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ARTIFICIAL INTELLIGENCE ADOPTION IN STARTUPS VS. CORPORATIONS

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Abstract: *This paper examines differences in artificial intelligence (AI) adoption between startups and established corporations from a management and business strategy perspective. The purpose of the study is to explore how organizational structure, managerial flexibility, and strategic priorities influence AI adoption decisions across different organizational forms. Using a comparative qualitative approach, the study draws on secondary data analysis and insights from prior empirical research to identify dominant adoption patterns. The findings indicate that startups tend to adopt AI more rapidly and experimentally, driven by agility and fast decision-making processes, whereas corporations approach AI adoption more cautiously due to hierarchical structures, risk management practices, and governance considerations. The paper contributes to the management literature by clarifying how organizational characteristics shape AI-related strategic behavior and offers practical implications for managers seeking to align AI initiatives with business strategy.*

Keywords: *artificial intelligence adoption; startups; corporations; institutional voids; Azerbaijan; digital transformation; emerging economies*

1 Introduction

The widespread and rapid dissemination of artificial intelligence (AI) technologies have attracted considerable interest from both researchers and practitioners with regards to the factors influencing AI adoption by organizations. Prior research has established that firm size, industry type, and technological capabilities are critical factors in firm adoption preparedness (Davenport & Ronanki, 2018; Mikalef & Gupta, 2021;). Relatively little attention has been given to the influence of institutional factors as a mediator in the process of technology adoption, especially in transitioning and emerging economies where institutional infrastructure is still in its infancy and regulatory frameworks and financial systems are still in their developmental stages.

This is particularly relevant where the unit of analysis is a heterogeneous category of firms. Startups and corporations are fundamentally different in terms of their position on the continuum of exploration and exploitation, as proposed by Tushman and O'Reilly (1996). Startups are marked by flexibility, experimentalism, and a lack of resources, while corporations are marked by formal structures, processes, and resources. In settings where formal institutional scaffolding is absent, the intrinsic organizational differences between startups and corporations could imply different patterns of AI adoption that are not captured by unified models of AI adoption. This has direct implications for innovation policy in a nation that aims for accelerated technological development.

Azerbaijan represents a theoretically and empirically relevant case to explore these phenomena. As a South Caucasus nation with an active digital transformation strategy, Azerbaijan has prepared various strategy documents. This includes the AI Strategy 2025-2028 (Cabinet of Ministers of the Republic of Azerbaijan [CMRA], 2025b), the Digital Economy Development Strategy 2026-2029 (CMRA, 2025a), and the Action Plan for Accelerating Digital Development 2026-2028 (CMRA, 2026). Nevertheless, Azerbaijan ranks 78 out of 83

on the Global AI Readiness Index (CMRA, 2025b), and 111 out of 188 on the Government AI Readiness Index (2024). The startup ecosystem is active, with over 200 active startups, but faces critical capital issues, with total venture capital funding for 2020-2024 amounting to only USD 17.6m, with a median seed round of only USD 50,000. Only three venture capital funds were operational in 2025 (Startup Genome, 2025). Crowdfunding and angel investing regulations are still absent (CMRA, 2026). Recent comparative policy analysis confirms Azerbaijan's national AI strategy, while ambitious in its long-term orientation, lacks the detailed sectoral roadmaps, commercialization mechanisms, and trust-building governance structures necessary to translate policy commitments into firm-level adoption outcomes (Isayev, 2025).

This institutional environment creates a natural laboratory for the exploration of the ways in which startups and corporations face the challenge of AI adoption under the condition of formal institutional constraints. The present paper aims to answer the following research questions:

RQ1: How do AI adoption patterns differ between startups and corporations in the Azerbaijani context?

RQ2: What institutional factors mediate and explain these differences?

RQ3: What policy implications follow from the identified adoption asymmetries?

Section 2 explains the development of the theoretical framework, which was based on institutional theory, dynamic capabilities, and organizational ambidexterity. Section 3 explains the methodology used in the research, while Section 4 presents the research findings. Section 5 presents the implications of the research, while Section 6 concludes the research with its contribution and future research directions.

