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Epidemic effects in the diffusion of emerging digital technologies: evidence from artificial intelligence adoption

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ABSTRACT

The properties of emerging, digital, general-purpose technologies make it hard to observe their adoption by firms and identify the salient determinants of adoption. However, these aspects are critical since the patterns related to early-stage diffusion establish path-dependencies which have implications for the distribution of the technological opportunities and socio-economic returns linked to these technologies. We focus on the case of artificial intelligence (AI) and train a transformer language model to identify firm-level AI adoption using textual data from over 1.1 million websites and constructing a hyperlink network that includes >380,000 firms in Germany, Austria, and Switzerland. We use these data to expand and test epidemic models of inter-firm technology diffusion by integrating the concepts of social capital and network embeddedness. We find that AI adoption is related to three epidemic effect mechanisms: 1) Indirect co-location in industrial and regional hot-spots associated to production of AI knowledge; 2) Direct exposure to sources transmitting deep AI knowledge; 3) Relational embeddedness in the AI knowledge network. The pattern of adoption identified is highly clustered and features a rather closed system of AI adopters which is likely to hinder its broader diffusion. This has implications for policy which should facilitate diffusion beyond localized clusters of expertise. Our findings also point to the need to employ a systemic perspective to investigate the relation between AI adoption and firm performance to identify whether appropriation of the benefits of AI depends on network position and social capital.

1. Introduction

The diffusion of general-purpose technologies (GPTs) emerging in the field of information and communication technology (ICT) has been more uneven across industries and geography than previous GPTs such as electricity (Helpman and Trajtenberg, 1996). This uneven distribution could be especially pertinent in the case of advanced digital GPTs such as artificial intelligence (AI) technology (Brynjolfsson and Petropoulos, 2021; Felten et al., 2021; Frank et al., 2019) which is still in the early stages of diffusion (Vannuccini and Prytkova, 2023; Rammer et al., 2022). Theoretically, pervasive use of AI could enable sustained increases in productivity based on continuous technological improvements (Bresnahan and Trajtenberg, 1995), and increased rates of innovation based on innovation complementarities (Barro and Davenport, 2019; Bekar et al., 2018; Cockburn et al., 2019; Krakowski et al., 2022). These developments could have substantial effects on knowledge production and organizational decision making (Paschen et al., 2020; Shrestha et al., 2019; von Krogh, 2018). However, concerns have been expressed about the narrow distribution of these benefits due to the deployment of AI technology creating technological dependencies on few economic actors (Franco et al., 2023; Lundvall and Rikap, 2022). Thus, adoption patterns established in the early stages of technology diffusion can lead to path dependencies and technological lock-ins/lock-outs and potentially divergent economic development across regions

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and industries (Crespo et al., 2013).

While understanding the determinants of adoption is a prerequisite for effective policymaking (Stornelli et al., 2021), the inherent properties of AI technology which is emerging, digital, and of general-purpose make it hard to capture its adoption by firms empirically and to propose a theoretical model of the factors affecting adoption. There is an absence of micro-level data which would allow us to trace the use of such emerging digital technologies (Cirillo et al., 2022; Rammer et al., 2022) as the technological dynamism exhibited by GPTs renders traditional indicators (such as patents) mostly unsuitable and outdated (Breznitz, 2021). This leads to a pacing problem between technological progress and scientific inquiry into the societal impacts of new technologies (Frank et al., 2019). Their digital manifestations are resulting in intangibility of the technology and lack of knowledge about the complementary investments in knowledge and skills required for substantial adoption (Brynjolfsson and Petropoulos, 2021). Traditional technology adoption models focus on the tangible investment in internal resources, the characteristics of the technology, and exogenous environmental factors (DePietro et al., 1990) to explain and form expectations about the economic returns from adoption (Karshenas and Stoneman, 1993).

It is useful to return to the idea that technology usage ultimately is the utilization of knowledge which spreads between firms through social processes (Griliches, 1957; Rogers, 1983; Irwin and Klenow, 1994; Borgatti and Foster, 2003). Previous technology diffusion research locates the drivers of technology adoption in a firm's exposure to and acquisition of information about the technology in its external environment (Mansfield, 1963; Cohen and Levinthal, 1990; Freeman, 1991; Salter et al., 2015). The adoption of a digital GPT such as AI is likely to depend primarily on the acquisition of knowledge about how to integrate and employ AI (Brock and von Wangenheim, 2019; Chen et al., 2021; OECD, 2019a). This knowledge does not necessarily need to be transferred from other adopters directly but may circulate within interfirm networks (Freeman, 1991; Mueller and Ramkumar, 2023). Since social capital determines exposure to sources of stimulation and knowledge, it constitutes an intangible asset relevant to the technology adoption process (Brynjolfsson and Petropoulos, 2021). Thus, the network structure could determine access to knowledge and other assets as well as overall patterns of diffusion. Although this idea lies at the core of epidemic models of technology adoption and diffusion is not new (Freeman, 1991; Powell et al., 1999), social capital and network perspectives have remained under-explored in this literature strand since the identification of channels of transmission of adoption-related knowledge at the micro-level is difficult empirically. By focusing on the specific case of AI technology, we seek to address these issues by investigating the following research question: *To what extent are epidemic effects associated with firm-level AI adoption?*

We build new measures based on self-collected web-data to enable a comprehensive modeling approach that explains the adoption and diffusion of emerging AI technology. We start from the assumption that adoption resembles a process of internal and external legitimation of organizational technological change which can be detected in organizational communication (Rogers, 1995), and consider the firm's website as an expression of the company's organizational identity (Esrock and Leichty, 2000; Powell et al., 2016; Scheiber, 2013; Oertel and Thommes, 2018). We define AI adopters as firms that have developed an AI identity which requires that AI is a core part of their products or processes (Ulucanlar et al., 2013). To identify relevant pieces of information from firm websites (Kinne and Lenz, 2021), we trained and employed a transformer language model to classify the depth of AI-related knowledge represented by individual paragraphs. Compared to simple keyword-based approaches, this allows more accurate classifications by avoiding false positives when working with textual data. We also processed hyperlink-connections among firm websites to model the spread of AI-related knowledge between firms (Krüger et al., 2020; Abbasiharofteh et al., 2021). This yielded comprehensive firm-level data from >1.1 million observations extracted from company websites from Germany, Austria, and Switzerland (hereafter DACH) in the year 2022, and network data for a subset of 380,805 firms.

We use these web-based metrics to expand traditional epidemic models of inter-firm technology diffusion (Mansfield, 1963; Rogers, 1983; Karshenas and Stoneman, 1993) by integrating the traditional mechanisms considered in firm-level adoption models (indirect mimetic pressure, direct transmission of knowledge) with relational measurements (network position) of firms. This allows us to extend traditional epidemic models explaining the diffusion of emerging digital GPT by considering the contingencies created by the depth of the knowledge exchanged between firms (Bierly, 1996; Christensen, 2006), and the cognitive and geographic proximity to sources of knowledge (Boschma and Frenken, 2010; Sorenson et al., 2006; Laursen et al., 2011; Criscuolo et al., 2018). We checked the robustness of our findings from this novel web-based data using a representative questionnaire-based survey sample of almost 1400 firms in Switzerland which gathered self-reported information on AI adoption for the years 2019 and 2020.

Our results show that AI adoption is related to three significant channels of epidemic effects. First, the firm's location in an industrial and/or regional hot-spot associated with the production of AI knowledge which exposes it to high levels of indirect mimetic pressure leading potentially, to bandwagon adoption behavior. Second, strong embeddedness of the firm in the AI knowledge network which resembles a rather closed system of AI adopters, likely to hinder broader diffusion. Third, existence of high intensity of direct firm links which increase the likelihood of AI knowledge transfer. However, the effectiveness of direct transmission of AI knowledge will depend on the cognitive proximity among the partners, link strength, and the depth of the knowledge being shared. High intensity direct firm links seem to defy geographic distance and thus, offer a potential focus for policy measures to promote diffusion beyond local clusters.

The article is organized as follows: Section 2 discusses the theoretical background to the drivers of technology adoption through an epidemic model lens. Section 3 describes the data collected and our empirical strategy. Section 4 presents the descriptive statistics and the results of the regression analysis. Section 5 discusses our findings and provides some implications for policy makers and practitioners, as well as it acknowledges some of the limitations of our study. Section 6 concludes the paper.

2. Theoretical considerations and hypotheses

2.1. Defining AI adoption

Historically, research on technology adoption focused on the first moment of the firm's adoption of a technology (Battisti and Stoneman, 2003; Hollenstein and Woerter, 2008). However, Battisti and Stoneman (2003) argue that this first moment of adoption and use says little about the dominance and importance of the technology to the individual firm or the industry more broadly and does not help our understanding of its diffusion dynamics. A more meaningful focus would include a sufficient degree of intra-firm diffusion of the technology (Battisti et al., 2009; Woerter et al., 2017) and the definition of adoption as the substantive integration of the technology within the organization. This is in line with the procedural understanding of the adoption process proposed by Rogers (1995) who considers technology adoption as requiring legitimation by the social environment of adopters and acknowledgement as part of the organization's identity. Ulucanlar et al. (2013, p. 98) propose it as the "discursive presence of the technology that delineates a particular set of attributed characteristics and performative expectancies as representative of the technology's distinctiveness and value." These aspects emerge through the social processes of local sensemaking and global legitimization in the discourse between organizations and stakeholders (Ulucanlar et al., 2013). In what follows, we understand *AI adopter* as meaning that the firm presents the technology as part of its organizational identity and actively communicates its integration in core parts of its products or processes.

2.2. Determinants of adoption and epidemic models of technology diffusion

Firm-level studies on technology adoption generally draw on three seminal theoretical models proposed by DePietro et al. (1990), Karshenas and Stoneman (1993), and Rogers (1983). Common to all three models are the determinants considered to drive technology adoption: i) Organizational characteristics and capabilities (e.g., firm size, workforce, organizational structure, managerial capabilities); ii) Technological context (e.g., relative advantage, compatibility, complexity); and iii) External environmental dynamics (e.g., competition, public funding, regulation). Empirical contributions which study the economics of AI along these lines focus mainly on organizational and technical dimensions to explain the adoption decision (Dauth et al., 2017; Graetz and Michaels, 2018; Felten et al., 2021; Acemoglu et al., 2022; Chen et al., 2021; DeStefano et al., 2022). However, although they control for institutional characteristics such as exogenous environmental influences, they do not account for a more endogenous relation between the firm and its engagement with external sources of relevant knowledge and inter-firm transmission of that knowledge.

Rogers (1995) notes that exposure to knowledge and persuasive signaling between organizations are often enabled through cosmolite (mass media) or local (interpersonal) communication channels. After the initial adoption decision, the process concludes with the stages of integration of technology into corporate practices, and importantly, confirmation. In this final stage, adopters seek to legitimize the decision by gathering positive responses from their environment. This highlights the importance of considering the inter-firm transmission of information which may produce positive network externalities likely to affect decisions about adoption of emerging technologies. These effects may be driven primarily by knowledge spillovers across firms (Cassiman and Veugelers, 2002; Roper et al., 2017). To understand how knowledge spillovers occur calls for consideration of the stream of work which compares the diffusion of innovations in the socio-economic system to the spread of a virus within the population (Karshenas and Stoneman, 1993; Sorenson et al., 2006). Karshenas and Stoneman (1993) argue that epidemic effects may be particularly relevant for the diffusion of emerging digital technologies, as these technologies require smaller financial investments and are associated with higher uncertainty about short-term returns. Epidemic effects refer "to endogenous learning as a process of self-propagation of information about a new technology that grows with the spread of that technology" (Karshenas and Stoneman, 1993, p. 509). Early infections of knowledge lead to more transmission of that knowledge and promote adoption as the uncertainty related to the technology reduces with the spread of information on the perceived benefits of its adoption through established networks (Griliches, 1957; Irwin and Klenow, 1994).

The dynamics of technology diffusion takes an S-shape of slow initial, rapid medium-term, and ebbing long-term growth before saturation (Sorenson et al., 2006). However, how the different channels of epidemic effects emerge in the initial stages preceding more rapid diffusion is unclear. The case of AI demonstrates the profusion and variety of types of AI-related information available to potential adopters via a range of different channels. This information is likely to be processed differently by different firms, leading to varying effects on technology diffusion. Karshenas and Stoneman (1993) refer to two types of mechanism enabling epidemic effects in relation to technology diffusion: mimetic pressure and direct transmission. The presence of these two mechanisms has been shown to matter for several different (digital) technologies such as electronic sales technologies (Battisti et al., 2009), the internet (Haller and Siedschlag, 2011), and energy savings technologies (Woerter et al., 2017).

2.2.1. Mimetic pressure

Epidemic dynamics can arise from the pressure to emulate observed adoption behavior through regular screening activities or other types of exposure (e.g., at industry events). Previous research shows that the rate of diffusion of a technology observed by a focal firm seems to affect its own decision to adopt it (Battisti and Stoneman, 2003; Haller and Siedschlag, 2011; Marsh et al., 2017). The underlying mechanism of mimetic pressure is based on the probability that the firm will observe adoption of the technology in its market environment through intentional market screening activities and/or through less intentional knowledge spillovers via the transmission channels of networking events, labor mobility, etc. (Audretsch and Keilbach, 2007; DiMaggio and Powell, 1983). Glückler (2013) defined observation as one mechanism of collective learning that is non-interactive. This indirect engagement allows the effects of mimetic pressure to transcend narrow network structures (Cooke, 2004).

The type of information that promotes emulation is more likely to be codified knowledge which is more easily transmissible and does not require direct contact (Brusoni et al., 2005; Audretsch and Lehmann, 2006). DiMaggio and Powell (1983) posit that the copying of best practice from another organization is particularly prevalent when organizations face uncertainties about application of a new technology which would be relevant to the case of AI. In what follows, we refer to the mechanism of indirect epidemic diffusion as *mimetic pressure*.

