic learning and sectoral innovation (Nelson, 1993). However, our findings challenge this expectation.

Multiple interviewees in Sweden described the AI innovation environment as fragmented and decentralised. While public actors such as Vinnova support thousands of projects, their impact on early-stage ventures is indirect and slow. As a founder from Anyolabs commented, "We're not invited to any meetings by the government." Others, like Cosmofoil, reported being unaware of how to navigate the system at all. This suggests that the Swedish NIS, while institutionally dense, lacks dynamic coherence. The various actors operate in silos, without a shared national AI vision or sufficient cross-sectoral orchestration. Contrary to Lundvall's (2007) emphasis on continuous learning and trust-based collaboration, we find evidence of procedural bottlenecks, delayed feedback loops, and regional disparities, particularly between Stockholm and secondary cities like Gothenburg.

This reveals a structural contradiction: a well-funded, mature NIS does not guarantee GPT-readiness if coordination and alignment are missing. AI adoption requires more than project-level support; it needs strategic orchestration, shared data infrastructure, and regulatory clarity, all of which are currently uneven in Sweden. The fact that some firms (e.g., Law Library AI) reach GPT-level integration while others remain isolated suggests that Sweden's NIS offers patchy support, benefiting those embedded in academic networks while excluding others.

In contrast, Rwanda represents an emerging, state-led NIS where formal institutions are still being built, but coordination and responsiveness are unusually strong. Actors from start-ups like Kayko, HarakaMeds, and Kapsule Tech reported close involvement with public agencies, from policy co-creation to regulatory sandboxes. These examples confirm one of NIS theory's foundational insights: that interactive learning between public and private actors can accelerate innovation diffusion (Lundvall, 1992). Rwanda's Ministries of ICT and Innovation, together with agencies like the ICT Chamber and Irembo, play an active role in shaping the innovation system. For instance, HarakaMeds was invited to rewrite regulations with the Rwanda Food and Drug Authority (FDA), article by article—an example of real-time policy iteration almost absent in the Swedish case.

Yet, this coordination has limits. Rwanda's ecosystem suffers from institutional thinness, limited funding diversity, and skill shortages. The absence of local compute infrastructure, weak AI-specialist pipelines, and donor dependency constrain start-ups' capacity to go beyond operational AI use. As Kapsule Tech noted, "We had to teach our programmers how to use AI." Although relational access to the state is strong, the absence of systemic enablers—compute power, data protection clarity, and long-term financing—means Rwanda's innovation system is coordinated but not capacitated.

This contrast refines NIS theory in several ways:

- Coordination without capacity (Rwanda) leads to inclusion and experimentation, but not yet to scale or sustainability.
- Capacity without coordination (Sweden) results in fragmentation and underutilisation of existing potential.

Neither system currently offers the full spectrum of conditions needed for GPT-level AI adoption. We thus argue that GPT adoption requires a qualitatively different form of NIS alignment—one that involves not only traditional institutional linkages but also:

- Cross-sectoral orchestration (linking research, policy, and private actors),
- Sovereign data and compute infrastructure,
- Flexible regulatory experimentation (e.g, sandboxes),
- Talent systems that support interdisciplinarity (e.g. AI + pharmacology, AI + law),
- And trust-based feedback loops that include early-stage actors.

This insight addresses a gap in the literature: while NIS frameworks describe how innovations emerge in coordinated systems, they do not specify what kind of coordination or material capacity is necessary for technologies with GPT dynamics—those that affect many sectors, require constant updating, and entail structural reconfiguration. In the case of AI, our findings indicate that NIS must adapt not just in terms of policy but in their operational logic: from linear R&D support to recursive, infrastructure-based, and problem-oriented governance.

In short, we confirm the value of the NIS lens but argue that for GPTs like AI, the framework must be extended to include:

- A focus on strategic coherence rather than structural abundance,

- An emphasis on capacity layering rather than just actor presence,
- And attention to temporal alignment between policy ambition and ecosystem readiness.

Sweden and Rwanda illustrate two sides of this incomplete alignment. Sweden has the parts but lacks the plan. Rwanda has the ambition but lacks the capacity. Neither system yet provides a full model for GPT-level AI integration—but together, they show what is missing, and thus what future innovation systems must strive to become.

7.3 The Evolving Role of the State in the Age of AI

An overarching goal of this research has been to consider how the state's function shifts in response to the spread of a GPT-type AI. The NIS framework, as developed by Freeman (1987), Lundvall (1992), and Nelson (1993), situates the state among a multiplicity of agents within an innovation ecosystem, yet more recent work has indicated that with the advent of infrastructural and complex technologies such as AI, the function of the state cannot be passive. Instead of playing a coordinating or funding role, the state is summoned more and more to mold markets, regulate digital dependencies, and guide the conditions for accountable technological experimentation (Mazzucato, 2018; Merhi, 2022).

