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Article — Published Version

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Journal of Product Innovation Management

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Suggested Citation: Soluk, Jonas; Miroshnychenko, Ivan; Nambisan, Satish (2025) : AI Adoption in Family Firms: A Mixed-Methods Study on the Paradoxical Roles of Passive and Active Family Involvement, Journal of Product Innovation Management, ISSN 1540-5885, Wiley, Hoboken, NJ, Vol. 43, Iss. 1, pp. 125-159,
<https://doi.org/10.1111/jpim.12789>

This Version is available at:

<https://hdl.handle.net/10419/335599>

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ORIGINAL ARTICLE OPEN ACCESS

AI Adoption in Family Firms: A Mixed-Methods Study on the Paradoxical Roles of Passive and Active Family Involvement

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Received: 29 October 2023 | **Revised:** 25 February 2025 | **Accepted:** 29 March 2025

Special Issue Guest Editors: Praveen Kopalle, Costas Katsikeas, Giampaolo Viglia, and Linda Hollebeek

Funding: The authors received no specific funding for this work.

Keywords: artificial intelligence | digital innovation | family firms | family involvement | network ties | stakeholder engagement

ABSTRACT

Artificial intelligence (AI) technologies have gained significance for all types of firms, including family firms. However, unlike other business contexts, family firms face unique challenges in adopting complex and generative technologies, such as AI. This is particularly evident when examining the heterogeneous nature of family firms distinguished by passive (i.e., family ownership) and active (i.e., family management) family involvement. Specifically, we adopt a social capital perspective and combine inductive qualitative and deductive quantitative research into a mixed-methods design. In the first step, we conduct a multiple case study of eight firms using rich data from 125 interviews and archival documents. While the case evidence shows that strong external network ties with suppliers, customers, and competitors help overcome the challenges related to AI technologies, we reveal opposing impacts of passive and active family involvement. Interestingly, our qualitative insights emphasize a negative moderation effect for passive family ownership exacerbating the challenges of AI and a positive moderation effect for active family management facilitating AI adoption. In the second step, we conduct a quantitative test of this conceptual model. On the basis of large-scale data from 1444 firms, we find empirical support that increasing strengths of external network ties with suppliers, customers, and competitors drive AI adoption. Moreover, we find support for the opposing roles of passive family ownership as a negative moderator and active family management as a positive moderator in the relationship between supplier ties on the one hand and AI adoption on the other. Our study contributes toward a nuanced understanding of the idiosyncratic challenges of AI adoption faced by different types of family firms and the role of social capital in this regard and, more broadly, to research on innovation and technology adoption in family firms.

1 | Introduction

Artificial intelligence (AI) involves computational systems and advanced algorithms capable of handling intricate tasks

and addressing challenging problems that typically rely on, or even surpass, human reasoning, predictive skills, and the ability to adapt to shifting conditions (Jia et al. 2024; Obschonka and Audretsch 2020; Vanneste and Puranam 2024). Specific

This paper is part of the special issue "Artificial Intelligence, Stakeholder Engagement, and Innovation Value"

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Summary

- Firms should strengthen external network ties with suppliers, customers, and competitors to access complementary knowledge and accelerate AI adoption, particularly in the face of internal resource and expertise constraints.
- AI strategies in family firms should explicitly account for the distinct effects of ownership and management involvement, recognizing that passive family ownership may impede, while active family management may facilitate AI-driven transformation.
- Passive family owners are advised to professionalize governance structures and delegate operational authority to enable more agile, evidence-based decision making in AI-related initiatives.
- Actively involved family managers should institutionalize long-term stakeholder collaboration and learning mechanisms to align AI adoption with the firm's strategic continuity and legacy-oriented objectives.

entrepreneurial opportunities emerging from the adoption of AI in organizations include the automation of resource-intensive tasks (Raisch and Krakowski 2021; Tursunbayeva and Chalutz-Ben Gal 2024) and the development of novel digital product or business model innovations based on generative AI (Cockburn et al. 2019; Seidel and Berente 2020; Soluk and Kammerlander 2021). Thus, AI is a critical factor for firms seeking to develop a sustainable competitive advantage in the digital economy (Gregory et al. 2021; Kemp 2024; Kumar et al. 2025). However, the core traits of AI—such as autonomy, learning, and inscrutability (Berente et al. 2021)—may “alter organizations in unprecedented ways” (von Krogh 2018, 405; see also Glikson and Woolley 2020), posing important challenges, particularly for family firms, due to families' desire to retain control and a unique culture that is mostly inward focused and described as change reluctant (Diaz-Moriana et al. 2020; König et al. 2013; Kotlar et al. 2013). AI-related challenges also include managers' fears about losing their jobs (Raisch and Krakowski 2021; Vanneste and Puranam 2024) and owners' fears about losing control, the risk of disintermediation (Chalmers et al. 2021), and issues concerning data privacy and security (Laine et al. 2024). Moreover, there are inherent conflicts of AI adoption in firms' supply chains, for instance, the potential to disrupt established and proven processes and relationships (Hendriksen 2023; Mithas et al. 2022). These and related challenges make the adoption of AI in family firms a particularly complex and knowledge-intensive endeavor.

Research indicates that the complexity and knowledge intensity of AI underscore a significant demand for internal expert knowledge (Berente et al. 2021; Jia et al. 2024; Neumann et al. 2024), an expertise often lacking within many companies (Chowdhury et al. 2023; Stohr et al. 2024), especially in family firms, which are considered particularly resource-constrained owing to their tendency for self-financing (De Massis et al. 2018; Duran et al. 2016). In addition, we know surprisingly little about the antecedent conditions and human factors affecting AI

adoption (Obschonka and Audretsch 2020), particularly in the context of family firms, as described in a recent call by Mariani et al. (2023).

This research gap relates to two aspects of AI adoption in particular: first, how family firms overcome the complexity and generativity of AI adoption through external stakeholder engagement (e.g., with suppliers, customers, and competitors) and compensate for a lack of internal specialist knowledge (Chalmers et al. 2021; Worek and Aaltonen 2023), and second, how passive and active family involvement affects AI adoption (Matzler et al. 2015; Villalonga and Amit 2006).

First, owing to the unique characteristics of AI (Berente et al. 2021), research suggests that insights into conventional innovation adoption might not be easily transferable to AI adoption (Gama and Magistretti 2024; Glikson and Woolley 2020; von Krogh 2018). The aforementioned AI skills gap (Chalmers et al. 2021) might prompt companies to explore external knowledge sources, pointing to the relevance of network ties. We propose that social capital theory (Adler and Kwon 2002; Sorenson and Rogan 2014) constitutes an appropriate theoretical lens for examining how social relationships might affect AI adoption. More specifically, we focus on *external social capital*, which describes the exchange and (re)combination of information between social entities such as companies (Nahapiet and Ghoshal 1998; Sorenson and Rogan 2014), and *family social capital*, which relates to social interaction between family members in family firms (Arregle et al. 2007; Herrero 2018), both of which aim to create unique resources such as new knowledge (de Groote, Soluk, et al. 2023; Inkpen and Tsang 2005; Pearson et al. 2008).

Second, the nexus between *family ownership*—defined as passive involvement through the concentration of shares in the hands of one or a few families—and *family management*—defined as active involvement through the presence of family members in the executive leadership of the company—creates unique organizational dynamics. At this intersection, economic and socioemotional priorities often converge and conflict, which intensifies the challenges associated with AI adoption (Chrisman and Patel 2012; Patel and Chrisman 2014). This intersection is particularly critical because family owners often emphasize preserving socioemotional wealth—such as legacy and identity—while family managers are directly responsible for operational decisions that require reconciling long-term family priorities (Berrone et al. 2010; Gómez-Mejía et al. 2007) with the requirements of AI. The fear of losing control and the risk of disintermediation—rooted in the generativity of AI—trigger competing demands for continuity and renewal and must be negotiated between owners and managers (Matzler et al. 2015). The pressure for owning families and family managers is particularly high, as all of the economic and noneconomic wealth that is concentrated in the business may potentially be at stake due to AI disruption (Gómez-Mejía et al. 2022; Souder et al. 2017). This paradigm shift remains unexplored, especially since previous studies have treated family involvement mostly as a monolithic block (König et al. 2013; Soluk, Miroshnychenko, Kammerlander, and De Massis 2021), largely neglecting critical nuances between family ownership and family management (Blanco-Mazagatos et al. 2016).

On the basis of the above, here, we focus on the following research questions: (1) *How do network ties influence AI adoption in organizations?* (2) *How is this relationship affected by passive and active family involvement?* To address these questions, we apply a sequential mixed-methods design, combining a qualitative multiple case study and quantitative regression analysis (Molina-Azorin et al. 2012). This mixed-methods approach allows us to explore the novel and underresearched topic of AI adoption in family firms as well as to validate the hypotheses derived from case evidence using large-scale data to provide generalizable insights beyond the case sample (Grimpe et al. 2017; Johnson and Onwuegbuzie 2004; Turner et al. 2017). Specifically, building on 125 semistructured qualitative interviews, we develop a set of hypotheses that apply a social capital perspective (Adler and Kwon 2002; Sorenson and Rogan 2014) and test these hypotheses on a rich quantitative dataset of 1444 German firms, a geographical context in which family firms account for approximately 90% of all companies and are thus considered the backbone of the economy (Kraiczky et al. 2015; Stiftung Familienunternehmen 2024).

Our study seeks to make the following contributions to the literature. First, by revealing the antecedent conditions of AI adoption and the stakeholder engagement mechanisms used to overcome AI-related challenges, we expand current insights into how to foster AI adoption in family firms to create competitive advantages (Kemp 2024; Raisch and Krakowski 2021). Second, we extend the literature on family firm innovation, which has treated family involvement mostly as a homogenous construct (König et al. 2013; Souder et al. 2017), thereby overlooking the paradoxical nature of passive and active family involvement (Matzler et al. 2015; Villalonga and Amit 2006). Moreover, we challenge previous studies indicating that family management might impede technological innovation (Ceipek et al. 2021; Martínez-Alonso et al. 2023; Migliori et al. 2020; Prügl and Spitzley 2021) and research that has assumed that family ownership facilitates its adoption (Bammens and Hünermund 2020; Cucculelli and Peruzzi 2020; Hsu et al. 2015; Soluk, Miroshnychenko, Kammerlander, and De Massis 2021), suggesting that the tension between passive and active family involvement is much more nuanced than previously recognized. Third, by revealing how external social relationships (external social capital) and family involvement, as a specific form of social interaction in many organizations (family social capital), affect AI adoption, we add to the research on social capital theory (Adler and Kwon 2002; Arregle et al. 2007), especially with respect to the debate on how, on the basis of their social relationships, organizations can address a lack of internal specialist knowledge to the particular challenges of AI adoption (Chalmers et al. 2021; Inkpen and Tsang 2005; Sorenson et al. 2006).

Our research also offers actionable strategies for integrating AI in organizations, emphasizing the importance of leveraging network ties to address adoption challenges and knowledge gaps (Chalmers et al. 2021; Stohr et al. 2024). Specifically, for family firms, we advocate for active engagement in managing knowledge and learning mechanisms, alongside the professionalization of external management and governance structures for passive family owners (Piyasinchai et al. 2024). For policymakers who aim to nurture long-term economic growth on the basis of AI, we recommend the expansion of initiatives to

strengthen network ties (e.g., UnternehmerTUM) and enhance accessibility to applied AI research (e.g., via the Fraunhofer Society), as well as policy measures such as grants and tax incentives to support AI investments, particularly for resource-constrained family firms (De Massis et al. 2018).

2 | Conceptual Background

2.1 | AI in Businesses

The quickly evolving field of AI includes a wide range of computer-assisted systems that involve automated reasoning, pattern recognition, machine learning, knowledge repositories, and natural language processing (Bessen et al. 2022; Kemp 2024; von Krogh 2018; Wang et al. 2021). Through technological progress, AI has become increasingly accessible for businesses, especially in recent years (Brock and von Wangenheim 2019; Jia et al. 2024; Lévesque et al. 2022). Today, firms may use AI, for example, to support their strategy or investment decisions (Iansiti and Lakhani 2020), new product development and innovation management (Bouschery et al. 2023; Freisinger et al. 2024), talent acquisition (Black and van Esch 2020), and sales organization (Hollebeek et al. 2024; Pachidi et al. 2021). With the potential to achieve human tasks more efficiently and effectively and to outperform humans at least in a predefined domain of work, AI creates novel entrepreneurial opportunities for businesses, which can result in sustainable competitive advantages (Gregory et al. 2021; Kemp 2024).

AI is differentiated from other forms of digital innovation by its three distinct but interrelated core traits of autonomy, learning, and inscrutability (Berente et al. 2021). *Autonomy* refers to the capacity of AI to work independently and to make decisions with minimal human intervention (Kopalle et al. 2022; Vanneste and Puranam 2024). *Learning* implies the capacity of AI to draw conclusions from experiences on the basis of large amounts of data and to adapt future decisions accordingly (Rahwan et al. 2019; Townsend et al. 2025). Closely related to the two aforementioned concepts is the notion of *inscrutability*, which refers to the underlying algorithms of AI being accessible only to a small audience and remaining opaque and incomprehensible not only to almost all users but also to designated insiders such as programmers (Kellogg et al. 2020; Lebovitz et al. 2022).

