Value Creation, Capture, and Delivery in Emerging AI Ecosystems: A Taxonomy of the German SME Context

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Dissertation written under the supervision of professor Dr. René Bohnsack and Cláudia Antunes Marante.

Dissertation submitted in partial fulfilment of requirements for the MSc in International Management with Specialization in Strategy and Consulting, at the Universidade Católica Portuguesa, 27.05.2026.

Abstract

AI adoption in German SMEs depends on the coordination of multiple ecosystem actors, yet existing research typically examines AI-driven business model innovation from a focal-firm perspective and treats SME adoption barriers as firm-internal limitations. This thesis investigates how value creation, capture, and delivery are configured across ecosystem actors and where bottlenecks constrain value realization. Drawing on 19 semi-structured expert interviews with AI-adopting SMEs, solution providers, consultants, and intermediaries, the study combines Gioia-style coding, actor-specific taxonomies, and value-flow mapping. The findings reveal that AI business model configurations differ systematically by actor type and follow a logic of risk-bounded incrementalism. Value flows extend beyond monetary transactions to include data, employee time, domain knowledge, and risk, yet these contributions are systematically undervalued. Bottlenecks are compound rather than isolated, and the most consequential is the absence of an actor that is simultaneously competent, affordable, and neutral. The thesis contributes a multi-actor, taxonomy-based analysis that reframes AI adoption failure in the German SME ecosystem as a structural alignment problem: the challenge is not making AI available to SMEs but aligning ecosystem roles, value flows, and responsibilities so that AI-enabled value can materialize.

Title: Value Creation, Capture, and Delivery in Emerging AI Ecosystems: A Taxonomy of the German SME Context

Keywords: AI ecosystem, business model innovation, German SMEs, value creation, value capture, value delivery, taxonomy development, qualitative research.

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Resumo

A adopção de IA nas PME alemãs depende da coordenação de múltiplos atores do ecossistema, contudo, a investigação tende a examinar a inovação do modelo de negócio impulsionada por IA numa perspectiva centrada na empresa focal, tratando as barreiras à adopção das PME como limitações internas. Esta tese investiga como a criação, captura e entrega de valor são configuradas entre os atores do ecossistema e onde os estrangulamentos condicionam a realização de valor. Com base em 19 entrevistas semiestruturadas a especialistas de PME adotantes de IA, fornecedores de soluções, consultores e intermediários, o estudo combina codificação ao estilo Gioia, taxonomias específicas por ator e mapeamento de fluxos de valor. Os resultados revelam que as configurações dos modelos de negócio de IA diferem sistematicamente consoante o tipo de ator e seguem uma lógica de incrementalismo delimitado pelo risco. Os fluxos de valor estendem-se para além das transações monetárias, incluindo dados, tempo dos colaboradores, conhecimento do domínio e risco, sendo estas contribuições sistematicamente subvalorizadas. Os estrangulamentos são compostos e não isolados, sendo o mais significativo a ausência de um ator que seja simultaneamente competente, acessível e neutro. A tese contribui com uma análise multi-ator baseada em taxonomias que reequaciona o insucesso na adoção de IA no ecossistema das PME alemãs como um problema de alinhamento estrutural: o desafio não está em tornar a IA disponível para as PME, mas em alinhar papéis, fluxos de valor e responsabilidades no ecossistema, de modo que o valor habilitado pela IA se materialize.

Titulo: Criação, Captura e Entrega de Valor em Ecossistemas Emergentes de IA: Uma Taxonomia do Contexto das PME Alemãs.

Palavras-chave: IA Ecossistemas, inovação de modelos de negócio, PMEs alemãs, criação de valor, captura de valor, entrega de valor, desenvolvimento de taxonomia, investigação qualitativa

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Acknowledgments

I would like to thank my Professor René Bohnsack and Cláudia Antunes Marante for their guidance and feedback throughout this research. A deep gratitude goes especially to Cláudia Antunes Marante for her detailed comments, continuous motivation, and ongoing support throughout the development of this thesis. Her insights and responsiveness at every stage have been fundamental in shaping the quality and direction of this work. I am sincerely grateful to the 19 experts who agreed to participate in the interviews for this study. Their generosity in sharing professional experiences and perspectives provided the empirical foundation that made this research possible. Finally, I would like to thank my family and friends for their patience, support, and encouragement throughout this journey.

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List of Abbreviations

Abbreviation	Full Term
AI	Artificial Intelligence
API	Application Programming Interface
BM	Business Model
BMC	Business Model Configurations
BMI	Business Model Innovation
C2E	Conceptual-to-Empirical
E2C	Empirical-to-Conceptual
EU	European Union
GDPR	General Data Protection Regulation
IfM	Institut für Mittelstandsforschung (Bonn) - (German Institute for SME Research)
IHK	Industrie- und Handelskammer - (German Chamber of Industry and Commerce)
ML	Machine Learning
R&D	Research & Development
ROI	Return on Investment
SLA	Service Level Agreements
SME	Small and Medium-Sized Enterprise
SP	Solution Providers

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1. Introduction

Firms' AI adoption is increasingly recognized as a source of competitive advantage, operational efficiency, and business model innovation (BMI). Yet AI-enabled value creation is not a purely firm-internal process (Jorzik et al., 2024; Adner, 2017; Burström et al., 2021). Applying Adner's (2017) structural approach, starting from the focal value proposition and identifying the actors whose alignment is necessary for it to materialize, this thesis identifies four actor types in the German SME AI ecosystem: AI solution providers, consultants and integrators, intermediaries, and AI-adopting SMEs. When this coordination succeeds, AI can reshape how firms create, capture, and deliver value. When it fails, the technology's potential remains unrealized, regardless of how capable the individual actors may be.

Understanding how AI-enabled value creation unfolds requires examining the broader set of actors whose alignment is necessary for the value proposition to materialize. This perspective is particularly consequential for small and medium-sized enterprises. German SMEs, often referred to as the Mittelstand, form the backbone of Europe's largest economy but exhibit structural characteristics that distinguish their AI adoption from that of larger enterprises: owner-management, limited internal AI and IT expertise, constrained budgets and time, and reliance on external partners for capabilities they lack (Müller et al., 2021; Drees et al., 2025). While AI adoption among German firms is growing, it remains unevenly distributed, and the gap between recognized opportunity and realized implementation points toward an ecosystem-level problem. AI adoption in the German SME context unfolds within an ecosystem of interdependent actors whose BMCs, incentive structures, and capabilities jointly determine whether an AI-enabled value proposition materializes. Drawing on Adner's (2017) ecosystem-as-structure perspective and Jacobides et al.'s (2018) role-based coordination logic, this study treats AI adoption as an alignment problem rather than a firm-internal technology decision.

Despite the analytical relevance of this ecosystem perspective, the existing literature leaves three significant gaps at the intersection of ecosystem theory, AI-driven BMI, and SME AI adoption. First, ecosystem frameworks for analyzing interdependence, alignment, and role-based coordination (Adner, 2017; Jacobides et al., 2018) have rarely been applied to emerging AI ecosystems and, to the best of this thesis's knowledge, have not yet been applied to the German SME context, where no dominant orchestrator exists. Second, the AI-driven BMI literature has grown rapidly but remains largely firm-centric (Jorzik et al., 2024; Burström et al., 2021; Sjödin et al., 2023). Even studies that acknowledge ecosystem interactions, such as Burström et al. (2021), tend to analyze the business model adoption of a single focal firm rather than comparing how BMC differ across multiple actors involved in enabling an AI-related value proposition. Third, the SME AI-adoption literature provides increasingly detailed accounts of adoption rates, barriers, and enablers in Germany (Ströbele et al., 2025; Bundesnetzagentur, 2025; Drees et al., 2025), yet consistently examines the adopting SME in isolation from the SPs, consultants, and intermediaries on whose capabilities and configurations the SMEs implementation depends.

Taken all together, the literature lacks a structured, comparative understanding of BMC across the full set of actors that constitute the German SME AI ecosystem. This thesis addresses these gaps by developing an empirically grounded understanding of how different ecosystem actors create, capture, and deliver value through AI-enabled offerings in the German SME context, and of how value flows and bottlenecks shape the value realization across the ecosystem. The thesis poses two research questions:

> **RQ1**: What business model configurations are emerging across actors in the German SME AI ecosystem, and how do value creation, capture, and delivery mechanisms differ by actor type?
>
> **RQ2**: How do value flows, monetary and non-monetary, distribute across ecosystem roles, and where do bottlenecks constrain value realization?

To address these questions, the thesis adopts a qualitative, exploratory design based on 19 semi-structured expert interviews across four actor types, analyzed through Gioia-style coding, actor-specific taxonomies following Nickerson et al. (2013), and ecosystem value-flow mapping. It contributes by moving AI-BMI research beyond the focal-firm perspective toward multi-actor comparison; applying Adner's (2017) and Jacobides et al.'s (2018) ecosystem frameworks to an emerging, non-platform-centric AI ecosystem; reframing SME adoption barriers as ecosystem-level bottlenecks linked to misaligned BMCs; and providing, to the authors' knowledge, the first actor-specific taxonomy of AI BMCs in the German SME ecosystem.