GPT theory and NIS theory are mutually supportive rather than opposing in this sense. GPTs such as AI, by their very nature, require a long-term, iterative process of complementary investments—skills, infrastructure, regulatory frameworks, and cultural readiness—all of which fall within the purview of the national innovation system (Bresnahan & Trajtenberg, 1995). What this research suggests is that GPT diffusion does not occur evenly or automatically. It demands deliberate institutional engineering, and in that sense, it reconfigures the tasks assigned to the state.

In Sweden, the government operates through specialized innovation agencies such as Vinnova and sectoral platforms like AI Sweden, which support research commercialization, facilitate cross-sectoral partnerships, and promote mission-driven innovation. However, whereas the infrastructure is strong, startups complained that most state actors are not in touch with the novel needs of AI-based enterprises, including adaptation through rapid iteration and shifting ethical-regulatory frameworks. Knodd's founder said, "Although we have regulations, it is hard to interpret them even for our lawyers." It is a paradox: whereas institutional frameworks in Sweden are well-established, the state is not able to keep up with the particular needs of AI entrepreneurs, particularly in how they can incorporate public sector agents into pipelines for innovation.

In Rwanda, the government has a more vision-setting and directive function, shown by 'National AI Policy (2022)' and policy goals like 'Vision 2050.' Interviewees from Irembo emphasized the government's desire to position AI as an essential facilitator of digital public services. Yet, this commitment remains largely aspirational, as the institutions necessary to support deep tech entrepreneurship are still emerging. For instance, the founder of AQS, the founder of BAG, a representative from Renew Capital (VC), and a member of Academic Bridge mentioned that while AI has been a priority of the government and policies are in place to enforce the priority, the government is slow in execution. Furthermore, what we can interpret from the findings is that, unlike Sweden, Rwanda does not have an innovation agency like Vinnova that is dedicated to funding and orchestrating systemic collaboration. Much of this is directly coordinated by the Ministry of ICT, incubators like Norrsken, and ad hoc grants. Startups like Umurava mentioned being invited by the Ministry of ICT to participate in panel discussions, however, these were on an ad hoc basis.

This asymmetry - Sweden's institutional maturity with limited collaboration and alignment, and Rwanda's strategic ambition with weak institutionalization - suggests that AI intensifies the state's responsibilities rather than diminishes them. Theories of, for example, Merhi (2022) regarding the governments' involvement in e-commerce adoption corroborate this. His work illustrates how digital technologies require not just investment in infrastructure, but legal frameworks and policy agility, domains in which the state is compelled to play a coordinating and facilitative function.

Moreover, our results align with the notion advanced by Bozeman (2000) that distinguishes among market failure, mission-oriented, and cooperative paradigms of government involvement. Sweden follows a hybrid model, with a bias towards cooperative involvement, in which government invests in funding public-private consortia but fails to bridge institutional silos. Rwanda, by contrast, is a mission-oriented state, in that it articulates robust goals but lacks framework ideas for co-funding innovation at scale. As AI becomes further integrated in fundamental economic and administrative activities, paradigms may need to change towards more reflexive and anticipatory governance, in particular about managing dependencies in ethical, geopolitical, and infrastructural areas.

Understanding the roles of government in Sweden and Rwanda when it comes to dealing with GPT like AI, we find that governments in both contexts are challenged by the systemic nature of AI. In Sweden, the challenge lies in mobilizing existing institutions toward coordinated AI innovation, especially when public-sector clients are risk-averse or structurally slow to adapt. In Rwanda, the challenge lies in converting national strategy into institutional scaffolding—funding mechanisms, regulatory sandboxes, and talent development programs—that allow startups to develop AI beyond mere discourse. Furthermore, in Rwanda, slightly mature startups like BAG and Academic Bridge mentioned that the government is trying to build everything on its own, for instance, in partnership with Irembo. They argued that this puts the government as a competitor to the startups. As Bozeman (2000) proposed, the role of the government should be a complement rather than competing in scenarios where innovation flows from government and academia is already low.

In this context, AI is not a test of technological capacity, but institutional imagination. According to Merhi (2022) and Mazzucato (2018), adopting technology in the new digital age demands that states transcend conventional industrial policy towards the curation of ecosystems, legal innovation, and diplomatic negotiation with international platforms. The GPT nature of AI demands that the state become a platform shaper, data steward, and ethical standard-setter, roles for which many governments, especially in emerging economies, are still underprepared.

Therefore, this thesis finds that the role of the state in the age of AI is not simply about providing funding or setting direction. It is about constructing adaptive, learning-oriented systems that can evolve with the technology itself, balancing regulatory foresight with entrepreneurial openness, and ensuring that NIS are not only robust but also resilient in the face of rapid technological change.