Since we are considering adoption behavior in the focal firm's environment as a relevant factor in that firm's adoption decisions, we need to define this environment. There is empirical evidence that the transmission of information generally decreases with geographical distance and that typically firms are myopic in terms of their surrounding landscape (Fleming and Sorenson, 2001; Sorenson et al., 2006). The effect of geo-spatial diffusion results in the geographic localization of the technology (Jaffe et al., 1993; Keller, 2002) and Dahl and Pedersen (2004) show that within these localized clusters, even informal contacts allow the transmission of useful knowledge. However, in our increasingly digitalized world, knowledge spillovers are increasingly less dependent on geo-spatial proximity which suggests the need to consider more than just the geographic dimension. The most prominent influence on the firm is the *industry* to which it belongs, representing the cognitive similarity among firms (Haller and Siedschlag, 2011; Woerter et al., 2017). Thus, we will consider mimetic pressure emanating from the local geographic and industrial environment.

H1: The firm's likelihood of adopting AI is related to the rate of inter-firm diffusion of AI in its local environment.

2.2.2. Direct transmission

The other epidemic effects channel refers to more direct, intentional transmission of information among firms (Karshenas and Stoneman, 1993). In contrast to indirect exposure to/observation of the technology in its environment, direct transmission of technological knowledge is the result of explicit linkages such as (R&D) co-operations and formalized business engagements with stakeholders which require regular contact. This social capital "binds collaborators together in knowledge exchange [s]" (Bozeman et al., 2001, p. 723) which can lead to innovative ways of producing value (Tsai and Ghoshal, 1998). The link between (R&D) co-operations and increased innovation efforts is well established (Cassiman and Veugelers, 2002; Laursen and Salter, 2006; Teixeira et al., 2008). Firms that engage in interactive search strategies seek to establish links with other socio-economic agents such as firms or public research institutions (Roper et al., 2017). This is aimed at leveraging a joint knowledge base facilitating the development and adoption of new technology (Borgatti and Halgin, 2011). Such cooperative behavior allows the transmission of both codified and tacit knowledge (Polanyi, 1966; Leonard and Sensiper, 1998) which has been shown to be an important driver of firm innovation activity (Cooke and Wills, 1999; Dosi, 1988; Hilpert, 2006) and to be relevant to adoption of ICT (Gourlay and Pentecost, 2002; Haller and Siedschlag, 2011; Oulton, 2002). These direct ties potentially can increase awareness of emerging ICT, facilitate access to intangible assets, and increase the willingness to adopt as the uncertainty attached to the application potential of new technology fleets (Karshenas and Stoneman, 1993). In what follows, we refer to such mechanisms as *direct transmission* of AI-relevant knowledge.

While we assume that ties to all types of co-operation partners increase the probability of exposure to AI-related knowledge circulating in firm networks (the firm's non-specific social capital), it does not guarantee transmission of relevant tacit knowledge (Audretsch and Lehmann, 2006). Transmission of tacit knowledge requires direct interaction with the AI adopting firm or a firm with relevant technical skills and resources (Bozeman and Corley, 2004). Therefore, at the individual firm-level, we consider the firm-specific intensive margin of exposure rather than the absolute number of linkages which measure the firm's openness to and access to relevant knowledge. In this study, we consider the specific number of AI-related linkages relative to the firm's total linkages.

H2: The share of direct AI-related linkages is associated to the firm's likelihood of adopting AI.

2.2.3. Embeddedness in inter-firm networks

Social capital theory suggests the firm's position in the network determines its access to informational resources (Lin, 2001; Burt, 1992). These, in turn, may trigger mimetic or osmotic processes (Friedkin and Johnsen, 1990; Granovetter, 1985; DiMaggio and Powell, 1983). The concept of homophily describes a process of convergence between firms embedded in inter-firm networks when being exposed to similar signals resonating through the network (Borgatti and Halgin, 2011; Owen-Smith and Powell, 2004; Schilling and Phelps, 2007). Thus, both mimetic behavior and direct transmission are functions of the firm's position in the socio-economic network and these network effects are likely to motivate technology adoption even beyond the mechanisms of direct links to knowledge sources and indirect screening of the environment. This is because relevant information may be relayed or even reinforced through a string of connected nodes, where the original source and the recipient must not be directly connected (Granovetter, 1985). Network embeddedness has been shown to explain varying levels of firm innovation output which suggests that firms that are part of a coherent network benefit from positive externalities through knowledge spillovers that are additional to direct transmission of information. These second-order dimensions of social capital and network theory tend not to be examined in firm-level epidemic models of technology diffusion but are assumed to play a decisive role in understanding the adoption of AI.

Considering the relational embeddedness of firms as an additional determinant of adoption not only contributes to a better understanding of the two classical mechanisms of direct and indirect epidemic effects but also captures the complexity of knowledge spillovers and their propagation through inter-firm networks. While the concept of embeddedness percolates research on the development and production of novel technologies (due to the possibility of leveraging patent networks) (Freeman, 1991; Powell et al., 1999; Ahuja, 2000; Phelps and Paris, 2010), we argue that it also explains the usage and diffusion of technological applications and suggest that this relational dimension should be considered in the context of technology adoption. In our empirical context, we propose that stronger embeddedness in the AI knowledge network of AI adopters and closely connected firms is a determinant of adoption of an emerging digital GPT.

H3a: The firm's centrality in the AI knowledge network is related to its likelihood of adopting AI.

Looking beyond the narrow frame of the AI knowledge network, the entire firm network provides additional insights on the rate of diffusion of AI based on the position of AI adopters in the network (Borgatti and Halgin, 2011). On the side of recipients, knowledge flows related to AI and complementary information can reach firms by being relayed through a string of connected firms, which does not necessarily require a direct connection to sources of AI knowledge, but merely a closeness to a multiplicity of loci of knowledge (Mueller and Ramkumar, 2023; Vaccario et al., 2022). On the side of transmitters, the diffusion of AI-related knowledge within networks depends on the AI- knowledge possessor filling structural holes in the network and relay knowledge among different communities within the network (Burt, 1992; Granovetter, 1985). Firms may be motivated to act as knowledge diffusers as they can achieve comparative advantages from the leveraging of different knowledge bases (Burt, 1992). Holding these bridging positions has been shown to be related to firm innovativeness (Abbasiharofteh et al., 2021). If we assume that AI adopting firms are innovative, we can expect them to be in a central position in the overall firm network, facilitating the transmission of AI knowledge between clusters of firms (Burt, 1992; Borgatti and Halgin, 2011).

H3b: The centrality of the firm in the overall firm network is related to its likelihood of adopting AI.

2.3. Contingencies

2.3.1. Proximity

It has been shown that the transfer of technical expertise is a major motivation for firms to engage with AI adopters (Rammer, 2022; OECD, 2019a). However, as the transmission of information requires firms to engage in efforts to locate, receive, process and appropriate the information (Nelson and Winter, 1982; Sorenson et al., 2006), effective transmission depends not only on the degree of exposure to the information and the quality of knowledge shared but also on the cognitive and geographical proximity to these sources of knowledge (Haegerstrand, 1953; Sorenson et al., 2006). How well the relevant knowledge is transferred across boundaries depends on these latter aspects (Gruber et al., 2013).

This then questions how these dimensions of proximity between two linked firms should be defined. We follow Krüger et al. (2020) and distinguish between geographic and cognitive proximity among linked firms. *Geographic proximity* describes how closely two firms are co-located, which has been identified as facilitating the transmission of information (Glückler, 2013; Hilpert, 2006; Teixeira et al., 2008) by increasing the likelihood of frequent personal interactions. *Cognitive proximity* refers to the similarity of cooperating firms' knowledge bases (Boschma and Frenken, 2010; Cantner and Meder, 2007). We therefore hypothesize that:

H4: The relation between transmission of AI-related knowledge and a firm's likelihood to adopt AI is moderated by the average proximity between the firm and the potential sources of knowledge.

2.3.2. Depth of AI-related knowledge and reciprocity

Bosch-Sijtsema et al. (2021) show that among digital technologies, AI exhibits one of the largest gaps between the available knowledge about the technology and its actual adoption. Although there is abundant information on AI, the quality of the information shared within the network might not be convincing or sufficient to motivate adoption. Much industry discourse around AI is described as "hot air" (Hockenhull and Cohn, 2021). We need to understand the type and depth (usefulness) of the knowledge shared between firms (Sorenson et al., 2006; Dahl and Pedersen, 2004). Technological knowledge depth refers to its comprehensibility and the firm's ability to exploit the technological solution. Its usefulness depends also on its limitations and the availability of alternative solutions. Technical knowledge depth affects the ability to link the new technological possibility to a market opportunity. It depends to a degree on the successful or negative experience of past technological solutions (Nelson and Winter, 1982; Subbanarasimha et al., 2003; Greve and Seidel, 2015).

The concept of knowledge depth is embedded in the knowledge-based view of the firm and can be a source of competitive advantage (Bierly, 1996; Zhou and Li, 2012). Here, we understand knowledge depth as the firm's technical expertise to manage the sophistication and complexity of the technological knowledge (Bierly, 1996; Christensen, 2006). The level of technical expertise is related to faster integration in and application of the technology in organizational practices and new products and processes (Hamel and Prahalad, 1989; Subbanarasimha et al., 2003). More superficial knowledge is easier to codify due to its lower level of complexity, but it is also less useful because it does not take account of the potential user's local context. Deeper knowledge tends to more complex and more tacit, making it more difficult to transmit but potentially more useful to a firm seeking to adopt a new technology (Sorenson et al., 2006). Finally, it should be noted that not all linkages transmitting knowledge are of equal strength. Granovetter (1973) describes reciprocity as one of the main determinants of link strength and Uzzi (1999) points out that reciprocal relationships facilitate knowledge transmission between firms. Thus, we assume stronger inter-firm linkages can be captured by observing reciprocal knowledge flows indicated by bidirectional connections between companies (Capaldo, 2007). We assume knowledge depth and reciprocity to constitute high-quality linkages and hypothesize that:

H5: The relation between transmission of AI-related knowledge and the likelihood that the firm will adopt AI depends on the quality of the firm's linkages.

3. Material and methods

The main analysis is based on a sample of web-scraped data on 1,140,494 companies. We use the textual content on their websites to identify superficial and deep AI knowledge to proxy for AI adoption. For 380,805 of our sampled firms, we can trace linkages between firms based on within-sample hyperlink connections to build inter-firm networks. We check the robustness of our results using survey data from a representative Swiss firm-level sample (for details see Supplementary Materials Section 2.1).

3.1. Web-scraped data

It has been shown that firm websites provide comprehensive self-representations of organizational identity (Esrock and Leichty, 2000; Powell et al., 2016; Scheiber, 2013; Oertel and Thommes, 2018). Esrock and Leichty (2000) show that firm websites are aimed at multiple audiences but tend to be aimed particularly at investors, customers, the broader public (press), and (to a lesser extent) at current and potential employees. The diversity of website target groups and content makes it a more comprehensive depiction of organizational identity than gained from traditional mass media and other channels (Powell et al., 2016; Scheiber, 2013). For instance, Oertel and Thommes (2018, p. 1714) argue that "websites offer the most comprehensive source of information for the study of organizational identities because they encompass the identity claims of organizations to all stakeholders, not only to specific groups, and because the data is not limited to the perception of specific groups such as employees."

Recalling the different stages of the adoption processes proposed in Rogers (1995), examination of firm websites allows identification of those firms that are more likely to engage in early-stage adoption of AI based on superficial information on the technology, and firms that could be described as mature adopters identified in terms of confirmation and signaling activities as part of their organizational identity. We describe AI adopters as firms that possess an AI identity expressed through deep AI knowledge self-represented on their websites. Since the transmission of both deep and superficial AI knowledge can trigger adoption of (different degrees of) an AI identity among recipient firms we identify AI-positive firms as including companies with both types of AI knowledge.

3.1.1. Identifying AI adoption and AI knowledge

Based on web scraping and machine learning technology which was further advanced by Kinne and Axenbeck (2020), we extracted web-based data including textual data, hyperlink-based relational data, and meta-data from the business websites of firms in Germany, Austria, and Switzerland. We trained a transformer (Vaswani et al., 2017) based language model (LM) to distinguish superficial and deep AI knowledge based on text paragraphs on company websites. We provide a brief description of this inference procedure and an overview in Fig. 1. A detailed description of the model training and validation is provided in the Supplementary Materials Section 1.

We obtained the web addresses (URLs) of all economically active companies in Austria, Germany, and Switzerland using the ORBIS database (Bureau van Dijk, 2022) as the basis for the web-scraping exercises which was conducted in first quarter of 2022. This first step resulted in a data-set containing the textual website content of 1.1 million firms. In the second step, we conducted a keyword search using a list of keywords related to different forms and applications of AI. We created our keywords list based on their frequency in a sample of websites of validated AI adopters. We then refined this list based on our expertise and the definitions of AI proposed by the OECD (2019a, 2019b) and the Annual AI Report (Perrault et al., 2019; Zhang et al., 2022). Section 1.1 in the Supplementary Materials contains the keyword list. We identified 247,846 text paragraphs that included at least one mention of at least one of our keywords. In the third step, we developed a manual classification scheme for the supervised training of the transformer model. Our categorization scheme allows manual labeling of a training data set of 3000 AI related text paragraphs differentiating between those providing superficial (informational content) and those representing deep knowledge (AI-related personnel, products/services, internal processes, use of third-party AI solutions). The training data was precisely tailored to our aim of proxying AI adoption, meaning the integration of AI technology rather than measuring only AI production (AI software developers / providers, which are nevertheless also covered in our training data). The final model is a cross-lingual paraphrase MiniLM model based on a sentence-transformer (Reimers and Gurevych, 2019); using a pre-trained foundation model reduces the requirement for labeled data when fine-tuning it for specific tasks (Malte and Ratadiya, 2019). In the inference phase, each AI-related paragraph is encoded with the domain adapted sentence transformer, and its category predicted by a logistic regression model. We rank a company as a *deep* AI knowledge company if our model categorized at least one of the paragraphs as containing *deep* AI knowledge. At the company level, when testing against a randomly sampled validation set of 204 companies, we found our model to be 91.67 % accurate. We also tested our model on a set of 750 European AI companies (EuroAI, 2022) and found that in 97.16 % of cases it correctly identified presence of deep AI knowledge and thus showed outstanding performance in the classification task. Appendix Table A.1 provides examples of paragraphs classified by our model as deep AI knowledge.

