SOCIAL CAPITAL AND THE ROLE OF SOCIAL BROKERS IN AI (NON) ADOPTION IN DEVELOPING COUNTRIES

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ABSTRACT
This research explores how social capital supports the adoption of artificial intelligence (AI) in developing countries, focusing on the role of "social brokers." A social broker is a trusted individual who occupies a unique position within a network, connecting individuals from different networks or maintaining connections with a larger number of individuals within the existing network. Based on input from the initial phase of the project, conducted in a developing country with high internet use but low AI adoption, we use qualitative research methods to better understand the practical aspects of AI adoption. Our early findings suggest that AI adoption goes beyond the right technology or skills and is strongly influenced by trusted communities and networks that shape decisions about AI adoption. "Social brokers" play a key role in this process. They help close knowledge gaps, address concerns of people who have not adopted AI or have adopted it at a low level, and show how AI can be relevant and useful for specific jobs and tasks. These "social brokers" are often seen as trusted friends, technology influencers, former colleagues, or respected local industry experts. Their presence and activities in tightly connected social networks appear to be very important for reducing the gap in AI adoption. The next phase of this research will focus on identifying the aspects of social capital that influence AI adoption, understanding the relationships that help overcome resistance to adopting AI, and developing strategies that use social capital to encourage faster AI adoption in developing countries.

Keywords: *AI, Technology adoption, Social brokers, Developing countries*

JEL classification: *O31, O32, O33*

1. INTRODUCTION

Artificial Intelligence (AI) is rapidly transforming various industries around the globe and presents a tremendous opportunity for development across industries, professions, and national boundaries (Agrawal *et al*., 2019). As generative AI is truly a general-purpose technology (McAfee, 2024), it has already begun to significantly alter our ways of living and working (Gordon and Gunkel, 2024). AI's global impact stems from its accessibility, affordability, and ease of use. This provides a unique opportunity for developing countries to overcome any existing gaps with developing countries and gain a competitive position (Alonso *et al*., 2020; Aly, 2020; Fan and Qiang, 2024) or at least minimize inequality due to technological change (Alonso *et al*., 2022; Freire, 2024). However, there is a very limited adoption of AI among the developing countries (Khan *et al*., 2024). Thus, the question is how AI adoption in developing

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countries can be increased? This is important because “the ultimate impact of generative AI on the economy depends on how quickly and intensively the technology is adopted” (Bick *et al*., 2024).

The existing research has identified key reasons for delayed AI adoption in developing countries, such as technological infrastructure, economic stability, policies, financial constraints, and workforce readiness (Ali *et al*., 2024; Al-Zahrani and Alasmari, 2025). However, developing or improving these conditions might take years, delaying the adoption and impact of artificial intelligence on these economies. Nevertheless, early research in the adoption of AI in the United States identifies inertia and adjustment costs as barriers to AI adoption (Eastwood, 2024; McElheran *et al*., 2023). Overcoming this and identifying how AI can be embedded in everyday work practices may speed up the adoption. In this direction, we are conducting research on how social capital can be used to overcome the inertia of AI adoption.

Despite widespread connectivity, AI uptake remains concentrated among a minority of firms and individuals, especially large “high performers”, while SMEs lag due to skills gaps, weak data readiness, uncertain ROI, compliance risk, and integration costs. Enabling factors include leadership commitment, workforce training, robust data infrastructure, and access to collaborative ecosystems (Eurostat, 2025; McKinsey, 2024; OECD, 2025). This paradox also appears in the European Union countries, where only about one in seven enterprises used AI in 2024, even though digital penetration is near universal, with roughly a threefold gap between large and small firms (Eurostat, 2025; OECD, 2025). Regarding social capital, the scholarly consensus, drawing on classic theory, is that strong ties within and between organizations build trust, ease knowledge sharing, and raise absorptive capacity, which in turn improve AI readiness and adoption. Recent empirical studies find that SMEs with richer relational networks are better positioned to identify use cases and manage cyber risk, and that collaboration ties to peers with AI experience accelerate uptake in scientific contexts (Nahapiet and Ghoshal, 1998; Ode *et al*., 2025; Bianchini *et al*., 2025). At the same time, social capital is not unambiguously beneficial; overly dense inward-looking networks can reduce autonomy and slow product innovation, which cautions against closed or hierarchical configurations when implementing AI (Wang *et al*., 2025).

Social capital refers to the resources individuals or groups acquire through their relationships within social networks, highlighting the mutual benefits that arise from trust, norms and collaboration, which strengthen social cohesion and cooperation (Nahapiet and Ghoshal, 1998; Putnam, 1994).

Through this research, we seek to address the following questions and provide insights into their implications:
RQ1: How do the structural, cognitive, and relational dimensions of social capital influence AI adoption in organizations?
RQ2: What specific elements of social capital contribute to overcoming inertia in AI adoption within organizations?
RQ3: What strategies leveraging social capital can be employed to accelerate AI adoption in organizations in developing countries?