7.4 Entrepreneurship and the Practice of Startup-Centered Innovation

The fundamental analytical decision of this thesis was to make the startup the primary unit of analysis, employing NIS theory not to analyze national systems in and of themselves, but to illuminate how startups engage with various institutional players. This method provided a more tangible and detailed image of innovation than assessments at the system level generally permit. It also supported current critiques of top-down innovation approaches that do not consider the distributed, relational, and improvisational character of entrepreneurial ecosystems (Autio et al., 2014; Spigel, 2017).

In both Sweden and Rwanda, startups were not mere passive beneficiaries of institutions. Instead, they were tactical agents working within gaps in institutions, scarcity of resources, and uncertainty of policy. In Rwanda, it meant improvising within constraints of little or no infrastructure or positioning AI capacity within frames that resonated with donors' expectations. In Sweden, it meant being able to adjust proposals to shifting grant priorities or establishing sectoral collaboration where government adoption lagged behind.

These results corroborate Welter's (2011) contention that context is not simply background, but is responsible for influencing entrepreneurship's dynamics. Founders do not dwell in an empty environment, but one in which local cultural, economic, and institutional logics inform their strategies, business ideas, and technological adoption. Even local expectations and abilities affect the definition or marketing of AI by startups.

In addition, data reveal that entrepreneurial ecosystems are not self-organizing but rather that players like donors, NGOs, and government ministries each support startups, yet lack effective execution in Rwanda. In Sweden, players are more integrated, yet still, entrepreneurs reported fragmentation, especially in AI-specialized policy and financing. For instance, the founder of Knodd aptly mentioned that "the regulations around the use of data in AI are quite complex to understand even for our lawyers." This is reminiscent of Isenberg's (2010) argument that ecosystems look fine on paper yet fail to engage dynamically in reality.

Furthermore, this means that successful startup support is about more than just institutional presence. It is about institutional responsiveness. Startups have short windows of time, scarce resources, and changing objectives. Institutions that are not able to respond to these dynamics, either by making accessible capital, mentorship, or incubating space, risk losing most of their most innovative players.

In the end, a startup-centric perspective enhances the NIS framework by emphasizing not how innovation is planned, but practiced. It places agency, creativity, and navigating constraints center stage and emphasizes that innovation systems not only need to generate resources but also to render them legible and accessible to entrepreneurs operating at the frontlines of technological transformation.

7.5 Global Digital Dependency and the Limits of NIS

One of the central assumptions in NIS literature is that innovation actors, including infrastructure, capital, knowledge, and skill, are either locally available or are possible to develop through national coordination (Freeman, 1987; Lundvall, 1992; Nelson, 1993). Yet, in the case of AI, this assumption is becoming more challenged, since AI is highly integrated in global platform infrastructures, proprietary data ecologies, and transnational value chains. In other words, AI innovation is less a question of national capacity and more one of having the proper structural position in the international digital architecture. Our results from both Sweden and Rwanda support this critique and both challenge and advance NIS theory by demonstrating how digital dependency may limit even well-crafted national systems.

In Rwanda, symptoms of digital dependency are apparent and pervasive. AI solutions depend extensively on hosted tools, including OpenAI's ChatGPT, Google Gemini, and commercial clouds like AWS. Not a single interviewed start-up has locally hosted LLMs or sovereign clouds. As BAG's co-founder stated, "AI is still too vague and out of the Rwandan context." This is an indication of what Mohamed et al. (2024) refer to as epistemic injustice: when technological systems are designed atop datasets and assumptions that fail to mirror the everyday lives of marginalised groups. Such a mismatch is not merely linguistic or cultural—it has functional consequences. AI systems designed for Western commercial environments are often inoperative in environments where users prefer oral rather than written modes of communication, need to operate offline, or support local dialects, as Irembo's Kinyarwanda language model experiments exemplify.

Moreover, Rwanda's reliance on foreign capital compounds the problem. As Pebla and Kapsule Tech observed, much of the available funding comes from donor organisations such as Mastercard Foundation or USAID, whose grant frameworks tend to incentivise compliance with externally defined metrics rather than long-term commercial sustainability. This leads to a distortion in business logic: companies structure their offerings to match funding calls rather than solve local problems, perpetuating a cycle of dependency that digital colonialism literature has identified as aid-driven platformisation (Couldry & Mejias, 2019). The consequences are serious: entrepreneurial strategies become reactive, local experimentation is narrowed, and innovation capacity is directed outward rather than embedded.