With AI now available on a broad scale, there is, for the first time, a considerable transfer of relevant decision authority from traditional human reasoning to generative automated systems, which presents several challenges for businesses. Closely related to autonomy, AI is often associated with a fear of job loss through automation (Raisch and Krakowski 2021). Although there is disagreement on the extent to which AI leads to job losses, as new jobs are expected to be simultaneously created by the adoption of AI (Hunt et al. 2022), studies do report that dramatic changes have taken place in the workforce, management, and organization as a consequence of AI (Daugherty et al. 2019; Huang and Rust 2018; Jia et al. 2024). Related to learning, another challenge of AI for companies is the risk of disintermediation (Chalmers et al. 2021; Kellogg et al. 2020). Disintermediation occurs when established intermediaries in value chains, such as distributors or service providers serving as key gatekeepers for information

and market access, are bypassed by an AI system that takes over those roles. The risk of disintermediation of an entire business is particularly prevalent in traditional industries, as AI-driven platforms can directly connect producers with consumers, rendering intermediaries (e.g., established distribution networks) obsolete (Chalmers et al. 2021; Marti et al. 2024).

Closely linked to the generativity and inscrutability of AI is that the outcomes of AI-based activities have a nondeterministic nature (Glikson and Woolley 2020), leading to high levels of interpretability and explainability and resulting in AI also being referred to as a “nested and nonlinear ‘black box’” (Chalmers et al. 2021, 13). Owing to this contradiction with the conventional understanding of human reasoning, which is used to obtain a general understanding of possible outcomes, the user must have a high level of trust in an AI-based system and its behavior, which may not be transparent (Castelvecchi 2016; Gregory et al. 2021; Vanneste and Puranam 2024). Thus, the application of AI can often also have a strong emotional component, as emotions have been shown to significantly influence human trust (Jones and George 1998). All of these challenges are further amplified by additional AI-related issues. These include, for instance, concerns about data privacy and security issues that may be linked to the data-rich nature of AI (Nambisan et al. 2019).

Recent research has also advanced our understanding of the antecedents shaping AI adoption in businesses. Therefore, organizational readiness emerges as a critical determinant, encompassing factors such as strategic alignment, resource availability, and cultural preparedness (Gama and Magistretti 2024; Tursunbayeva and Chalutz-Ben Gal 2024). Additionally, studies have highlighted the pivotal role of technological infrastructure, including data quality, IT capabilities, and integration flexibility, in facilitating AI adoption (Dora et al. 2022; Rahman et al. 2023; Vial et al. 2023; Weber et al. 2023). Leadership support represents another crucial aspect, with effective sponsorship and commitment being essential for overcoming resistance and driving AI initiatives forward (Kolbjørnsrud 2024; Neumann et al. 2024; Taherizadeh and Beaudry 2023). Moreover, scholars emphasize the importance of developing employee capabilities and fostering a learning-oriented culture to harness the full potential of AI technologies (Chowdhury et al. 2023; Jia et al. 2024; Stohr et al. 2024). Mitigating concerns related to job displacement through upskilling and reskilling programs is vital for addressing resistance and ensuring workforce readiness (Zirar et al. 2023). While extant research beyond the family business domain provides initial insights into the (particularly internal and technical) antecedents of AI adoption, it largely ignores the role of external networks and human factors beyond the traditional workforce and individual users, particularly with respect to the tension between family ownership and family management, which highlights the need for more in-depth investigation (Broekhuizen et al. 2023; Kemp 2024; Matzler et al. 2015; Worek and Aaltonen 2023).

2.2 | Social Capital in Businesses and Business Families

Autonomy, learning, and inscrutability make AI adoption a particularly complex and knowledge-intensive endeavor (Gregory et al. 2021; Kellogg et al. 2020). However, most firms lack the

appropriate skills and knowledge needed to implement complex AI systems (Chalmers et al. 2021). To cope with these AI-related challenges, firms may seek external information and knowledge sources that are conceptualized in the extant research as *external social capital* (Gedajlovic et al. 2013)—more formally defined as “the ability of actors to secure benefits by virtue of membership in social networks or other social structures” (Portes 1998, 6; see also Adler and Kwon 2002; Bowden et al. 2018). The underlying premise of social capital theory is that the relational networks between social entities—businesses, for instance—constitute unique resources, which, through the exchange and (re)combination of information and knowledge, facilitate the creation of intellectual capital such as new knowledge (Nahapiet and Ghoshal 1998; Nambisan 2013; Sorenson and Rogan 2014). The intense exchange of information and knowledge in social relationships as well as the density and cognitive proximity between network partners create not only intellectual capital but also trust (Baer et al. 2015; Gulati 1995; Kwon and Adler 2014).

Prior studies have conceptualized the different dimensions of social capital in a tripartite way (Kwon and Adler 2014; Nahapiet and Ghoshal 1998). First, the *structural* dimension of social capital refers to the configuration of the network that provides access to partners and thus sources of information and knowledge (e.g., the presence or absence of network ties and how they can be reached). Second, the *relational* dimension refers to a shared history of interactions and examines the personal and emotional aspects of such interactions (e.g., friendships and mutual respect). Third, the *cognitive* dimension refers to the narratives, codes, and shared language between knowledge sources and recipients that effectively enable the (re)combination and interpretation of knowledge.

In addition to external social capital, there are internal forms of social capital (Daniel et al. 2018; Gedajlovic et al. 2013). Internal social capital is often dependent on the top managers or the shareholders of a business, as their decisive functions allow them to coordinate and control social relationships particularly well (Johnson et al. 2013; Li et al. 2021; Pearson et al. 2008). In this regard, previous research has paid increasing attention to the social capital of owning families in businesses (Arregle et al. 2007; Bendig et al. 2020; Bird and Zellweger 2018; Carr et al. 2011; Habbershon et al. 2003) and *family social capital*, which is defined as “the sum of all actual and potential resources stemming from relationships between family members within family firms” (Herrero 2018, 1).

There are several explanations for the enduring significance of the social capital developed in the family (Arregle et al. 2007). First, family social capital not only occurs in the context of family-influenced firms but also naturally determines how family members interact (Portes 1998), resulting in an “emotional attachment [between the family members and] their organization’s strategic positions” (Kellermanns and Eddleston 2006, 812). Second, family social capital often evolves over a long period of time (Arregle et al. 2007; Querbach et al. 2020), as family-influenced firms are particularly prone to intergenerational entrepreneurship, passing on their knowledge to succeeding generations (Cabrera-Suárez et al. 2015; Kotlar et al. 2020). Family social capital particularly hones the shared norms, commitment, aligned values, common vision, and shared language in

the owning family, which can be described as the family culture (Sanchez-Ruiz et al. 2019). Third, through their intimate social relationships, family members share noneconomic utilities derived from the business, which are sometimes referred to as socioemotional wealth (SEW; Gómez-Mejía et al. 2007).

To protect their SEW, family members tend to retain decision-making authority over the business, that is, family control (Chrisman et al. 2015). To sustain the family culture and control that emerge through and with the social relationships in the family, families pursue two distinct forms of family involvement. On the one hand, passive family ownership involves the family as shareholders who do not engage in daily operations (Lee and Chu 2017; Matzler et al. 2015; Villalonga and Amit 2006). In contrast, active family management involves family members in managerial roles in which they actively guide the company's direction (Blanco-Mazagatos et al. 2016; Eddleston et al. 2013). Family ownership and family management often function as distinct dimensions with potentially opposing influences on strategic decision-making; however, findings remain inconsistent (Eddleston et al. 2013; Lee and Chu 2017). Villalonga and Amit (2006) reported that family ownership creates firm value only when the founder acts as CEO or chairperson, whereas Matzler et al. (2015) reported that family management leads to lower R&D intensity but higher innovation output—attributable to unique family resources. Moreover, other studies view family ownership as fostering knowledge accumulation, spurring risky long-term investments to safeguard economic and non-economic wealth (Bammens and Hünermund 2020; Cucculelli and Peruzzi 2020; Hsu et al. 2015; Soluk, Miroshnychenko, Kammerlander, and De Massis 2021). Conversely, some scholars suggest that family management hampers technological innovation through rigid mental models and elevated risk aversion (Ceipek et al. 2021; Martínez-Alonso et al. 2023; Migliori et al. 2020; Prügl and Spitzley 2021).

While we lack research on family involvement in the context of AI adoption, the few studies on digital innovation in family-involved firms paint a divided picture (Soluk and Kammerlander 2021): whereas Ceipek and colleagues (Ceipek et al. 2021, 1) indicate that increasing family involvement in management “constrains the development of exploratory IoT [internet of things] innovation,” Soluk and colleagues (Soluk, Miroshnychenko, Kammerlander, and De Massis 2021) reveal that family ownership is positively associated with digital business model innovation. Given these fragmentations and ambiguities, the following theory building aims to develop nuanced insights into the mechanisms underlying AI adoption in the context of both passive and active family involvement in businesses.

3 | Theory Building With Qualitative Data

3.1 | Method

To explain the mechanisms underlying AI adoption in businesses and to derive testable hypotheses with respect to our research questions, we opted for a qualitative multiple case study approach (Eisenhardt 1989). Multiple case studies are particularly suited for identifying similarities and differences in the case of firms' AI adoption and thus for developing novel

theories or extending existing theories (Yin 2013). Thus, with our multiple case study, we aim to answer the “how” and “why” of the examined mechanisms. Owing to their replication logic, multiple case studies are more likely to produce robust and generalizable theories than single cases are (Eisenhardt and Graebner 2007).

Our sample consists of eight case firms whose AI adoption we followed; Table 1 contains an anonymized summary of the case firms (the firms are named using Greek letters from Alpha to Theta). In line with the theoretical definition of an incumbent company (König et al. 2013) and the aforementioned emphasis, we built on the following sampling criteria: (1) medium or large company size, (2) belonging to a more traditional industry, (3) varying levels of passive and active family involvement, and (4) company headquarters in Germany. The selection of case firms was an iterative process guided by the potential contribution to theory building. We identified case firms mainly from business magazines, industry reports, and publications from chambers of commerce. We followed a theoretical sampling approach and added new, diverging case firms to the sample once the first cases were analyzed to account for variance in the sample in terms of AI adoption, network ties, and family involvement (Eisenhardt and Graebner 2007; Yin 2013). With this addition of case firms, it was possible to replicate or extend theory until we reached theoretical saturation and new data did not affect theory, ruling out alternative explanations of observed mechanisms (Corbin and Strauss 2008; Eisenhardt 1989).

The context of our study is AI adoption in established, that is, incumbent, German companies with varying levels of family involvement. This context is particularly well suited for our research, as the relevance of AI for companies in Germany has been increasingly recognized in recent years, which is also reflected in the federal government's own AI strategy (Rammer et al. 2022; The Federal Government 2020). While AI in new ventures is reasonably well researched, we focus on the under-researched area of AI adoption in incumbent firms in more traditional industries (Chalmers et al. 2021). Such companies represent the majority of economic activity, and their long-term success determines the economic prosperity of entire countries (Baumgärtner et al. 2025; Duran et al. 2016; König et al. 2013). Given these characteristics, our context is comparable to those of other German-speaking countries (e.g., Austria, Switzerland) and, to a large extent, to those of other Central European and North American countries that exhibit similar attributes (Miroshnychenko et al. 2021; Soluk and Kammerlander 2021). We did not include small companies in the analysis because their idiosyncrasies might distort the analysis (Leonidou et al. 2007; Mallett and Wapshott 2014; Soluk et al. 2023).

3.2 | Data Collection and Analysis

To collect a rich database, we exploited different data sources: (1) semistructured interviews with CEOs, other C-level executives, directors, heads of departments, members of supervisory boards, and other key informants from the case firms; (2) semistructured interviews with clients, suppliers, competitors, business partners, industry analysts, journalists, academics, and other external informants to assess the company's

TABLE 1 | Overview of cases.

	Case firm	Employees	Industry	Status	Family involvement	Foundation (incl. legal predecessor)	Location
1	Alpha	10,000–14,999	Services	Private	No family involvement	1850–1874	Germany
2	Beta	1000–4999	Manufacturing	Public	No family involvement	1825–1849	Germany
3	Gamma	1000–4999	Services	Public	39% Family ownership + Family management	1975–1999	Germany
4	Delta	20,000–24,999	Retail	Public	70% Family ownership + Family management	1950–1974	Germany
5	Epsilon	5000–9999	Manufacturing	Private	80% Family ownership	1900–1924	Germany
6	Zeta	20,000–24,999	Manufacturing	Private	100% Family ownership + Family management	1875–1899	Germany
7	Eta	1000–4999	Engineering and Manufacturing	Private	100% Family ownership	1925–1949	Germany
8	Theta	10,000–14,999	Manufacturing	Private	100% Family ownership + Family management	1900–1924	Germany

Note: All names of companies and interviewees are anonymized throughout the paper, as confidentiality was guaranteed to all interview partners.

initiatives from the outside; (3) corporate documents such as presentations, reports, annual reports, analyses, or brochures within the case firms; (4) archival data such as articles, secondary interviews, and reports from media and internet resources outside the case firms. Table 2 provides a summary of the data sources.