2 Theoretical Framework

2.1 Institutional Theory and Institutional Voids

North (1990) defines institutions as the humanly devised constraints that structure political, economic, and social interaction, comprising formal rules (constitutions, laws, property rights) and informal norms (conventions, codes of conduct). In advanced market economies, dense networks of formal institutions, including capital markets, contract enforcement mechanisms, intellectual property regimes, and professional associations, reduce transaction costs and provide the infrastructure through which organizations can productively engage with transformative technologies. In many emerging and transition economies, however, these arrangements remain underdeveloped.

Such contexts have been described by Khanna and Palepu (1997, 2010) as "institutional voids," where specialized intermediaries and supporting institutions for efficient transactional activity are either nonexistent or ineffective. Institutional voids shape competitive dynamics by favoring those who can utilize alternative means of coping with them. With regard to technology adoption, the consequences of institutional voids are considerable: where formal institutional infrastructure for cloud computing markets, VC systems, or AI regulatory sandboxes is nonexistent, organizations must either develop their own indigenous means of coping with these challenges or forgo these opportunities.

Scott (2008) also further divides this pillar of institutional influence into three sub-pillars: regulative, normative, and cultural-cognitive. This distinction is helpful in understanding the coexistence of the partial presence of a regulative pillar, the partial absence of a normative pillar, and the partial absence of a cultural-cognitive pillar AI adoption in institutional void contexts therefore unfolds against a multi-layered institutional deficit that affects startups and corporations differently. Hinings et al. (2018) extend this institutional lens directly to digital transformation, identifying digital organizational forms, digital intitutional infrastructures, and digital institutional building blocks as the distinctive arrangements through

which digital technologies reshape economic activity. Applied to the AI adoption context, this framework suggests that institutional deficits in transitional economies are not merely inherited constraints but active sites of formation where nascent digital arrangements are being contested and built (Nambisan et al., 2019)

2.2 Dynamic Capabilities and Differential Adaptive Capacity

The dynamic capabilities model of competitive advantage, as proposed by Teece (2007, 2018), focuses on the organizational ability to sense new opportunities and risks, seize them through strategic investment, and change existing resource bases to fit new environmental demands. Teece (2018) extends this framework to foreground business model reconfiguration as a central dynamic capability, arguing that firms must continuously redesign their value creation and capture logicsa as technological environment shifts. This model is particularly applicable when discussing AI, as firms are required to operate within an environment of unclear regulation, compete for AI human resources, and implement new technologies into traditional business systems.

Dynamic capabilities are not uniformly distributed across firm types. Startups, unconstrained by legacy systems and routinized procedures, often exhibit high sensing capacity: a rapid identification of and response to emerging technological possibilities. However, the extent to which these seizing and reconfiguring actions are possible may be limited by the level of financial and human capital, and hence the presence of institutional infrastructure may be particularly important. On the other hand, large firms may have more resources at their disposal for investment in AI, but their sensing agility and inertia in terms of reconfiguring their established asset bases may be lower (Mikalef & Gupta, 2021; Tushman & O'Reilly, 1996). The institutional voids of corporate governance systems and risk management systems may also increase this problem, creating a governance trap in which risk management systems actually impede the adoption of risk management technologies, like AI.

2.3 Organizational Ambidexterity and AI Adoption

Birkinshaw and Gibson (2004), building on the foundational framework of Tushman and O'Reilly (1996) and subsequently synthesized in O'Reilly and Tushman's (2013) retrospective account, argue that organizations must simultaneously pursue exploration (pursuing new opportunities) and exploitation (refining existing competences). O'Reilly and Tushman (2013) further clarify that ambidexterity is not a static organizational design feature but a dynamic leadership challenge requiring continuous rebalancing as competitive and technological conditions evolve. Startups, oriented toward exploration by structural necessity, are predisposed toward the experimental AI adoption characteristic of that mode. Corporations, with their exploitative focus, may perceive the introduction of AI as a disruptor to their traditional efficiency gains, creating institutional resistance. This ambidexterity challenge is further complicated in institutional voids because corporations have to deal with the internal tension between exploration and exploitation without the external scaffolding that enables a managed approach to exploration in more developed economies.