In Sweden, dependency is more subtle and systemic in nature. The nation is generally regarded as a leader in innovation, but our interviews also uncover a surprising dependency on non-European infrastructures and root technologies. As Cosmofoil mentioned, "Sweden is behind in language model development. There is nothing in the Nordics." Most start-ups—even those developing proprietary products like Anyolabs or Law Library AI—still rely on U.S.-based infrastructure and pre-trained models for experimentation and deployment. While this is often framed as a pragmatic choice, it embeds Swedish innovation within a foreign technological substrate, raising concerns about sovereignty, resilience, and long-term strategic control.

Moreover, Sweden lacks national data spaces, and regulatory uncertainty prevents firms from pooling or sharing industrial data. As Chalmers Industriteknik explained, projects are abandoned when legal teams cannot resolve data protection concerns, not because the law is restrictive, but because it is poorly understood. This results in what one director called a "chilling effect": an environment where firms are unwilling to take legal risks, and thus avoid innovation involving sensitive or large-scale data. This reinforces dependence on external infrastructures where such ambiguities are pre-resolved, even if it means sacrificing data sovereignty.

Taken together, these findings suggest that both high-capacity and low-capacity innovation systems are subject to structural limits imposed by the global digital order. The difference lies in visibility, not vulnerability:

- In Rwanda, dependency is overt: lack of infrastructure, capital, and locally trained talent.
- In Sweden, this dependency is masked by competence: while companies can construct advanced applications, they remain dependent on international platforms for training models, storing data, and even conceptual frameworks.

This requires an essential expansion of NIS theory. Traditional accounts assume that national systems are closed and governable by policy instruments. Yet, for AI, even the best of intentions by national strategies are bounded by exogenous asymmetries—in Srnicek's (2017) parlance, by platform capitalism, in which innovation infrastructure is monopolised by a small number of global entities. The diffusion and regulation of AI, therefore, cannot be explained completely from a domestic perspective. We need instead to see NIS as nested in and structured by global digital hierarchies.

In sum, our findings demonstrate that digital dependency is now a defining constraint on the capacity of national systems to adopt and govern GPTs like AI. The assumption that innovation inputs are nationally accessible must be reconsidered. For AI to become a truly transformative and sovereign technology, countries must engage not only in domestic ecosystem-building but in strategic decoupling and localisation efforts—whether through sovereign data centres, open-source model development, or transnational alliances that resist platform monopolies. Without these interventions, NIS risk becoming, at best, intelligent users rather than strategic creators of the next technological paradigm.

Chapter 8

Conclusion and Recommendations

The thesis aimed to explore how Swedish and Rwandan startups embrace AI and what role the innovation actors play in influencing it. Based on the NIS framework and GPT theory, it was shown that adopting AI is not uniform or automatic, but is strongly conditioned by institutional preparedness, international dependency, and startup strategy.

To conclude, we go back to our research question and sub-questions and briefly answer them below:

What roles do innovation actors of Sweden and Rwanda play in AI adoption in startups, and how does context shape their approaches?

AI adoption in startups does not merely depend on the presence of innovation actors—it depends on how these actors define their role and coordinate their efforts. In both Sweden and Rwanda, such actors play a central role, but they do so within two very different institutional settings.

Sweden reflects a model of decentralised abundance, while Rwanda operates through centralised ambition. In Sweden, the innovation ecosystem is highly developed, offering an extensive network of funding agencies, research institutions, and incubators. Startups have access to resources, but not necessarily to direction. Rather than a unified strategy, the system is characterised by parallel initiatives, each driven by its own logic and priorities. This leads to a diffusion of responsibility: everyone is doing something, yet no one is orchestrating the whole. For a technology like AI, whose transformative impact depends on cross-sectoral coordination, long-term vision, and regulatory clarity, this lack of alignment becomes more than a managerial inconvenience; it becomes a systemic risk. The abundance of support, paradoxically, fragments the ecosystem's ability to respond to AI's complexity.

Rwanda, unlike Sweden, does not have a wide network of institutions. But it benefits from strong central direction. The government plays an active role—setting goals, building digital infrastructure, and involving start-ups in policy work. Innovation actors here are not just supporters; they help shape the system. This gives Rwanda speed and clarity, which is useful for working with new technologies like AI. Still, the model has clear limits. It depends heavily on foreign funding and external platforms. This makes it hard to build local skills, tools, and control. The system moves quickly but lacks depth. Without strong technical talent, stable funding, and local infrastructure, Rwanda may struggle to grow AI adoption in a way that lasts.

These contrasts point to a deeper insight: the success of AI adoption does not hinge on how many innovation actors exist, but on how well they align with each other and with the technological realities of AI as a GPT. In Sweden, the problem is not capacity, but coherence. In Rwanda, the problem is not vision, but institutional depth. In both cases, the traditional roles of innovation actors are being stretched. They are no longer just providers of support—they must become strategic integrators in a landscape shaped by fast-moving, cross-cutting technologies.