2. Literature Review

2.1 Digital Ecosystems: Foundation and Evolution

2.1.1 From Value Chains to Ecosystems

Over recent decades, the unit of strategic analysis in inter-firm relationships has moved from the individual firm to the ecosystem. Porter's (1980, 1985) value chain framework treated value creation primarily as a firm-internal process shaped by industry structure, whereas Moore (1993) introduced the business ecosystem concept to show that value propositions depend on coordination among independent actors that co-evolve, compete, and cooperate across industry boundaries. Iansit and Levien (2004) extended this view by identifying distinct ecosystem roles, such as keystones, dominators, and niche players, and showing that ecosystem health depends on interactions among these roles rather than on a single firm's capabilities. Yet, much of this literature remained descriptive and focused on large technology firms in platform-like settings (Gawer & Cusumano, 2014; Jacobides et al., 2018). With digital technologies such as AI increasing cross-actor interdependence, a more analytically precise ecosystem framework is needed. AI-enabled value propositions often require data, algorithms, implementation expertise, and domain knowledge distributed across multiple actors. For a study examining why such value propositions reach some SMEs and not others, membership-based definitions are insufficient: the key issue is not which actors are nominally present, but whether their activities and incentives align around the focal value proposition. This is precisely the question addressed by a structural ecosystem approach.

2.1.2 Ecosystem-as-Structure: Adner Framework

Adner (2017) defines ecosystems as "*the alignment structure of the multilateral set of partners that need to interact for a focal value proposition to materialize*" (p. 42). First, it is anchored in a value proposition rather than in a focal firm, so the proposed benefit to the end user determines which actors and activities fall within its boundaries. Second, the construct is multilateral: a contract between an SME and an SP may be undermined by the absence of a skilled consultant or by an intermediary's failure to facilitate data access. Third, the defining strategic challenge is alignment; misalignment of activities, incentives, and expectations can make the proposition fail even when all required actors are present (Adner, 2017). Adner contrasts this ecosystem-as-a-structure view with ecosystem-as-affiliation, which defines ecosystems by membership ties. The structural view reverses this by starting with the value proposition and working backwards to the actors whose alignment is needed (Adner, 2017, p. 44). This thesis adopts the structural approach because it directs attention to activity configuration and interdependencies rather than cataloguing present actors (Kapoor, 2018).

To operationalize this perspective, Adner (2017, p. 43) identifies four elements: activities, actors, positions, and links, understood as transfers of material, information, influence, or funds, including indirect connections. Links are important for ecosystem-level analysis, as an SME may depend on a relationship between its consultant and a cloud provider to which it has no direct connection. Jacobides et al. (2018) complement Adner's framework by explaining why ecosystems emerge. Modularity allows interdependent organizations to coordinate through standardized interfaces rather than hierarchical control, creating the structural precondition for ecosystems. Complementarity is distinguished between generic and non-generic forms. Generic complementarities exist between substitutable inputs and do not bind actors together. Non-generic complementarities define ecosystems through specific interdependencies that create mutual dependence and cannot be redeployed without cost (Jacobides et al., 2018). In AI, they arise when an SP's model is trained on an SME's proprietary data such that neither component retains its full value outside the relationship. Ecosystems manage these interdependencies by assigning actors to roles governed by shared rules (Jacobides et al., 2018). The four actor types examined in this thesis, SPs, consultants, intermediaries, and SMEs, are distinguished not by firm size or sector but by their functional roles in enabling AI-related value propositions.

2.2 Value Creation, Capture, and Delivery in Ecosystems

2.2.1 Defining Value Creation, Capture, and Delivery

The ecosystem perspective separates value creation, capture, and delivery into analytically distinct processes: different actors may be involved in each, and the success of one does not guarantee the success of the others (Burström et al., 2021). Value creation refers to the generation of worth through complementary resources across organizational boundaries, such as the integration of an SP's machine learning model trained on an SME's operational data. Value capture refers to the mechanisms through which actors appropriate portions of collectively created value, including price structures, licensing, data ownership, and contractual terms (Jacobides et al., 2018). Critically, structure can shape the distribution of surplus alongside productive contributions, as actors' roles, links, and control over key resources influence how collectively created value is captured (Adner, 2017; Jacobides et al., 2018; Lepak et al., 2007). Value delivery refers to the process through which created value reaches the intended recipient (Priem, 2007). Burström et al. (2021) treat delivery as a separate BM dimension involving new service routines, customer interfaces, and role distributions distinct from creating the AI solution itself. Failures in delivery, such as inadequate consultant handover or insufficient end-user training, can prevent collectively created value from reaching the production process (Burström et al., 2021; Sjödin et al., 2023). To make these flows empirically traceable, this thesis distinguishes four types drawing on Adner (2017) and Jacobides et al. (2018): monetary flows (subscription fees, implementation fees, public funding), data flows (access rights, sharing arrangements), capability and service flows (technical training, advisory support, maintenance), and risk flows (allocation of performance or compliance risk through contracts or SLAs) (Ströbele et al., 2025).

2.2.2 Value Distribution Across Ecosystem Roles

When value creation, capture, and delivery are distributed across actors, the question of how this distribution is structured becomes central. Ecosystem theory suggests that the answer lies in roles, the functional positions actors occupy within the alignment structure (Adner, 2017; Jacobides et al., 2018). Adner (2017) argues that whether value materializes and how surplus is divided depends on each actor's position in the flow and the quality of the links connecting them. Value distribution is thus a structural property of the ecosystem, built into the way roles are defined and aligned. The ecosystem literature identifies several recurring role categories. Orchestrators coordinate the alignment structure, set technical standards, and shape how participation is rewarded (Iansiti & Levien, 2004; Burström et al., 2021). Complementors provide specialized offerings that enhance the value proposition without controlling its architecture. Enablers supply implementation capacity, integration, or advisory services that translate technological possibilities into practical reality. Intermediaries reduce search and coordination costs by brokering connections between actors that might not find each other otherwise (Jacobides et al., 2018; Adner, 2017). These roles are defined by function, not firm identity: an SP might simultaneously act as a complementor, an orchestrator, or an enabler. How each of the four actor types maps to these role categories is examined empirically in the results.

2.3 AI-Driven Business Model Innovation

2.3.1 Business Models and Business Model Innovation: Foundations

Business models describe how firms operate and describe the logic through which a firm creates, captures, and delivers value (Teece, 2010, 2018; Burström et al., 2021). The most widely adopted framework is Osterwalder and Pigneur’s (2010) Business Model Canvas (BMC), which clusters the BM into nine components into a descriptive vocabulary useful for practitioners but offering limited analytical guidance on the drivers of value.Amit & Zott address exactly this gap by introducing their four design themes, novelty, efficiency, lock-in, and complementarity, which help identify the sources through which BM generate actual value (Amit & Zott, 2001; Zott & Amit, 2010).

BMI refers to the design of new, or nontrivial modification of existing, business models (Foss & Saebi, 2017; Jorzik et al., 2024). BMI concerns the logic of value creation, capture, and delivery rather than what is produced and how.BMI, though, can emerge through different pathways. Jorzik et al. (2024) distinguish between active and evolutionary BMI. Active BMI thereby describes where management deliberately redesigns the business model and aligns the firm anew in response to strategic opportunities. Evolutionary BMI describes the process by which a company changes incrementally through experimentation and adoption without a deliberate overarching design. This distinction is consequential to understanding AI-related BM changes as some firms proactively build AI-centered offerings, while others focus on integrating AI functionalities into existing models without intending to fundamentally redesign their BM and value creation process (Jorzik et al., 2024). The term BMC, as it is used in this thesis, refers to a specific combination of BM dimensions, including, e.g., value proposition type, revenue logic, and delivery mode. These dimensions characterize how particular ecosystem actors create, capture, and deliver value. It is these configurations, across the four actors, that the thesis taxonomy aims to classify.

2.3.2 How AI Reshapes Business Models

The relationship between AI and BMI attracts growing scholarly attention, but the field remains fragmented across mechanisms, industries, and levels of analysis (Brynjolfsson & Mitchell, 2017; Jorzik et al., 2024). Jorzik et al. (2024) provide a central contribution towards structuring this landscape, as they distinguish between AI as peripheral to value creation, supporting existing processes without altering the BM core logic, and AI as central to value creation, where BM fundamentally depends on the AI capabilities. This distinction between peripheral and core AI integration is critical for the present thesis, as an SME that is using chatbots for internal customer services operates under a different BM logic than a SP whose entire offering is built around a proprietary ML platform.

Burström et al. (2021) provide one of the most explicit treatments of how AI drives BMI at an ecosystem level. As they studied large industrial incumbents, they defined four AI functionalities: forecasting, monitoring and control, optimization, and autonomy, and then traced how these AI functionalities affect value creation, capture, and delivery. Their findings show that AI-based value processes are not sequential but strongly interdependent and concurrent, disrupting traditional value management approaches.

Sjödin et al. (2023) link three AI capabilities (perceptive, predictive, prescriptive) with dynamic capabilities for commercialization, value discovery, realization, and optimization, stressing that translation into a workable BM requires ecosystem value alignment routines (Madanaguli et al., 2024; Nambisan et al., 2019).

2.3.3 Business Models Across Ecosystem Actors

The so far reviewed literature shares one limitation in common: they tend to analyze BM from the perspective of a single focal firm. Even in the papers that acknowledge ecosystem interactions, the analytical focus remains on one firm, usually a large incumbent or SP, and their BM adaptation in response to AI (Burström et al., 2021; Sjödin et al., 2023). This firm-centric default obscures a feature of AI ecosystems that the previous chapters have identified as central: the BMC of different actors within an ecosystem is interdependent. The ability of an SME to create, capture, and deliver value through AI depends not only on the SMEs own choices but also on the revenue logic that was adopted by its SP, the service scope that was defined by its consultants, and the matchmaking quality offered by the intermediaries it engages.