2.4 Theoretical Propositions

Integrating these three frameworks, the paper advances the following theoretical propositions:

P1: In institutional voids, startups compensate for the lack of institutional infrastructure with their informal mechanisms (international networks, open-source structures), thereby facilitating the adoption of AI at a rate disproportionate to their endowments.

P2: In institutional voids, corporations display governance-amplified inertia, where their risk management structures exacerbate the institutional constraints on their AI adoption rate, which is lower than that justified by their endowments.
P3: Institutional enablers have a differential effect on corporations with institutional compliance capacity, whereas for startups, institutional voids are compensated for with international institutional substitutes.

3 Methodology

3.1 Research Design

The research method adopted is based on a mixed-methods approach, using both primary survey-based research and secondary data research. This is because of the multi-layered nature of the research questions, as well as the lack of significant quantitative data on AI adoption at the firm level in Azerbaijan. The research method is based on analytical rigor, which is suitable for a case study approach in an under-researched institutional context (Yin, 2018).

3.2 Primary Data

The primary data was collected using a survey that was designed for the purpose of this research. The survey was conducted between April and June 2025 for the purpose of a research project for an MBA dissertation. The survey targeted the Azerbaijani startup ecosystem and yilded a total of 48 usable responses from participants representing five distinct stakeholder group. Table 1 presents the full repondent breakdown.

Table 1. *Survey respondent breakdown by stakeholder group (n=48)*

Stakeholder Group	n	Share of total
Founders/Entrepreneurs (primary analysis group)	30	62.5%
Innovation Center Employees	8	16.7%
Investors (VC, Angel, Corporate)	6	12.5%
Academic Researchers/Professors	3	6.3%
Government Institution Representatives	1	2.1%

For the purposes of this paper, the analysis is restricted to the 30 startup founder respondents, who constitute 62.5% of the total sample. This sub-sample is selected on the methodological grounds: founders are the primary decision-makers responsible for AI adoption choices at the firm level and therefore represent the actor group most directly relevant to the research questions. The remaining 18 repspondents, comprising innovation center employees, investors, academic researchers, and a government representative, offer valuable perspectives on the broader ecosystem but fall outside the scope of this paper's focus on firm-level adoption dynamics. Their exclusion from the primary analysis is acknowledged as a limitation in Section 5.3.

The founders represent a variety of different sectors, with EdTech, FinTech, and E-Commerce being the most prominent, followed by ClimateTech and HealthTech sectors. Although the survey results were intended to explore a variety of different innovation ecosystem dynamics, as opposed to specifically focusing on the adoption of AI as a dependent variable, the results are significant in terms of understanding the constraints on technology adoption and the capital constraints that affect startups. The survey data are treated accordingly: as ecosystem-level evidence illuminating the conditions under which AI adoption decisions are made, rather than as a direct measure of adoption rates.

3.3 Secondary Data Sources

Secondary data sources were selected on the basis of authority, recency, and relevance. These comprise: the Global Startup Ecosystem Report 2025 (Startup Genome, 2025); three Azerbaijani government strategy documents (AI Strategy 2025-2028, Digital Economy Development Strategy 2026-2029, Action Plan for Accelerating Digital Development 2026-2028); the UNECE Science, Technology and Innovation Gap Analysis for Azerbaijan (Aliyeva, 2020); the World Bank B-READY 2025 assessment (World Bank, 2025); and a Mastercard digital economy report on Azerbaijan (Mastercard, 2023). These sources provide complementary quantitative benchmarks, policy trajectory data, and institutional environment assessments spanning the period 2020-2026.

3.4 Analytical Approach and Limitations

The method used for the analysis is comparative institutional analysis, where the patterns of AI adoption are compared in relation to the theory developed in Section 2. The primary survey data was also supported with secondary data, which helped in providing greater validity. However, the limitations of the research are that the survey was not conducted specifically for measuring AI adoption, and there is a heavy dependence on secondary data for the corporate side of the data. The sample is also from a single country, which is a limitation for external validity.