We are conducting our research in North Macedonia, a developing country with high internet penetration and competitive average net salaries. Given this context, the very low adoption of AI can neither solely be attributed to a lack of digital access nor the low purchasing power.

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Instead, we believe that it points to more complex factors that we aim to explore.

2. METHODOLOGY

At this stage, we are performing exploratory interviews with a diverse set of professionals to get a better understanding of their awareness of AI and benefits, concerns, usage patterns, and motivation. The professionals selected for the exploratory interviews were chosen because they represent diverse industries, roles, and levels of familiarity with digital technologies, which provides a broad spectrum of perspectives on AI adoption. By engaging individuals with varying experiences, expertise, and organizational contexts, the research captures a more comprehensive understanding of awareness, perceived benefits, concerns, usage patterns, and motivations surrounding AI. This diversity enhances the reliability of the findings, ensures that the analysis is not narrowly confined to one sector or professional background, and allows for richer insights into the social and organizational dynamics that influence AI adoption.

In the next stage of interviews, we will explore the nuances of social capital. By focusing on qualitative data and two cycles of interviews, we aim to uncover insights into the perceptions and behaviors influencing adoption. We utilize Reflexive Thematic Analysis (RTA) (Braun *et al*., 2019) to analyse and interpret qualitative data collected through interviews. Interpretive qualitative research provides a comprehensive approach to exploring human experiences in particular contexts (Rahman, 2016), allowing for a deeper understanding of how social capital impacts adoption.

Reflexive Thematic Analysis is appropriate because it offers a flexible yet rigorous approach for identifying patterned meanings across interviews while preserving the contextual richness of participants' accounts. It aligns with our exploratory, interpretivist stance and two-cycle design by supporting iterative movement between data and analysis, allowing themes to evolve as understanding deepens. RTA emphasizes the researcher's active role in knowledge production and requires reflexivity, which is essential when examining how social capital shapes perceptions, motivations, and behaviors. Its compatibility with semi-structured interviews, transparent auditability through coding notes and analytic memos, and capacity to capture both semantic and latent meanings make it well-suited to unpack the nuanced mechanisms through which relationships, trust, and norms influence AI adoption.

3. INITIAL FINDINGS

While our initial findings reaffirm the existing key challenges in AI adoption, including a lack of awareness and privacy concerns, they surface a unique factor named "social brokers" that play a significant role in bridging the adoption gap. Through our analysis, we have identified the emergence of a main theme and three sub-themes:

- Main Theme: Social brokers are key catalysts for AI adoption: Social brokers facilitate and shape attitudes towards AI.
- Subtheme 1: Social brokers bridging information gaps: Social brokers reduce uncertainty about AI by providing trusted information.
- Subtheme 2: Social brokers showing "how": Social brokers offer hands-on experiences on AI for specific tasks.
- Subtheme 3: Social brokers alleviating perceived risks: Social brokers help reduce perceived risks in adopting AI.

4. CONCLUSION

Our initial findings about the key role of "social brokers" bring to light a new perspective of looking at AI adoption that goes beyond the traditional. Many developing countries are characterized by strong social ties where trust-based networks often drive decision-making. Our findings on the adoption of AI in a developing country are unique in the specific context but align with the general literature on social influence on technology adoption (Vannoy and Palvia, 2010; Hasija and Esper, 2022).

While these findings provide valuable insights in a developing country context, their generalisability is currently limited due to the geographical limitation of this project. Future research should extend this study across other developing countries. As we continue, we will explore the social capital dimensions and their impact on AI adoption. By focusing on qualitative data and using two cycles of interviews, this study aims to uncover nuanced insights into the perceptions and behaviors influencing AI adoption.

This study contributes to the literature on technology adoption by introducing the concept of social brokers as a critical mechanism for AI adoption in developing-country contexts. Existing frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) emphasize perceived usefulness, ease of use, and social influence as key determinants of adoption. Our findings refine these models by showing that in dense, trust-based networks, social influence operates less through diffuse peer norms and more through the mediation of structurally central and trusted actors. Brokers act as translators, validators, and endorsers of new technologies, thereby shaping perceptions of usefulness and ease of use and mitigating perceived risks.

This perspective also challenges assumptions within diffusion of innovation theory, which traditionally highlights the role of early adopters and innovators. Instead, our evidence suggests that adoption is often accelerated by brokers who bridge otherwise disconnected groups, facilitating cross-cluster diffusion even when technological uncertainty is high. Integrating insights from social capital theory, we argue that the structural position (brokerage), relational trust, and cognitive alignment of these actors jointly create conditions for effective adoption. Finally, in contexts where institutional trust and formal evaluation mechanisms are weak, brokers serve as substitutes for missing intermediaries, highlighting boundary conditions under which their influence is most pronounced. Collectively, these contributions extend and refine dominant theories by foregrounding the structural and relational mechanisms that drive AI adoption under uncertainty in developing countries.

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