What our study shows is that contextual differences—whether in governance style, infrastructure, or institutional maturity do not just influence how AI is adopted. They reshape what it means to adopt AI in the first place. Innovation actors must adapt not only to the internal demands of their ecosystems but also to the external pressures of digital interdependence. In this sense, AI forces a shift: from static roles and predefined policy functions to more flexible, adaptive forms of ecosystem leadership. Ultimately, the path to meaningful AI adoption is not about replicating best practices but about building institutional capabilities that fit local realities while engaging global dynamics. This is the new frontier for innovation actors, not to control AI, but to co-evolve with it.

Sub-question 1: How do innovation actors affect AI adoption in each country, and what does this reveal about the institutional strengths and coordination gaps in each context?

In both Sweden and Rwanda, innovation actors significantly shape the possibilities for AI adoption in startups, but they do so through markedly different institutional logics. In Sweden, actors such as Vinnova, AI Sweden, and university-affiliated incubators provide a fragmented yet high-capacity support landscape. Our findings point to a paradox: the system is resource-rich but direction-poor. Swedish entrepreneurs described a support environment that is broad but fragmented, where no single actor assumes responsibility for guiding AI adoption across different stages of startup growth. As a result, founders often struggle to navigate the ecosystem, bouncing between disconnected programmes. This institutional fragmentation becomes particularly problematic in the case of AI, a technology that demands long-term, cross-sectoral coordination. Without stronger alignment between actors, even a well-funded ecosystem risks falling short of creating the conditions necessary for transformative, GPT-level adoption.

In Rwanda, the situation is completely the opposite. The ecosystem is thin in terms of formal institutions but strong in centralised coordination. Entrepreneurs benefit from high-level visibility and quick policy responsiveness, but they operate in an ecosystem where support is often ad hoc, underfunded, and overly dependent on foreign donors. Our findings show that AI adoption is not simply a function of whether innovation actors exist, but whether they are strategically aligned, responsive to technological complexity, and embedded within a system capable of long-term coordination. Sweden's challenge is in bridging silos; Rwanda's is in deepening institutional roots. Neither system is fully equipped yet to manage the dynamic demands of a GPT-like AI, but each reflects different institutional strengths and weaknesses that shape the nature and pace of adoption.

Sub-question 2: To what extent does the role of the state need to evolve to support the adoption of AI as a GPT, or can traditional functions suffice?

Historically, GPTs were mostly developed within national systems. States played a central role by aligning internal actors, financing infrastructure, and adapting institutions, without depending on global platforms or foreign infrastructure. But AI operates differently. Its foundational components, data, compute power, and pre-trained models, are often owned or controlled across borders. This interconnectedness forces a reconsideration of what the state can and should do. To give an example, LLMs, in contrast with the steam engine, work differently regarding the context. AI models that were trained on an American dataset will not align with the African settings. The steam engine or electricity will work the same, no matter the country. In Sweden, the state continues to act through traditional policy channels: funding research, supporting start-ups, and promoting digitalisation. However, our findings suggest that these historical roles are no longer relevant to follow the scale and complexity of AI. Without a strong coordinating body that closely collaborates with the ecosystem, the adoption of AI will remain slow. In this sense, traditional policy tools have not entirely kept pace with the demands of governing a transformative, cross-sectoral technology like AI.

Rwanda might be a better example in this case. The state plays a central and directive role, setting national visions, launching platforms, and leading policy discourse. This strong state involvement has enabled rapid mobilisation and clear strategic direction. However, much of Rwanda's AI activity remains limited due to still undeveloped ecosystem. Both contexts point to the same conclusion. Governing AI as a GPT demands more than conventional support; it requires governments to evolve into system integrators and long-term strategic coordinators. Without new approaches to governance, including stronger coordination, adaptive regulation, and a more strategic approach to digital sovereignty, states risk remaining reactive rather than directive. What the study suggests for future research is clear: understanding how governments should change to meet the demands of new and upcoming GPTs adoption.

Sub-question 3: How do dependencies on foreign platforms, tools, and funding shape the capacity of NIS to localise AI adoption?

Dependencies on foreign technologies and capital significantly constrain how NIS can localise AI adoption, though the form and visibility of these dependencies differ across contexts. In Rwanda, our findings reveal a clear reliance on external infrastructure, including cloud computing, large language models, as well as donor-funded systems. Startups often shape their business models around the availability of foreign grants, which was confirmed by our interview with the co-founder of Pebla.