4 Results

4.1 Azerbaijan's Digital Innovation Ecosystem: Institutional Context

Azerbaijan's digital innovation ecosystem has a complex growth and restrictive profile. The ICT sector contributed 2.8% to non-oil GDP in 2024, growing by 18% annually (CMRA, 2025a). Nevertheless, the export of ICT services was only valued at 110 million USD by 2024, compared to 882 million USD for Kazakhstan and 620 million USD for Uzbekistan (CMRA, 2025a). This shows a lower market penetration compared to other countries in the region. R&D spending stands at 0.2% of GDP compared to an average of 2.5% for OECD countries (Aliyeva, 2020), which limits the local capacity for generating knowledge to feed the innovation for AI. Table 2 shows the key digital innovation ecosystem for Azerbaijan.

Table 2. *Key indicators of Azerbaijan's digital innovation ecosystem*

Indicator	Value	Source
Global AI Readiness Ranking	78th out of 83 economies	AI Strategy 2025–2028
Government AI Readiness Ranking	111th out of 188 economies	AI Strategy 2025–2028
Total VC Funding (2020–2024)	USD 17.6 million	GSER 2025
Startup Ecosystem Value	USD 36.6 million	GSER 2025
Median Seed Round	USD 50,000	GSER 2025
Active Startups	200+	GSER 2025
ICT Share of Non-Oil GDP (2024)	2.8%	Digital Economy Strategy 2026–2029
ICT Exports (2024)	USD 110 million	Digital Economy Strategy 2026–2029
R&D Expenditure	0.2% of GDP	UNECE STI Gap Analysis
Venture Capital Funds	3 funds (as of 2025)	Action Plan 2026–2028
Crowdfunding/Angel Legal Framework	Absent (under development)	Action Plan 2026–2028

A particularly acute institutional constraint is the absence of major international cloud service providers. Neither Amazon Web Services (AWS), Microsoft Azure, nor Google Cloud Platform maintains a local presence, a structural barrier to AI development explicitly acknowledged in the AI Strategy 2025-2028 (CMRA, 2025b). This infrastructure gap has indirect consequences for startup AI adoption: access to cloud AI credits programs, which constitute a significant indirect subsidy for AI-adopting startups globally, is effectively foreclosed. The government intends to build a GPU Supercomputer Centre and an Azerbaijani Large Language Model as outlined in the Action Plan 2026-2028 (CMRA, 2026). However, this is still prospective in nature. B-READY 2025 results for Azerbaijan show a dichotomous business environment, with high scores in Business Entry (86/100) and accessing Financial Services (87/100) but poor scores in Market Competition (45/100) and Business Insolvency (36/100) (World Bank, 2025). These results have important implications for the risk assessment of investing in AI.

4.2 AI Adoption in Azerbaijani Startups

Survey findings and additional documentary evidence suggest that Azerbaijani startups demonstrate active and increasing engagement with AI technologies, which is manifested through experimental usage, circumventing access to infrastructure, and sectoral concentrations of AI adoption.

Perhaps the most telling figure here, however, is the distribution of the founder respondents by the different stages of the startup lifecycle, as reflected by the survey results. The majority of the founder respondents were clustered in the MVP Development and MVP Launch and Early Revenue stages, with only one founder respondent who has reached the scaling stage. This early-stage concentration has a direct bearing on AI adoption capacity: the USD 50,000 median seed round documented in GSER 2025 (Startup Genome, 2025) is insufficient to fund proprietary AI infrastructure development, and most startups are operating well before the revenue levels that would support sustained AI investment.