We further characterized our measure of AI adoption by exploring the type of textual topics co-occurring in the paragraphs that included the AI keywords. We took a random sample of 100,000 paragraphs and computed a neural topic model (TM) using the BERTopic architecture (Grootendorst, 2022). The full TM of the 199 topics covered in the AI-related paragraphs identified is presented in Supplementary Material Section 1.3. Based on the topic probability distribution, the model shows that the functionalities of tangible products with integrated AI-components constitute a dominant pattern. In addition, we identified topics related to a wide variety of procedural use cases such as robots, manufacturing, and maintenance, big data analytics, cloud computing, marketing, customer relations and chatbots, cyber security, autonomous driving, health diagnostics, supply chain management, finance, and other cases. The model also isolated shallow informational topics (news, blogs, podcasts, etc.) and website artifacts which shows the relevance of our training of the transformer model to allow it to classify this type of information as superficial knowledge (keyword-based identification on its own would have produced false positives for AI adoption in this case).

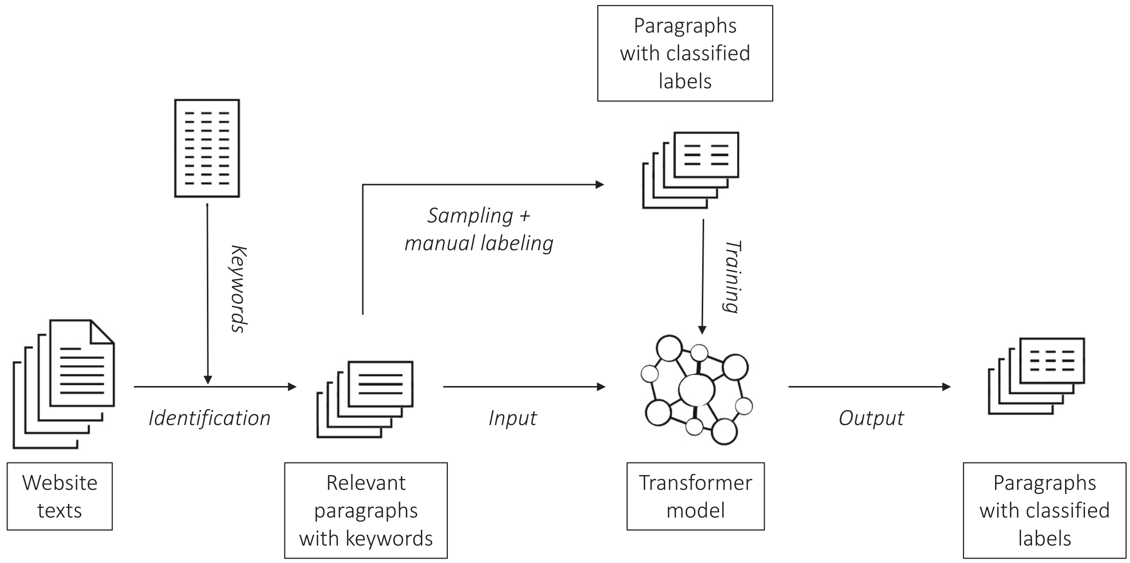

Fig. 1. Inference procedure using supervised training of a transformer model to identify AI-related knowledge represented in the text on company websites.

3.2. Empirical strategy

3.2.1. Econometric framework

Our empirical strategy is aimed at testing indirect (mimetic pressure to adopt AI), direct epidemic effects (linkages allowing transmission of AI knowledge), and the association between network embeddedness and AI adoption. Fig. 2 provides a conceptual illustration of these three main mechanisms which are the core of our econometric model (for simplicity, Fig. 2 differentiates only between AI-positive and AI-negative firms (either deep or superficial AI knowledge) rather than between superficial and deep AI knowledge. Table 1 presents the variables, concepts, hypotheses, and variables coverage for the two data-sets.

Given the bivariate nature of our dependent variable for AI adoption (AIA), we estimate Eq. (1) using a generalized linear model, specified as a binomial with a logit link function. The condensed form regression model in vector notation is written as:

$$AIA_{i,j,r} = \alpha + MIM_{j,r}\beta_1 + LINK_{i,j,r}\beta_2 + PROX_{i,j,r}\beta_3 + RELAT_{i,j,r}\beta_4 + FIRM_{i,j,r}\beta_5 + EE_{i,j,r}\beta_6 + \lambda_j + \lambda_r + \epsilon_{i,j,r}, \tag{1}$$

where i is the focal firm and the subscripts j (r) are sectors (regions).

3.2.2. Specification of variables

3.2.2.1. AI adoption (AIA). Our web-based indicators allow us to measure the representation of (different depths of) AI-related knowledge. Our binary variable for AI adoption takes the value 1 if the firm's website features deep AI knowledge. The choice to represent deep knowledge on AI implies that use of AI technology is part of the firm's organizational identity which the website is communicating externally. In our robustness checks using survey data, we specify a binary variable which takes the value 1 if the firm self-reports using AI in any of its business units or processes. Since both sets of data rely on self-reporting of AI use, we acknowledge the ambiguity linked to the term AI. For the web-indicators, we describe AI using the set of keywords employed to identify the relevant paragraphs on websites (see above). The survey respondents were provided with a definition based on the OECD definition, which describes an AI system “as a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments” (OECD, 2019a, p.7).[1]

3.2.2.2. Indirect mimetic pressure (MIM). To model mimetic pressure, we constructed a vector of two variables to capture inter-firm diffusion of AI technology around a focal firm. We measured the relative frequency of AI adopters around the focal firm as the share of AI adopters external to the focal firm in the related NUTS3 region (*AI_reg*) and industrial branch at the NACE 3-digit level (*AI_sec*). Eq. (2) is an exemplary formula to construct the variable at the regional level:

$$AI\_reg_{i,r} = \frac{\left|X_r^{AI}\right| - X_{i,r}^{AI}}{|X_r| - 1}, \tag{2}$$

where X_r (X_r^{AI}) is the set of companies in region r (adopting AI) around the focal firm i in that region ($X_{i,r}$) which is subtracted from the count to avoid simultaneity. The same formula but substituting regions (r) for sectors (j)is used for the sectoral ad option rate around the given focal firm.

3.2.2.3. Direct linkages transmitting knowledge (LINK). The second epidemic effects mechanism is direct transmission of superficial or deep AI knowledge through inter-firm linkages. We operationalized the variable to measure firm linkages by using the in- and outbound hyperlinks connected to each company website in our sample (Krüger et al., 2020; Park, 2003). In this case, we differentiate between unidirectional (*AIshare*) and reciprocal (*AIrecshare*) linkages, and between the two AI knowledge types - superficial (*supAIshare*) and deep (*deepAIshare*). We constructed a ratio variable for the number of the firm's linkages to sources of deep AI knowledge relative to the number of its total linkages. Rather than an extensive (absolute) measure of connectivity, this effectively is an indicator for the given firm's the intensity of direct exposure to AI knowledge (which also differentiates this variable from network measures of degree centrality in the model). This construction provides the ancillary benefit of lower positive skewness (6.55) and lower kurtosis (53.15) values than the absolute measure of the number of deep AI knowledge ties (12.48 and 470.54, respectively). For these ratios of AI-related linkages to all linkages, we tested the moderating influences of geographic and cognitive proximity to account for the

[1] Supplementary Materials Section 2.1 provides more detail on the collection of the survey data.

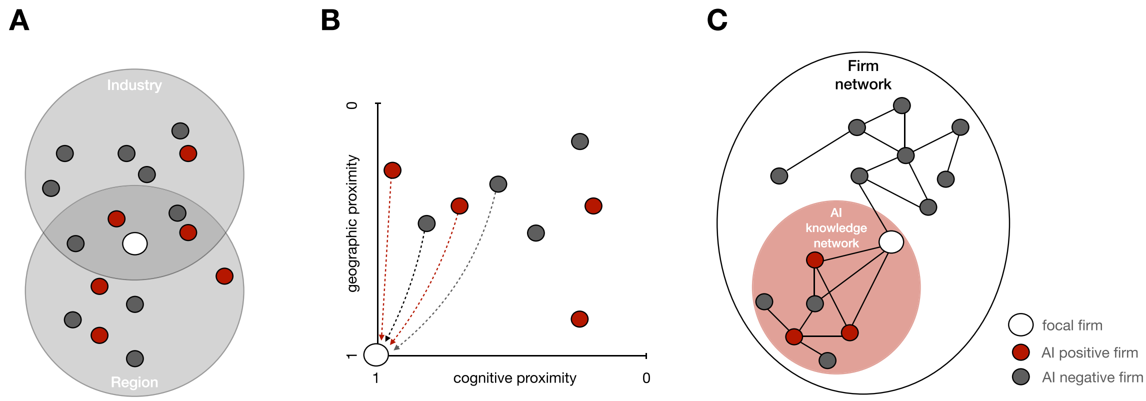

Fig. 2. Stylized conceptualization of the empirical strategy.
Note: (A) depicts the firm's environmental boundaries in the regional and industrial space; in these environments, adoption rates creating mimetic pressure through indirect exposure can be calculated by counting the AI-positive firms (representing either deep or superficial AI knowledge) relative to AI-negative firms (representing no AI knowledge). (B) depicts the direct linkages to other firms with or without AI knowledge which allows calculation of an intensity variable for the share of AI linkages in the firm's total linkages firm whose effect for AI adopters may be moderated by the firm's average cognitive and geographic proximities of direct linkages. (C) depicts the focal firm's position in the relational AI-positive and negative firm network. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

firm's relational capacity (see Eq. (3)).

$$AIA_{i,j,r} = \alpha + MIM_{j,r}\beta_1 + LINK_{i,j,r}\beta_2 + PROX_{i,j,r}\beta_3 + RELAT_{i,j,r}\beta_4 + (AI\_LINK_{i,j,r} \times PROX_{i,j,r})\beta_5 + FIRM_{i,j,r}\beta_6 + EE_{i,j,r}\beta_7 + \lambda_j + \lambda_r + \epsilon_{i,j,r} \quad (3)$$

3.2.2.4. Geographic and cognitive proximities (PROX). Following Krüger et al. (2020), we computed different dimensions of relational proximity as the average over all of the firm's linkages. Cognitive proximity (*cogn_mean*) is a measure of the similarity between a pair of firms and is measured first by vectorizing the individual sub-pages on the companies' websites using the BERT-based sentence transformer library (Reimers and Gurevych, 2019). Second, we represented the entirety of the text on the company website in the vector space based on the mean values of the vectors of the individual sub-pages. This allowed us to calculate the text similarities between pairs of company websites by relating their representative vectors via cosine similarity. Eq. (4) provides the formula to compute the average cognitive proximity of all of the firm's linkages.

$$cogn\_mean_i = \frac{\sum_{k=1}^{K_i}\left[1 - \frac{u_i \cdot v_k}{||u_i||_2 ||v_k||_2}\right]}{K_i}, \quad (4)$$

where K_i denotes the number of firms K to which the focal firm i has links, and u_i and v_k are the vectorized website texts of the focal firm *i* and the website texts of each of the linked firms *k* used to compute the scalar product as an expression of Euclidean distance.

Geographic proximity is a measure of physical distance based on a straight-line distance between the geocoded locations of the linked firms (*geo_mean*). All proximities are normalized $\in$ (0;1), and geographic proximity (originally measured in absolute meters) is inverted to take the same range of values. Higher values indicate greater cognitive or geographical proximity.

3.2.2.5. Relational network position (RELAT). For the set of explanatory variables capturing the position of firms in the relational inter-firm network, we build two undirected networks of hyperlink connections among firms using the library *graph-tool* in Python which is better than other libraries at handling big data. The first network includes all the interconnected firms in our sample, i.e., the entire inter-firm network. For the second network we employ sub-graph filtering to construct a network that includes firms that are connected to other firms with either superficial or deep AI knowledge, and their linkages to AI-negative firms. We call this the AI knowledge network. Table 2 presents the basic network characteristics for both networks which resemble scale-free networks with the AI knowledge network exhibiting a slightly fatter right tail in the degree distribution (see Appendix Fig. A.1).

We calculate the degree centrality of the firms in the AI knowledge network to obtain an indicator for the level of embeddedness in the network circulating AI knowledge (*degree_ai*). To characterize structural position of firms in the entire inter-firm network, we compute both betweenness (*betw_all*) and closeness (*close_all*) centrality. The former captures firms bridging between firm clusters; the latter captures the average length of the shortest path between the focal firm and all other firms in the inter-firm network which can be used to measure the focal firm's efficiency in relation to receipt and transmission of information from and throughout the entire network. Since path length to all other nodes in the network is needed to compute closeness centrality, to obtain a consistent measure requires that the whole network is interconnected. To exclude fragmented subgraphs, we calculated this measure based on the largest component which includes 331,462 firms.

4. Results

4.1. Descriptives

Application of our web-based AI adoption identification model to the sample of 1,140,494 companies identified overall adoption of AI at 2.2 % (see Table 3). We observe 1.5 % of all companies with *deep* AI knowledge and 1.3 % of all companies with *superficial* AI knowledge (with some overlaps between the two types). While most regions and industries host only a few or no firms with AI knowledge, the share of AI-positive firms (i.e., with superficial or deep AI knowledge) in a few selected regions and sectors is relatively high. A high share of AI-positive firms is in sectors such as ICT services (>11 %), electronics (>6 %), consulting (>5 %), and financial services (>4 %). Those sectors with a relatively high proportion of deep compared to superficial AI knowledge include ICT, engineering, and retail and wholesale. Appendix Fig. A.1 provides more detailed statistics.

Fig. 3 presents the geographic distribution of AI adoption and shows that it is confined to certain regions. Although urban areas and selected regional capitals show relatively high shares of AI-positive companies with rates of up to 6 % of the total firm population, there is large variance among metropolitan regions (e.g., between Hamburg and Munich, Germany). There is also a high concentration of AI-positive firms in otherwise inconspicuous smaller cities. These hot-spots are associated

Table 1
Overview of variables of interest and controls and availability by sample.