What is more, most of the AI products in Rwanda are built on top of Western AI tools, which are not tailored to local contexts nor fully controllable. This creates a double bind situation, where on one hand, external support accelerates digital capacity in the short term, but at the same time limits the development of sovereign, locally embedded AI solutions. The ecosystem becomes forced to adapt to a foreign setting rather than set its own. In Sweden, despite the country's digital maturity, much of the AI development is dependent on foreign infrastructure. These tools are convenient and widely adopted, but they come with trade-offs. Startups may scale faster, but they do so within ecosystems that are structurally reliant on external providers. This raises deeper questions about digital sovereignty and long-term innovation control: Can a country truly localise AI when its core tools remain outside its regulatory, technical, and economic influence?

These findings challenge a core assumption of the NIS framework, that critical innovation inputs can be developed domestically. In the case of AI, some of the most important inputs, like data pipelines, computing power, and foundational models, are externalised and centralised. This means that even well-functioning national systems operate within a global architecture they do not fully control. Unless countries, especially those outside the US-China axis, invest in shared, open, or regional alternatives, the localisation of AI will remain partial and path-dependent. Our findings suggest that future research must move beyond national frameworks to understand how transnational asymmetries shape what innovation systems can realistically achieve in the age of digital General-Purpose Technologies.

8.1 Synthesis and Implications

The thesis reinforces the value of employing GPT theory, NIS, and startup-focused approaches to explain AI adoption or constraints in various national contexts. But these results also pinpoint key limitations necessary to render these frames analytically effective within an environment of global digital asymmetries.

First, GPT theory is still a compelling means of characterizing AI's transformative potential. In support of it, as argued by Bresnahan and Trajtenberg (1995) and by Lipsey et al. (2005) as well, GPTs only become systematically valuable where there are complementary skills, infrastructure, and institutions. This thesis verifies that assertion empirically: in Sweden, where lots of such complements abound, AI adoption is real, though gradual. In Rwanda, where underlying complements are still in development, AI is still mostly symbolic or outsourced. GPT potential is hence contingent, not absolute.

Second, the NIS framework proved to be important to understand innovation shaped not by autonomous firms or markets, but by interdependent actors within certain institutional configurations (Lundvall, 1992; Nelson, 1993). The Swedish case showed that an advanced, relatively mature NIS, marked by public funding agencies, research organizations, and coordinated policy instruments, provides an easier path for startups to move into AI. Rwanda, on the other hand, is an emergent innovation system in terms of AI, where there is the vision and direction from the government, but not yet an organized structure, driven by small funders, donors, and externally linked.

Significantly, this thesis also illustrates that institutions alone do not ensure coordination. In both nations, startups experience friction, be it in coordination with funding priorities (Sweden) or dealing with dispersed programs (Rwanda). This affirms Mazzucato's (2018) assertion that mission-led innovation policies, which do not merely provide funding for R&D, require coordinating agents, harmonizing incentives, and reducing experimentation risks in a uniform and inclusive process.

Third, the startup lens offers an applied corrective to excessively structural perspectives.

Startups not only act within systems, but tend to do so in spaces in between them. Their experiences demonstrated that visibility, mentoring, funding, and regulation clarity were not universally distributed, even within well-resourced systems such as Sweden. Entrepreneurial agency is always contextually contingent, as Welter (2011) and Spigel (2017) maintain, and startups in both locations made strategic accommodations, but these accommodations were contingent upon their levels of institutional support, talent, and legitimacy.

Lastly, this thesis establishes an acute need to extend NIS theory to more adequately explain digital dependency and transnational asymmetries. In Rwanda, not only is the base for AI underdeveloped, but it is also externally controlled. Cloud resources, pretrained models, and even technical skills are frequently supplied from outside the country. This restricts not just capacity, but also freedom, raising fundamental issues of technological sovereignty and long-term capability to innovate (Couldry & Mejias, 2019). NIS, as Chaminade and Edquist (2006) observe, are being increasingly shaped by transnational flows of capital and knowledge, yet, in the absence of symmetric influence, nations like Rwanda risk ending up as consumers, not creators of the AI revolution.

8.2 Policy Recommendations for Strengthening Entrepreneurial Ecosystems

The study concludes that fostering AI adoption in startups is best done by taking a multilevel approach whereby startups' needs, institutions, and structural placement are taken into consideration. The following suggestions directly stem from data and analysis.

8.2.1 For Rwanda: Strengthen Institutional Depth and Responsiveness

- Create a specific innovation intermediary (similar to Vinnova) to coordinate research partnerships, experimentation, and funding among sectors.
- Close the policy–practice gap by translating AI strategy into specific programs, regulatory sandboxes specifically for AI, and AI-focused funding instruments.
- Invest in cross-border AI infrastructure such as compute platforms, domestic data platforms, and university-led AI laboratories to minimize reliance on foreign providers. This can be done on a smaller scale so that AI-based startups do not have to rely on costly foreign infrastructures.
- Strengthen technical talent pipelines by matching university curricula to industry requirements. Establish subsidized AI fellowships and public-private training programs.