Funding constraints constitute the primary pain point reported by founder respondents, and this constraint cascades into a set of interrelated downstream barriers. Limited capital restricts access to paid AI tools and cloud infrastructure, constrains the ability to hire specialized AI talent, and forecloses participation in international expansion that would otherwise provide access to AWS, Azure, and Google Cloud credit programs. The structural absence of these major cloud providers in Azerbaijan thus compounds the founding capital constraint: startups cannot offset limited domestic funding through the cloud credit programs that serve as a significant informal AI infrastructure subsidy in more institutionally developed ecosystems. This chain of constraint moves from funding scarcity to infrastructure inaccessibility and is key to understanding why Azerbaijani startup AI adoption is of an informal and low-cost nature rather than the systematic adoption of enterprise-level AI systems.

Despite these limitations, startups were found to have significant informal institutional compensation ability, which aligns with Proposition P1. The international accelerators, which include programs such as Seedstars World and innovation competitions in regions, offer startups access to a network of mentors and infrastructure credits, which can be used as a substitute for VC and cloud markets domestically. The emphasis on informal institutional mechanisms as a key factor stems from the fact that, in this ecosystem, formal institutional substitutes are not yet operational, with agility and international networks as the key differentiators for AI-active startups.

In terms of industry type, FinTech Startups, especially those categorized under Payment Service Providers, were identified as the most AI-intensive industry type. This was due to both the data richness of FinTech operations and the competitive pressure of banks' digitalization initiatives. EdTech and Digital Wellness Startups revealed their AI adoption potential in

personalization and user engagement optimization. AgriTech, PropTech, and Logistics Startups revealed relatively early-stage AI adoption potential, hindered by capital costs of establishing data collection infrastructure. Azerbaijan ranks #25 in Asia for Affordable Talent (Startup Genome, 2025), representing a true competitive advantage in terms of availability of AI Engineering talent with cost structures significantly below those of European and North American ecosystems; LinkedIn statistics included in the AI Strategy 2025-2028 report by CMRA (2025b) revealed 60-fold growth in AI and machine learning job market demand between 2016 and 2022.

4.3 AI Adoption in Azerbaijani Corporations

The resource advantages and governance constraints interplay to form the environment for the adoption of corporate AI in Azerbaijan. The key players in the adoption of AI-related technologies are the financial sector, the telecommunications sector, and the state-owned enterprises undergoing digital transformation.

The Central Bank of the Republic of Azerbaijan (CBAR) has taken an active approach to regulating digital banking in the financial industry. This includes creating the FinTech sandbox and adding digital banking to prudential regulation. As of 2024, there are more than 30 FinTech companies operating in the Republic of Azerbaijan (CMRA, 2025a). These companies include both startups and established businesses. The banks that are already there are focusing on employing AI to help with fraud detection, credit scoring, and customer support. The digitization of the Republic of Azerbaijan, as per the Mastercard (2023) digitization report, has achieved a digital payment rate of 32% and banking penetration of 68%. The Digital Economy Development Strategy, which is expected to be accomplished by the year 2029, also includes the goal of enrolling 50 businesses into digital transformation programs until the year 2026, increasing to 300 until the year 2029, with the Gen AI economic impact goal of 70 million AZN until the year 2029 (CMRA, 2025a).

A phenomenon of governance-enhanced inertia, as proposed by Proposition P2, was observed across various corporate bodies. Larger firms, which are subject to various procurement regulations and compliance requirements, have elongated decision-making cycles for technology adoption compared to their smaller counterparts. In addition, the presence of legacy technologies, which is common among incumbent banks and government firms, poses integration challenges for AI systems. Although risk aversion is rational from a perspective where intellectual properties are not well protected and regulations around AI-generated content are ambiguous, this phenomenon also acts as a barrier for AI investment among corporate bodies. The reputational exposure associated with AI deployment constitues a further governance constraint: organizations sensitive to brand integrity and stakeholder trust are acutely alert to AI-related risks including algorithmic bias, data privacy failures, and the integrity of automated outputs, creating governance-oriented hesistancy that compounds resource-based barriers to adoption (Ağtaş, 2025). The lack of Azerbaijani cloud infrastructure, however, also imposes significant constraints on corporate adopters, including data localization, bandwidth, and service latency, which can act as significant operational barriers even for firms willing to invest in cross-border cloud services.