Our primary data source is semistructured interviews with case-internal and case-external informants. We conducted 54 interviews with internal informants and 71 with external informants, for a total of 125 interviews (with a duration of 35 to 92 min). The interviews were conducted in German and either recorded or transcribed verbatim, depending on the preferences of the interviewees. For the semistructured interviews, we prepared an interview guide, which was divided into the following three categories: (1) initiatives in the company to adopt digital technologies and AI; (2) insights into how the owners of the company (the owning family, if any) affect decision-making in the company; and (3) the role of network ties, success factors, and challenges in the adoption of digital technologies and AI. Open-ended questions in the interviews provided an opportunity to explore developments in the company over time, examine which measures were (or were not) implemented, as well as why and how, and gather examples and anecdotes about them. The field work lasted from November 2016 to August 2018.

Five to nine internal interviews and an additional 7–11 external interviews per case firm gave us the opportunity to gather rich nonpublic information, validate it, and eliminate possible biases. We also took the following additional measures to ensure data validity. (1) At the beginning of the field work, we collected data on AI initiatives whose outcomes were still uncertain to minimize retrospective sense-making (Huber 1985). (2) Our interview questions had a nondirective character to increase the accuracy of the statements (Huber and Power 1985). (3) We interviewed internal and external informants from different levels and with different professional backgrounds to obtain a more complete picture of the observations compared with exchanges with individual informants (Solarino and Aguinis 2021). (4) We combined interviews with archival data from different time periods (spanning a period of 12 years) to objectify the statements. (5) We promised anonymity to the interview partners to obtain honest insights into sensitive areas (e.g., failures; Solarino and Aguinis 2021). We were also able to examine different levels of the case firms: both individual motivations and behaviors as well as organizational measures were derived on the basis of the rich divergent data and the different backgrounds of the interview partners.

We began our data analysis by compiling a document for each case firm, on the basis of the interviews and archival data, that

TABLE 2 | Case data sources.

Case firm	Number of interviews	Insider informants	Number of interviews	External informants	Number of articles	Sample sources	Corporate documents and press releases
1 Alpha	9	2 × Member of the Executive Board, Chief Technology Officer, 2 × Director 1, Director 2, 2 × Manager, Project Manager	10	Client, Academic, Strategic Partner, Supplier, Business Analyst, Competitor	42 articles	Chamber of Commerce, Handelsblatt, Manager Magazin, Wirtschaftswoche, Die Zeit, Business Insider	74
2 Beta	8	Chief Executive Officer, 2 × Director 1, Director 2, Director 3, Head of Department 1, Head of Department 2, Project Manager	9	Supplier, Distributor, Client, Former Employee, Advisor	17 articles	Rheinische Post, Wirtschaftswoche, Handelsblatt, Neue Presse, Industriemagazin	35
3 Gamma	6	2 × Director, Manager 1, Manager 2, Project Manager, Specialist	7	Sales Agency, Client, Strategic Partner, Advisor, Academic, Business Analyst	35 articles	Capital, Yahoo Finance, Süddeutsche Zeitung, Tagesschau	14
4 Delta	8	Member of the Supervisory Board, Managing Director, Director, Head of Department 1, Head of Department 2, Project Manager, 2 × Specialist	9	Sales Agency, Client, Academic, Competitor	29 articles	Die Welt, Capital, Wirtschaftswoche, Brand Eins, Süddeutsche Zeitung	19
5 Epsilon	6	Chief Technology Officer, Director, Head of Department 1, Head of Department 2, Head of Department 3, Manager	8	Advisor, Academic, Supplier, Customer, Business Analyst	18 articles	Chamber of Commerce, Handelsblatt, Der Spiegel, Manager Magazin, Business Insider, Finance Magazin	27
6 Zeta	6	Director 1, Director 2, Head of Department 1, Head of Department 2, Manager 1, Manager 2	11	Investor, Technology Analyst, Journalist	22 articles	Handelsblatt, Wirtschaftswoche, Frankfurter Allgemeine Zeitung, Neue Züricher Zeitung, Neue Osnabrücker Zeitung	41
7 Eta	6	Director 1, Director 2, Head of Department 1, Head of Department 2, Manager, Specialist	7	Customer, Industry Expert, Former Employee, Advisor	19 articles	Manager Magazin, Wirtschaftswoche, RedaktionsNetzwerk Deutschland	25

(Continues)

TABLE 2 (Continued)

Case firm	Number of interviews	Insider informants	Number of interviews	External informants	Number of articles	Sample sources	Corporate documents and press releases
8 Theta	5	Chief Executive Officer, Head of Department 1, Head of Department 2, Manager, Project Manager	10	Industry Expert, Client, Strategic Partner, Technology Analyst, Academic, Advisor	38 articles	<i>Die Welt am Sonntag, Manager Magazin, Süddeutsche Zeitung</i>	57
Data Sources		54 Internal Interviews	71 External Interviews			512 Additional Data	

chronologically listed their activities in the adoption of AI. With the triangulation of different sources, we thus developed a comprehensive case history per firm and carefully cross-checked individual feedback from interviewees with other interviews and insights from the archival data. We coded these case summaries, interviews, and archival data and, using an open coding technique, marked relevant passages on AI, passive/active family involvement, and network ties, in line with our research questions (Corbin and Strauss 2008). In a second step, we switched from within-case to cross-case pattern analysis and compared the findings across the case firms. Building on an axial coding approach, we developed relevant coding categories and associated subcategories and identified commonalities and differences (Corbin and Strauss 2008). Once we had a strong correspondence based on the data, constructs, and theory, we iteratively developed and finalized our conceptual model. As our theoretical insights emerged, we compared them to those of previous studies to ensure alignment with existing concepts (Eisenhardt et al. 2016).

3.3 | Findings

While all the case firms were well aware of the concept of AI and had already discussed use cases in different parts of their business, our case evidence indicates that some case firms had successfully adopted AI technologies, whereas others had encountered significantly more challenges with AI adoption. The evidence also indicates that the reasons for these differences among the case firms are related to the specific network ties and passive or active family involvement that existed in most of the case firms. In this section, we outline these factors and the related mechanisms and summarize them in terms of our hypotheses. Figure 1 represents our conceptual model, whereas Table 3 reveals alternative explanations not highlighted in the following elaborations.

3.3.1 | Influence of Network Ties on AI Adoption

In the adoption of AI, *supplier ties* played a particularly important role for most of the case firms (Alpha, Beta, Gamma and, to a lesser extent, Delta, Zeta, Eta, and Theta). Strong supplier ties not only increased transparency with respect to the supplier interface but also enhanced supply chain optimization potential (Dora et al. 2022; Franke et al. 2024; Yan et al. 2020). These optimizations were related to achieving desired efficiency gains and adhering to regulations (e.g., the new German Supply Chain Act passed to protect the environment and human rights along global supply chains; Baumann et al. 2020). As the number of entities increased, conventional optimization efforts reached their (methodological and technical) limitations. This led the case firms to address the nonlinearity and complexity of the optimization potential in the supply chain with (often self-learning) AI agent systems (*learning*). A director from the case firm Delta stated the following:

The highest expenses occur in our purchasing department, so the supplier interface is constantly under pressure for optimization. [...] When we have

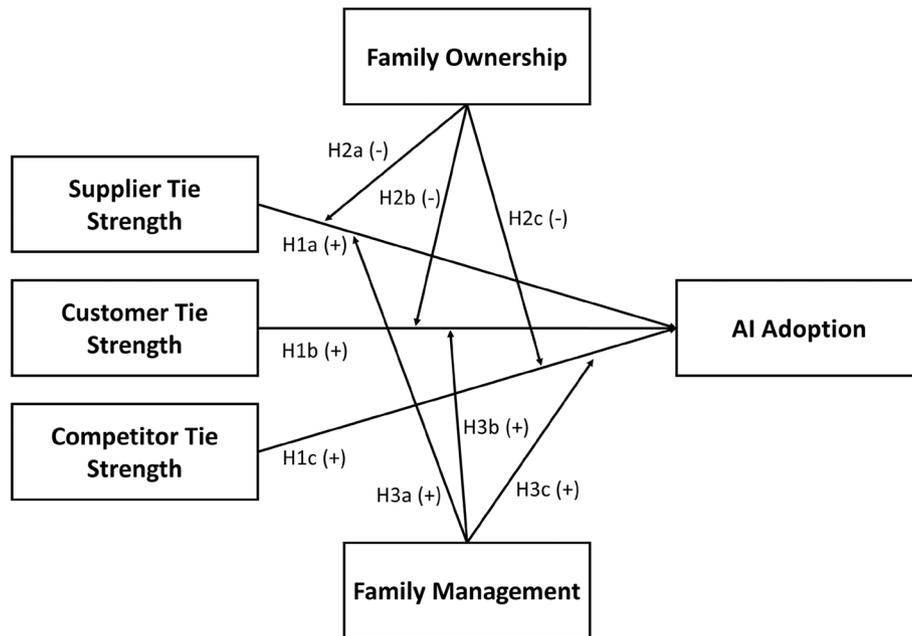


FIGURE 1 | Conceptual model.

a good connection to suppliers, then the chances are much better to optimize this interface together. Learning from the large amount of data [with the help of AI] is something we have already successfully implemented.

It also appeared that close supplier relationships helped develop common goals to prevent disruptions and risks in the supply chain—and thus avoid cost increases, profit losses, and reputational damage (Chae et al. 2020; Kocabasoglu-Hillmer et al. 2023). According to the case firms, these risks increased with trade wars and global competitive pressures (Fan et al. 2022). To address this, the firms increasingly turned to AI’s *autonomy* to overcome traditional forecasting limitations, leading to the adoption of AI-based tools. A director from case firm Gamma commented as follows:

We would need unrealistically large teams to keep track of the variables we can now monitor with automation. [...] [This AI system] can cope with significantly less input from our employees.

The case evidence also showed that robust social contacts and associated trust with suppliers reduced concerns about sharing data and risking trade secrets (Blome et al. 2023; Hendriksen 2023). This openness enabled joint trials of new AI-based technological solutions, despite AI’s opacity (*inscrutability*), to leverage big data opportunities at the supplier interface (e.g., for performance evaluation or accelerating make-or-buy decisions; Dubey et al. 2024). The CEO from case firm Beta, which launched, together with a semiconductor supplier, an AI-based real-time interaction solution of users, objects, and their machines, explained this as follows: “We don’t need AI for AI’s sake; we need a business case. [...] Testing that with a supplier helps a lot.”

Customer ties were another key driver of AI adoption (Alpha, Beta, Gamma, Delta, Zeta, and, to a lesser extent, Theta). Strong customer ties provided the case firms with deep insights into changing customer needs, fostering a stronger push for customer centricity (Schmidt et al. 2024; Sheth et al. 2023; Verganti et al. 2020). The case firms found that AI, such as autonomous marketing techniques (*autonomy*; Agarwal et al. 2024), more effectively supported this approach. This made the case firms more likely to implement AI, as an executive board member from Alpha noted:

We need a radical focus on the customer these days. [...] Customers are extremely individual. [...] We have automated important functions in order to implement a customer journey end to end, which address the individual requirements of our customers. For us, that means higher customer lifetime value.

The case evidence also revealed that strong customer relationships enabled the firms to gain deep insights into customer behavior across devices, platforms, and products (Bilro et al. 2023; Hollebeek et al. 2024; Zhang et al. 2024). The companies used these data to generate customer insights and learn for their own business (*learning*; Plangger et al. 2023), prompting AI adoption. The case firm Zeta introduced an AI-based product to aggregate and learn from customer behavior insights, as noted by Zeta’s CDO in a media interview:

Digital twins of our customers are taking on a key role. [...] Algorithms and artificial intelligence make it possible [to exploit this data opportunity].

Insights from strong customer ties allowed the companies to sense customer preferences across channels (Maier and

TABLE 3 | Further qualitative insights and alternative explanations.