8.2.2 For Sweden: Improve Coordination and Long-Term Vision

- Clarify and advertise the national AI strategy to ensure that national funding programs (e.g., Vinnova) support long-term AI goals in various sectors and all the actors within the ecosystem are aware of it.
- Encourage cross-agency collaboration to prevent siloed innovation initiatives and support more intensive integration of research, public procurement, and private sector initiatives.
- Develop incentives to encourage public sector experimentation, to get national agencies and municipal government entities to be early users of AI solutions created by a startup.
- Provide fair access to networks and financing outside Stockholm, enhancing support and visibility for startups outside of Stockholm, like Gothenburg.

8.2.3 Cross-Cutting Recommendations: Toward Inclusive AI Systems

- Involve startups as proactive co-creators, not as passive beneficiaries, by engaging them in strategy discussions, ecosystem mapping, and design of funding programs.
- Reframe donor and grant programs within Rwanda and analogous contexts to focus on capacity development, long-term testing, and investment in infrastructure, rather than simply pilot results.
- Develop global partnerships based on equity: With AI increasingly becoming more infrastructural in nature, next-generation ecosystems need to require seat-at-the-table agreements in determining standards, governance, as well as training data practices.

8.3 Contributions and Future Research Directions

The thesis provides several contributions to theory, practice, and the emerging comparative innovation studies field, most notably where AI, entrepreneurship, and systems of institutions converge.

8.3.1 Theoretical Contributions

First, this research extends the application of the NIS framework to use it not at the macro-system level, but at the level of startup engagement. Instead of comparing Rwanda's and Sweden's formal structure at an entire-system level, this research viewed each national system to consider what specific elements of them, their respective innovation agencies, financiers, universities, and policymaker institutions, are engaging with startups, and more specifically, AI startups. In doing so, this analysis upholds current calls to turn innovation analysis towards practice-centered, actor-focused, and sector-sensitive approaches (Autio et al., 2014; Chaminade & Edquist, 2006).

Second, the thesis deepens GPT theory by demonstrating that transformative technologies such as AI receive only partial adoption under circumstances of locally misaligned institutional and infrastructural conditions. With an integration of GPT theory and NIS, this study also proves that AI's influence is not an intrinsic property of the technology itself, but depends on absorptive capacity, coordination systems, and relational work by entrepreneurs.

Moreover, the findings suggest that recent as well as upcoming GPTs will depend more on foreign actors compared to the past GPTs, which solely relied on the internal ecosystem. This observation is linked to our last contribution. Our study contributes to nascent critiques of technological sovereignty and digital dependency. In this case of Rwanda, constraints on national potential for innovation result from not being able to completely possess or control AI infrastructure, tools, or data sets despite strong intent behind policy, and this augments the framework of NIS by extending beyond its incomplete conceptualization of transnational power asymmetry, particularly in digital economies where domestic control of technology is bounded by transnational knowledge and infrastructure flows managed outside of home countries. If this trend continues, we will observe a growth in digital dependencies, and as stated in the introduction of our paper, AI will benefit only a small portion of global society.

8.3.2 Empirical Contributions

Empirically, it offers one of the few comparative, interview-driven analyses of AI adoption in startups in two strongly dissimilar contexts. Based on rich primary data drawn from 30+ interviews, it brings to light grounded findings on:

- How startups conceptualize, implement, or structure AI in day-to-day product creation.
- How founders manage scarce resources, donor dynamics, and policy uncertainty.
- How innovation agencies (or their functional equivalents) influence early-stage adoption of technology.

How governments are navigating (or failing to navigate) the changes in their roles brought forth by technologies like AI.

By looking not only at what institutions exist, but at what it is like to be a startup engaging with them, the research provides a richer picture of what "support" actually is, in reality.

8.3.3 Practical Contributions

For practitioners and policymakers, the findings offer a few takeaways:

- Startups need adaptability in institutions, not fixed programs.
- Adoption of AI needs to be facilitated not only by financing but by trust networks, regulation clarity, and coordinated experiment pathways.
- Policy ambition is not sufficient; policy usability and execution are crucial. The most effective strategies become those that directly translate into user-accessible programs, clear mechanisms, and user feedback loops.
- In Rwanda specifically, there is a pressing need to move away from short-term, donor-driven funding support to locally centered, capacity development, and innovation infrastructure. The infrastructure could have been built together with neighboring countries in East Africa.

Finally, with fast-changing technology like AI, especially that comes with the possibility of becoming a GPT, the government's role should also evolve in a way to support AI adoption and development.

8.3.4 Limitations and Future Research Directions

The study is limited in various ways. Firstly, the sample, although rich and diverse, is not statistically generalizable in its claims. It is based on chosen startups, supporters, and ecosystem players and is representative of qualitative depth, as opposed to breadth. Findings from the interviews are only from those who agreed to be interviewed.