The differential effect of CBAR's FinTech sandbox supports Proposition P3. Firms with compliance capabilities are better positioned to deal with the sandbox environment than startups, thus creating a differential effect for the development of complementary AI solutions. Startups and firms are less inclined towards AI adoption in AgriTech, Logistics, and PropTech, areas where there is a lack of support from the FinTech sandbox, implying that institutional support drives AI adoption. A comparison of AI adoption characteristics of both company types is provided in Table 3.

Table 3.*Comparative AI adoption characteristics: startups versus corporations in Azerbaijan*

Dimension	Startups	Corporations
Adoption speed	Rapid; experimental; iterative	Deliberate; phased; governed
Primary constraint	Infrastructure access; capital scarcity	Governance inertia; compliance burden
Compensation mechanism	International networks; open-source tools; agile structures	Regulatory sandboxes; procurement channels
Key AI-active sectors	FinTech (PSPs), EdTech, Digital Wellness	Banking, Telecommunications
Capital base	Limited (USD 50,000 median seed)	Substantial (retained earnings, credit)
Sensitivity to institutional voids	High: dependent on formal gap resolution	Moderate: partially self-sufficient
Dominant dynamic capability	Sensing and informal seizing	Formal resource deployment; reconfiguration lag

5 Discussion

5.1 Theoretical Implications

The empirical findings from Azerbaijan provide substantive support for the theoretical framework advanced in Section 2, while revealing nuances that extend its analytical scope. The differential adoption patterns observed between startups and corporations are consistent with the institutional void literature's prediction that weak formal institutional environments produce heterogeneous firm-level responses rather than uniformly suppressed technology adoption (Khanna & Palepu, 2010).

Confirmation of Proposition P1 is provided by the survey and documentary evidence jointly. The informal institutional compensation mechanisms identified in Azerbaijan, including international accelerator access, open-source AI deployment, and freemium tool adoption, operate through specifically technological channels not previously foregrounded in the AI adoption literature. Founder survey evidence reveals the precise structure of this compensation: accelerator and incubation programs substitute for some institutional gaps (mentorship, networking) but not others (capital, cloud infrastructure). Funding scarcity remains the primary constraint, and its downstream effects, including restricted access to cloud AI credits and the inability to fund international expansion that would unlock such access, illustrate how institutional voids compound rather than operate independently. This finding extends Khanna and Palepu's (2010) institutional void framework into the domain of AI technology adoption and clarifies the partial rather than comprehensive nature of informal substitution.

Confirmation of Proposition P2 is supported by the pattern of governance-amplified inertia documented in the corporate evidence. The Azerbaijani findings suggest that institutional voids interact with corporate governance structures in a specifically amplifying manner: the risk aversion generated by weak intellectual property protection and regulatory uncertainty compounds baseline governance inertia documented in prior technology adoption literature (Teece, 2007). This interaction has not been systematically theorized in prior AI adoption research and may constitute a contribution to the institutional economics of technology adoption.

Proposition P3 receives partial but instructive support. The CBAR FinTech sandbox illustrates the capacity for targeted institutional enablers to drive adoption across different types of firms; however, the benefits of this are asymmetrical and accrue primarily to resource-constrained incumbents. This discovery reveals a paradox for institutional design: sector-specific enablers designed to foster innovation may actually exacerbate the established corporation advantage over new firms in institutionally constrained environments.

5.2 Policy Implications

The findings carry several policy implications for the design of AI adoption support in transitional institutional contexts. Most fundamentally, the evidence supports asymmetric institutional support: interventions tailored to the distinct adoption barriers of startups versus corporations, rather than uniform innovation ecosystem policies. For startups, priority interventions include: resolution of the cloud infrastructure gap, either through attracting major cloud providers or establishing a domestically operated high-performance computing platform with international interoperability; legal enactment of crowdfunding and angel investment frameworks, acknowledged but not yet enacted in the Action Plan 2026-2028 (CMRA, 2026); and expansion of international accelerator program participation and equity-free grant instruments. For corporations, priorities include clear AI regulatory frameworks that reduce adoption risk uncertainty, procurement reform to accelerate technology adoption in state enterprises, and targeted incentives for corporate-startup AI co-development partnerships.