Related hypotheses	Further qualitative observations	Identified in cases	Case evidence
H1a-c	Supplier, customer, competitor ties were by far the strongest influencing factors on AI adoption, but case firms also utilized other network ties (e.g., to startups, universities, government agencies)	Alpha, Delta, Epsilon, Zeta, Eta, Theta Partially: Beta, Gamma	<p>“We have set up a program for collaboration with start-ups and have already tried out a lot. [...] Many collaborations didn't materialize or even had to be broken off because there were far too many different approaches and working methods. [...] The mindset of start-ups is simply different, and not always compatible with such a big company like us.” (Head of Department, Epsilon)</p> <p>“[We] have discontinued an incubator program [for novel start-up ideas] as it did not bring the desired impact.” (Chief Technology Officer, Alpha)</p> <p>“This lead to intensive dealings with local universities. [...] [Regarding AI] it turned out that the [university] researchers were much closer to [theoretical] fundamental research than to applicable knowledge, which would have helped us.” (Director, Zeta)</p> <p>“There is an initiative in [our industry association] that aims to make member companies fit for novel technologies. [...] So far, we have perceived this as more of a PR initiative with very little substance behind it.” (Head of Department, Eta)</p>
H1a-c	Due to its relevance, the case firms have utilized network ties in particular for AI adoption, but with some distance, they have also been working on other technologies (e.g., IoT, robotics, metaverse)	Alpha, Beta, Delta, Epsilon, Zeta, Eta, Theta Partially: Gamma	<p>“It's been years since we started, but we're in a continuous process of working on our Internet of Things capabilities, which is an important topic for us. [...] We keep realizing how dependent we are on external partners to supplement our expertise here.” (Director, Zeta)</p> <p>“As far as heat recovery is concerned, we are working with a competitor who has already implemented something very successfully here. [...] Here we can learn how to implement this technology in a very practical way and with the greatest possible benefit for our business operations.” (Project Manager, Theta)</p> <p>“Our products are closely related to robotics technologies. Our aim is to lead even more strongly in this area. But we clearly need technology partners to achieve this.” (Head of Department, Epsilon)</p> <p>“Thanks to the help of [a supplier], we have formed a Metaverse core team a year ago. It is exploring possible options for us and will look at how this technology can be used for us and our customers.” (Member of the Executive Board, Alpha)</p>

(Continues)

TABLE 3 (Continued)

Related hypotheses	Further qualitative observations	Identified in cases	Case evidence
H1a-c	Some cases have experienced negative influences on their AI adoption related to both internal (e.g., legacy systems, resource constraints, employee resistance) and external factors (e.g., regulatory concerns, perception as hype)	Alpha, Beta, Gamma, Delta, Epsilon, Zeta, Eta Partially: Theta	<p>“To be honest, we have a completely outdated ERP system. [...] I’m really unsure whether we even have the data in the quality we need for AI applications.” (Director, Beta)</p> <p>“The business environment is currently really difficult, which is reflected in our [revenue] figures. [...] For me, the focus is more on consolidating the business than on uncertain technological investments.” (Director, Alpha)</p> <p>“We are struggling with a fatigued workforce that is going through multiple transformations. [...] We run the risk of no longer being able to fully reach our employees.” (Specialist, Delta)</p> <p>“Data handling is already highly regulated in Germany. I also expect further comprehensive EU regulations on AI. It might make sense to wait for a while and see where the journey takes us.” (Member of the Executive Board, Alpha)</p> <p>“AI is of course a hype topic with currently too little substance to make an all-in worthwhile.” (Head of Department, Epsilon)</p>
H2a-c, H3a-c	Beyond our hypotheses, other forms of family involvement emerged in some cases with direct effects on AI adoption (e.g., generational differences, family conflicts, number of families) or marginal moderating effects on the baseline hypotheses (e.g., family involvement in advisory/supervisory boards)	Gamma, Delta, Epsilon, Zeta, Eta, Theta	<p>“It’s been a while since the generational handover here [at Delta]. But it’s clear that the younger generation is much more enthusiastic about new technologies.” (Head of Department, Delta)</p> <p>“Conflicts in family businesses are a common thing and can take many different forms. [...] [The family conflicts] can distort the focus and slow down other important decisions such as on AI.” (External Advisor, Theta)</p> <p>“With us, it has always been the two families [...] who set the tone. It wasn’t always easy. [...] It complicated things.” (Head of Department, Zeta)</p> <p>“We have an external management, but the family is involved in the supervisory board. This is not an operational involvement, but rather a high-level monitoring role, with the chance to intervene in the major decisions.” (Director, Eta)</p>

(Continues)

TABLE 3 (Continued)

Related hypotheses	Further qualitative observations	Identified in cases	Case evidence
H2a-c, H3a-c	In addition to family involvement, the case evidence revealed other moderators in certain cases that marginally affected the base line hypotheses (e.g., cash opportunities, competitive intensity, literacy, culture)	Alpha, Beta, Gamma, Delta, Epsilon, Zeta, Eta, Theta	<p>“After participating in a tender, we received a federal grant for an R&D project in which we are applying AI at the supplier interface. Of course, this external funding was an important lever to push the project forward.” (Director, Eta)</p> <p>“Competitive pressure remains the main driver. If the competition is moving fast, then we also have to be faster and do everything we can to successfully complete existing [AI] initiatives [based on network ties]. [...] Things have to go live, that’s all that matters.” (Chief Executive Officer, Beta)</p> <p>“Our workforce is not yet ready, which is slowing us down. [...] We are investing heavily in upskilling and getting our workforce ready for AI innovation. [...] This is currently the point that means that even projects conceived in partnerships are too slow and too often come to nothing.” (Head of Department, Zeta)</p> <p>“I think the corporate culture is the be-all and end-all. [...] This is what determines what is successful or not.” (Managing Director, Delta)</p>

Baccarella 2024; Zhou et al. 2022). They also identified openness to AI and replaced less efficient sales assistants with AI solutions (*autonomy*; Ferraro et al. 2024). For example, based on a resilient technological infrastructure (Rahman et al. 2023), Gamma developed an AI bot in customer service, which was tested extensively with lead users from prior projects, as highlighted in a company presentation.

Within the case firms, strong customer ties highlighted growing customer awareness of ethical issues, such as privacy and data protection (*inscrutability*; Hermann 2022; Wirtz et al. 2023). The trust gained from these ties fostered shared values and norms (Kwon and Adler 2014), leading to greater customer willingness (and less resistance) for AI and faster company adoption decisions. A Beta department head commented as follows:

We can't work against [our] customers. If we use AI, it is only if the customer wants it and accepts it. [...] This is a decision that we explore in detail with our customers beforehand.

The cross-case pattern analysis also revealed that *competitor ties* determine AI adoption (Alpha, Beta, Delta, and, to a lesser extent, Gamma, Zeta, and Theta). Most of the case firms showed at least informal relationships with the competition (Wang and Gao 2021; Yang et al. 2022). Closer social ties were observed in C-level executive friendships (Shu et al. 2012). In the case of particularly strong competitor ties, the case firms were able to provide evidence on prior experiences with joint development projects. Such collaborations were particularly appealing in the case of relatively unexplored AI technologies, since the uncertainty associated with AI allowed the involved companies to share (e.g., financial, reputational) risks (*inscrutability*). A director from the case firm Beta explained why such collaborations facilitated AI adoption in the company:

If we develop something on our own, then we can earn a lot of money with it as a first mover, at least temporarily. [...] But I have to get to the finished development first. [...] Such [AI] development projects [with competitors] mainly serve to spread risk, which is an important factor for us. If we know we can spread risk when the outcome is unclear, then we are more likely to commit to the project.

Some case firms revealed that AI remained experimental (Geissdoerfer et al. 2022; Wang et al. 2024). Strong competitor ties with basic cooperativeness were frequently utilized (Ritala and Hurmelinna-Laukkanen 2013). Owing to AI's experimental nature, with appropriate leadership support (Neumann et al. 2024; Taherizadeh and Beaudry 2023), information leaks were seen as less threatening than those for near-commercial products, which were shielded as assets (*inscrutability*). This facilitated AI adoption, as a Theta department head explained:

We are often still trying things out as far as AI is concerned. If we close ourselves off to that, then we

won't get far with our [limited internal] expertise. [...] Joint approaches with peers has helped us understand a distinct value in AI for us.

Additionally, shared values and norms from strong competitor ties created a common agenda for the industry's future viability (Corbo et al. 2023; Randolph et al. 2020). Enabled by a learning-oriented culture (Jia et al. 2024; Stohr et al. 2024), the dynamic industry environment highlighted that cross-company analytics improve assessments of technology impacts and changes (*learning/autonomy*; Boysen 2020). AI adoption supported this goal. A director from Alpha commented as follows:

We have implemented an AI-powered tool with the help of competitors and our industry association to develop [data-driven] future scenarios for our industry. [...] We can't keep up with usual strategy approaches.

This leads us to hypothesize the following:

H1. (a–c) *The stronger a company's supplier, customer, and competitor ties, the greater its level of AI adoption.*

3.3.2 | The Moderating Role of Family Ownership and Family Management

The case evidence also revealed how *family ownership*, which exists in most of the cases, impeded the impact of these mechanisms (especially in Epsilon and Eta, and to a lesser extent in Zeta, Theta, and Delta). With respect to *supplier ties* and AI adoption, the family-owned firms had less transparent supplier interfaces (König et al. 2013; Polat 2021). The reasons included low formalization and tacit knowledge from passive family members and long-tenured employees (Ge and Campopiano 2021). This limited processable information weakened the potential of supplier links and ultimately stalled AI utilization. In this context, Eta's specialist stated the following:

We could do way more [with suppliers]. [...] We simply lack processable data, we are not up to date. Frankly, this was never our focus,

A manager from Eta reflected as follows:

With our long history as a reliable employer and family business, we have a culture at our company that doesn't really allow latest technologies to permeate.

High levels of family ownership often led to overemphasis on family goals due to the strong desire to preserve the family business (Becerra et al. 2020; Pinelli et al. 2024). This reduced the focus on and sponsorship of common goals with suppliers (Manelli et al. 2023; Taherizadeh and Beaudry 2023), hindering AI use. An Epsilon department head commented as follows:

Naturally, the family is in the foreground with the owners. [...] That's where other issues take a back seat to some extent.

Higher levels of family ownership increased owner control to protect economic and noneconomic assets (Gómez-Mejía et al. 2007, 2022). This heightened concerns about knowledge leaks, reducing openness to sharing data with suppliers. As a result, AI adoption was impeded, as a director from the case firm Delta described:

We reach limitations [in AI adoption] because we can't fully mine data treasures due to the lack of commitment [by the owning family].

The case evidence also indicated how family ownership affected the association between *customer ties* and AI adoption (Epsilon, Eta, and, to a lesser extent, Delta, Zeta, and Theta). Historical habits and family culture in the family-owned firms favored personal customer contacts over technologically driven customer behavior analysis (Duran et al. 2016; Rajan et al. 2023). As a result, these firms saw little need to adopt AI for the customer interface, revealing a strategic and cultural misalignment (Gama and Magistretti 2024). An Eta department head commented as follows:

In our company, [we] are in very close personal exchange [with our customers], which is also the way we want it. [...] [Our sales team] is more likely to call [the customers] than we are to set up a fancy automation solution. That doesn't really suit us. [...] We have built up relationships [as a family-owned firm] over decades that will continue to be cultivated very personally in the future.

These patterns were evident in the continuity of customer relationships in family-owned firms (Chrisman et al. 2024; Soluk 2022). This applied to both customer interactions and behavior analysis (Duran et al. 2016). The family-owned firms relied on proven, conventional approaches, which hindered AI adoption on the basis of customer ties. An Epsilon department head stated the following:

[Customer interaction] is something where our [family] owner acts as a role model. [...] We play it safe and don't like to experiment with our customers.

The pattern analysis revealed that the desire for control in the family-owned firms (Chrisman and Patel 2012; De Massis et al. 2018) led to negative associations with AI's inscrutability. Fears of delegating decision-making or disintermediation (Hu et al. 2023) were evident. Additionally, the desire for long-term autonomy was strong in the family-owned firms (Gómez-Mejía et al. 2007), leading to introspection and lower commitment to exploiting AI at the customer interface. Theta's project manager explained as follows:

Self-reliance has always been very important to our business. [...] We have good contacts with our

customers, but we make quite little out of it in my opinion.

In addition, the case firms showed that family ownership weakened the link between *competitor ties* and AI adoption (Epsilon, Zeta, Eta, and, to a lesser extent, Gamma, Delta, and Theta). The desire for autonomy led to skepticism about joint projects with competitors, despite existing social contacts (Kammerlander et al. 2015; Kotlar et al. 2013). Emotional attachment to the business outweighed potential cooperation benefits (de Groote, Feninger, et al. 2023). Although several initiatives were taken to develop AI solutions internally, these efforts repeatedly failed due to a lack of resource availability and expertise (Tursunbayeva and Chalutz-Ben Gal 2024). A specialist from the case firm Eta stated the following:

Our [non-family] CEO has a close exchange with owners from the competition. [...] Despite the exchange, however, there is a noticeable distance, and little comes across in the day-to-day business. [...] When it comes to something like AI, we are left to our own efforts, which often overwhelms us [due to the lack of expertise and resources].

The family-owned firms also showed high uncertainty regarding AI's impact on their business (Soluk and Kammerlander 2021; Worek and Aaltonen 2023). This uncertainty, amplified by the owners' desire for control and fear of losing autonomy (Kathuria et al. 2023), was more emotionally charged than in nonfamily firms. As a result, the families restricted AI-related information exchange with competitors, even when they were not involved in management. This hesitation slowed AI adoption. An Epsilon department head explained as follows:

We have a strong sense of loyalty to the owning family that has built the whole business. [...] There is an assumption that the ranks remain closed to the competition and that not too much will spill out.