Burström et al. (2021) gestured towards this multi-actor reality as they argued that AI-enabled BMI requires the change of the whole involved ecosystem, including reconfiguration of roles, structures, and partnerships, and not the adjustment of a single firm's adjustment in their value architecture. Jacobides et al. (2018) provide the theoretical underpinning that ecosystems coordinate through role-based structures governed by shared rules. E.g., a complementor's revenue models differ structurally from an orchestrator, or the delivery mode differs between an enabler and an intermediary. These differences are not identical and show that actors and their alignment structure within the ecosystem are positioned around the focal value proposition (Lepak et al., 2007).

The central analytical point is this: in an AI ecosystem, the value that is created, captured, or delivered by a single actor is bounded by the configurations of the actors around it. This is a theoretical consequence of the non-generic complementarities that define ecosystem structures (Jacobides et al., 2018). When interdependent components of a value proposition are distributed across actors with misaligned business model logics, the result is unrealized value, a proposition that could materialize under a different alignment but does not under the current one. Classifying these configurations systematically is therefore not a descriptive exercise but a prerequisite for identifying where and why alignment failures occur.

2.4 SMEs and AI Adoption: The German Context

For the context of this thesis, the term German SME must be defined precisely, as there are many different definitions by various defining organizations. Table 1 summarizes the three most relevant definitions.

Table 1: Different applicable SME definitions

Criterion	EU Commission	World Bank Group	IfM Bonn
Employees	< 250	≤ 300	< 500
Revenue / Sales	≤ €50 m	≤ $15 m	< €50 m
Additional criteria	Balance sheet ≤ €43 m	Total assets < $15 m; Loan size < $2 m	-
Geographical focus	European Union	Global	Germany

This thesis adopts the IfM Bonn definition as its working framework. The defined higher employee threshold of 500, compared to the 250 defined by the EU, reflects the reality that many German firms in manufacturing or industrial services sectors exceed the EU threshold. That is the case as they still exhibit the structural characteristics, e.g., owner-management, limited internal AI expertise, long term strategical expectation, or constrained budgets, that makes functionally comparable to smaller firms in their approach to AI adoption (Müller et al., 2021; Drees et al., 2025). Since the thesis examines ecosystem-level dynamics around AI-adoption, the defining criterion is not the employee size of the company but whether the firm faces the resource constraints and external dependencies that characterize the firm's SME experience of AI implementation (Bundesnetzagentur, 2025).

2.4.1 SMEs vs. Large Enterprises: Why SMEs Warrant Separate Study

The German Mittelstand is a term that represents a distinctive economic context in which AI adoption unfolds differently than in larger corporate settings (Drees et al., 2025). These are the structural characteristics described in the previous chapter, which affect not only how firms relate to external partners but also how they absorb and act on new technological knowledge.

Müller et al. (2021) provide direct evidence for this divergence. Examining 221 German manufacturing firms, they found that business model design in the context of Industry 4.0 differs significantly between SMEs and large enterprises. The results show that for SMEs, the potential absorptive capacity, or the ability to acquire external knowledge, is a stronger predictor of BMI than realized absorptive capacity, which captures the ability to transform and exploit their knowledge (Cohen & Levinthal, 1990; Zahra & George, 2002). Transferred to the AI context of this thesis, this means that many SMEs can recognize AI-related opportunities in their environment and ecosystem, but struggle to convert the opportunities into operational implementations. On the other side, large firms tend to have more developed processes for both stages of the absorption process and can draw on dedicated R&D units, larger IT departments, and broader partner networks to close the gap between knowledge acquisition and application, resources that most SMEs have not or only partially (Müller et al., 2021).

2.4.2 AI Adoption in German SMEs: State, Barriers, and Ecosystem Dependencies

Empirical data on AI usage in German firms confirm that adoption is growing but remains unevenly distributed. Drees et al. (2025) report that approximately 33% of German SMEs already use AI solutions productively, and another 24% are running pilot projects. The Bundesnetzagentur (2025) provides more granular data from a survey with 808 firms and reports that around 30% of German companies already use AI, though most of them remain in a testing phase.

Only 6% of the firms in the dataset report that AI plays a central role within their business model, with a notably higher percentage in small and micro companies (10%) compared to large firms (4%) and SMEs (3%) (Bundesnetzagentur, 2025). The barriers to AI implementation in German SMEs have been documented with increasing specificity. Ströbele et al. (2025) identify ten obstacles along what they term the SME implementation journey, of which three are particularly relevant to the ecosystem perspective adopted in this thesis: skill gaps, data availability, and quality problems, and difficulty in selecting the right tool. The Bundesnetzagentur (2025) adds empirical weight to these barriers as 66% of surveyed firms cite time constraints, 59% report a lack of skilled personnel or know-how, 54% identify legal uncertainty as a limiting factor, 23% face budget constraints, and 15% report insufficient technical infrastructure.

The observation that SMEs rarely navigate the AI adoption process independently connects the above-described adoption patterns and barriers to the thesis ecosystem lens. Yet the existing literature tends to examine these actors in isolation, missing the interdependencies that shape value creation, capture, and delivery (Adner, 2017; Ströbele et al., 2025).

2.5 Taxonomy Development as a Research Strategy

The German SME AI ecosystem involves actor types with distinct but interdependent BMCs not yet classified in existing literature, requiring a classification approach that can accommodate empirical variety and produce transparent results. A taxonomy, as defined by Nickerson et al. (2013, p. 340), *"... is a set of n dimensions, each consisting of mutually exclusive and collectively exhaustive characteristics, such that each object under consideration has only one characteristic per dimension*". This definition clearly distinguishes taxonomies from adjacent classification concepts. A typology derives its categories conceptually, constructing ideal types through deductive reasoning from theory (Bailey, 1994; Doty & Glick, 1994; Nickerson et al., 2013). A framework organizes the relationship between constructs or actors but does not necessarily classify objects into discrete categories. A taxonomy is placed in between as it is developed iteratively through both conceptual reasoning and empirical observation.

Nickerson et al. (2013) propose a method to develop a taxonomy that proceeds in the following steps. The progress starts with defining the meta-characteristics, which are the overarching property that guides the selection of all dimensions and characteristics in the taxonomy. The meta-characteristics serve as a guiding principle, as every element of the taxonomy must be a logical consequence of the meta-characteristics. In this thesis, the meta-characteristics are defined as mechanisms by which ecosystem actors create, capture, and deliver value through AI-enabled offerings in the German SME context.

From the meta-characteristics, the method proceeds through iterative cycles that alternate between two approaches. The method alternates between empirical-to-conceptual (E2C) iterations, deriving dimensions from observed patterns, and conceptual-to-empirical (C2E) iterations, testing theoretically informed dimensions against the data (Nickerson et al., 2013). This suits the present thesis well, as the reviewed literature provides strong conceptual starting points that the interview data will refine. Iteration continues until predefined objective and subjective ending conditions are met, requiring the taxonomy to be concise, robust, comprehensive, and explanatory (Nikerson et al., 2013).

A taxonomy is well-suited here because the field remains emergent and configurations are diverse (Jorzik et al., 2024), and because separate actor-specific taxonomies connected via a value-flow map capture both within-role variation and between-role interdependencies (Adner, 2017; Jacobides et al., 2018). Based on the revised literature, the thesis's author created the following conceptual value-flow framework (see Figure 1):

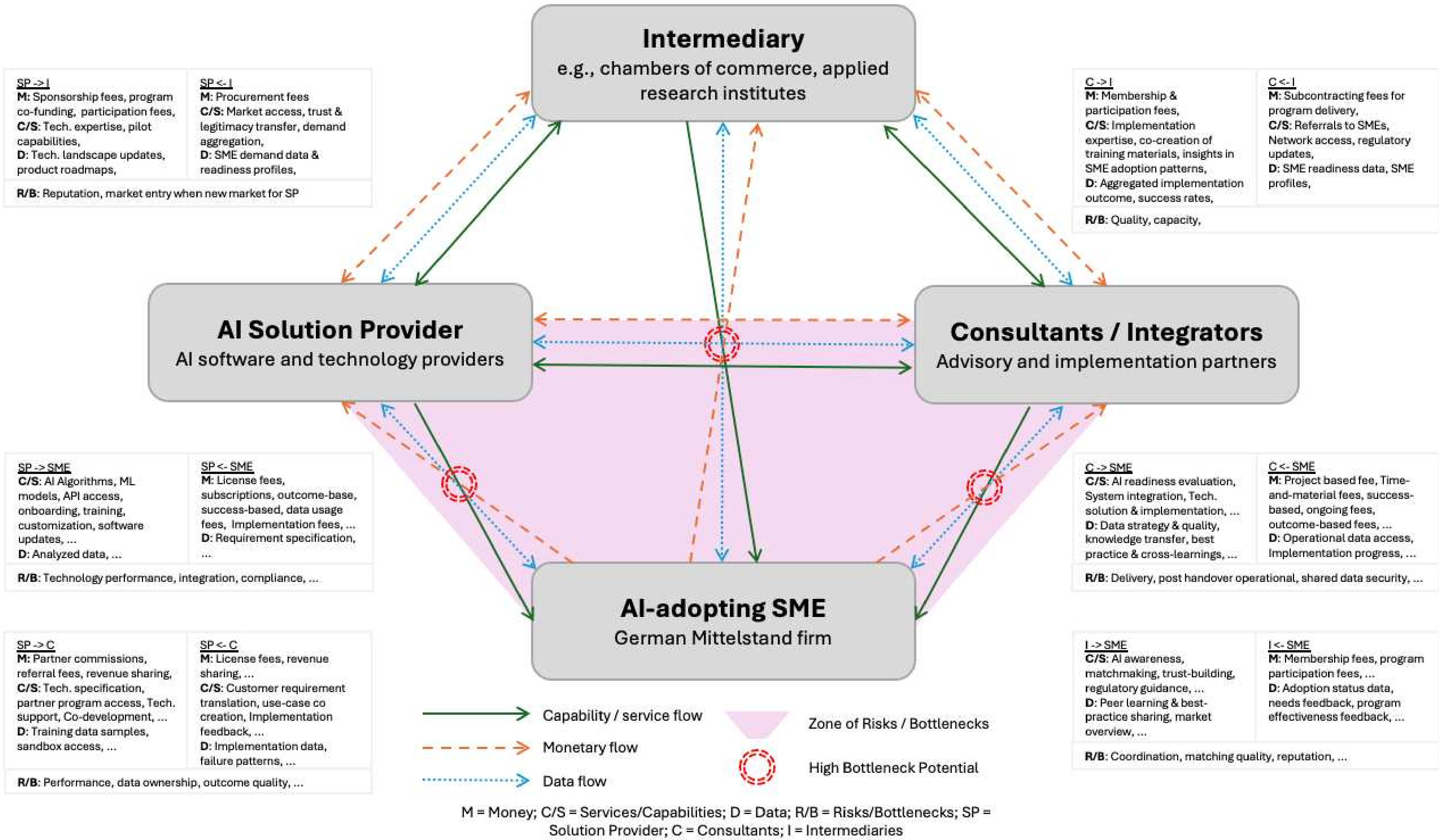

Figure 1: Literature-based AI-adopting SME ecosystem framework in the German context