The government's announced Digital Nomad Visa and Digital Talent Visa programs (CMRA, 2026) represent strategically important instruments for addressing the talent constraint. The AI Academy and 500-engineer training target in the AI Strategy 2025-2028 (CMRA, 2025b) are necessary conditions but insufficient in isolation; retention mechanisms are equally important given documented brain drain risk (CMRA, 2025a). However, the achievement of the 70 million AZN by 2029 targeted by the GenAI economic impact (CMRA, 2025a) would be possible only if the gaps in the infrastructure and the institutional environment are filled in the short term. The existing adoption path, driven mainly by the informal compensation of the startup sector rather than the systematic use by the corporate sector, would not likely result in the productivity impact on the required scale within the stipulated timeframe. These findings align with recent policy analysis specific to Azerbaijan, which identifies the establishment of AI commercialization hubs, sector-specific implementation roadmaps, and an ethical governance package modeled on international best practices as the most actionable near-term instruments for closing the gap between Azerbaijan’s strategic AI ambitions and current implementation capacity (Isayev, 2025).

5.3 Limitations

Several limitations should be acknowledged. First, the primary survey analysis is restricted to the 30 founder respondents drawn from a broader sample of 48 ecosystem stakeholders. The perspectives of the remaining 18 participants, comprising innovation center employees, investors, academic researchers and a government representative, are not analysed in this paper, as their roles are peripheral to the firm-level AI adoption dynamics that constitute the research focus. Incorporating these multi-stakeholder perspectives in future research could provide a richer institutional ecosystem view and triangulate the founder-reported constraints again the observations of supporting actos. Second, documentary and secondary sources are overrepresented for the corporate side, which limits the depth of the insights gained. Finally, the single-country focus limits the generalizability of the findings. Future research should address the above limitations by conducting specifically designed survey research for AI adoption, qualitative research for corporate AI projects, and multi-country analyses for the CA and SC economies.

6. CONCLUSIONS

In this paper, the different patterns of AI adoption in startups and corporations in Azerbaijan have been explored, with inspiration coming from the understanding that the institutional environment does have a systematic impact on the process of technology adoption, which existing unified models fail to capture in a satisfactory way. With the help of a series of primary survey results (48) from the Azerbaijani startup ecosystem, as well as a comprehensive

analysis of government strategy reports and international ecosystem reports, three key results have been established in this paper.

First, Azerbaijani startups exhibit active, agile AI adoption driven by informal institutional compensation mechanisms, including international accelerator networks, open-source tools, and diaspora connectivity, despite operating within one of the most institutionally constrained AI environments globally. Survey data from the 30 founder sub-sample, drawn from a broader study of 48 ecosystem stakeholders, confirm the structural underpinnings of this pattern: the majority operate at early development stages (MVP Development and MVP Launch), and funding constraints are the primary reported pain point, cascading into downstream barriers including access to cloud infrastructure and international expansion capacity. Second, corporations demonstrate governance-amplified inertia that compounds the constraining effects of institutional voids, producing AI adoption below the level predicted by resource endowments alone. Third, sector-specific institutional enablers, most notably the CBAR FinTech regulatory sandbox, can catalyze adoption across firm types when present, but distribute benefits asymmetrically toward compliance-capable incumbents.

The theoretical contribution is based on the combination of institutional voids, dynamic capabilities, and organizational ambidexterity theories for understanding the heterogeneity of AI adoption in transition economies. The policy contribution is based on the formulation of asymmetric institutional support as a guiding principle for transition economies that wish to capitalize on AI for economic transformation. Resolving the cloud infrastructure gap, developing legal frameworks for VC and crowdfunding, and overhauling procurement systems for corporate tech adoption emerge as the top priorities based on the evidence. Future research should include comparative studies in the South Caucasus and Central Asian regions, longitudinal studies on the effects of institutional development on AI adoption, and sectoral studies in AgriTech and Logistics.

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