Family ownership made the owners and nonfamily managers more likely to seek advice from nonexecutive family members on strategic issues such as AI (Herrero 2018; Sanchez-Ruiz et al. 2019). To align with family norms (De Groot et al. 2022), they consulted family owners over external experts, even when competitors had more relevant market expertise. This reduced openness to leveraging competition interfaces for AI utilization. Zeta's manager commented as follows:

The owning families have evolved over generations. This is not simply left aside when critical issues arise. [...] You have to respect that and I sympathize with it.

Thus, we hypothesize the following:

H2. (a–c) *Family ownership weakens the positive relationship between supplier, customer, and competitor tie strength and AI adoption.*

In contrast to the aforementioned impeding mechanisms, the evidence revealed how *family management* strengthened the baseline hypotheses (especially for Gamma, Delta, Zeta, and Theta). With respect to the relationship between *supplier ties* and AI adoption, firms with active family management were revealed to have stronger ability to monitor and control the emerging risks associated with AI (Gómez-Mejía et al. 2007; Patel and Chrisman 2014). Proximity to daily operations enabled ad hoc decision-making (Matzler et al. 2015) and integration flexibility (Vial et al. 2023; Weber et al. 2023) with key suppliers. Aligning external input with family norms mitigated risks and facilitated decisions. Unlike long-tenured managers, the family managers' direct personal stakes in the business amplified their motivation to preserve relationships. A Theta manager explained as follows:

We have many long-standing and trusting supplier relationships. [...] There are suppliers where the fathers' generation on both sides have already signed contracts. [...] Family management has agreed to an AI pilot project with a long-term supplier and [the family management] also been involved in the negotiations in light of the shared history and to oversee the involved contingency risk.

Additionally, family managers, who are much more secure in their positions than conventional managers are, can prioritize long-term goals over short-term results (Bendig et al. 2020; Sciascia et al. 2015). This is evident in AI adoption, which is fueled by supplier ties and where—due to its complexity—knowledge and learning are developed over time (Berente et al. 2021). Family management fosters iterative learning and knowledge accumulation with suppliers without questioning foundational premises. Delta's manager director explained as follows:

While other companies have to meet short-term shareholder expectations, we have patience. [...] With [the family managers] being convinced, we can withstand ups and downs in the implementation of novel AI technology, having the bigger picture in mind.

In family management, decision-making authority is concentrated among a few family members (de Groote and Kammerlander 2023; Radu-Lefebvre et al. 2022). This streamlines decisions at the supplier interface, bypassing bureaucracy (Burt et al. 2021). While even long-tenured managers must contend with external shareholder pressure, the reduced formalization for family managers enables quicker implementation of supplier initiatives for AI adoption. In a recent newspaper article, Zeta's family CEO was quoted as follows:

As a family, we are fully committed to investing in future-ready areas such as AI and making quick decisions for the benefit of the company.

The case evidence also illustrates how family management influenced the relationship between *customer ties* and AI adoption (Gamma, Delta, Zeta, and Theta). Driven by their desire to preserve the family legacy toward long-standing partners, the

family managers exceeded standard decision-making by personally engaging with customers and tailoring solutions to their specific needs (de Groot, Feninger, et al. 2023; Kellermanns and Eddleston 2006). This 'extra mile,' for which family managers have a much stronger economic and noneconomic incentive than conventional managers do, was particularly apparent at the customer interface, which the family firms believed was crucial for creating long-term value (De Massis et al. 2018). The family managers prioritized AI success in this area. Gamma's director stated the following:

The customer is king for our family management. In the development of our AI bot [in customer service], the [family manager] therefore required the utmost discipline and little tolerance for errors. We conducted many insights and tests with customers to ensure the success of this [AI] bot. [...] The project had an incredibly high priority for family management, [they] were very involved.

Family management involves deep knowledge of customer relationships and their management (Duran et al. 2016; Rajan et al. 2023). This includes a shared language, refined over time, that resonates with customers (Herrero 2018). Family managers decode this language and integrate it into daily business routines, making it applicable for AI adoption. A director of Zeta shared the following:

[Our family manager] is known and appreciated by the customers; there is a relationship of trust. [...] When developing an AI solution for energy efficiency on the customer side, it was crucial to involve the family at key points to press the right buttons in the minds of the customers involved, especially the older and higher-ranking ones.

The case firms revealed that family managers' visibility in operations, particularly in customer environments, enhanced their charismatic presence and perceived authority (Qerbach et al. 2020; Skorodzyevskiy et al. 2024; Zellweger et al. 2012). Customers felt valued by this involvement, even when limited, which encouraged them to engage in AI adoption and share expertise. This distinct presence arises from the family managers' symbolic representation of the family's heritage, a dynamic not typically possessed by even long-tenured managers. Delta's director commented as follows:

Direct interaction with family management matters to customers. It reflects deep-rooted relationships and fosters trust. [...] Customers feel encouraged [by this interaction with family management] to actively participate in collaborative AI developments. This trust matters.

Finally, case evidence revealed how family management affected the association between *competitor ties* and AI adoption (Zeta, Theta, and, to a lesser extent, Gamma, Delta). Family managers

strongly identify with their business; because of their shared history, they view it as an extension of themselves (Hjorth and Dawson 2016; Kammerlander et al. 2015). This and the strong bond between personal and business reputation (Radu-Lefebvre et al. 2024) drive them to adopt novel AI solutions and encourage knowledge sharing with competitors to showcase progress. Theta's family CEO exemplified this by initially establishing a knowledge hub as a CDO to formalize collaboration. Currently, as CEO, he promotes AI knowledge transfer, frequently highlighting these efforts via the media (over 40 appearances between 2018 and 2023), industry associations, and conferences.

Despite tense competitor relationships, the family firms in our sample often relied on decades-old ties (Deferne et al. 2023; Neubaum et al. 2012). These long-standing connections, shaped by shared histories, build trust and credibility (De Massis et al. 2018). Competitors view family managers as reliable partners for knowledge exchange, enabling collaboration grounded in mutual respect and aligned interests. A director from Zeta explained as follows:

Competitors share knowledge with us because we are trusted. [...] This would otherwise be unimaginable because people would be afraid of losing their IP. [...] The [family manager] in particular plays an important role in curating cooperation projects and using his name to stand up for the fair handling of information.

The owning families have developed tacit knowledge over several decades and have passed through generations (Ge and Campopiano 2021; Le Breton-Miller and Miller 2015). Family managers leverage this inherited expertise to facilitate AI adoption (Soluk, Kammerlander, and De Massis 2021). Their involvement in daily business routines reduces agency conflicts and translation errors, ensuring the efficient utilization of knowledge gained from competitors. A Delta's department head stated the following:

There are skills you can't learn at university. This includes finding the right approach and making uncertain decisions about AI. [...] Dealing with competitors requires a delicate instinct, which the family management provides. [...] It's crucial to have the [family manager] involved. [...] We couldn't have completed the AI product so quickly without them.

Therefore, we propose the following hypothesis:

H3. (a-c) *Family management strengthens the positive relationship between supplier, customer, and competitor tie strength and AI adoption.*

3.4 | Summary of Findings and Limitations

Our qualitative multiple case study revealed that supplier, customer, and competitor tie strength is positively associated with AI adoption; interestingly, however, passive and active family involvement play opposite paradoxical roles. While

family ownership inhibits the relationships between the three network ties and AI adoption, family management instead has a facilitating effect. Although we were able to achieve theoretical saturation through within- and cross-case pattern analysis, this qualitative methodological approach is more suitable for theory building than for theory testing (Eisenhardt and Graebner 2007). Thus, a limitation of our multiple case study is that although we considered the recommended number of case firms and ensured the highest possible validity (Eisenhardt 1989), we could not test the hypothesized relationships with statistical considerations. This test would be of enormous importance for achieving generalizability beyond the sample cases.

To test whether our hypotheses are generalizable to other companies with varying degrees of AI adoption, network ties, and family involvement, we tested them in a second step via a quantitative research approach. To address the limitations of our qualitative approach, demonstrate a comprehensive understanding of the subject under consideration, and achieve a full-cycle research approach (Elsbach and Ghai 2020), we collected and analyzed large-scale data for our quantitative investigation in a more controlled statistical investigation.

4 | Quantitative Investigation

4.1 | Survey Construction and Implementation

Owing to the lack of existing databases with comprehensive information on AI adoption, network tie strength, and family involvement in businesses, we decided to collect primary data and establish our own database. For this purpose, and in line with our qualitative exploration, we chose Germany as the empirical context and conducted the survey there, including businesses with varying degrees of AI adoption, network tie strength, and family involvement (including nonfamily firms). We consider Germany a suitable empirical setting because of the considerable importance of family-influenced firms as well as the emerging relevance of AI in this country (De Massis et al. 2018; The Federal Government 2020).

Given their peculiarities, and in line with the focus of our qualitative study, we excluded micro and small enterprises with fewer than 50 employees from our data collection. Research indicates that these enterprises have a minimal degree of formalization, which could confound our variables of interest (Leonidou et al. 2007; Mallett and Wapshott 2014; Soluk et al. 2023; Stock et al. 2022). We also excluded regional authorities, religious institutions, households generating products for their own use, and companies with legal domiciles abroad. On the basis of information from the Amadeus database (Bureau van Dijk), this left us with a population of 72,840 businesses with Germany as their place of business. On the basis of the availability of contact data, we were able to address 14,260 companies from all industries for the study.

The web survey was conducted on the basis of the EFS survey tool (QuestBack). All companies with contact data were first contacted with an e-mail that outlined the purpose of the study. These e-mails also included further information about the

academic institution of the first author and provided an opportunity to opt out. We specifically asked CEOs, other C-level managers, and senior executives involved in digital technologies, innovation, and strategy to respond to our inquiry. We incorporated validated construct measures from prior research. To preserve the original meaning of the items, we carefully translated them into German and then translated them back into English (Dillman 2007; Kriauciunas et al. 2011). Additionally, the survey questionnaire was subjected to a pilot test (Andrews et al. 2003; Collins 2003) and a pretest (Kriauciunas et al. 2011). The survey was fielded from May 23 to October 31, 2018, and after two reminders, a total of 1992 questionnaires were returned. This represents a response rate of 13.97%, which is consistent with comparable studies in the innovation and entrepreneurship domain (Garcés-Galdeano et al. 2017; Schulze et al. 2003; Zellweger et al. 2012). Owing to the sensitive nature of some of the questions, only 1444 surveys were fully completed.

The breakdown by industry shows a relatively widespread distribution of firms. The most diffuse industries are information and communication technology (11.15%), machine construction (9.35%) and other commercial services (8.93%). The agriculture, forestry and fishing, mining, and art, entertainment and recreation industries have the smallest number of firms in our sample (0.14%, 0.42%, and 0.69%, respectively). Approximately 52% of our respondents have a C-level role in the company (35% of CEOs/presidents and 17% of CxOs/members of executive management boards), 24% of our respondents are directors, and another 12% are department heads.

To meet the challenges of common method bias from the beginning, we included various procedural and statistical remedies in the survey (Podsakoff et al. 2003, 2012). First, the survey participants were assured that their data would only be processed anonymously and that the highest level of confidentiality would be guaranteed for further procedures. As a result, we were able to minimize evaluation apprehension and the effect of social desirability. Second, in developing the questionnaire, we ensured that the items were arranged in such a way that the participants would not be able to draw direct conclusions about possible relationships between the constructs. Third, we used existing measures from previous research for our study. Fourth, we conducted Harman's single-factor test loading all survey items into one single factor. This test allowed us to extract six factors with an eigenvalue greater than one (together accounting for approximately 70% of the total variance). The total variance of the first factor was approximately 15%, whereas the remaining factors accounted for 55% of the total variance. Therefore, common method bias does not seem to be a problem in terms of both ex ante procedures and ex post statistical evidence.

4.2 | Variables

4.2.1 | Dependent Variable

To capture the proxy of *artificial intelligence (AI) adoption*, we adapted an established technology adoption measure (Chen and Kamal 2016; Neirotti and Paolucci 2011; Tucker 2008). We

chose an ordinal measure to account for the different levels of AI adoption in an organization, which are particularly important for emerging technologies, because some businesses might still be in an experimentation phase (Comin and Hobijn 2010). The respondents had to rate whether they had adopted AI-based technologies in their day-to-day business on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). We used a single-item measure for AI adoption in our study for two main reasons. First, our approach is in line with Badir et al.' (2020) and Bergkvist and Rossiter's (2007) conditions for operating with single-item measures. Since our construct refers to a concrete attribute (AI adoption) and a concrete object (the respondent's company), which was also confirmed in our pre-test and pilot test, it is suitable for measurement with a single item. Second, there is also good empirical reasoning for doing so because most studies published on single-item measures show that they are often as valid and reliable as their multi-item counterparts are (Allen et al. 2022; Bergkvist 2014; Matthews et al. 2022). We therefore follow the procedure adopted by recent studies in the innovation domain and beyond (e.g., Endres et al. 2023; Kraemer et al. 2023; Stephan et al. 2023; Wunderlich et al. 2024).