This literature-based framework served as an anchor point during data collection, with interviewees invited to validate and revise the depicted value flows against their experience.

2.6 Research Gap and Conceptual Framing

2.6.1 Synthesis of Research Gaps

Three research gaps emerge from the intersection of the four bodies of literature reviewed. Ecosystem frameworks for analyzing interdependence, alignment, and role-based coordination (Adner, 2017; Jacobides et al., 2018) have rarely been applied to emerging AI ecosystems, and, to the best of this thesis's knowledge, have not yet been applied to the German SME context, where no dominant orchestrator exists. The AI-driven BMI literature remains largely firm-centric (Jorzik et al., 2024; Burström et al., 2021; Sjödin et al., 2023), with a multi-actor perspective, examining how BMCs differ across the full set of actors enabling an AI-related value proposition, largely absent. The SME AI adoption literature provides detailed accounts of barriers and enablers in Germany (Ströbele et al., 2025; Bundesnetzagentur, 2025; Drees et al., 2025) but consistently examines the adopting SME in isolation from the actors on whom its implementation depends. Taken together, the literature lacks a structured, comparative understanding of BMCs across the full ecosystem and of how value creation, capture, and delivery are distributed among actors.

This thesis addresses these gaps by treating the German SME AI ecosystem as an alignment structure (Adner, 2017) held together by non-generic complementarities and governed through role-based coordination (Jacobides et al., 2018). Each actor operates under distinct BMCs shaped by ecosystem position, AI-related capabilities, and revenue and delivery logic (Burström et al., 2021; Jorzik et al., 2024). Actor-specific taxonomies are developed following Nickerson et al. (2013) and connected through a value-flow map tracing monetary, data, service, and risk flows to identify where ecosystem misalignments constrain value realization.

3. Methodology

3.1 Research Design

This thesis employs a qualitative, exploratory research design. AI-driven BMI in the German SME ecosystem remains nascent, fragmented, and insufficiently standardized as a research domain (Jorzik et al., 2024). The goal of the thesis is not statistical generalization but analytical generalization through systematic classification and ecosystem mapping.

The study adopts an interpretivist epistemological stance. The accounts of expert interviewees are treated as meaning-laden interpretations of their ecosystem experience, shaped by their organizational position, role logic, and professional context (Gioia et al., 2012; Magnani & Gioia, 2023).

A multi-actor design is not merely methodologically convenient but theoretically mandated. In this thesis, AI-enabled value propositions in German SMEs cannot be understood from the focal firm alone, as SMEs depend on SPs for technology and technology access, consultants for the problem definition and implementation support, and on intermediaries for orientation and funding navigation. Studying a single actor in isolation would produce a structurally incomplete account of how value flows materialize, or fail to, across the ecosystem. Jacobides et al. (2018) reinforce this logic by demonstrating that ecosystem value creation rests on role-based complementarities as different actor types follow distinct business model logics, and it is precisely their interaction and interdependence that shape whether the AI-enabled value proposition reaches the SMEs.

3.2 Sample and Data Collection

The empirical basis consists of 19 semi-structured expert interviews across the four actor types, conducted between April 24 and May 8, 2026, via video call. Interviews lasted 30–90 minutes and were audio-recorded with informed verbal consent following an explanation of the study's purpose, voluntary nature, and anonymized data use. Transcripts were produced using Microsoft Teams' built-in transcription function, manually corrected, and fully anonymized; no identifying details appear in this thesis or its appendices. As all interviews were conducted in German, transcripts were machine-translated into English using Microsoft’s built-in translation option and reviewed by the researcher, a native German speaker, against the German originals. Both versions remained accessible during coding to ensure first-order codes preserved informant meaning. The interview guides followed a common thematic structure oriented around actors, activities, value flows, and bottlenecks in line with Adner's (2017) framework, while remaining open enough for respondents to elaborate on dynamics specific to their role and organizational context.

The sample was constructed through purposive and snowball sampling. Purposive sampling guided the initial selection across the four actor types, including SMEs at different AI maturity stages, SPs with distinct BM archetypes, consultants from boutique to large firms, and intermediaries spanning different mandates and funding models. Snowball sampling extended the sample where direct outreach proved insufficient, as the German SME AI ecosystem constitutes a fragmented expert population without a shared registry (Parker et al., 2019). This approach carries selection bias risk and potential overrepresentation of well-connected actors (Parker et al., 2019), mitigated by balanced sampling across four structurally different actor types and deliberate inclusion of critical perspectives such as a non-adopting SME. The sample does not claim statistical representativeness; the aim is analytical variation sufficient to support cross-actor comparison. Table 2 summarizes the sample.

Table 2: Overview of Actor-Specific Interview Partners

Actor Type	No.	Interviewee Roles / Org. Types	AI-Related Scope	Main Relevance
AI-adopting SMEs	5	Managing directors and decision-makers across sectors and AI maturity stages; one non-adopter included	Adoption decision, internal use cases, value capture, partner dependencies, bottlenecks	Demand-side BM configurations and SME-level value flows
AI solution providers	4	Founders, sales leads, senior consultants; vertical E2E, horizontal platform, and consulting implementation hybrid archetypes	Offerings, revenue models, deliver models, data dependencies, SME engagement	Supply-side BM configurations and SP-side bottleneck perceptions
Consultants / AI implementation partners	6	Boutique, mid-sized, and large consultancies spanning pure advisory to hybrid advisory-implementation models	Usa-case identification, provider selection, implementation, change management, advisory BMs	Intermediating role between SMEs and SPs; neutrality and vendor-alignment tension
Intermediaries	4	Regional economic development agency, applied research institutions, cooperative AI associations, all based in southern Germany	Awareness-building, matchmaking, funding navigation, regulatory guidance, ecosystem coordination	Public and semi-public support structures and ecosystem coordination dynamics
Total	19			

3.3 Data Analysis

The data analysis proceeds in three sequential but iterative stages. The stages are analytically distinct from one another yet closely connected, as actor-specific coding and thematic analysis provide the empirical foundation for the taxonomy development, while both together inform the ecosystem value-flow map. RQ1 is addressed primarily through stages 1 and 2, and RQ2 in stage 3.

3.3.1 Stage 1: Interview coding and actor-specific thematic analysis

The interview transcripts were analyzed following the Gioia methodology (Gioia et al., 2012), moving from first-order codes close to informant language through second-order themes to aggregate dimensions (Magnani & Gioia, 2023). The analysis used a hybrid procedure combining manual and AI-assisted coding. Five transcripts were coded manually at the outset, selected to represent the four actor types and to cover variation in AI integration and ecosystem positioning. Manual coding was conducted in Microsoft Excel, with each code linked to a verbatim excerpt. This phase established interpretive familiarity with the data and a baseline coding logic grounded in informant language before AI-assisted support was introduced.

All 19 transcripts were subsequently processed using two large language models as structured support tools. Because AI-assisted qualitative coding remains an emerging practice with limited established guidance, its use was deliberately bounded. Before each session, identifying information was removed from the transcript. Both models received the same structured prompt instructing them to identify possible first-order codes in informant-centric language, link every proposed code to a verbatim excerpt, avoid interpretation beyond what the evidence directly supported, and flag ambiguous or potentially underweighted passages. The models were not asked to produce second-order themes, aggregate dimensions, or any form of theoretical interpretation.

All AI-generated suggestions were compared against the original transcripts. Codes were revised, merged, or discarded where they were too abstract, insufficiently grounded, duplicative, or inconsistent with the baseline coding logic. Only suggestions supported by traceable transcript evidence were retained. The initial coding round produced 2,084 first-order codes across 19 transcripts. Following review and consolidation, these were reduced to 112 first-order concepts, grouped into 100 second-order themes, and condensed into five aggregate dimensions. Throughout this process, coding decisions were discussed with the supervisor, and analytical memos documented the reasoning behind coding choices and the development of themes. Final codes, themes, aggregate dimensions, and their connecting logic were determined by the researcher. Figure 2 presents a condensed version of the data structure for readability; the full coding output, including all 112 first-order codes, second-order themes, aggregate dimensions, and source references, is provided in the Appendix.