Second, the structure, although effective, is predominantly national in scope. Future studies ought to leverage it by creating cross-scalar innovation models, integrating regional dynamics, ecosystems at the city-to-city level, and cross-border entrepreneurship activity. An appropriate next step would be of triangulated study involving funders, policymakers, and regulators in more engaged discussions, particularly from underrepresented systems.

Third, although AI was emphasized, startups mentioned using combined technologies, like automation, data science, and cloud infrastructure. Future studies might analyze how various up-and-coming technologies (AI, blockchain) interplay within systems within institutions and whether innovation frameworks today can represent this convergence effectively.

Lastly, it paves the way for rethinking theory on innovation systems within the context of global asymmetries of infrastructure. With digital colonialism and platform dependency remodeling innovation, scholars need to confront how the dominance of digital resources, computing, data, models, and platforms influences national and entrepreneurial agency. A theory of innovation in the future has to be global in consciousness, but local in application.

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Appendix A

Interview Guide

1. Introduction and Context

- Speaker introduction: what is your role in the company, and how long have you been working here?
- Can you briefly describe your startup and its core business?
- What industry does your startup operate in, and what is your target market?
- How long has your startup been in operation, and what stage of development are you in (e.g., seed, growth)?

2. AI Adoption and Usage

- Does your startup currently use any AI tools or technologies? If yes, which ones?
- How do you use AI in your business? (Probe for specific use cases, e.g., customer service, data analysis, product development.)
- Do you use off-the-shelf AI tools (e.g., ChatGPT, DeepSeek) or develop custom AI solutions?
- Is AI a core part of your business model, or is it used to support operations?

3. Strategic Importance of AI

- How does AI contribute to your startup's competitive advantage? Would you be able to work without it?
- Have you developed any AI-based products or services? If yes, can you describe them?
- Do you have a dedicated team or budget for AI development and implementation?

4. Challenges and Barriers

- What challenges have you faced in adopting AI (e.g., lack of talent, funding, infrastructure)?
- Are there any regulatory or policy barriers that limit your use of AI?
- How do you address ethical concerns related to AI (e.g., bias, privacy)?

5. Enabling Factors

- What resources or support have been most helpful in adopting AI (e.g., government programs, partnerships)?
- Do you collaborate with universities, research institutions, or other organizations for AI development?
- How important is access to funding and talent for your AI initiatives?

6. Policy and Ecosystem

- How do government policies or regulations influence your use of AI?
- Are there any local or national initiatives that support AI adoption in startups?
- How would you describe the overall AI ecosystem in Rwanda (e.g., talent pool, investor interest, infrastructure)?

7. Future Outlook

- What are your future plans for AI adoption or development?
- What changes (e.g., policy, funding, talent) would help your startup leverage AI more effectively?

Appendix B

Additional Tables

Table B.1: Sample Coding Table: Qualitative Coding Structure

Code Type	**Initial Code**	**Description (Paraphrased)**	**Thematic Category**	**Country Context**
Descriptive	Lack of local data infrastructure	"We don't have enough quality datasets to train AI tools locally."	Infrastructure & Technical Readiness	Rwanda
Descriptive	Policy ambiguity	"There is no clear regulation around AI or customer data use."	Governance and Policy Environment	Sweden
Interpretive	AIa as a legitimacy-seeking tool	Startups claiming to use AI mainly for attracting investors, without clear use cases.	Strategic Use of AI / Symbolic Adoption	Both
Descriptive	Dependence on foreign cloud services	"We use AWS, but the latency and care is an issue here."	Infrastructure & Technical Readiness	Rwanda
Interpretive	Institutional fragmentation	Multiple government bodies involved, lacking coordination in AI policy.	Governance and Policy Environment	Sweden
Descriptive	Entrepreneurial workaround strategies	"We trained ourselves via YouTube tutorials because no one could help locally."	Human Capital & Learning Mechanisms	Rwanda
Interpretive	AI adoption as donor-driven	Adoption primarily influenced by international grants or NGO partnerships.	External Influence on Innovation Dynamics	Rwanda

Code Type	Initial Code	Description / Example (In Vivo or Paraphrased)	Thematic Category	Country Context
Descriptive	Ecosystem trust gaps	"Startups don't always know where to go to test AI ideas safely."	Institutional Support and Network Gaps	Sweden
Descriptive	Talent bottleneck in AI	"It's hard to find AI engineers who understand both tech and business here."	Human Capital & Learning Mechanisms	Both
Interpretive	Regulatory aspiration vs. implementation	Strong AI vision in policy documents but lacking in enforcement or infrastructure.	Governance and Policy Environment	Rwanda