Variable	Description	Operationalization	Hypothesis	Web data	Survey data
AI adoption (AIA)	Adoption of AI identity by focal firm				
deepAI	firm website featuring deep AI knowledge	= 1 if yes		Yes	
supAI	firm website featuring superficial AI knowledge	= 1 if yes		Yes	
AI_qn	firm self-reports usage of AI within company	= 1 if yes			Yes
Indirect mimetic pressures (MIM)	Knowledge transmission through observation and emulation	Average rate in related space subtracting focal firm			
AI_reg	Prevalence of AI adoption in relevant geographic unit	Average in NUTS3 around focal firm	H1	Yes	Yes
AI_sec	Prevalence of AI adoption in relevant industry	Average in NACE class (3-digit) around focal firm	H1	Yes	Yes
AI_size	Prevalence of AI adoption in relevant size class				
AI_sec_reg	Prevalence in overlapping sectoral and geographical space	Inner join of AI_reg, AI_sec	H1	Yes	Yes
AI_sec_reg_size	Prevalence in overlapping sectoral, geographical, and size class space	Inner join of AI_reg, AI_sec, AI_size	H1		Yes
Direct transmissions (LINK)	Knowledge transmission through linkages				
AIsum	Number of links to AI positive firms	Sum of AI links	H2	Yes	Yes
supAIsum	Number of links to firms with superficial AI knowledge	Sum of informational AI links	H2	Yes	
deepAIsum	Number of links to firms with deep AI knowledge	Sum of knowledge-intensive AI links	H2	Yes	
AIshare	AI links over all links	Ratio	H2	Yes	
supAIshare	superficial AI knowledge links over all links	Ratio	H2, H5	Yes	
deepAIshare	deep AI knowledge links over all links	Ratio	H2, H5	Yes	
rec_supAIshare	Only reciprocal links in supAIshare	Ratio	H4	Yes	
rec_deepAIshare	Only reciprocal links in deepAIshare	Ratio	H4	Yes	
Proximities (PROX)	Similarities of firm characteristics over linkages				
cogn_mean	Cognitive similarity to linked firms	Averaged indicator over all linkages of a firm between (0;1)	H4	Yes	Yes
geo_mean	Geographic proximity to linked firms	Averaged indicator over all linkages of a firm between (0;1), normalized	H4	Yes	Yes
Relational position (RELAT)	Position in relational inter-firm networks linkages				
degree_ai	Degree centrality of firm in subgraph of AI knowledge network	normalized between 0 and 1	H3a	Yes	Yes
close_ai	Closeness centrality of firm in subgraph of AI knowledge network	sum of edges to firm with deep AI knowledge	H3a	Yes	Yes
betw_all	Betweenness centrality of firm in undirecteed graph of firm network	normalized between 0 and 1	H3b	Yes	Yes
Controls					
lnsize	Firm size (log)	total number of current employees		Yes	Yes
lnage	Firm age (log)	= current year - founding year		Yes	Yes
urban_d	Urban location	= 1 if firm is located in an area where population ≥ 50,000		Yes	Yes
export	Firm exports	= 1 if firm exports >1			Yes
hrict	ICT experts	= 1 if employed ICT experts >1			Yes
foreign	Foreign ownership	= 1 if company is foreign owned			Yes
acad	Academics	Share of employees with academic degree			Yes
profit	Profit margin	= (turnover - costs) / turnover			Yes
rnd	Research and development	Sales share of R&D expenditure			Yes
inno	Innovativeness (survey)	= 1 if firm pursued innovation activities in last 3 years			Yes
InnoProb	Innovativeness (web)	Predicted probability of innovativeness based on firm website		Yes	
digit	Additional digital technologies	= 1 if number of other digital tech used >3			Yes
compet	Competition	categorical indicating number of close competitors			Yes

Table 2
Network statistics.

Network	Nodes	Edges	Avg. degree	Std. dev.
Inter-firm network	392,406	1,140,494	6.023	0.017
AI knowledge network	39,151	145,185	7.421	0.061

with the locations of the six AI research institutions which make up the German Network of National Centers of Excellence for AI Research and feature relatively higher shares of deep rather than superficial AI knowledge.

These silos of AI knowledge also emerge clearly in the context of interfirm networks. Analysis of the hyperlink connections among the firms in our sample shows that 4 % of all firms are linked to AI-positive firms, among which only 1 % is involved in links to multiple sources of AI knowledge (see Fig. 4). It seems, at first glance, that beyond their geographical and relational proximity these firms are highly interconnected, but most linkages are between firms in AI hot-spots with sparser connections in the geographic periphery. In terms of the position of AI adopters in the relational (hierarchically clustered) space, we observe that again AI adopters seem to be highly interconnected across firm clusters but are located almost exclusively at the lower hierarchical levels of the inter-firm network. They seem not to be positioned centrally at higher hierarchical levels which would constitute pathways for information flows between the distant parts of the inter-firm network.

Table 3
Descriptive statistics for variables of interest.

Variable	Observations	Mean	St. Dev.	Min	Max
AI	1,140,494	0.022	0.15	0	1
supAI	1,140,494	0.013	0.11	0	1
deepAI	1,140,494	0.015	0.12	0	1
employees	1,140,494	32.11	975.95	1	294,134
age	1,140,494	24.46	21.90	3	787
InnoProb	1,140,494	0.28	0.17	0.04	0.92
urban_d	1,140,494	0.43	0.50	0	1
links_count	1,140,494	4.76	7.63	0	139
cogn_mean	719,526	0.51	0.16	0.00	0.95
geo_mean	736,682	0.76	0.16	0.00	1.00
AI_reg	1,140,494	0.02	0.01	0.00	0.06
AI_sec	1,140,494	0.02	0.03	0.00	0.19
AIshare	1,140,494	0.01	0.03	0.00	1.00
supAIshare	1,140,494	0.002	0.02	0.00	1.00
deepAIshare	1,140,494	0.003	0.03	0.00	1.00
supAIrecshare	1,140,494	0.0001	0.003	0.00	0.50
deepAIrecshare	1,140,494	0.0001	0.004	0.00	0.50
degree_ai	380,805	0.003	0.02	0.00	1.00
close_all	331,462	0.53	0.12	0.00	1.00
betw_all	380,805	0.002	0.01	0.00	1.00

4.2. Estimations

Our results are summarized in Table 4 which presents the standard coefficients of the regressions testing our hypotheses; Fig. 5 presents the respective average marginal effects (AME) for the variables of interest. Appendix Table A.3 presents the bootstrapped standard errors and confidence intervals for a selection of the models. We observe that in all the models, mimetic pressure, direct transmission, and network measures are highly significant for explaining variance in AI adoption. If they are added hierarchically, all contribute incrementally to improving the model fit.

In terms of the indirect epidemic effects capturing mimetic pressure, we find that the significance ($p \leq 0.000$) and AME of the AI adoption rate in the region and sector were among the strongest explanatory variables. The rate of diffusion in the firm's regional environment is associated with an AME of 0.192 (for model 3), with sectoral mimetic pressure showing equally large effect sizes (AME 0.200) and a narrower confidence interval. These results provide clear evidence of indirect epidemic adoption pressure faced by firms in AI hot-spots which does not reject H1.

Direct linkages to firms with deep AI knowledge show a significant positive association with AI adoption ($p \leq 0.000$). However, AI adoption is more strongly correlated with connections allowing the transmission of deep AI knowledge which does not allow us to reject H2.

For link strength, our results suggest that stronger links based on reciprocal connections have a significant ($p \leq 0.000$) and even stronger positive relation to AI adoption (AME 0.201), closer to the effects of mimetic pressure. We observe also that reciprocal linkages transmitting only superficial AI knowledge turn insignificant ($p \geq 0.795$). The evident stronger effects of reciprocal linkages transmitting deep AI knowledge do not allow us to reject H5.

Our network measures capturing relational embeddedness in the firm network reveal two things. First, a strongly positive significant effect of embeddedness in the AI knowledge network ($p \leq 0.000$) based on degree centrality in this sub-network showing extremely high AME (0.259) on AI adoption which does not allow us to reject H3a. It corresponds also to our descriptive findings that many AI adopters are highly inter-connected and suggests possible homophily among AI adopting firms. Second, we observe a positively significant ($p \leq 0.000$) betweenness centrality of focal firms bridging communities of firms but with rather small marginal effects on AI adoption. While we cannot reject H3b, the effect size (AME 0.059) is relatively smaller compared to other measures of epidemic effects. This suggests that it is not a prime motivation of AI adopters to achieve a brokerage position among firm communities.

When we consider closeness centrality it is even clearer that AI adopters do not tend to be in central positions, which are important for receiving and relaying knowledge throughout the entire firm network. Although we cannot entirely reject H3b ($p \leq 0.000$), the marginal effects of the variable in model 11 are minuscule (AME of 0.023). Based on our

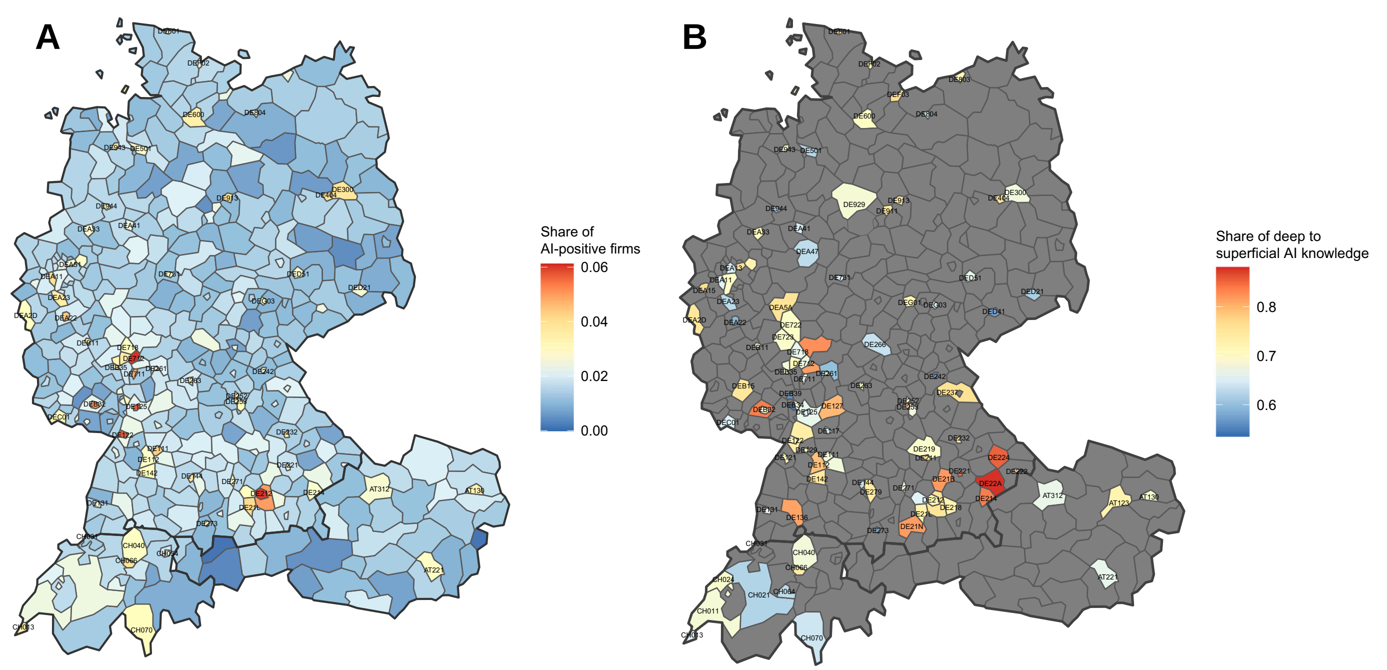

Fig. 3. Descriptive statistics for AI diffusion in the geographic space of the DACH region (n = 1,140,552)
Note: (A) depicts the ratio of AI-positive firms to all firms in each NUTS3 region and shows the presence of a few regional hot-spots and many barren regions. (B) depicts regions with AI adoption rates above the average (>2 % of AI-positive firms and >15 AI firms) and the share of deep AI knowledge represented across all AI-positive (deep and superficial) firms in the region. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

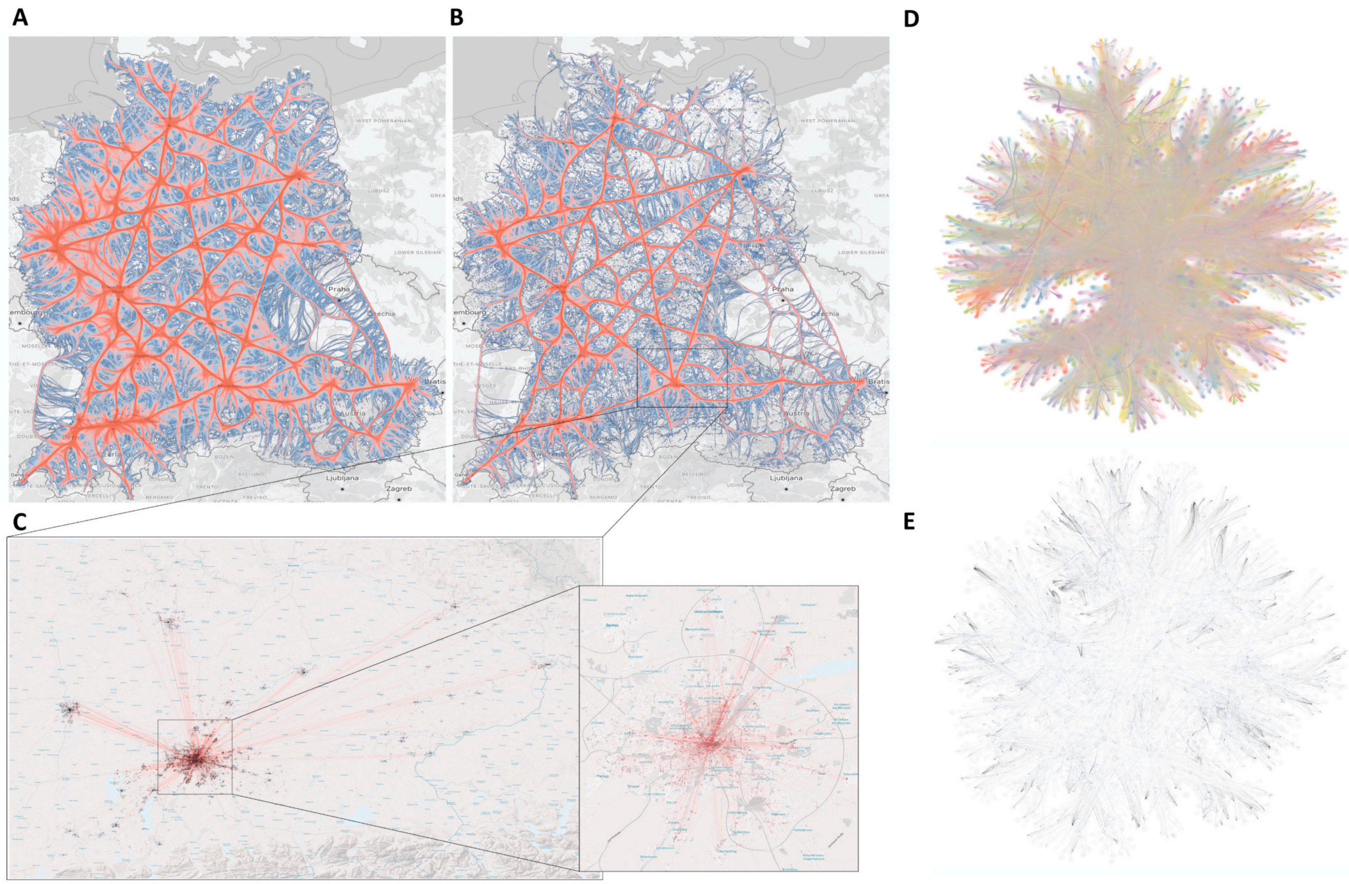

Fig. 4. Descriptive AI diffusion networks in the DACH region geographic space (n = 380,805)
Note: (A) depicts the geographic space related to the sampled firms and the bundled density of all their hyperlink connections. (B) depicts the bundled hyperlink connections filtered for linkages from or to AI-positive firms across geographic space and shows a much sparser network with linkages mainly confined to establish between large metropolitan hubs. This would suggest that geographic distance matters less for AI diffusion since AI hot-spots are interlinked. (C) shows the good quality of our micro-level data depicting unbundled AI-relevant linkages in and around the hotspot of Munich (GER) only (linkages outside this frame are not shown). (D) depicts the communities (different colors) in the relational space for all the firms in the sample (largest component, hierarchically clustered). (E) depicts the relational network for all of the sample firms (largest component, hierarchically clustered) with AI-positive firms colored black, highlighting their peripheral positions.