The coding was conducted within each actor group first, producing four actor-specific analysis reports before cross-actor synthesis was attempted. This sequence preserves the distinctive BM logic of each actor type rather than averaging them. The four actor-specific analyses were then compared systematically to identify shared patterns confirmed across all 19 interviews, as well as divergence reflecting structurally different ecosystem positions.

3.3.2 Stage 2: Taxonomy development

Actor-specific taxonomies were developed following Nickerson et al. (2013). A taxonomy consists of mutually exclusive and collectively exhaustive categories organized around a meta-characteristic: the unifying concept specifying what the taxonomy classifies. The meta-characteristic of this thesis is the mechanisms by which ecosystem actors create, capture, and deliver value through AI-enabled offerings in the German SME context. Taxonomy development is warranted because no established classification system captures the variations in AI-enabled BMCs across multiple actor types, a gap identified by Jorzik et al. (2024). The four taxonomies are developed separately by actor type; actor type therefore functions as an organizing principle rather than a within-taxonomy dimension.

The process alternated between empirical-to-conceptual and conceptual-to-empirical cycles (Nickerson et al., 2013): interview patterns informed new dimensions, while theory-derived dimensions were tested against the empirical material. Candidate dimensions included value proposition, AI role in the offering, value creation and capture mechanisms, revenue logic, delivery model, ecosystem and data dependency, risk profile, implementation depth, and vendor neutrality. In the first two iterations, dimensions were drawn primarily from the theoretical framework, producing six to eight candidates per actor type. Iterations three and four refined these through empirical evidence, splitting, merging, or dropping dimensions that did not differentiate meaningfully among cases. The fifth iteration produced no reclassifications, confirming that the taxonomy had reached a stable structure. Iteration terminated when the ending conditions of Nickerson et al. (2013) were satisfied: no new dimensions emerged, all cases could be classified, and the taxonomy demonstrated conciseness, robustness, and explanatory value.

3.3.3 Stage 3: Ecosystem value-flow mapping

After actor-specific configurations were classified, value flows were mapped across six bilateral relationships (SP↔SME, C↔SME, I↔SME, SP↔C, I↔SP, I↔C) using Adner's (2017) framework. Four primary flow types were traced: monetary, data, capability/service, and risk. Trust, legitimacy, and hidden employee-time costs were traced as supplementary dimensions. Bottlenecks were identified where flows were blocked, misaligned, or underdeveloped, and interpreted as ecosystem alignment failures, points where individually viable BMCs fail to deliver their combined value proposition.

Qualitative credibility rests primarily on cross-actor triangulation: when the same pattern is independently described across all four actor types, the analytical claim is substantially stronger than if derived from a single perspective. A transparent chain of evidence from first-order codes through aggregate dimensions to taxonomy characteristics, supported by representative quotes and the data structure figure (Figure 1), strengthens confirmability (Gioia et al., 2012).

4. Results

The empirical findings are structured around five aggregate dimensions emerging from the Gioia coding process: AI BMCs, Ecosystem Value Flows, Adoption Barriers and Bottlenecks, Ecosystem Roles and Coordination, and Structural Dependencies and Power Asymmetries (Figure 2). Each dimension is developed as an analytical argument, with interview quotes used as evidence rather than as substitutes for analysis.

4.1 AI business model configurations

The central finding of this dimension is that AI BMCs in the German SME ecosystem are organized around risk-bounded incrementalism rather than transformative innovation. Across all four actor types, the dominant logic is containment: contain the customization cost, the investment threshold, the organizational disruption. This is a structural response to the readiness conditions in SME markets, shaping how AI is packaged, priced, and delivered. SP4 illustrates this logic: *"In the beginning, we did a lot about project business, i.e., one-time implementation and then maintenance contracts. This was not economically sustainable"* (SP4). The shift toward subscription-based recurring revenue is a risk containment mechanism designed to make AI commercially viable within SME cost tolerance.

SPs have converged on a hybrid architecture combining a standardized software core with a bounded customization and implementation layer. The subscription provides recurring revenues, while the implementation fee covers customer-specific integration. What this model conceals is a transfer of effort to the SME. *"There is still an implementation effort"*(SP3, SP4) understates what the data reveal: the implementation effort is often the majority of what the SME experiences. The subscription price is visible and appears modest; the total cost of adoption, including employee time, data preparation, process redesign, and change management, is neither priced nor disclosed. This cost visibility asymmetry is a structural feature of the hybrid model.

In the most advanced adoption case (SME5), AI has become entirely invisible as a customer-facing proposition. The SME sells reliability and guaranteed delivery windows; AI is the internal mechanism that makes these commitments feasible. *"AI is not the value proposition; the customer buys reliability"* (SME5) captures a configuration in which AI functions as margin-protecting infrastructure rather than a differentiated product.

Figure 2: Gioia coding results

This contrasts sharply with how SPs frame their offerings, which consistently foreground AI as the source of customer value. The gap between these two framings is not merely rhetorical, as it reflects a fundamental difference in how AI is integrated into business model logics. For the advanced SME adopter, AI has been absorbed into the operational core; for the SP, AI remains the product. This divergence is visible not only in how SMEs describe their own adoption but in how consultants observe the SP-SME interaction. C1 describes the pattern directly: "*They come into the first demo and show the glossy version. The medium-sized company is enthusiastic. And then in the implementation, you realize it doesn't work with your data.*" (C1).

A third configuration pattern, visible across both consultants and SME interviews, is the progressive erosion of the boundary between technology provision and advisory work. SMEs report experiencing their SP and consultants as a single integrated delivery team, as captured in the observation that "*solution provider and consultant are one team for us*" (SME4).

4.2 Ecosystem Value Flows

The German SME AI ecosystem operates on a broader range of value flows than conventional commercial framing suggests. The central finding of this dimension is that non-monetary flows, data, domain knowledge, employee time, trust, and reputational legitimacy are often preconditions for monetary flows to occur yet are systematically undervalued by the actors who supply them.

SMEs do not simply pay a subscription fee; they contribute operational data for model training, invest employee time in testing and feedback, expose proprietary process knowledge, and provide reference legitimacy that SPs use to acquire subsequent customers. The hidden cost dimension is confirmed from both sides. From the SME perspective: *"data preparation cost us the most effort and actually took longer than the actual AI implementation. The service provider needed three months just to prepare the data"* (SME1). From the provider side: *"Our customers invest weeks of employee time in data cleansing, workshops, testing. This is nowhere in the framework as flow, but it is a huge factor"* (SP4). The practical consequence is that ROI calculations are built on an incomplete cost base: employee time invested in data preparation, workshop participation, and iterative testing is a real cost that appears in no invoice and figures in no business case.

Data flows create a structural ambiguity at the heart of the SP–SME relationship. SPs depend on customer data to train and improve their models, yet SMEs provide this data typically without formal valuation or contractual clarity about what happens to the model once trained on proprietary process knowledge. *"The trained model belongs to us, but it is a grey area"* (SP4) points to an ownership ambiguity that neither party has resolved. From the SME's perspective, providing data access is necessary to move from a standard product to a customized solution, but the resulting asset remains outside the SME's full control.

Trust and referral flows function as the primary acquisition infrastructure for both SPs and consultants. The majority of SP–SME and consultant–SME matches in the sample originated through personal networks and informal referrals rather than through institutional channels. *"Word of mouth is our most important sales channel"* (C2, SP2, SP4) reveals that the ecosystem's actual connectivity runs through informal relationships rather than the institutional intermediary layer designed to facilitate it. *"Reference customers are a huge added value for us, reviews, case studies, that's a very important reference value for new customers"* (SP1).

4.3 Adoption Barriers and Bottlenecks

The dominant finding of this dimension is that AI adoption in the German SME context is constrained not by the technology itself but by the organizational and data preconditions required for it to function. Across all 19 interviews, data readiness emerged as the most consistently cited barrier. The structural conditions for AI value creation are frequently absent before implementation begins, orders arriving by phone and spreadsheet, processes existing only as tacit knowledge in long-tenured employees, ERP systems too outdated to export clean records, customer data scattered across disconnected tools. SP4 describes the typical conditions: *"The data is there, but chaotic. Inconsistent article titles, duplicates, missing categorizations, and sometimes even data that is only stored in Excel lists. [...] I would say 80 percent of our project delays come from the fact that the customers data is not what it needs to be"* (SP4). For non-adopters, data readiness is not merely a delay but a decisive adoption blocker: *"The provider had told us that we first had to get our data master in order ... and that was also a reason why we decided against it"* (SME2). The cost of resolving this precondition falls almost entirely on the SME, whose subscription fee does not include the data preparation work that makes the subscription valuable.

The ROI measurement problem is structurally distinct from data readiness, though the two reinforce each other. SMEs cannot calculate the return on AI investment because the causal structure of AI-enabled improvement resists attribution, compounded by the hidden costs described in section 4.2. Efficiency gains in routing, error reduction, and administrative processing are real, but none can be cleanly separated from simultaneous changes in staffing, market conditions, or concurrent process improvements. *"We don't know how to calculate the ROI"* (SME2) is not an admission of weakness but a structurally correct observation. This uncertainty extends to adopters: *"The return on investment of the individual tools has not been* *properly calculated"* (SME1). The consequence is that SMEs who have adopted AI remain strategically uncertain about whether to expand, unable to demonstrate to themselves or their funders that the current investment has delivered.

The shadow AI phenomenon inverts the conventional adoption framing. In multiple SME cases, employees had adopted consumer-grade AI tools privately before any organizational decision had been made, with company email addresses registered on external AI platforms without the managing director's knowledge. *"We didn't want to block AI, it would be like banning the internet"* (SME3). The organization moved to adopt a formally governed enterprise solution to contain the data security exposure created by informal employee behavior. Formal AI adoption was driven not by the prospect of operational improvement but by the governance risk of uncontrolled shadow use. This pathway has direct implications for RQ1: BMCs at the SME level are sometimes reactive rather than strategic, and security positioning can be the primary value proposition for SPs serving this entry condition.