4.2.2 | Independent Variables

We followed Gao et al. (2017) to measure the strength of three types of network ties (supplier, customer, and competitor ties) in our sample (see Table 4 for details and the questionnaire items). First, a proxy of *supplier tie strength* was derived with the help of principal component factor analysis (PCFA) via varimax rotation, a statistical technique used for data reduction (Jackson 1991). Specifically, the PCFA produced a linear combination of items with the highest variance such that the respondents had to answer on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree) satisfying both validity (total variance explained = 83%) and reliability (Cronbach's alpha = 0.897) criteria (Jackson 1991). The three items included (also for the customer and competitor ties) questions such as whether the business has invested heavily in building relationships with its suppliers, the extent to which the business has ensured the development of close relationships with its suppliers, and whether maintaining and developing good relationships with its suppliers is very important to the business.

Second, a proxy of *customer tie strength* was constructed by adopting the PCFA (using varimax rotation), which satisfies both validity (total variance explained = 72%) and reliability (Cronbach's alpha = 0.804) criteria (Jackson 1991). This construct covered the corresponding three items that the respondents had to answer on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). Third, a proxy of *competitor tie strength* was captured by adopting the PCFA (using varimax rotation), which satisfies both validity (total variance explained = 82%) and reliability (Cronbach's alpha = 0.887) criteria (Jackson 1991). This proxy also covered the aforementioned three items that the respondents had to answer on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree).

4.2.3 | Moderating Variables

To distinguish between different types of family involvement, we constructed family ownership and family management proxies. To capture the *family ownership* of a firm, we used the percentage of shares held by the controlling family or families (Evert et al. 2018; Miroshnychenko et al. 2023; Sciascia et al. 2015). The average value of family ownership in the sample is 43%. The *family management* variable was constructed with the help of PCFA (using varimax rotation). The items of the variable covered questions such as whether family members, nonfamily members, or a combination of both family and nonfamily members are involved in the management of a firm. The composite scale of the *family management* variable was found to be reliable (Cronbach's alpha = 0.615) and explained 98% of the total variance. The PCFA-transformed *family management* variable reports the influence of family management on the decision-making processes of a firm. It is a continuous variable with more positive (negative) values capturing higher (lower) levels of the family management of a firm. Nonfamily firms are coded as the lowest value of -1, serving as the baseline for the comparison¹.

4.2.4 | Control Variables

We included firm- and industry-level variables in our analysis that can affect AI adoption in family firms. Detailed definitions of our control variables and data sources are provided in Table A2.

TABLE 4 | Description of the main variables of interest.

Statements (translated from German to English)	Variable and its properties
Response categories range from 1 (strongly disagree) to 5 (strongly agree)	
We have adopted artificial intelligence (AI) technologies in our day-to-day business.	<i>AI adoption</i>
We have invested heavily in building relationships with our suppliers.	<i>Supplier tie strength</i> (CA = 0.897, VE = 83%)
We ensure that we have developed close relationships with our suppliers.	
Maintaining and developing good relationships with our suppliers is very important to us.	
We have invested heavily in building relationships with our customers.	<i>Customer tie strength</i> (CA = 0.804, VE = 72%)
We ensure that we have developed close relationships with our customers.	
Maintaining and developing good relationships with our customers is very important to us.	
We have invested heavily in building relationships with our competitors.	<i>Competitor tie strength</i> (CA = 0.887, VE = 82%)
We ensure that we have developed close relationships with our competitors.	
Maintaining and developing good relationships with our competitors is very important to us.	

TABLE 5 | Descriptive statistics.

	Mean	SD	Min.	Max.
AI adoption	2.427	1.085	0.000	5.000
Supplier tie strength	0.034	0.938	-4.297	1.450
Customer tie strength	0.042	0.868	-6.180	0.886
Competitor tie strength	0.023	0.973	-3.144	2.660
Family ownership	43.294	48.132	0.000	100.000
Family management	-0.525	0.853	-1.000	1.326
R&D intensity	0.046	0.207	0.000	1.000
Internationalization	3.167	1.437	1.000	5.000
Financial performance	3.616	0.900	1.000	5.000
Firm age	3.759	0.877	0.000	6.426
Firm size	6.054	1.787	1.099	13.122

4.3 | Descriptive Statistics and Correlations

Tables 5 and 6 report descriptive statistics and the correlation matrix for the whole sample. The *AI adoption* variable has a positive and statistically significant correlation with the majority of the proxies of network tie strength ($p < 0.001$), except for *supplier tie strength*. All of the variance inflation factors are less than 3, suggesting that multicollinearity does not significantly affect our regression estimates (O'Brien 2007). The level of AI adoption exhibits substantial heterogeneity across industries in our sample, as shown in Table A1.

4.4 | Main Results

To test our hypotheses, we adopt the ordinary least squares (OLS) regression estimator using Huber-White standard errors to correct for the heteroscedasticity problem following common practice in the field (Batt and Colvin 2011; De Clercq et al. 2013; Heimeriks et al. 2012). Table 7 presents the results of the OLS with heteroscedasticity-corrected (HEC) standard errors.

H1a states that the stronger a company's supplier ties, the greater the level of its AI adoption. In Model (2), the regression coefficient of the *supplier tie strength* variable is positive and highly statistically significant ($\beta = 0.066, p = 0.034$). Specifically, for a one-unit increase in the supplier tie strength of a firm, there is a 0.066 increase in the level of AI adoption, with all other variables held constant. Thus, we find strong empirical support for H1a. H1b states that the stronger a company's customer ties, the greater its level of AI adoption. Model (3) shows that the *customer tie strength* variable has a positive effect on AI adoption ($\beta = 0.154, p = 0.000$). In particular, for a one-unit increase in the customer tie strength of a firm, there is a 0.154 increase in the level of AI adoption, with all other variables held constant. Thus, we find strong empirical support for H1b. H1c states that the stronger a company's

TABLE 6 | Correlations.

	1	2	3	4	5	6	7	8	9	10	11
1 AI adoption	1										
2 Supplier tie strength	0.041	1									
3 Customer tie strength	0.174***	0.337***	1								
4 Competitor tie strength	0.128***	0.190***	0.191***	1							
5 Family ownership	-0.069**	0.151***	0.079**	-0.035	1						
6 Family management	-0.094***	0.062*	0.025	-0.033	0.549***	1					
7 R&D intensity	0.120***	-0.075**	0.014	0.071**	-0.087***	-0.048	1				
8 Internationalization	0.200***	0.145***	0.154***	-0.054*	0.102***	-0.018	0.078**	1			
9 Financial performance	0.105***	0.160***	0.217***	0.007	0.040	0.015	-0.010	0.091***	1		
10 Firm age	-0.047	0.032	0.011	-0.055*	0.169***	0.042	-0.155***	0.187***	0.023	1	
11 Firm size	0.229***	0.020	0.038	-0.054*	-0.136***	-0.227***	-0.116***	0.292***	0.069**	0.363***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE 7 | Main results.

Dependent variable: AI adoption	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
R&D intensity	0.371 (0.013)	0.403 (0.007)	0.383 (0.009)	0.346 (0.022)	0.412 (0.006)	0.383 (0.009)	0.356 (0.018)
Internationalization	0.151 (0.000)	0.147 (0.000)	0.136 (0.000)	0.146 (0.000)	0.142 (0.000)	0.136 (0.000)	0.146 (0.000)
Financial performance	0.070 (0.020)	0.057 (0.060)	0.038 (0.205)	0.066 (0.025)	0.056 (0.065)	0.037 (0.220)	0.066 (0.025)
Firm age	-0.090 (0.011)	-0.094 (0.008)	-0.100 (0.004)	-0.101 (0.003)	-0.089 (0.012)	-0.099 (0.004)	-0.102 (0.003)
Firm size	0.133 (0.000)	0.138 (0.000)	0.138 (0.000)	0.142 (0.000)	0.136 (0.000)	0.138 (0.000)	0.143 (0.000)
Family ownership		0.001 (0.080)	0.001 (0.100)	0.001 (0.070)	0.002 (0.030)	0.001 (0.091)	0.001 (0.067)
Family management		-0.017 (0.625)	-0.018 (0.610)	-0.013 (0.703)	-0.040 (0.267)	-0.015 (0.663)	-0.013 (0.718)
H1a: Supplier tie strength		0.066 (0.034)			0.192 (0.000)		
H1b: Customer tie strength			0.154 (0.000)			0.150 (0.004)	
H1b: Competitor tie strength				0.150 (0.000)			0.116 (0.021)
H2a: Supplier tie strength × Family ownership					-0.002 (0.022)		
H3a: Supplier tie strength × Family management					0.112 (0.004)		
H2b: Customer tie strength × Family ownership						-0.000 (0.678)	
H3b: Customer tie strength × Family management						-0.031 (0.430)	
H2c: Competitor tie strength × Family ownership							0.001 (0.209)
H3c: Competitor tie strength × Family management							0.005 (0.892)
Industry fixed effects	YES						
Constant	1.301 (0.000)	1.247 (0.000)	1.371 (0.000)	1.266 (0.000)	1.225 (0.000)	1.375 (0.000)	1.268 (0.000)
N	1444	1444	1444	1444	1444	1444	1444
Adjusted R ²	0.200	0.204	0.215	0.218	0.208	0.214	0.218
AIC	4040.44	4040.718	4020.362	4014.273	4035.146	4022.941	4015.563

Note: This table shows the coefficients and *p* values (in parentheses) using the OLS regressions with HEC standard errors.

competitor ties, the greater its level of AI adoption. In Model (4), we find that the regression coefficient of the *competitor tie strength* variable is positive and highly statistically significant ($\beta = 0.150, p = 0.000$): for a one-unit increase in the competitor tie strength of a firm, there is a 0.150 increase in the level of AI adoption, with all other variables held constant. Hence, H1c is empirically supported.

With respect to the negative moderating effects of family ownership, Model (5) shows that the interaction term between *supplier tie strength* and *family ownership* is negative and statistically significant ($\beta = -0.002, p = 0.022$). To further interpret this interaction and verify its significance across different levels of family ownership, we calculated the average predicted probabilities of AI adoption in firms with zero, average, and maximum levels of family ownership for the full range of possible scores of AI adoption in Table A3 and plotted them in Figure 2. Figure 2 shows that the positive effect of supplier tie strength on AI adoption diminishes as the level of family ownership increases, although it is not significant at the maximum level of family ownership. The contrasts of average predicted probabilities, reported in Table A3, are statistically significant at the 5% level. Thus, H2a is confirmed. Models (6) and (7) indicate that the positive effects of the strength of customer and competitor ties on AI adoption do not seem to differ across firms with varying degrees of family ownership. Thus, we do not find any empirical support for H2b or H2c.

Regarding the positive moderating effects of family management, Model (5) also shows that the interaction term between *supplier tie strength* and *family management* is positive and statistically significant ($\beta = 0.112, p = 0.004$). To further interpret this interaction and verify its significance across different levels of family management, we calculated the average predicted probabilities of AI adoption in firms with zero, average, and maximum levels of family management for the full range of possible scores of AI adoption in Table A4 and plotted them in Figure 3. Figure 3 shows that the positive effect of supplier tie strength on AI adoption increases as the level of family management increases. The contrasts of average predicted probabilities, reported in Table A4, are statistically significant at the 1% level. Thus, H3a is confirmed. The positive effects of the strength of customer and competitor ties on AI adoption do not seem to differ across firms with

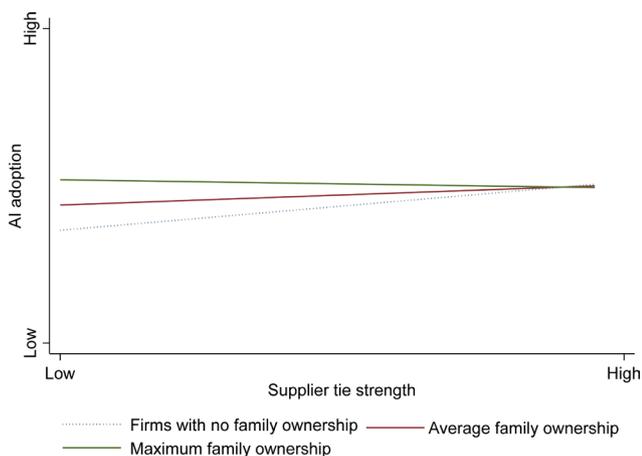


FIGURE 2 | The negative moderating effect of family ownership on the positive relationship between supplier tie strength and AI adoption.