previous findings, we tried to isolate this effect further by accounting simultaneously for the focal firm's embeddedness in the AI knowledge network (model 13). Closeness centrality maintains it significance ($p \leq 0.010$), but its effect even turns slightly negative (AME −0.006).[2]

Controlling for interconnectedness in the AI knowledge network provides further evidence that AI adopters are not in the most central positions in the extant inter-firm network. This confirms our descriptive finding from the social network analysis that AI adopters tend to belong to an exclusive network rather than occupying central positions in wider networks that would facilitate flows of knowledge to distant parts of the inter-firm network. The potential existence of closed inter-firm clusters of AI adopters possibly explains the overall sluggish rate of diffusion of AI technology.

Considering general relational capacities of firms across all linkages, our results suggest that firms that are connected to other firms which on average are cognitively more proximate and geographically more distant are slightly more likely to adopt AI. Although both general measures capturing the proximity across all AI and non-AI linkages exhibit negligibly small AME, these metrics become more relevant in terms of their role in moderating the effects of direct AI linkages (see Section 4.3). The variables capturing firm-level characteristics show a significant positive correlation between AI adoption and firm size and a negative correlation with firm age. An urban location seems to promote adoption of AI-related knowledge. Also, our web-based indicator of firm innovativeness is highly significant ($p \leq 0.000$) and, depending on the model, shows positive effect sizes for AME of around 0.075. It is not surprising that innovative firms are generally more likely to adopt AI but is an indication also of the relevance of absorptive capacity and innovation capabilities – both are characteristics that we explore further in the moderator analysis and the robustness checks using our richer survey data.

4.3. Interactions

To address H4, we constructed interaction terms to test whether the epidemic effects captured by direct linkages are moderated by relational proximity. Fig. 6 depicts the predicted probabilities of AI adoption for different levels of the variables capturing epidemic effects in combination with the moderating variables. Table 4 shows that the interaction terms are positively significant for dependence between the share of AI-related linkages and average cognitive proximity. The coefficients hint at the relevance of a base of common knowledge between connected firms which facilitates successful transmission and absorption of AI knowledge.

[2] We checked for variance inflation using two measures of centrality but found nothing to raise any concern (see Appendix Fig. A.3).

Table 4
Main regression models explaining AI adoption though epidemic mechanisms.

	Dependent variable												
	deepAI												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Indirect mimetic pressures (MIM)													
AI_sec			10.387***	9.865***	9.877***	9.864***	9.865***	10.507***	10.343***	9.786***	9.760***	9.879***	9.710***
			(0.495)	(0.494)	(0.493)	(0.494)	(0.494)	(0.499)	(0.494)	(0.501)	(0.530)	(0.494)	(0.538)
AI_reg			10.304***	9.463***	9.450***	9.463***	9.209***	9.474***	10.201***	8.356***	9.579***	9.399***	8.703***
			(1.123)	(1.132)	(1.132)	(1.132)	(1.169)	(1.130)	(1.125)	(1.157)	(1.199)	(1.132)	(1.225)
Direct transmissions (LINK)													
supAIshare				1.427***	1.430***	1.427***	1.428***	1.408***		0.146	1.106***	1.390***	0.216
				(0.226)	(0.226)	(0.226)	(0.226)	(0.227)		(0.279)	(0.244)	(0.228)	(0.281)
deepAIshare				4.258***	2.244***	4.296***	4.061***	5.252***		3.405***	3.728***	4.241***	3.039***
				(0.131)	(0.506)	(0.588)	(0.287)	(0.194)		(0.144)	(0.143)	(0.131)	(0.155)
supAIrecshare									−0.354				
									(1.433)				
deepAIrecshare									9.821***				
									(0.837)				
Proximities (PROX)													
cogn_mean		0.414***	0.404***	0.372***	0.261***	0.372***	0.372***	0.370***	0.372***	0.448***	0.417***	0.387***	0.446***
		(0.074)	(0.075)	(0.076)	(0.077)	(0.076)	(0.076)	(0.075)	(0.075)	(0.078)	(0.084)	(0.076)	(0.085)
geo_mean		−1.394***	−1.380***	−1.410***	−1.411***	−1.408***	−1.412***	−1.416***	−1.407***	−1.450***	−1.340***	−1.416***	−1.430***
		(0.082)	(0.082)	(0.082)	(0.082)	(0.086)	(0.082)	(0.082)	(0.082)	(0.085)	(0.092)	(0.082)	(0.093)
LINK x PROX													
deepAIshare x cogn_mean					3.550***								
					(0.866)								
deepAIshare x geo_mean						−0.049							
						(0.731)							
MIM x LINK													
AI_reg x deepAIshare							7.116						
							(9.444)						
AI_sec x deepAIshare								−17.414***					
								(3.006)					
Network embeddedness (RELAT)													
degree_ai										12.946***			12.643***
										(0.688)			(0.752)
close_all											1.069***		−0.312***
											(0.110)		(0.120)
betw_all												2.892***	
												(0.476)	
Firm characteristics													
lnsize		0.177***	0.178***	0.176***	0.176***	0.176***	0.176***	0.176***	0.177***	0.124***	0.148***	0.167***	0.123***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
lnage		−0.214***	−0.217***	−0.206***	−0.207***	−0.206***	−0.206***	−0.207***	−0.214***	−0.206***	−0.211***	−0.207***	−0.208***
		(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)	(0.020)
InnoProb		4.071***	3.787***	3.676***	3.677***	3.676***	3.676***	3.675***	3.774***	3.536***	3.662***	3.671***	3.585***
		(0.066)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.069)	(0.072)	(0.068)	(0.074)

(*continued on next page*)

Table 4 (*continued*)

	Dependent variable												
	deepAI												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
External environment													
urban_d		0.336***	0.195***	0.193***	0.193***	0.193***	0.193***	0.193***	0.193***	0.178***	0.190***	0.191***	0.185***
		(0.025)	(0.029)	(0.029)	(0.030)	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)	(0.031)	(0.030)	(0.032)
Constant	−4.444***	−4.798***	−5.015***	−4.986***	−4.923***	−4.988***	−4.980***	−4.993***	−4.972***	−4.840***	−5.391***	−4.973***	−4.563***
	(0.272)	(0.287)	(0.288)	(0.288)	(0.288)	(0.289)	(0.288)	(0.288)	(0.287)	(0.289)	(0.297)	(0.288)	(0.298)
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.116	0.207	0.215	0.225	0.225	0.225	0.225	0.226	0.217	0.245	0.23	0.226	0.25
Observations	380,805	380,805	380,805	380,805	380,805	380,805	380,805	380,805	380,805	380,805	323,703	380,805	323,703
Log Likelihood	−37,226.930	−33,706.530	−33,402.560	−33,012.400	−33,005.000	−33,012.390	−33,012.150	−32,997.910	−33,312.860	−32,220.090	−28,994.130	−32,994.190	−28,324.440
Akaike Inf. Crit.	74,575.870	67,547.060	66,943.130	66,166.790	66,154.000	66,168.790	66,168.300	66,139.820	66,767.710	64,584.180	58,132.260	66,132.390	56,794.890

Note: Robust standard errors.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

To examine this in more detail, panels A-B present the interdependent effects of the share of linkages connected to deep AI knowledge and cognitive or geographic proximity. While we observe a positive relationship, the probability of AI adoption by firms with a high intensity of deep AI knowledge linkages and high average cognitive proximity to knowledge sources seems to occur only at very high values of both variables. This could be a natural consequence of the fact that adoption of AI in the early stages of its diffusion is not pervasive but is limited to certain economic niches.

We also tested the moderating effect of average cognitive proximity and embeddedness in the AI knowledge network measured in terms of degree centrality (see Panel F). We found a strong positive additional effect for a given linkage intensity for an increasing average cognitive proximity. The curvature of the lines plotting the predicted probabilities would seem to suggest that these added effects are particularly pronounced for cognitive proximity increasing from very low to medium levels, whereas additional increases to higher levels of cognitive proximity show a smaller additional effect on the outcome of AI adoption. This finding implies that the effects of strong network embeddedness are to an extent conditional on fostering a medium level of cognitive proximity across linkages to enable absorption of the relevant knowledge.

The interaction term in regression model 7 for the moderating effect of geographic proximity is insignificant. Fig. 6 panel B shows that the change in the predicted probabilities for different levels of both variables is marginal and that the majority of observations are found at low levels of intensity of connecting to deep AI knowledge which counters the potentially negative effect that can be seen at higher levels of intensity but for fewer observations. This latter indication suggests that firms with a high number of linkages to sources of deep AI knowledge seem to be able to overcome the effects of geographic distance for the effective exchange of knowledge. In combination with the strong effect of AI knowledge network embeddedness, these findings are in line with our descriptive assessment of the network of AI linkages which suggested that AI hot-spots tend to be highly inter-connected regardless of their geographic location but that connections to peripheral locations are sparse.

We examined potential additionalities by interacting the indirect epidemic mechanisms of regional and sectoral diffusion dynamics (panels C and D) with the direct mechanisms of linkages. In the case of mimetic pressure stemming from the region, most observations show few or no additional effects. Mimetic pressure from the sectoral space is a more interesting case. Although on average we observed no significant effects, the plotted predicted probabilities suggest that increased mimetic pressure from the sectoral environment has a considerable positive effect on the likelihood of AI adoption at lower levels of AI linkages. These additional effects dissipate for firms with higher relative levels of AI linkages and start to turn negative at the very highest levels. This is in line with the intuition since high levels of indirect environmental pressure are likely to be less relevant for companies that maintain good links to deep AI knowledge.

To support our theoretical arguments about absorptive capacity, we examined the interactions between the firm's overall innovation capacity and the share of deep AI knowledge connections it maintains. Panel E shows that for the vast majority of our observations (lower left triangle) this interaction seems not to be associated with an increased likelihood of AI adoption.

4.4. Robustness checks

We ran a series of robustness checks on our candidate web-based data models. First, following the argument in Acemoglu et al. (2022), we excluded the ICT sector from our regression analysis. Second, we substituted our dependent variable for deep AI knowledge as a proxy for AI adoption with a binary variable which takes the value of 1 if the firm is AI-positive (deep or superficial AI knowledge). Third, we use a categorical scale, binning the number of AI-relevant linkages of firms.

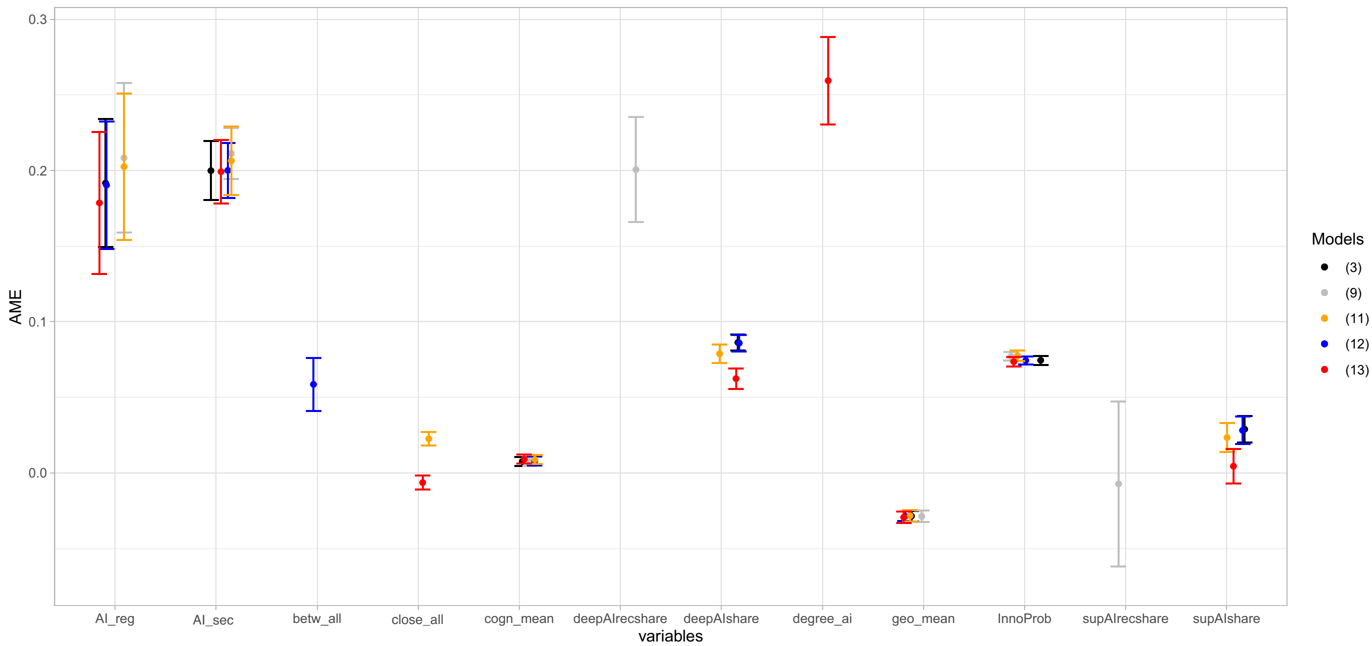

Fig. 5. Average marginal effects of the variables of interest and for selected models
Note: This figure shows the AME with confidence intervals for the models explaining adoption of deep AI knowledge. The regression model numbers correspond to the numbering in Table 4. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Although the results are nuanced, they do not cast doubt on the consistency of our main results. Fourth, using our complementary measurements from the representative Swiss innovation survey, we observe that the significance of all the epidemic effects channels holds when we test their explanatory power against self-reported AI usage for this much smaller sample. The survey data reveal also a potential mediating effect between skilled human capital and AI-relevant social capital. The Supplementary Material Section 2 reports the results of the robustness checks.