4.4 Ecosystem roles and coordination

The coordination architecture of the German SME AI ecosystem is structurally misaligned with the needs it claims to serve. Intermediaries define themselves as orientation providers rather than implementation actors: *"we do not implement; we orient"* (I3) captures a self-conception that is institutionally coherent; these organizations are publicly funded and prohibited from commercial recommendation, but practically insufficient for SMEs that need concrete guidance on provider selection and implementation readiness. The commitment to neutrality simultaneously builds credibility and renders the intermediary's most valuable potential service, a trusted provider recommendation, structurally unavailable. The SME perspective confirms this: *"The IHK events are too general and are not really aimed at our industry"* (SME2).

The impact measurement gap compounds this problem. Intermediaries measure outputs through activity-based indicators: events organized, participants reached, and awareness levels recorded. *"We measure awareness, but not adoption"* (I3) acknowledges that institutional funding metrics do not capture the outcomes the ecosystem needs. This reflects the incentive structure created by public funders who define success as reach rather than transformation: when reporting obligations reward events and participants, intermediaries rationally optimize for events and participants. The consequence is that the coordination layer is calibrated to the earliest stage of the adoption journey with no visibility into what happens after handover. *"Implementation outcomes disappear after handover"* (I4), the intermediary cannot track whether a referral led to a successful implementation, an abandoned pilot, or no follow-up at all.

The consultant's role as boundary-spanning translator between business logic and technical feasibility is functionally critical. The SME lacks the technical vocabulary to specify a solvable AI problem; the provider lacks the organizational context to determine whether its technology addresses the right problem. The consultant occupies this gap: *"We give providers SME requirements and market feedback"* (C3), functioning as a bidirectional bridge neither side can replace. However, the boundary between neutral translation and commercially motivated direction is narrow. Large consultancies with substantial vendor alliances translate business problems in directions shaped by their own capability portfolios rather than by the optimal solution for the SME. *"If I have 50 Azure consultants and 3 AWS consultants, the recommendation tends one way"* (C6) is not an allegation of bad faith but a structural observation: the investments that make a large consultancy technically credible also make its recommendations systematically non-neutral. SME clients cannot assess this bias because they lack the technical knowledge to evaluate whether the recommendation reflects the best available solution or the best available within the consultant's alliance portfolio (Eisenhardt, 1989). The ecosystem's fragmented coordination compounds this: with *"too many parallel structures"* (I3), SMEs face not only biased advice but a support landscape so fragmented that navigating it becomes an adoption barrier.

4.5 Structural dependencies and power asymmetries

A structurally consequential finding is located not in any single bilateral relationship but in the upstream architecture underlying all of them. The German SME AI ecosystem rests on an infrastructure layer of hyperscalers, LLM providers, and ERP/CRM vendors that none of the four focal actor types controls and most SMEs cannot see. SPs build their offerings on models and cloud infrastructure whose pricing and availability they do not govern (Rochet & Tirole, 2003). "*Hyperscalers and LLM providers determine what we can offer and at what price*" (SP4) describes precisely where structural power sits in the ecosystem. The consequence is a cost and risk pass-through mechanism running from infrastructure providers through SPs to SMEs, with each layer absorbing some risk and passing the remainder downstream. The SME subscribing to a logistics optimization platform does not know that its subscription pricing is partly determined by the commercial relationship between its SP and an upstream model provider whose terms neither party negotiated. "*If OpenAI doubles API prices, it changes our business model*" (SP3). The upstream pricing power is not hypothetical but a live commercial risk that SPs manage by passing cost increases downstream. From the SME side, this layer is invisible: "*Our provider buys a cloud and an AI model; we don't know who is behind it*" (SME4).

The ERP/CRM vendor layer introduces a second upstream dependency. AI solutions requiring integration with existing enterprise systems must connect through interfaces that ERP vendors control and can modify. *"If ERP providers change their interface, we have a problem"* (SP1). A technically functioning AI solution can be disrupted by an interface change the SP did not initiate, and the SME did not anticipate. *"SAP, Microsoft Dynamics, SAGE interfaces are critical"* (SP4) names a dependency that determines whether an AI solution can be operationally deployed in a given SME's system environment. SPs who cannot guarantee interface stability cannot guarantee delivery. The SME, which often selected its ERP system years before considering AI adoption, inherits a compatibility constraint it did not anticipate and cannot easily resolve.

Risk allocation follows a consistent asymmetric logic. SPs carry technical and platform risk but disclaim accountability for business outcomes. Consultants bear reputational risk but limit contractual liability to process deliverables. Intermediaries carry no commercial risk by institutional design. The actor bearing full commercial risk of adoption failure, the SME, is also the actor with the least financial resilience, the least technical capability to evaluate solutions, and the highest key-person dependency. *"Risk lies with the customer"* (SP1, SP2, SP4, C2, C4, C5) was stated across SP and consultant interviews as a structural fact: it reflects the difficulty of guaranteeing performance when outcomes depend on data quality, organizational readiness, and change management variables the provider does not control. The structural result is an ecosystem where the party most exposed to failure has the fewest tools to prevent it. *"Afraid of dependencies"*(SME1) captures a concern that the adoption decision creates reliance on actors whose performance the SME cannot control.

SMEs consistently articulate a need for an advisor who is simultaneously technically competent, financially accessible, and commercially neutral. The ecosystem does not supply this actor. Large consultancies possess the technical depth but are priced beyond most SMEs and carry vendor alliance biases. Boutique consultancies are more accessible and neutral but may lack the capability to evaluate complex offerings. SPs are technically competent but structurally conflicted as recommenders of their own products. Intermediaries are neutral but non-technical and non-operational. *"Competent, affordable, and neutral at the same time"* (C6) names a combination that every actor partially provides and none fully delivers. *"Large consultancies are too expensive, boutiques lack technical depth, providers have conflicts of interest"* (C2) confirms this from a second perspective. This is not a market failure in the conventional sense. In Adner's (2017) terms, it is a coordination failure: the combination of attributes the focal value proposition demands does not correspond to any viable actor configuration currently operating in the ecosystem.

4.6 Taxonomy Development

Actor-specific taxonomies were developed following the iterative method of Nickerson et al. (2013), as described in Section 3.3.2. The process ended after five iterations when the objective and subjective ending conditions were satisfied (see Section 4.6.5).

4.6.1 AI-adopting SMEs Taxonomy

The objects classified are the AI adoption and BMCs of the five interviewed SMEs. The initial dimensions of AI role and value capture mechanisms were derived from the literature (Jorzik et al., 2024; Burström et al., 2021). Two dimensions emerged inductively from the interview evidence: adopting trigger, which captures the distinct pathways through which AI entered SME operations (including shadow AI use as a security-driven trigger (SME3)), and dominant readiness bottleneck, which was elevated to a taxonomy dimension because the findings in Section 4.3 show that bottlenecks are not merely contextual barriers but structural determinants of whether and how SMEs create value through AI.

Table 3: AI-adopting SME Taxonomy

Dimension	Characteristics	Value Mechanism
D1: AI role in business model	(a) No productive AI use - (b) Peripheral productivity support - (c) Internal operations infrastructure - (d) AI-enabled customer-facing offerings	Value creation
D2: Adoption trigger	(a) Operational problem-driven use - (b) Competitive / curiosity driven - (c) Shadow AI / security-driven	Value creation
D3: Implementation mode	(a) No external support - (b) Provider-led - (c) Sequential: consultants first, then SP - (d) Internal experimentation with tool access	Value delivery
D4: Value capture mechanism	(a) No measurable capture - (b) Cost avoidance - (c) Margin protection - (d) Revenue activation	Value capture
D5: Dominant readiness bottleneck	(a) Data quality - (b) Internal capability / sponsor absence - (c) ROI uncertainty - (d) Time / resource constraint - (e) Multiple simultaneous bottlenecks	Value delivery
D6: Ecosystem dependency position	(a) Low dependency - (b) Single-provider dependency - (c) Multi-actor dependency - (d) Unaware of upstream dependencies	Value capture / risk

Table 4: AI-adopting SME Case Classification

Case	D1	D2	D3	D4	D5	D6
SME1	(c) Operational infrastructure	(a) Operational problem	(b) Provider-led	(b) cost avoidance	(a) Data quality	(b) Single provider
SME2	(a) No productive AI use	(a) Operational problem	(a) No external support	(a) No measurable capture	(e) Multiple simultaneous bottlenecks	(a) Low dependency
SME3	(b) Peripheral productivity support	(c) Shadow AI / security-driven	(d) Internal experimentation with tool access	(b) cost avoidance	(b) Internal capability / sponsor absence	(b) Single provider
SME4	(c) Operational infrastructure	(b) Competitive / curiosity driven	(b) Provider-led	(b) cost avoidance	(a) Data quality	(b) Single provider
SME5	(d) AI-enabled customer-facing offerings	(a) Operational problem	(c) Sequential: consultants first, then SP	(d) Revenue activation	(a) Data quality	(c) Multi-actor dependency

4.6.2 AI Solution Providers Taxonomy

The objects classified are the BMCs of the four interviewed AI SPs. The literature-derived dimensions of revenue logic (Kohtamäki et al., 2019) and offering architecture were refined empirically: the interview evidence related three distinct SP archetypes (vertical end-to-end, horizontal platform, consulting-implementation hybrid) that the Servitization literature does not directly map. Two dimensions were added inductively: upstream dependency exposure, which captures the finding from Section 4.5 that hyperscalers' and LLM-providers pricing directly conditions what SPs can offer, and consulting functions absorption, which classifies the extent to which SPs have taken over the advisory functions traditionally performed by consultants.