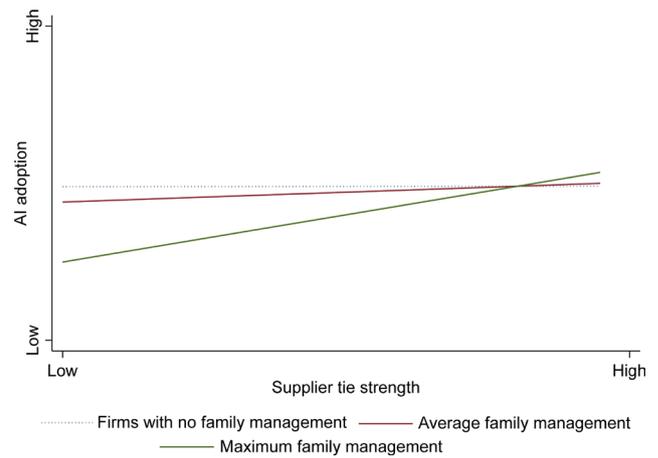


FIGURE 3 | The positive moderating effect of family management on the positive relationship between supplier tie strength and AI adoption.

varying levels of family management, as shown in Models (6) and (7). Thus, H3b and H3c are not supported.

4.5 | Robustness Check

To verify the sensitivity of our findings, we conducted a battery of robustness tests, reported in the Appendix A. First, we reestimated our explanatory model using the ordinal logit estimator to account for the ordinal nature of our dependent variable (Wooldridge 2010). Table A5 reports the estimates derived from the ordinal logit regressions, confirming our main results. We further adopted the ordinary probit regression estimator (Wooldridge 2010). Table A6 shows the estimates derived from the ordinary probit regressions, providing a similar empirical picture. In short, both checks provide empirical support for H1a–c, H2a, and H3a. We then reestimated our main explanatory model controlling for the cluster of firms owned and managed by the family (a dummy variable that equals 1 if a family has more than 50% ownership and if at least one family member is involved in management) (Amore et al. 2014). This additional check provides empirical support for our hypotheses (see Table A7). Furthermore, we assessed the plausibility of the reverse causality problem between family involvement and AI adoption in our model. Family involvement in firm ownership and management is very stable over time (Franks et al. 2006), particularly in Germany (Gugler and Weigand 2003). In addition, the influence of large shareholders (including the controlling family) on organizational outcomes in Germany has been shown to be exogenous (Gugler and Weigand 2003). Therefore, given the low probability of endogenous changes in firm family involvement in our focal context during a one-year study period, the potential reverse causality bias (if any) from these changes is likely to be rather low.

5 | Discussion

In this study, we sought to examine the role of external network ties as well as (active and passive) family involvement in AI adoption. Our qualitative and quantitative study findings make several contributions to theory and practice in the areas of

AI adoption, family firm innovation, and social capital theory, which we discuss below.

5.1 | Contributions to Theory

First, our study contributes to our understanding of the role of stakeholder engagement (specifically, external knowledge flows from customers, suppliers, and competitors) in AI adoption. Thus far, we lack valuable insights into the antecedent conditions of AI adoption and how the challenges associated with AI's core traits such as autonomy, learning, and inscrutability can be addressed by businesses (Berente et al. 2021; Lebovitz et al. 2022). Previous research has tended to investigate the internal (e.g., strategic alignment, leadership support; Gama and Magistretti 2024; Tursunbayeva and Chalutz-Ben Gal 2024) and technical (e.g., data quality, IT infrastructure; Rahman et al. 2023; Vial et al. 2023) antecedents of AI adoption. However, owing to the complexity and knowledge intensity of AI, many businesses find it challenging to manage these aspects solely internally (Glikson and Woolley 2020; Jia et al. 2024; von Krogh 2018). Our study contributes to the current understanding by emphasizing the role of external knowledge flows in facilitating AI adoption. Specifically, we reveal how businesses leverage strong ties with suppliers, customers, and competitors to overcome the barriers associated with AI adoption. We extend the literature on AI adoption by demonstrating how experimental collaborations with suppliers can address concerns related to the opacity of AI (Dora et al. 2022; Franke et al. 2024; Yan et al. 2020) and how robust supplier relationships facilitate essential data sharing (Blome et al. 2023; Hendriksen 2023). Additionally, we contribute to the discourse on customer interaction and AI by showing that strong customer ties foster trust, thereby mitigating ethical and data privacy concerns and facilitating AI adoption (Ferraro et al. 2024; Hermann 2022; Wirtz et al. 2023). Furthermore, our research highlights how strong competitor ties promote openness to sharing risks and collaborating, thus advancing the emerging debate on co-competition and AI (Boysen 2020; Corbo et al. 2023; Randolph et al. 2020).

Second, our study contributes to research on innovation and technology adoption in family firms (Ceipek et al. 2021; Prügl and Spitzley 2021; Soluk and Kammerlander 2021; Soluk, Kammerlander, and De Massis 2021; Soluk, Miroshnychenko, Kammerlander, and De Massis 2021). While the literature shows mixed findings on family firm innovation (Diaz-Moriana et al. 2020), it generally suggests that family firms have a higher conversion rate between innovation input and output (Duran et al. 2016). However, a recent replication study challenges these meta-analytical insights, indicating a decline in innovativeness in family firms over the past years (Block et al. 2023). A major limitation in current research is the tendency to treat family involvement as a homogenous concept (König et al. 2013; Soluk, Miroshnychenko, Kammerlander, De Massis 2021; Souder et al. 2017), overlooking the heterogeneity among family firms (Blanco-Mazagatos et al. 2016; Villalonga and Amit 2006). We contribute to this research stream by building on the nascent approach of distinguishing between *passive* and *active* family involvement, offering a nuanced explanation of the paradoxical effects observed in family firms (Eddleston et al. 2013; Matzler et al. 2015). Specifically, given that family

ownership (passive family involvement) acts as an obstacle, we challenge the prevailing notion that family ownership facilitates knowledge flows and technology adoption (Bammens and Hünermund 2020; Cucculelli and Peruzzi 2020; Hsu et al. 2015; Soluk, Miroshnychenko, Kammerlander, and De Massis 2021). Conversely, we provide evidence that family management (active family involvement) positively moderates the relationship between network ties and AI adoption, countering previous research suggesting that family management impedes complex technological innovation (Ceipek et al. 2021; Martínez-Alonso et al. 2023; Migliori et al. 2020; Prügl and Spitzley 2021). Thus, we highlight a paradoxical tension between passive and active family involvement that has been largely overlooked (Smith and Lewis 2011). Drawing on existing tensions in the family firm innovation literature and in contrast to other ownership structures and types of executives (e.g., long-tenured managers) (Chrisman et al. 2015; Guenther et al. 2023), we argue that understanding the mechanisms underlying family ownership and management is essential for family firm success (Erdogan et al. 2020; Ingram et al. 2016). Interestingly, the hypothesized moderating effects for customer and competitor ties were not significant for either family management or family ownership. One explanation may be that the deep trust in long-standing customer relationships or the strong IP-related risks in competitor collaborations overshadow the additional influence of family involvement, rendering family-driven interventions less visible. This unanticipated deviation highlights that the paradoxical dynamics of passive versus active family involvement may hinge on tie-specific characteristics (e.g., the intensity of trust or potential for opportunism), thereby calling for deeper inquiry into contextual factors that constrain or amplify the impact of family involvement. While our German context is commonly used as a typical setting for family business research (De Massis et al. 2018), we acknowledge the need for further research to generalize these findings across different geographic areas due to cultural, regulatory, or technological differences (Wright et al. 2014).

Third, we contribute to social capital theory (Adler and Kwon 2002; Baer et al. 2015; Gedajlovic et al. 2013). While we confirm the importance of external social capital with respect to digital innovation (Brodie et al. 2011; Daniel et al. 2018; Eiteneyer et al. 2019; Viglia et al. 2018), we also go beyond the existing knowledge and emphasize the role of social relations in the processing and utilization of knowledge for the highly complex and knowledge-intensive endeavor of AI adoption. Whereas existing research often treats external social capital as a uniform entity (Barroso-Castro et al. 2016; Cuevas-Rodríguez et al. 2013; Kobarg et al. 2019), we show how it can affect AI adoption through both horizontal and vertical network ties (Inkpen and Tsang 2005). These in-depth insights also extend previous knowledge on how the different dimensions (structural, relational, and cognitive) of external social capital can help overcome the challenges associated with AI adoption in businesses (Gedajlovic et al. 2013; Maurer and Ebers 2006). In addition, we contribute to research on family social capital, an important and emerging area of social capital research (Arregle et al. 2007). In line with previous research, we highlight the dominance of family social capital in firms with different degrees of family involvement (Carr et al. 2011; Pearson et al. 2008). However, in contrast to extant studies that largely consider family social capital only as a beneficial attribute (Chang et al. 2009; Salvato and Melin 2008)

and even investigate how nonfamily firms might imitate it (Herrero 2018), we reveal that the consequences of family social capital, which are dependent on whether it is rooted in passive or active family involvement, might be more nuanced than previously thought. Without active involvement in the company, owning families run the risk of not being able to take advantage of the entrepreneurial opportunities offered by AI, as their family social capital cannot fully unfold within the organization.

5.2 | Contributions to Managerial Practice and Policy-Making

Our research contributes to managerial practice, especially with respect to the adoption of novel digital technologies for innovation. With AI offering significant potential for efficiency gains and growth, business owners, managers, and advisors are increasingly tasked with integrating generative AI across various areas (Katsikeas et al. 2019; Kemp 2024; von Krogh 2018). Our findings can inform practitioners in leveraging network ties to address AI adoption complexities and internal knowledge gaps (Soluk and Kammerlander 2023). Concrete opportunities to drive AI with existing suppliers, customers, and competitors include coinvestments with suppliers in AI infrastructure or supplier (AI) innovation challenges; customer cocreation labs (e.g., with lead users); customer advisory panels on AI; and “coopetition” research and development projects or cofunded industry consortia for AI standards. In addition, practitioners might want to leverage further formal (e.g., industry associations, chambers of commerce) or informal (e.g., social relationships and personal networks between decision-makers) network ties to facilitate knowledge flows and exchange. All these initiatives require (e.g., contractual) protection of intellectual property to ensure that there is no undesired outflow of expertise. Initiatives such as the Maschinenraum in Berlin, where dozens of family firms have joined forces to explore AI and related topics with shared resources and a common cultural understanding, offer a rather novel avenue for trustful collaboration. For family managers, our study motivates active engagement in managing knowledge flows and learning mechanisms (e.g., by leading AI awareness and literacy initiatives or participating in cross-functional teams to ensure diverse perspectives) to facilitate AI adoption. For passive family owners, potentials emerge in the professionalization of their external management (e.g., through the alignment of incentive structures toward innovation and AI); the professionalization of governance structures (e.g., to increase transparency and accountability and prevent agency conflicts); and the diversification of board memberships (e.g., broadening team composition with innovation and AI experts, ensuring that decisions are made on objective grounds) (Piyasinchai et al. 2024).

Our findings have important implications for policy-makers in government and quasigovernment agencies. Policy-makers who view AI adoption as vital for long-term economic development (Lundvall and Rikap 2022; Teece 2018) must realize that adoption rates lag behind (Chui et al. 2023), even more so in family firms (Kammerlander et al. 2020). In Germany, the National Strategy for AI was launched in 2018, recognizing AI's potential for economic growth and productivity (The Federal Government 2020). To realize this potential, we advise publicly funded measures to strengthen network ties between

organizations. One example is the UnternehmerTUM initiative in Munich, where programs aimed at engaging in AI projects have been created at the interface between universities (i.e., Technical University of Munich), corporations, Mittelstand firms, and the startup ecosystem. Extending similar initiatives, with public research infrastructure at the center, to other regions of Germany would broaden access for numerous companies, enabling scalability. Another suggestion is to make the application-oriented research of institutions such as the Fraunhofer Society even more accessible to companies (e.g., with AI readiness checks, customized technology scouting, and licensing to access intellectual property), thereby alleviating their concerns. Learning about the characteristics and needs of family firms can help decision-makers in the public sector accompany family managers and owners in effectively professionalizing their companies. Further policy measures include grants for AI programs and favorable depreciation options or other tax incentives for AI investments in companies, as such measures could particularly benefit resource-constrained family firms.

5.3 | Limitations and Future Research Directions

Although the complementary design of our mixed-methods approach already considers some of the shortcomings that are inherent to qualitative and quantitative investigations, our study still presents some limitations that leave promising directions for future research. Owing to our cross-sectional research design, we cannot claim causal relationships in our study (Bowen and Wiersema 1999). With the use of panel data, future longitudinal studies might consider this aspect and investigate the time-varying effects of AI adoption and social capital (Maula and Stam 2020). In a similar vein, alternative quantitative measures that are not based on self-perception but rather on objective criteria (e.g., measuring AI adoption on the basis of novel products introduced or patents granted) can help provide additional perspectives on our research questions. Our use of a single-item measure for AI adoption may limit reliability and construct validity, suggesting that future research could benefit from multi-item measures to better capture the nuances of the construct. Moreover, we would like to encourage future research to consider not only family involvement but also other forms of heterogeneity among family firms and to determine the corresponding differences in their outcomes. Future work could also explore how tie-specific characteristics—such as deep trust or IP-related risks—amplify or attenuate passive and active family involvement, clarifying why similar hypotheses diverge across supplier, customer, and competitor ties.