5. Discussion

The findings from our web-data are consistent with the basic characterization of AI adopters in other studies of AI adoption that use more traditional indicators (Calvino and Fontanelli, 2023; Rammer, 2022). Although the share of AI adopters identified using the web data is substantially lower compared to the share based on the survey data which is around 10 % for several European countries (see e.g. Calvino and Fontanelli (2023); Supplementary Materials Section 2.1), this is because the data published on firms websites are less likely to capture cases of minimal usage and are aimed more at indicating integration of the technology in core business practices. The adoption rates observed are in line with other studies using similar web-based empirical strategies including Calvino et al. (2022) whose study uses web data and finds the rate of AI adoption to be 6 %. However, their study relies only on a keyword approach which is likely to produce more false positives. In terms of patterns of adoption, we found concentration of AI adoption in a few geographical, sectoral, and relational parts of the DACH economy, similar to the findings in other works on the economics of AI (Acemoglu and Restrepo, 2020; Acemoglu et al., 2022; Calvino et al., 2022; Felten et al., 2021; Vannuccini and Prytkova, 2023).

We found that mimetic pressure had very high AME on the probability of AI adoption at both the regional and sectoral levels. The relevance of mimetic pressure is generally in line with the literature on inter-firm diffusion of other types of complex technologies (Battisti and Stoneman, 2003; Audretsch and Keilbach, 2007; Haller and Siedschlag, 2011); however, the magnitude of the effects for AI technology is of particular importance. Since environmental pressure to emulate observed adopters is transmitted through indirect channels, its effect can lead to bandwagon adoption behavior by firms surrounded by many AI adopters. Previous much-hyped technologies have produced similar effects (Gurbaxani, 1990; Kumar and Kumar, 1992).

Our relational measures of network position show that AI adopters tend to be highly interconnected within the AI knowledge network and to have relevant social capital (Calvino and Fontanelli, 2023; Rammer, 2022; Yli-Renko et al., 2001). However, other centrality measures suggest that AI adopters generally belong to a closed system of actors beyond which the technology does not diffuse to the entire firm network.

The intensity of the firm's linkages is associated positively with AI adoption and opportunities to access tacit knowledge such as participation in AI-related projects (Rammer, 2022) and to increase technical AI-related expertise (Alekseeva et al., 2021). While the overall effect size is relatively small, linkage intensity has a stronger effect on the probability of AI adoption in relation to flows of deep rather than superficial knowledge, and reciprocity. We found that greater cognitive proximity strongly moderates the positive effects of inter-firm linkages allowing the transmission of deep AI knowledge (Boschma, 2005; Sorenson et al., 2006). This implies that AI-related cooperation is motivated not only by access to AI expertise but also depends on the identification of partners working in a related business context to enable transfers of knowledge.

In contrast to research that emphasizes the importance of geographic proximity for the transmission of complex (technological) knowledge (Sorenson et al., 2006; Boschma and Frenken, 2010), we observed high

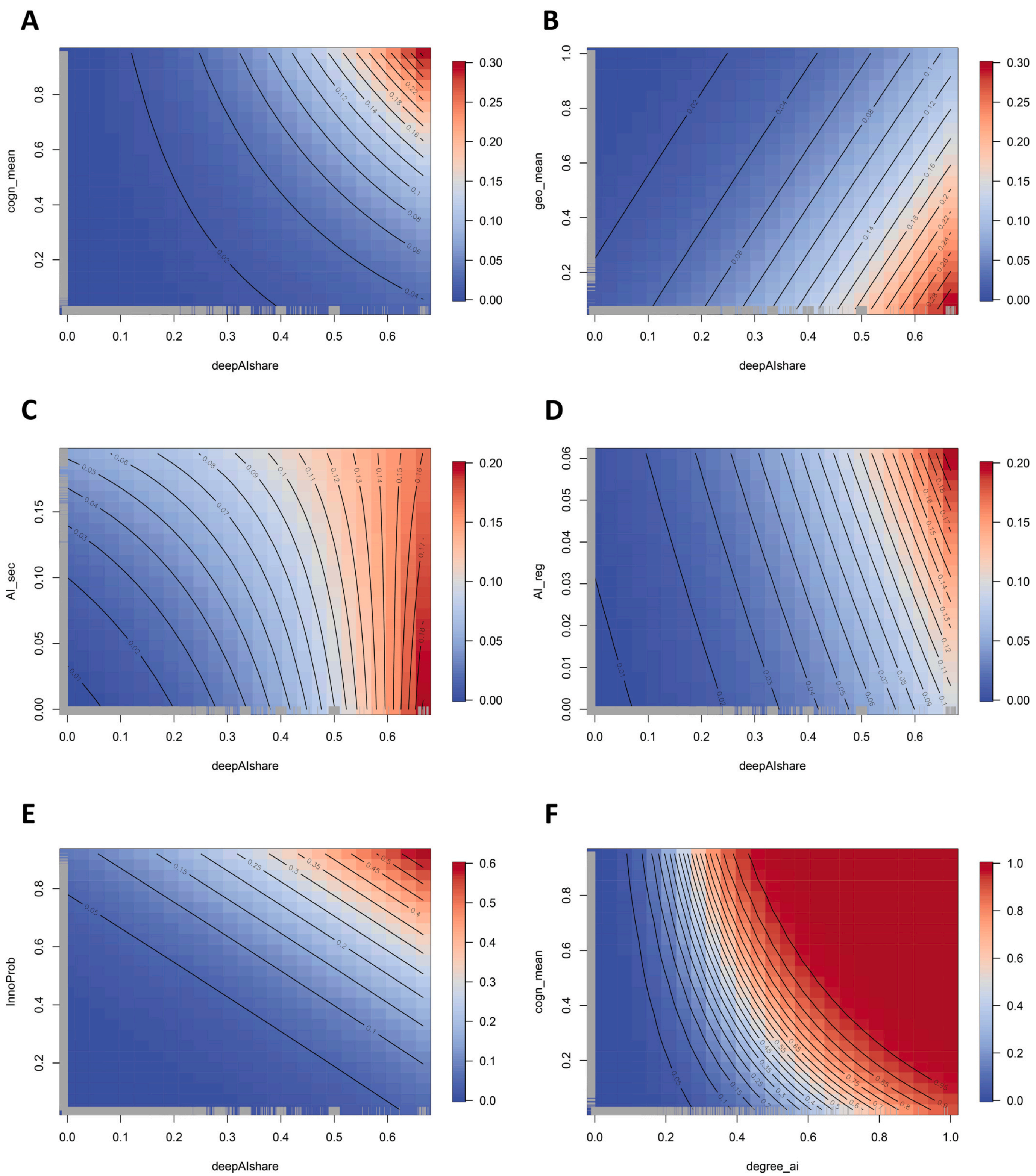

Fig. 6. Predicted probability of AI adoption based on levels of variables capturing epidemic mechanisms

Note: This figure depicts the predicted probabilities of AI adoption for interactions of variables along varying levels. The axes represent variables (rugs indicate observation density); the lines represent isoquants along (between) which the predicted probabilities for AI adoption are stable (change). The lines correspond to the colouring going from low (blue) to high (red) to represent the predicted probabilities. (A) and (B) depict the predicted probabilities of interactions between intensity of linkages to deep AI knowledge and levels of cognitive (left) and geographic (right) proximity. (C) and (D) are the predicted probabilities of the interdependencies between sectoral (left) and regional (right) environmental mimetic pressure. (E) depicts the added effect of absorptive capacities on the predicted probabilities considering level of firm innovativeness vis-à-vis deep AI linkage intensity. (F) depicts the contingent effects of cognitive proximity and degree of embeddedness in the AI knowledge network (degree centrality, normalized). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

negative interaction effects between geographical proximity and AI linkage intensity on the probability of AI adoption. This suggests, first, that the transmission of deep AI knowledge is not affected by geographic distance, and second, this expresses the tendency of AI adopters to network with other regional AI hot-spots, albeit across geographical distance in the DACH region.

5.1. Socio-political implications

National strategies to develop AI competencies in the DACH countries, especially Germany, are designed to create local hubs of knowledge generation. This is enabled by investments in specific competence centers of AI research excellence, innovation funding for specific sectors and geographical areas, and networking programs designed to connect actors within and between knowledge hubs (Van Roy et al., 2021). Our results show that AI adoption emerges in close proximity to these AI production hot-spots and are aligned to the geographical focuses of national AI strategies. This results in both a regional and industry-specific concentration of explicit AI knowledge. Large parts of the remaining geographic and relational space have no exposure to AI-relevant knowledge which is in line with literature on the cluster premium in relation to the production and diffusion of knowledge (Audretsch and Feldman, 1996; Baptista and Swann, 1998; Spencer et al., 2010). Felten et al. (2021, p. 2210) found strong geographic localization patterns related to AI knowledge and argue that “it is possible that a region's exposure to AI generates tacit knowledge about how to work with and benefit from the technology that in turn constitutes a capability upon which future innovation will build.” This highlights the risk of creation of economic disparity induced by cluster policies, as they may further disadvantage structurally weaker regions (Hassink and Gong, 2019) and create threats of technological lock-in (Boschma and Frenken, 2010; Crespo et al., 2013).

In AI adoption clusters, early exposure to knowledge can lead to virtuous cycles of knowledge spillovers through network effects (Sorenson et al., 2006; Hekkert and Negro, 2009) which ultimately will affect the performance of selected firms in local hot-spots (Cassiman and Veugelers, 2002; Roper et al., 2017). Broekel et al. (2015) show that policy interventions can exacerbate these disparities by increasing likelihood of obtaining an R&D subsidy, further intensifying embeddedness in relevant R&D networks (Chowdhury et al., 2022).

While a non-neutral strategy in relation to region and sectors (Foray, 2016) and support for the production of a given technology may be warranted by the need for complex and related knowledge (Balland and Boschma, 2021), diffusion of applications of the technology may need different types of policy instruments which overcome the local cluster effect. Too great an emphasis on the production of knowledge within specific regions or specific industries could lead to closed systems of adoption which exclude numerous national regions and sectors. These path dependencies could lead also to a narrow distribution of value creation across firms, lowering the societal returns from AI as expertise and intangible assets become concentrated among a few suppliers of AI solutions and impede technological autonomy of those firms that depend on these suppliers (Franco et al., 2023). Rikap and Lundvall (2022) describe this as resulting from emerging corporate innovation systems where valuable intangible assets are pooled among central firms (see also Lundvall and Rikap, 2022) leading to what Bodrožić and Adler (2022) call a digital oligarchy which often is correlated with geographic localization.

The development of large language models (LLM) and their applications in generative AI can be associated with our research in relevant ways. First, open access to use LLMs as platform technology (foundation model) could enable greater access to state-of-the-art technology by reducing the amount of deep knowledge and the computational infrastructure needed to employ AI-based technologies. The reduced need for deep knowledge and intangible assets would overcome the problem of silos of adoption identified in our paper. However, reliance on foundation models could lead to a greater concentration of the benefits of the technology (Franco et al., 2023). While the emergence of foundation models could spur diffusion of AI-based augmentations to users' existing processes, reliance on these models could hamper more innovative use of AI technology, and especially if an intended use is incompatible with the dominant foundation model design. Were both these scenarios to apply (Dahlke and Ebersberger, 2023), this would further muddy the picture of the link between AI technology and economic development at the larger scale. This calls for more research investigating the relationship between technology usage (aggregate diffusion) and firms' economic performance (economic systems).

In our study we identified large-scale quantitative indicators for the dimensions of diffusion which reveal concentrations of economically useful AI knowledge. However, the closed nature of what we call the AI knowledge network can be represented only in static, structural terms. Future research could focus on the qualitative nature of firm linkages by specifically identifying buyer-supplier relationships within these networks in the form of digital value chains. Our hyperlink data allowed us to identify the network positions of firms and to relate their centrality to the level of accumulated expertise (and potential returns) over time. From a policy perspective, this could increase the ability to monitor the diffusion and impact of AI technology (e.g., Manzoni et al., 2022; Arranz et al., 2023) by capturing a systemic perspective based on firm-level data rather than individual cases or loosing structural properties in broad aggregates on the industry or regional level. A systemic perspective allows selection among promising candidate firms (or communities) to broaden diffusion through inter-firm networks (Abbasiharofteh et al., 2021), or detect patterns of adoption among firms that could lead potentially to technological lock-ins and lock-outs. A production-oriented technology policy could be complemented by a technology policy with diffusion-based incentive schemes to motivate technology producers to engage in knowledge and technology dissemination activities (Hahn and Yu, 1999). However, the question remains how these policies may transcend local clusters if production and application are closely linked. Chowdhury et al. (2022) suggest following the US establishment of geographically dispersed research centers as part of any national AI strategy. However, in the DACH region in particular, the level of capabilities required to establish AI research institutions is unclear.

Balland and Boschma (2021) suggest that that cooperation among regions with sufficient relatedness among economic activities can facilitate transfers of complex knowledge and could help less developed regions to diversify into more complex technologies. Our results suggest that a similar mechanism might support the diffusion of AI application across firms. Since we show that a certain level of cognitive proximity among connected firms can facilitate the transfer of deep AI knowledge, but that geographical proximity is not a necessary condition. As establishing links between cognitively proximate firms or communities of firms is not feasible within some regions, Janssen et al. (2020) show that cognitive proximity can be substituted by the presence of systemic innovation intermediaries able to bridge cognitive distance between otherwise distant actors and facilitate exchanges of know-how instead of creating unidirectional dependencies.