Table 5: AI Solution Provider Taxonomy

Dimension	Characteristics	Value Mechanism
D1: Offering architecture	(a) Vertical end-to-end - (b) Horizontal platform - (c) Consulting-implementation hybrid	Value creation
D2: Revenue logic	(a) Subscription-only - (b) Subscription + onboarding fee - (c) Subscription + consultants day rates - (d) Per-user + consumption-based API	Value capture
D3: Customization depth	(a) No customization - (b) Configurations within standard product - (c) Significant customization	Value delivery
D4: SME data dependency	(a) No customer training data required - (b) Historical business data required - (c) Real-time operational data required	Value creation
D5: Upstream dependency exposure	(a) Low - (b) LLM/API cost exposure - (c) Cloud + LLM exposure - (d) Cloud + LLM + ERP interface exposure	Value capture / risk
D6: Consulting function absorption	(a) No consulting - (b) Light consulting - (c) Full consulting	Value delivery

Table 6: Solution Provider Case Classification

Case	D1	D2	D3	D4	D5	D6
SP1	(a) Vertical end-to-end	(a) Subscription-only	(b) Configurations within standard product	(c) Real-time operational data required	(a) Low	(c) Full consulting
SP2	(b) Horizontal platform	(d) Per-user + consumption-based API	(a) No customization	(a) No customer training data required	(c) Cloud + LLM exposure	(a) No consulting
SP3	(c) Consulting-implementation hybrid	c) Subscription + consultants day rates	(c) Significant customization	(b) Historical business data required	(c) Cloud + LLM exposure	(c) Full consulting
SP4	(a) Vertical end-to-end	(b) Subscription + onboarding fee	(c) Significant customization	(b) Historical business data required	(d) Cloud + LLM + ERP interface exposure	(b) Light consulting

4.6.3 Consultants Taxonomy

The objects classified are the BMCs of the six interviewed consultants. The most consequential dimension to emerge from the empirical data is vendor neutrality, which the interview evidence shows inversely correlates with firm size and technical depth. Boutique consultancies maintain strict neutrality as a competitive differentiator, while large consultancies trade neutrality for scale advantages through certifications, co-selling, and license resale revenue. This dimension was separated from advisory scope because it captures a distinct value mechanism, whose interests the recommendations serve, rather than a scope question.

Table 7: Consultants Taxonomy

Dimension	Characteristics	Value Mechanism
D1: Advisory scope	(a) Strategy and readiness only - (b) Use-case identification through provider selection - (c) End-to-end: strategy through implementation and operations	Value creation
D2: Technical depth	(a) Business-only advisory - (b) Technology-aware advisory - (c) Technical implementation capability	Value delivery
D3: Vendor neutrality	(a) Strict neutral - (b) Selective partnerships - (c) Alliance-driven	Value capture / risk
D4: Revenue logic	(a) Daily rates - (b) Fixed-price packages - (c) Daily rates + license/resale margin	Value capture
D5: SME segment served	(a) Small SMEs - (b) Mid-sized SMEs - (c) Large SMEs and enterprises	Value delivery
D6: Primary risk exposure	(a) Reputational risk - (b) Delivery risk - (c) Alliance bias risk	Risk

Table 8: Consultants Case Classification

Case	D1	D2	D3	D4	D5	D6
C1	(b) Use-case identification through provider selection	(b) Technology-aware advisory	(b) Selective partnerships	(a) Daily rates	(b) Mid-sized SMEs	(a) Reputational risk
C2	(b) Use-case identification through provider selection	(b) Technology-aware advisory	(a) Strict neutral	(b) Fixed-price packages	(a) Small SMEs	(a) Reputational risk
C3	(c) End-to-end: strategy through implementation and operations	(c) Technical implementation capability	(c) Alliance-driven	(a) Daily rates	(c) Large SMEs and enterprises	(b) Delivery risk
C4	(c) End-to-end: strategy through implementation and operations	(c) Technical implementation capability	(c) Alliance-driven	(a) Daily rates	(c) Large SMEs and enterprises	(c) Alliance bias risk
C5	(c) End-to-end: strategy through implementation and operations	(c) Technical implementation capability	(c) Alliance-driven	(a) Daily rates	(c) Large SMEs and enterprises	(b) Delivery risk
C6	(c) End-to-end: strategy through implementation and operations	(c) Technical implementation capability	(c) Alliance-driven	(c) Daily rates + license/resale margin	(c) Large SMEs and enterprises	(c) Alliance bias risk

4.6.4 Intermediaries Taxonomy

The objects classified are the support configurations of the four interviewed intermediary representatives. This taxonomy is the most inductively driven of the four, as the literature provides limited guidance for intermediary-specific dimensions. Operational depth emerged from the findings that the single “intermediary” label conceals at least four distinct configurations, ranging from information-only event providers to applied research organizations that perform consulting and prototyping. Impact measurement was elevated to a taxonomy dimension because it directly explains why intermediaries struggle to demonstrate value capture.

Table 9: Intermediaries Taxonomy

Dimension	Characteristics	Value Mechanism
D1: Primary function	(a) Awareness and orientation - (b) Matchmaking and network facilitation - (c) Applied research and consulting - (d) Ecosystem orchestration and consortium building	Value creation
D2: Operational depth	(a) Information-only - (b) Initial orientation advisory - (c) Structured assessment and referral - (d) Hands-on project support	Value delivery
D3: Neutrality constraint	(a) Strict institutional neutrality - (b) Curated neutrality - (c) Selective engagement in funded projects	Value capture / risk
D4: Funding model	(a) Fully publicly funded - (b) Membership funded - (c) Mixed: public + membership contributions - (d) Mixed: basic funding + industrial project revenue	Value capture
D5: Impact measurement	(a) Activity metrics only - (b) Awareness metrics - (c) Referral tracking - (d) Adoption outcome tracking	Value capture

Table 10: Intermediaries Case Classification

Case	D1	D2	D3	D4	D5
I1	(a) Awareness and orientation	(a) Information-only	(a) Strict institutional neutrality	(a) Fully publicly funded	(a) Activity metrics only
I2	(c) Applied research and consulting	(d) Hands-on project support	(c) Selective engagement in funded projects	(d) Mixed: basic funding + industrial project revenue	(c) Referral tracking
I3	(b) Matchmaking and network facilitation	(b) Initial orientation advisory	(a) Strict institutional neutrality	(b) Membership funded	(b) Awareness metrics
I4	(d) Ecosystem orchestration and consortium building	(c) Structured assessment and referral	(b) Curated neutrality	(c) Mixed: public + membership contributions	(c) Referral tracking

4.6.5 Ending Conditions Check

The developed taxonomies were checked against the objective and subjective ending conditions specified by Nickerson et al (2013). Tables 11 and 12 summarize the results:

Table 11: Objective conditions (Nickerson et al., 2013)

Condition	Status
1. All objects or representative sample classified	Met. All 19 cases classified.
2. No new dimensions or characteristics in last iteration	Met.
3. No dimensions or characteristics merged or split in last iteration	Met.
4. Every dimension unique and not repeated	Met across all four taxonomies.
5. Every characteristic unique within its dimension	Met.
6. At least one object per characteristic	Mostly met. Single-case characteristics (e.g. SME D4(d) revenue activation: SME5 only; SP D1(b) horizontal platform; SP2 only) are retained as empirically observed and analytically important configurations.

Table 12: Subjective conditions (Nickerson et al., 2013)

Condition	Assessment
Concise	Met. Taxonomies contain 5-6 dimensions each.
Robust	Met. Dimensions differentiate meaningfully among cases within each actor type.
Comprehensive	Met for the observed sample. All 19 cases classifiable.
Extendible	Met. New characteristics or dimensions can be added without restructuring.
Explanatory	Met. Each dimension links to value creation, capture, delivery, or risk mechanisms.

One classification observation warrants a note. I2 operates across the boundaries of intermediary and consultant roles, a boundary case that is not merely a taxonomic difficulty but an analytically productive finding. It suggests that the single 'intermediary' label in the German SME AI ecosystem conceals at least two structurally distinct configurations with different value mechanisms, funding logics, and operational depths. This finding is developed further in the discussion.

5. Discussion

5.1 AI Adoption as an Ecosystem Alignment Problem

The findings of this thesis converge on a central interpretive conclusion: AI value realization in the German SME ecosystem is constrained not by the availability of AI technology, nor by SME reluctance, but by the structural misalignment of BMCs, value flows, ecosystem roles, and dependencies across the actors whose coordination is required for an AI-enabled value proposition to materialize. The ecosystem possesses the component capabilities needed for AI value creation. Solution providers offer technically functional products. Consultants possess implementation expertise and business-process knowledge. Intermediaries maintain contact networks with SMEs. SMEs themselves recognize AI-related opportunities and, in several cases, have already begun informal adoption. What the ecosystem lacks is the alignment configuration that would allow these distributed capabilities to combine effectively.

This interpretation connects directly to Adner's (2017) definition of ecosystems as alignment structures in which the coordination of multilateral partners determines whether a focal value proposition materializes. The German SME AI ecosystem does not fail because a critical actor is absent; it fails because the actors that are present operate under business model configurations that are individually rational but jointly insufficient. The solution provider's subscription pricing assumes a cost base that excludes the SMEs hidden implementation effort. The consultant's advisory scope often stops where the SMEs implementation needs begin. The intermediary's coordination function is calibrated to awareness rather than adoption outcomes. The upstream infrastructure layer conditions pricing and feasibility in ways that neither the solution provider nor the SME fully controls.