Although we investigate one of the world's largest economies, our German context is characterized by idiosyncrasies, particularly the prevalence of Mittelstand firms, which constitute part of our samples (De Massis et al. 2018). The study of AI adoption, external network ties, and family involvement in other geographical regions might differ from our context in terms, for instance, of their technological, cultural, and institutional regimes, thus limiting the generalizability of our findings beyond the German-speaking parts of Europe (Kopalle et al. 2022; Soluk, Kammerlander, and Darwin 2021; Weber et al. 2019; Wright et al. 2014). We encourage future research that validates the framework hypothesized here in other business cultures and

contexts. In addition to studying other foreign contexts, we also invite future research to highlight regional differences within Germany. This might include investigating whether regional proximity to research facilities (e.g., Fraunhofer Institutes or universities) or historical economic influences (e.g., decades of socialist policies in East Germany) influence the relationships among network strength, family involvement, and AI adoption. We also encourage future scholarly work on how different types of companies approach AI adoption. In addition to private family firms, public companies, state-owned enterprises, and nonprofit organizations might offer promising paths for future studies.

Finally, beyond applying the social capital lens, we encourage future research to investigate AI adoption and family influence from alternative theoretical perspectives. Building on affordance research, defined as “the possibilities for goal-oriented action recognized by a specified user group” (Markus and Silver 2008, 622), future studies might investigate how evolving AI technologies intersect with the evolving abilities and intentions of decision-makers (e.g., the owners of a company) and how these dynamics affect the uncertainty of (adoption) decisions (Gibson et al. 2022; Townsend et al. 2025). Moving further into the microissues of idiosyncratic adoption decisions in family-influenced firms, future researchers could draw on behavioral theory to explain, for instance, the creation and preservation of family wealth over generations (De Groot et al. 2022) or on prospect theory to examine how the risks associated with AI inform adoption decisions (Tversky and Kahneman 1974) in family firms.

Acknowledgments

Earlier versions of this manuscript have greatly benefited from thoughtful feedback provided at various conferences and academic seminars. We are indebted to the insightful comments received during the Academy of Management (AOM) Annual Meeting 2022 in Seattle, Washington; the European Academy of Management (EURAM) Conference 2022 in Winterthur, Switzerland; the International Family Enterprise Research Academy (IFERA) Conference 2022 in Santander, Spain; and the European Institute for Advanced Studies in Management (EIASM) Conference 2021 (held remotely). We also gratefully acknowledge the constructive suggestions offered by participants in research seminars at the House of Innovation at the Stockholm School of Economics, the Center for Design Research at Stanford University, and the Faculty of Business, Economics and Social Sciences at the University of Bern. For their valuable individual feedback, we would like to thank Mattias Nordqvist, Nadine Kammerlander, and Larry Leifer. We are honored that earlier versions of this manuscript were recognized with the *Best Paper Award* at the IFERA Annual Conference 2022 and the *Best Paper Award* at the EURAM Conference 2022. Finally, we thank the anonymous reviewers and the editorial team for their developmental guidance during the review process. Open Access funding enabled and organized by Projekt DEAL.

Ethics Statement

The authors have read and agreed to the Committee on Publication Ethics (COPE) international standards for authors.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Endnotes

¹We thank the anonymous reviewers for this insightful suggestion.

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Appendix A

The document is composed of four parts. The first part (Table A1) depicts the average and range of AI adoption by industry in our sample. The second part (Table A2) provides a detailed definition of the control variables used in our estimations. The third part (Tables A3 and A4) presents average predicted probabilities and their contrasts for firms with different degrees of family ownership and family management that are only briefly mentioned in the article. The fourth part (Tables A5–A7) shows the detailed results of the robustness tests.

TABLE A1 | Average and range of AI adoption by industry.

Industry type (% of the sample)	Mean	SD	Min.	Max.
Agriculture, forestry and fishing (0.139%)	2.500	0.707	2	3
Art, entertainment and recreation (0.693%)	2.400	0.843	1	4
Automotive (5.194%)	2.258	1.005	0	5
Building/construction (4.363%)	2.143	0.969	0	5
Chemicals and synthetic materials (4.432%)	2.245	0.928	0	4
Education and teaching (1.247%)	1.833	0.786	0	3
Electrical (4.640%)	2.455	1.086	1	5
Energy and power supply (4.086%)	2.599	1.005	1	5
Finance and insurance services (4.086%)	3.008	1.061	1	5
Food (3.047%)	1.852	0.736	0	4
Health and social services (5.125%)	2.041	0.943	0	5
Hotel and restaurant (1.731%)	1.960	1.060	0	4
Housing and real estate (1.316%)	2.368	0.895	1	5
ICT (11.150%)	3.110	1.205	0	5
Machine construction (9.349%)	2.519	1.046	0	5
Metal working and processing (3.463%)	2.263	0.902	0	4
Mining (0.416%)	2.167	1.169	0	3
Other commercial (8.934%)	2.639	1.229	0	5
Other manufacturing (7.133%)	1.917	0.707	0	4
Other public services; nonprofit organizations (1.108%)	1.844	1.151	0	5
Pharmaceutical (1.177%)	1.961	0.807	1	4
Professional, scientific and technic services (4.155%)	2.567	0.899	1	5
Public administration, defense and security (0.346%)	2.000	1.414	0	4

(Continues)

TABLE A1 (Continued)

Industry type (% of the sample)	Mean	SD	Min.	Max.
Trading/retail; maintenance and repair of cars (3.324%)	2.146	0.945	0	5
Transportation and warehousing (5.540%)	2.504	1.103	0	5
Water supply (0.970%)	2.500	1.019	1	5
Wood working and processing (0.970%)	2.286	0.611	2	4
N/A (1.870%)	2.630	1.445	0	5
Total	2.427	1.085	0	5

TABLE A2 | Definition of control variables.

Variable	Description
R&D intensity	Dummy variable that equals 1 if a firm's R&D intensity is equal to or above 15%, 0 otherwise ^a
Internationalization	Respondents were asked to indicate how intensively their company conducts business abroad on a five-point scale (1 = none; 5 = very intense)
Financial performance	Respondents were asked to indicate how successful in terms of ROA their company was over the last 3 years on a five-point scale (1 = very unsuccessful; 5 = very successful)
Firm size	Natural logarithm of the firm's number of employees ^b
Firm age	Natural logarithm of the number of years for which the firm has existed
Industry dummies	28 dummy variables that capture industry fixed effects, based on International Standard Industrial Classification of All Economic Activities (ISIC) classification

^aAdoption of the alternative R&D intensity proxy (estimated as a dummy variable that equals 1 if a firm's R&D intensity is equal to or above the industry mean and 0 otherwise) does not alter our main findings. We thank one anonymous reviewer for this insightful suggestion.

^bAdoption of the alternative firm size proxy (estimated as the sales growth over the past 3 years) does not alter our main findings. We thank one anonymous reviewer for this insightful suggestion.

TABLE A3 | Average predicted probabilities of AI adoption in firms with different degrees of family ownership.

Firm type	Average predicted probability (p)	Contrast of average predicted probabilities		
		Contrast of (2)–(1) (p)	Contrast of (3)–(2) (p)	Contrast of (3)–(1) (p)
Firms with no family ownership (1)	0.133 (0.001)	–0.078 (0.022)		
Average family ownership (2)	0.055 (0.074)		–0.078 (0.022)	
Maximum family ownership (3)	–0.022 (0.655)			–0.155 (0.022)

Note: This table presents the average predicted probabilities of AI adoption and their contrasts in firms with different degrees of family ownership, keeping all other variables constant.

TABLE A4 | Average predicted probabilities of AI adoption in firms with different degrees of family management.

Firm type	Average predicted probability (p)	Contrast of average predicted probabilities		
		Contrast of (2)–(1) (p)	Contrast of (3)–(2) (p)	Contrast of (3)–(1) (p)
Firms with no family management (1)	0.001 (0.970)	0.053 (0.004)		
Average family management (2)	0.054 (0.081)		0.205 (0.004)	
Maximum family management (3)	0.259 (0.000)			0.258 (0.004)

Note: This table presents the average predicted probabilities of AI adoption and their contrasts in firms with different degrees of family management, keeping all other variables constant.

TABLE A5 | Ordinal logit regressions.

Dependent variable: AI adoption	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Family ownership	0.002 (0.119)	0.002 (0.124)	0.002 (0.134)	0.003 (0.050)	0.002 (0.105)	0.002 (0.148)
Family management	-0.031 (0.657)	-0.039 (0.583)	-0.017 (0.809)	-0.070 (0.323)	-0.035 (0.618)	-0.013 (0.859)
Supplier tie strength	0.153 (0.013)			0.384 (0.000)		
Customer tie strength		0.328 (0.000)			0.347 (0.003)	
Competitor tie strength			0.332 (0.000)			0.259 (0.013)
Supplier tie strength × Family ownership				-0.004 (0.026)		
Supplier tie strength × Family management				0.193 (0.014)		
Customer tie strength × Family ownership					-0.001 (0.473)	
Customer tie strength × Family management					-0.045 (0.615)	
Competitor tie strength × Family ownership						0.002 (0.240)
Competitor tie strength × Family management						0.001 (0.993)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1444	1444	1444	1444	1444	1444
McFadden <i>R</i> ²	0.077	0.082	0.084	0.079	0.082	0.085
AIC	4465.333	4443.668	4433.669	4461.552	4445.745	4435.28
Log pseudolikelihood	-2177.666	-2166.8334	-2161.835	-2173.776	-2165.873	-2160.640

Note: This table shows the coefficients and *p* values (in parentheses) using ordinal logit regressions with HEC standard errors.

TABLE A6 | Ordered probit regressions.

Dependent variable: AI adoption	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Family ownership	0.001 (0.086)	0.001 (0.106)	0.001 (0.069)	0.002 (0.028)	0.001 (0.084)	0.001 (0.065)
Family management	-0.017 (0.657)	-0.018 (0.644)	-0.013 (0.733)	-0.045 (0.261)	-0.019 (0.640)	-0.013 (0.747)
Supplier tie strength	0.081 (0.018)			0.234 (0.000)		
Customer tie strength		0.176 (0.000)			0.196 (0.002)	
Competitor tie strength			0.181 (0.000)			0.139 (0.016)
Supplier tie strength × Family ownership				-0.002 (0.011)		
Supplier tie strength × Family management				0.134 (0.002)		
Customer tie strength × Family ownership					-0.001 (0.411)	
Customer tie strength × Family management					-0.009 (0.853)	
Competitor tie strength × Family ownership						0.001 (0.163)
Competitor tie strength × Family management						0.007 (0.864)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1444	1444	1444	1444	1444	1444
McFadden <i>R</i> ²	0.074	0.078	0.080	0.076	0.078	0.081
AIC	4481.07	4461.22	4451.295	4474.076	4463.974	4451.908
Log pseudolikelihood	-2185.535	-2175.61	-2170.648	-2180.038	-2174.987	-2168.954

Note: This table shows the coefficients and *p* values (in parentheses) using the ordered probit regressions with HEC standard errors.

TABLE A7 | Controlling for the cluster of family-owned and -managed firms.

Dependent variable: AI adoption	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Family ownership	0.001 (0.665)	0.001 (0.573)	0.001 (0.659)	0.001 (0.567)	0.001 (0.590)	0.001 (0.655)
Family management	-0.018 (0.619)	-0.017 (0.629)	-0.014 (0.693)	-0.040 (0.272)	-0.015 (0.677)	-0.013 (0.707)
Family ownership and management	0.023 (0.924)	-0.019 (0.935)	0.022 (0.928)	0.021 (0.930)	-0.011 (0.963)	0.022 (0.925)
Supplier ties	0.066 (0.034)			0.192 (0.000)		
Customer ties		0.155 (0.000)			0.150 (0.004)	
Competition ties			0.150 (0.000)			0.116 (0.022)
Supplier ties × Family ownership				-0.002 (0.022)		
Supplier ties × Family management				0.112 (0.004)		
Customer ties × Family ownership					-0.000 (0.677)	
Customer ties × Family management					-0.031 (0.434)	
Competition ties × Family ownership						0.001 (0.209)
Competition ties × Family management						0.005 (0.894)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.246 (0.000)	1.372 (0.000)	1.265 (0.000)	1.224 (0.000)	1.375 (0.000)	1.267 (0.000)
<i>N</i>	1444	1444	1444	1444	1444	1444
Adjusted <i>R</i> ²	0.203	0.214	0.217	0.207	0.214	0.218
AIC	4042.708	4022.355	4016.264	4037.138	4024.938	4017.553

Note: This table shows the coefficients and *p* values (in parentheses) using the OLS regressions with HEC standard errors.