Analysis of our complementary survey data shows the significance of ICT experts and high-skilled human capital for building social capital to enable adoption of AI technology and suggests that these seed investments could trigger virtuous cycles of AI knowledge diffusion (Alekseeva et al., 2021). However, investments in AI-specific education are unlikely to reap rewards without the presence of related skills and activities, and this underlines the importance of interregional linkages (to AI hot-spots). To avoid the construction of digital oligarchies, Rikap and Lundvall (2022, p. 408) suggest the need for a “global knowledge commons with an equal and fair distribution of the tools to access and use knowledge both within and across national borders.”

5.2. Managerial implications

The impact of epidemic transmission of AI knowledge through various channels has practical implications for managers. First, we have shown that indirect mimetic pressure from the firm's environment has a stronger effect on AI adoption than the intensity of direct linkages while environmental pressure from the industry sector matters especially for firms with low intensity AI linkages. In the regional case, these two transmission channels are orthogonal which suggests that for some firms, the adoption of AI is based on bandwagon behavior (Abrahamson and Rosenkopf, 1993) that is a herd mentality to adoption of the technology reinforced by positive feedback loops. While the decision to leverage positive externalities may be as much rational as the result of social conformity, future research could examine more accurate ways to identify relevant peer groups with better information on AI technology adoption and reduce potentially irrational decision-making based on a bandwagon effect and response to mimetic pressure from the general environment.

Lanzolla and Suarez (2012) show that bandwagon behavior related to technology adoption decisions can be the result of the different types of information processed at different managerial levels within the organization. Indirect mimetic pressure is more likely to be received and absorbed by higher level managers who may not be completely aware of the technical expertise in the organization's lower hierarchical levels. In turn, this could determine how long it takes to progress from the initial moment of adoption to intensive use of the technology. In some cases, misalignment in the motivations to adopt AI across managerial hierarchies could create tensions and frustrations that are a barrier to the organization's effective integration of the technology in the company's processes (Strang and Macy, 2001; Lanzolla and Suarez, 2012). Since for selected firms in AI hot-spots these mimetic pressures can be strong, the decision to adopt AI technology requires reflexive and inclusive processes and practices across multiple hierarchical levels within the organization. Future research could explore how these organizational practices and capabilities could be better aligned across hierarchical levels which would improve our understanding of these relationships and their implications for AI adoption and performance.

Second, we offer evidence on the positive effects of deep AI knowledge transmitted through direct linkages but also show how sensitive these effects are with respect to contingent factors such as cognitive proximity and strength of linkages. This suggests a strong need for managerial attention in building up the right social capital and their ability to search, acquire, assimilate, and transform knowledge relevant to facilitate AI adoption. These multiple relations to These types of social capital and capabilities instill trust in the reliability of the new technological knowledge (Uzzi, 1996; Smith and Papachristos, 2016), and reduce uncertainty about emerging technology. The fostering of direct linkages to sources of deep AI knowledge may be especially important if mimetic pressure is otherwise encouraging sub-optimal adoption decisions. Knowledge transmitted through direct linkages often is channeled through lower levels of managerial hierarchies that embody the firm's practical realities (Strang and Macy, 2001; Lanzolla and Suarez, 2012).

Search to facilitate AI adoption needs to go beyond the firm's immediate geographic vicinity. Our results suggest that fostering links with distant sources of knowledge are feasible and cooperation partners should be selected on the basis of a shared knowledge base which will enable transfers of context-specific knowledge on AI applications. This adds to the findings in Rammer (2022) by showing the importance of absorptive capacity in sourcing deep AI knowledge (Cohen and Levinthal, 1990) and the importance also of the compatibility between the external knowledge and the firm's existing knowledge (Ebersberger and Herstad, 2011).

5.3. Limitations

Our study suffers from several limitations related to use of nontraditional, non-longitudinal data to map new and emerging digital technologies. First, our web-based measurements are related to information provided on company websites and the presence of hyperlink connections established between firms. They rely on a firm's efforts, capabilities, and needs to advertise their usage of technology. This raises questions about whether this communication strategy would be equally important for firms in different sectors, size classes, regions, and so on. Our model is particularly capable of identifying the types of AI adopters that specifically develop AI solutions, as these firms advertise this very prominently. Our model can identify less obvious AI adopters, but maybe with less accuracy. For example, cases of AI application in the human resources function might not be advertised on the firm's website which creates a reporting bias and underestimation of AI adoption. Another question refers to the types of relationships among firms captured by hyperlinks. Our analysis shows that reciprocal links have high levels of explanatory power in relation to AI adoption but inferring types of cooperation across millions of linkages is an ongoing challenge.

Bearing in mind that other traditional innovation metrics do not come without similar baggage, we may address this caveat by pointing toward the geographic and sectoral distribution of our web-sample which seems to carry external validity when compared to other studies of technology diffusion (Bresnahan, 2021; Acemoglu and Restrepo, 2020; Acemoglu et al., 2022; Vannuccini and Prytkova, 2023), and especially those focused on the same region (Rammer, 2022). Our control variables capture basic firm characteristics and technological complementarities and are in line with other recent AI adoption studies (Chen et al., 2021; DeStefano et al., 2022; Felten et al., 2021) which adds to the validity of our results. Most importantly, we replicated our results for the core mechanisms of epidemic effects using a smaller and representative survey sample of Swiss firms.

Second, there might be concern related to our empirical strategy and cross-sectional data. We emphasize that our model must be interpreted in a correlational, non-causal manner. Considering the correlative diffusion patterns revealed provides some first indications for policy makers and managers. To limit concerns about simultaneity in the modeling of indirect mimetic pressure, we excluded the focal firm in our computation of aggregate indicators and constructed an intensity variable for direct transmission (share of AI linkages). However, our network-based metrics involve some endogeneity issues. There could be some degree of reverse causality which is frequent in the context of homophilous behavior (in contrast to contagion) in social networks (Granovetter, 1985). To introduce some degree of exogeneity, we conducted a very simplistic test using the survey-based AI adoption indicator and the two waves of observations collected. Appendix Table A.4 shows that when explaining AI adoption at time t using the lagged adoption indicator in addition to the sum of deep AI knowledge ties as explanatory variable, the interaction between these latter two variables is positively significant, providing a slight indication that the delta in AI adoption over time correlates with network embeddedness. Future research could address the question of causality employing longitudinal data and more intricate network measures.

6. Conclusions

Our findings suggest that patterns of diffusion of AI are strongly related to epidemic and network effects and are also strongly localized and predominant in narrow industry sectors and regions. This is particularly true for indirect mimetic pressures emanating from the environment, but network measurements show that AI adoption also resembles a process of homophily in the inter-firm relational space. AI adoption seems to primarily take place within a closed network of AI-related knowledge where deeper embeddedness in these networks is associated with an increased likelihood of AI adoption by individual firms. However, rather than occupying central positions in the entire firm network these firms are located on the periphery. This might explain the slow rate of adoption at the macro-economic level since the locations of the sources of AI knowledge do not facilitate diffusion of AI-related knowledge across the entire inter-firm network. In the long run, these dynamics could potentially create structural competitive disadvantages and economic inequality related to the transformative potential of AI technology. However, our results suggest a potential lever to transcend local clusters, as direct linkages between firms seem to transmit AI knowledge even over longer geographic distances. This channel of transmission is complex, and its potential can be exploited only in the presence of specific conditions. These include links to sources of deep as opposed to superficial AI knowledge, reciprocal relations, extended search for sources of deep AI knowledge, and a sufficient number of linkages to cognitively similar firms. At the policy level, this calls for more fine-grained efforts to monitor technology diffusion using more dynamic and timely innovation metrics such as web-based measurements focused on individual firm clusters. Policy instruments to promote use of AI technologies should support both the production and application of AI technologies and linkages across disconnected clusters. At a managerial level, our results highlight the relevance of investigating how different channels of knowledge transmission are related to effective adoption of AI technology. Finally, the comprehensive modeling approach proposed in this paper could be used to study diffusion of related emerging technologies.

CRediT authorship contribution statement

Johannes Dahlke: Conceptualization, Formal analysis, Methodology, Project administration, Software, Visualization, Writing – original draft, Writing – review & editing. **Mathias Beck:** Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Jan Kinne:** Data curation, Methodology, Software, Writing – original draft, Writing – review & editing. **David Lenz:** Data curation, Methodology, Software, Writing – original draft, Writing – review & editing. **Robert Dehghan:** Data curation, Writing – review & editing, Visualization. **Martin Wörter:** Conceptualization, Supervision, Writing – review & editing. **Bernd Ebersberger:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Research support

Johannes Dahlke reports financial support was provided by the Heinrich-Böll Foundation [grant number P143003].

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Relationships

Jan Kinne, David Lenz, Robert Dehghan report a relationship with ISTARI.AI that includes employment and equity or stocks.

Johannes Dahlke reports a relationship with ISTARI.AI that includes employment.

Patents and intellectual property

There are no patents to disclose.

Other activities

There are no other additional activities to disclose.

Data availability

The data underlying this study comes from the following three main datasets: The Mannheim Enterprise Panel (MUP), the KOF Enterprise Panel, and an online company data set (webAI Database), including data such as websites textual contents and hyperlink connections. The MUP is edited by the ZEW Centre for European Economic Research and can be accessed by researchers via the ZEW research data center (https://kooperationen.zew.de/en/zew-fdz/home). The KOF Enterprise Panel is edited by the KOF Swiss Economic Institute at ETH Zurich and can be accessed by researchers via the KOF Micro Data Centre (https://kof.ethz.ch/daten/kof-micro-data-centre.html). The webAI database on the other hand has been provided by the private company ISTARI.AI, which collects company web data, analyses the data using webAI (an artificial intelligence) and sells derived information. The authors DL, RD and JK are the founders of the company and author JD has been part of the ISTARI Research Partner program which allowed him to work on the indicator development and validation and granted him access to the webAI data used in this article. The data can therefore be acquired from ISTARI.AI in the context of a paid subscription (https://istari.ai) or free-of-charge via a research collaboration.

Appendix A

Table A.1
Examples of paragraphs classified as deep AI knowledge.

Category	Examples
Deep AI knowledge (general AI identity)	"We are a leading specialty chemicals company based in [German city]. The core business is the development, manufacturing and marketing of chemical intermediates, additives and consumer protection products with annual sales of EUR [number] billion (2022). We manage our operating business through four segments: Advanced Industrial Intermediates, Specialty Additives and Consumer Protection. […] We focus on our customers' requirements in order to drive progress and reliably provide innovative product, material and service solutions. When developing new materials, **we also work with artificial intelligence to reduce development times for our customers**. Our manufacturing, administration and logistics processes are designed efficiently and with a focus on performance. Sustainability and responsibility are key factors behind our successful business operations. They help us become an even more efficient and competitive company while also supporting social goals such as protecting the environment. Our products also play a role in this, providing sustainable solutions in key areas such as electric mobility. This is [company]."
Deep AI knowledge (products)	"In addition, [company producing household equipment] developed the pioneering Cold Brew Process – a refreshing top innovation in the truest sense of the word. Cold water is slowly pulsed through freshly ground coffee under high pressure offering a coffee that is refreshing, energizing and with a wonderfully balanced aroma. The superlative and fully automatic machine can be controlled via a twice as fast 4.3" touch display and a Blue Crystal Rotary Switch. The specialty selection menu and **artificial intelligence make operation particularly easy and intuitive**" (translated from German).
Deep AI knowledge (services)	"Our approach offers a new level of precision in flower thinning. It is able to reach an optimum thinning rate even in highly variable environments and, at the same time, it avoids overspray completely, reducing the volume of chemicals sprayed by a vast amount, meaning much less environmental impact and much less chemical residue left on harvested apples. […]. **Thanks to artificial intelligence methods, it will be able to reach an optimum thinning rate** even in highly variable environments and it will significantly reduce the volume of chemicals sprayed."
Deep AI knowledge (processes)	"How **artificial intelligence is making our logistics fit for the future**. [employee's name] works in Sales & Supply Chain Management at [company]. With the expansion of the pacemaker® solution, he ensures efficient and green supply chains. For our #DigiJob series, he explained to us what tomorrow's logistics will look like thanks to digital innovations."
Deep AI knowledge (talent)	"Basic apprenticeship year at the vocational training center (BBC) in [city] and learn important basics for your job. In the subsequent three years of training at [company], you will expand your skills and knowledge in the frontend and backend and get to know modern and agile working methods. You help determine the focus for the final year of training based on your interests and skills. **Digital transformation is a big topic at [company] ,** which is why you will work on various exciting future topics such as robotics or **artificial intelligence** during your apprenticeship" (translated from German).
Deep AI knowledge (external)	"[partner company] has been supporting [company, "us"] in the **exploitation of emerging technologies such as artificial intelligence (AI) and machine learning (ML)** to improve both the quality and efficiency of numerical weather prediction. Recently, [company, "we"] signed an agreement with [partner company] to explore the benefits of AI/ML for enhancing the use of satellite and environmental data to enhance their mission of better protecting lives and property through more accurate and timely forecasts […]"

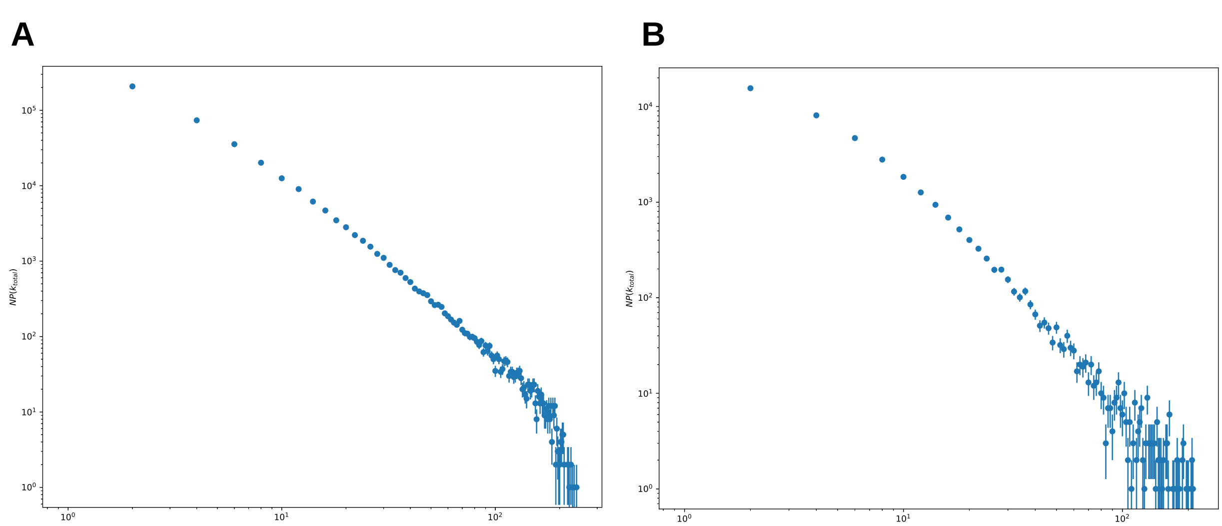

Fig. A.1. Total degree distribution for (A) the entire inter-firm network and (B) AI knowledge network.

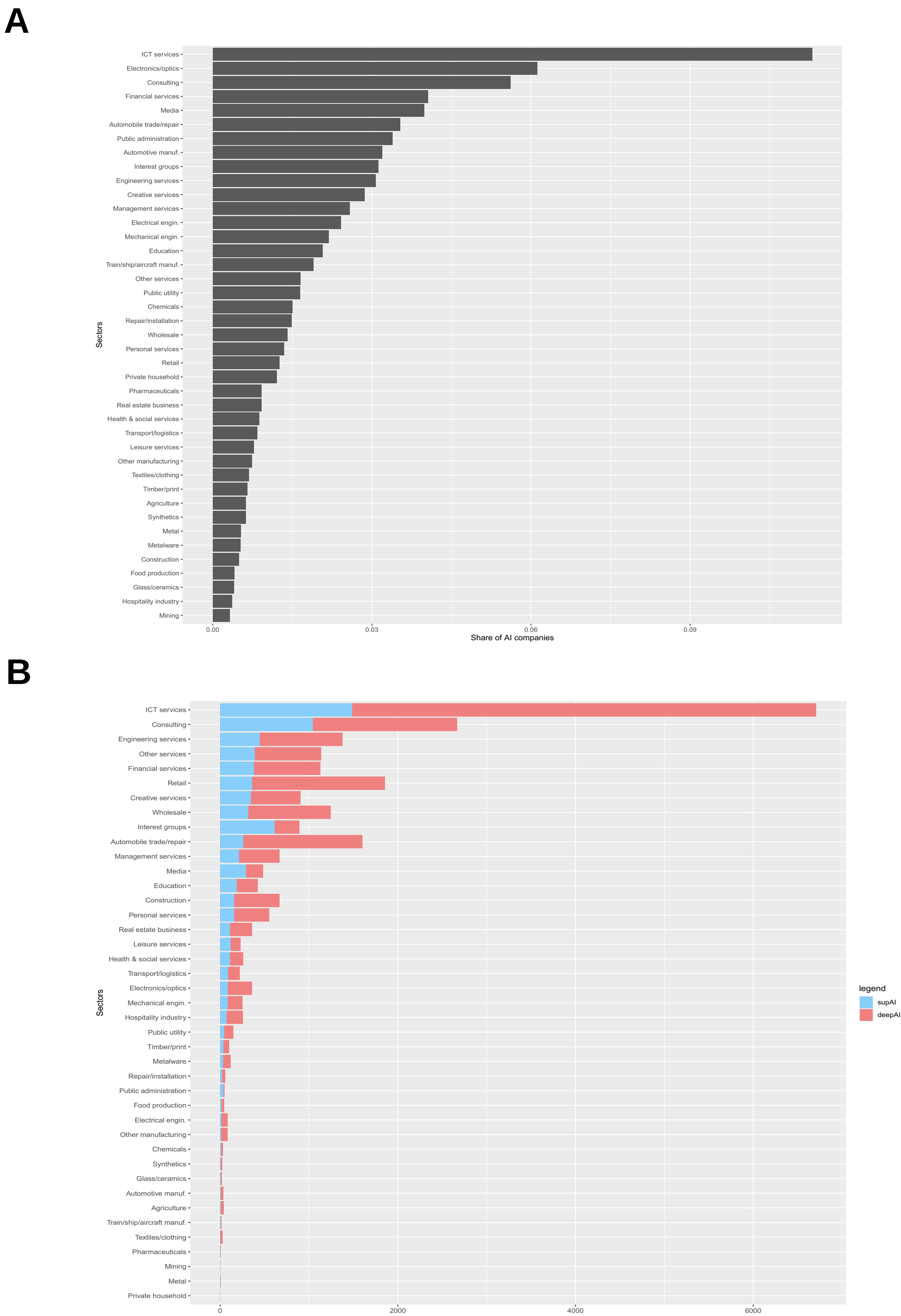

Fig. A.2. Descriptive statistics on share of AI companies by sector.
Note: (A) depicts share of AI-positive firms by sector in the DACH-region; (B) depicts absolute number of companies in various sectors with superficial or deep AI knowledge (where both exist, we count only deep knowledge).

Table A.2
Correlation matrix for variables of interest.

	AI	deepAI	supAI	AI_sec	AI_reg	cogn_mean	geo_mean	supAIshare	deepAIshare	supAIrecshare	deepAIrecshare	degree_ai	betw_all	close_all	InnoProb	urban_d	lnsize
AI																	
deepAI	0.81***																
supAI	0.79***	0.43***															
AI_sec	0.22***	0.19***	0.18***														
AI_reg	0.10***	0.08***	0.09***	0.16***													
cogn_mean	0.02***	0.01***	0.02***	0.01***	0.02***												
geo_mean	−0.08***	−0.07***	−0.07***	−0.09***	−0.08***	0.07***											
supAIshare	0.05***	0.03***	0.05***	0.08***	0.04***	0.01***	−0.02***										
deepAIshare	0.10***	0.10***	0.08***	0.12***	0.04***	0.01***	−0.03***	0.01***									
supAIrecshare	0.02***	0.01***	0.03***	0.02***	0.01***	0.01***	0.00	0.18***	0.00								
deepAIrecshare	0.05***	0.05***	0.03***	0.03***	0.01***	0.02***	0.00	0.00	0.15***	0.01***							
degree_ai	0.28***	0.21***	0.25***	0.14***	0.08***	0.01***	−0.05***	0.16***	0.21***	0.03***	0.04***						
betw_all	0.07***	0.05***	0.06***	0.06***	0.05***	0.00**	−0.01***	0.03***	0.04***	0.00	0.00	0.55***					
close_all	0.08***	0.06***	0.08***	0.07***	0.07***	0.00**	−0.10***	0.09***	0.10***	0.00*	0.00*	0.28***	0.34***				
InnoProb	0.23***	0.20***	0.19***	0.40***	0.18***	0.00	−0.22***	0.06***	0.10***	0.02***	0.03***	0.16***	0.09***	0.13***			
urban_d	0.08***	0.06***	0.07***	0.14***	0.55***	0.02***	−0.06***	0.04***	0.03***	0.01***	0.01***	0.07***	0.05***	0.07***	0.13***		
lnsize	0.07***	0.06***	0.06***	−0.02***	0.02***	0.07***	−0.04***	0.01***	0.02***	0.01***	0.01***	0.12***	0.14***	0.19***	0.15***	0.03***	
lnage	−0.03***	−0.04***	−0.03***	−0.11***	−0.06***	0.02***	0.06***	−0.02***	−0.03***	0.00	−0.01***	0.01***	0.04***	0.08***	−0.07***	−0.04***	0.33***

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

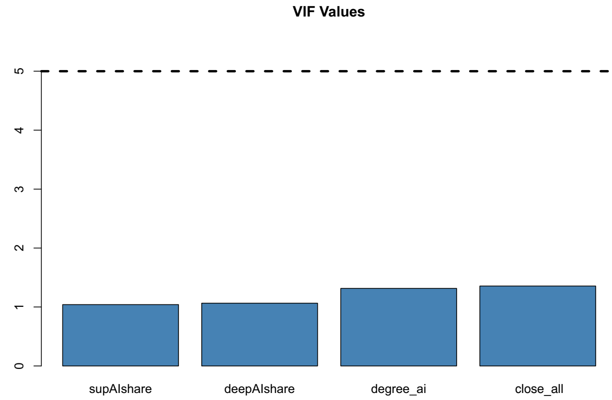

Fig. A.3. Variance inflation factor for variables constructed using network centrality measures and direct linkages included in model 13 (see Table 4).
Note: The dashed line indicates a threshold of 5 suggesting severe collinearity is affecting the estimates. In this model the regressors are well below this threshold at close to 1.

Table A.3
Average marginal effects for candidate models.

Model	Variable	AME	SE	z	p	lower	upper
3	AI_reg	0.1917	0.0216	8.8706	0.0000	0.1494	0.2341
3	AI_sec	0.1999	0.0100	20.0534	0.0000	0.1804	0.2194
3	cogn_mean	0.0075	0.0015	4.9445	0.0000	0.0045	0.0105
3	deepAIshare	0.0863	0.0027	32.1401	0.0000	0.0810	0.0915
3	geo_mean	−0.0286	0.0018	−16.1426	0.0000	−0.0320	−0.0251
3	InnoProb	0.0745	0.0015	48.9033	0.0000	0.0715	0.0775
3	supAIshare	0.0289	0.0044	6.5009	0.0000	0.0202	0.0376
9	AI_reg	0.2084	0.0252	8.2646	0.0000	0.1590	0.2578
9	AI_sec	0.2113	0.0086	24.4570	0.0000	0.1943	0.2282
9	cogn_mean	0.0076	0.0016	4.8464	0.0000	0.0045	0.0107
9	deepAIrecshare	0.2006	0.0177	11.3219	0.0000	0.1659	0.2353
9	geo_mean	−0.0287	0.0019	−14.9833	0.0000	−0.0325	−0.0250
9	InnoProb	0.0771	0.0014	53.9156	0.0000	0.0743	0.0799
9	supAIrecshare	−0.0072	0.0279	−0.2597	0.7951	−0.0618	0.0474
11	AI_reg	0.2026	0.0247	8.1934	0.0000	0.1541	0.2510
11	AI_sec	0.2064	0.0115	17.9087	0.0000	0.1838	0.2290
11	close_all	0.0226	0.0023	9.9858	0.0000	0.0182	0.0270
11	cogn_mean	0.0088	0.0015	5.8631	0.0000	0.0059	0.0118
11	deepAIshare	0.0788	0.0031	25.3630	0.0000	0.0727	0.0849
11	geo_mean	−0.0283	0.0019	−14.5843	0.0000	−0.0322	−0.0245
11	InnoProb	0.0774	0.0018	44.1039	0.0000	0.0740	0.0809
11	supAIshare	0.0234	0.0049	4.7495	0.0000	0.0137	0.0330
12	AI_reg	0.1904	0.0215	8.8648	0.0000	0.1483	0.2324
12	AI_sec	0.2001	0.0093	21.4495	0.0000	0.1818	0.2184
12	betw_all	0.0586	0.0089	6.5503	0.0000	0.0410	0.0761
12	cogn_mean	0.0078	0.0015	5.2541	0.0000	0.0049	0.0108
12	deepAIshare	0.0859	0.0028	30.7391	0.0000	0.0804	0.0914
12	geo_mean	−0.0287	0.0016	−17.4362	0.0000	−0.0319	−0.0255
12	InnoProb	0.0743	0.0014	54.4261	0.0000	0.0717	0.0770
12	supAIshare	0.0281	0.0046	6.1162	0.0000	0.0191	0.0372
13	AI_reg	0.1786	0.0240	7.4394	0.0000	0.1315	0.2256
13	AI_sec	0.1992	0.0107	18.6512	0.0000	0.1783	0.2202
13	close_all	−0.0064	0.0024	−2.6912	0.0071	−0.0111	−0.0017
13	cogn_mean	0.0092	0.0015	6.1612	0.0000	0.0062	0.0121
13	deepAIshare	0.0624	0.0034	18.2656	0.0000	0.0557	0.0690
13	degree_ai	0.2594	0.0148	17.5879	0.0000	0.2305	0.2884
13	geo_mean	−0.0293	0.0019	−15.4571	0.0000	−0.0331	−0.0256
13	InnoProb	0.0736	0.0017	44.4817	0.0000	0.0703	0.0768
13	supAIshare	0.0044	0.0058	0.7604	0.4470	−0.0070	0.0158

Table A.4
A crude attempt at addressing simultaneity of AI adoption and fostered AI linkages.

AI_qn$_t$ (0/1), *OLS*	(1)	(2)	(3)	(4)
AI_qn$_{t-1}$	0.526***	0.491***	0.484***	0.439***
	(0.067)	(0.075)	(0.072)	(0.079)
deepAIsum	0.063***	0.035	0.051**	0.023
	(0.020)	(0.028)	(0.026)	(0.030)
AI_qn$_{t-1}$ x deepAIsum		0.073*		0.108*
		(0.040)		(0.056)
lnsize			0.021**	0.021**
			(0.009)	(0.009)
lnage			0.005	0.004
			(0.015)	(0.015)
export			0.008	0.010
			(0.024)	(0.024)
ICTexperts			−0.013	−0.012
			(0.020)	(0.020)
foreign			−0.020	−0.020
			(0.027)	(0.027)
inno			0.006	0.010
			(0.020)	(0.020)
R&D_int			−0.185	−0.389**
			(0.260)	(0.198)
digit			0.034	0.031
			(0.030)	(0.030)
urban_d			0.034	0.032
			(0.025)	(0.025)
compet			−0.004	−0.005
			(0.007)	(0.007)
Constant	0.051	0.058	−0.065	−0.052
	(0.037)	(0.037)	(0.070)	(0.069)
Sector	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Obs.	790	790	733	733
R2	0.261	0.265	0.252	0.260
R2_adj	0.251	0.255	0.231	0.238

Robust standard errors.
[*] $p < 0.1$.
[**] $p < 0.05$.
[***] $p < 0.01$.

Appendix B. Supplementary material

Supplementary material to this article (including a detailed account of the procedures to train and validate the web-based AI indicator) can be found online at https://doi.org/10.1016/j.respol.2023.104917.

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