Jacobides et al. (2018) provide the complementary theoretical explanation for why these alignment failures persist. Non-generic complementarities bind the ecosystem's actors into mutual dependence but do not guarantee that their business model logics are compatible. A SP whose model is trained on an SMEs proprietary data creates a non-generic complementarity: neither component retains its full value outside the relationship. But this complementarity does not resolve who owns the trained model, who bears the risk of implementation failure, or whether the SMEs total adoption cost is visible before the project begins. The findings show that it is precisely in these unresolved spaces, between complementarity and alignment, that the ecosystem's bottlenecks are located.

5.2 Actor-Specific Configurations and the Limits of Firm-Centric BMI

The findings demonstrate that AI business model configurations differ systematically across actor types, shaped by each actor's ecosystem position rather than by a single shared transformation logic.

The dominant business model logic across all four actor types is risk-bounded incrementalism. Jorzik et al. (2024) distinguish between AI as peripheral and AI as central to value creation, and between active and evolutionary BMI. The present findings confirm this distinction but reveal an additional asymmetry: even where AI is central to the solution provider's offering, it remains peripheral in the SMEs business model. SME5 uses AI to guarantee delivery windows and operational reliability, but the customer-facing value proposition is reliability, not AI. This configuration represents evolutionary rather than active BMI in Jorzik et al.'s terms and suggests that the transformation narrative overstates what is happening in business model terms within the German SME context.

This finding is sharpened by the framing divergence between SPs and SMEs. SPs consistently foreground AI as the source of customer value; advanced SME adopters have absorbed AI into operational infrastructure, where it becomes invisible to the end customer. The gap between how AI is sold and how it is experienced is not merely rhetorical. It reflects a structural difference in how AI is integrated into business model logics: for the SP, AI is the product; for the SME, AI is the mechanism that enables a non-AI value proposition.

Burström et al. (2021) argued that AI-enabled BMI requires reconfiguration of the whole ecosystem. The present findings empirically confirm this claim but reveal its limitation: Burström et al. analyzed ecosystem adaptation from the perspective of a single focal firm. When the analytical lens expands to four actor types simultaneously, the BMCs that emerge are not adaptations of a single firm's value architecture but distinct, actor-specific logics. The SP taxonomy identifies three offering architectures. The consultant taxonomy reveals an inverse correlation between vendor neutrality and technical depth

Sjödin et al. (2023) identify value discovery, value realization, and value optimization as dynamic capabilities for commercializing AI. The present findings extend this by showing that these capabilities are distributed across the ecosystem. Value discovery occurs when a consultant identifies a viable AI use case. Value creation occurs when a SP deploys a model trained on the SMEs data. Value capture occurs when the SME achieves measurable efficiency gains. The alignment of these three steps depends on the BMCs of at least three different actors, and misalignment between any two is sufficient to prevent value realization.

5.3 Multi-Currency Value Flows and the Hidden Cost Architecture

The findings reveal that value flows in the German SME AI ecosystem extend well beyond monetary transactions. SMEs contribute not only subscription fees but operational data, employee time, domain knowledge, process exposure, and reference legitimacy. These non-monetary flows are essential preconditions for AI value creation, yet they are systematically undervalued.

This dynamic was independently described by respondents across all four actor types, suggesting that it is a recognized but unresolved feature of the ecosystem. The practical consequence is that ROI calculations are built on an incomplete cost base, making AI adoption appear more attractive before implementation begins and more expensive once it is underway.

The data ownership ambiguity surrounding trained models represents one of the clearest value-flow asymmetries. In Jacobides et al.'s (2018) terms, this is a case where non-generic complementarity creates mutual dependence without resolving value appropriation. The findings show that in the German SME AI context, it has occurred without the governance mechanisms, contractual clarity, or pricing transparency that would make it equitable.

Trust and referral flows constitute the ecosystem's actual acquisition infrastructure, a finding with structural consequences for intermediary relevance. This finding suggests that the formal intermediary architecture is not performing its intended bridging function for most observed transactions.

5.4 Compound Bottlenecks and the Absorptive Capacity Conversion Gap

The bottleneck architecture identified in the findings is compound rather than sequential. Data readiness, internal capability gaps, time constraints, and ROI uncertainty occur simultaneously and reinforce each other. An SME whose data is inadequate cannot demonstrate ROI; an SME that cannot demonstrate ROI cannot justify the time investment required to improve its data. This circularity distinguishes the present findings from the adoption barrier lists provided by Ströbele et al. (2025) and Bundesnetzagentur (2025), which identify barriers individually but do not theorize their interaction. In Adner's (2017) framework, this compound structure represents an alignment failure at the activity level: the activities required for value proposition materialization are interdependent, and the failure of any one prevents the others from succeeding.

This finding connects to the absorptive capacity literature. Müller et al. (2021) found that potential absorptive capacity, is particularly relevant for business model design in SMEs in the context of Industry 4.0. The present findings suggest that in the German SME AI ecosystem, the gap between potential and realized absorptive capacity is not solely a firm-level phenomenon. SMEs across the sample can identify where AI might add value, but cannot convert these opportunities into productive implementations because the conversion depends on the alignment of the solution provider's delivery model, the consultant's advisory scope, and the intermediary's coordination depth with the SMEs readiness conditions. The compound bottleneck structure is the ecosystem-level manifestation of this conversion failure: SMEs possess the potential absorptive capacity to recognize AI opportunities but lack the ecosystem alignment that would enable them to realize that capacity productively.

5.5 The Coordination Gap: Why "Competent, Affordable, and Neutral" Does Not Exist

The finding that SMEs require advisory support that is simultaneously technically competent, financially accessible, and commercially neutral, while no current actor provides this combination, deserves full theoretical development. It is not merely one bottleneck among many. It is the ecosystem's defining structural constraint, because it is the point at which the misalignment between actor-specific BMCs becomes most consequential for SME value realization.

Each actor type partially occupies this structural position but cannot fully occupy it. Large consultancies possess technical depth but are priced beyond most SME budgets and carry vendor alliance biases that shape their recommendations toward their own certification portfolios. Boutique consultancies are more accessible and often more neutral but may lack the technical capability to evaluate complex AI offerings. SPs offer technical competence but are structurally conflicted as recommenders of their own products. Intermediaries are neutral and accessible but non-technical and non-operational. The result is a structural gap: the combination of attributes that SMEs need does not correspond to any viable commercial or institutional model currently operating in the ecosystem.

In Adner's (2017) terms, this represents a bottleneck that arises not from a missing capability but from a missing position. The present finding extends this by showing that in emerging ecosystems, bottlenecks can also arise from structural gaps where the required combination of role attributes is incompatible with the business models available to fill that role. No actor can simultaneously be technically deep, commercially neutral, and affordable to SMEs, because technical depth requires investment that creates either pricing pressure (consultancies) or commercial incentives (vendor alliances, product sales). The structural gap is therefore not a temporary market failure that competitive entry will resolve but a persistent coordination failure rooted in the incompatibility of the actor-specific economic logics that sustain the actors who could fill the position.

The I2 boundary case provides empirical evidence that this structural gap is recognized within the ecosystem and that some actors are experimenting with configurations that partially bridge it. I2, an applied research institute, explicitly describes its function as consulting rather than coordination, performing requirements elicitation, software selection, and process optimization. It demonstrates that the intermediary category as theorized in ecosystem literature, defined by its brokerage function (Jacobides et al., 2018), does not hold empirically as a coherent role category. I2's hybrid configuration shows that the structural gap is recognized and partially addressable through institutional models that combine public funding with technical capability, though a limited scale.

This coordination gap also points toward a broader observation about the role of public and institutional actors in emerging AI ecosystems. Drawing on the entrepreneurial ecosystem literature, which has examined the role of institutional conditions in ecosystem performance rather than merely contextual conditions (Isenberg, 2010; Stam, 2015), the present findings suggest that the public policy layer in the German SME AI ecosystem is more visible through its constraints than through active coordination. Autio et al. (2014) further show that institutional arrangements determine not only the pace but the form of innovation activity, a finding that maps directly onto how public funding mandates constrain what forms of ecosystem coordination German intermediaries can perform. Whether a reorientation of public funding toward outcome-based metrics and technically capable advisory services could partially close the "competent, affordable, and neutral" gap is a question that the present data raises but cannot answer; it remains a direction for future research and policy experimentation.

5.6 Upstream Dependencies, Power Asymmetries, and the Porous Actor Framework

The upstream dependency layer, hyperscalers, LLM providers, and ERP/CRM vendors introduce a structural influence that the four-actor framework used in this thesis does not fully capture. These actors were not part of the original research design and were identified inductively through the accounts of the four focal actor types. The finding that upstream pricing and interface decisions condition what SPS can offer, at what price, and through which interfaces identifies a cost and risk pass-through mechanism that runs from infrastructure providers through SPs to SMEs, with each layer absorbing some risk and passing the remainder downstream to the actor, which is least equipped to bear it.

This upstream layer should be treated as a structural dependency condition of the ecosystem rather than as a fifth actor type. The present data does not support the full characterization of upstream BMCs, since no direct interviews were conducted with hyperscale or ERP vendor representatives. The upstream layer functions as a boundary condition: it does not participate in the value proposition directly but determines the parameters within which the participating actors must operate.

A critical reflection on the four-actor framework itself is warranted. The framework served the thesis well as analytical scaffolding, but the empirical evidence revealed that actor boundaries are operationally porous at two points. The SP–C boundary is eroding as SPs absorb consulting functions, discovery workshops, needs analysis, change management, and some consultants develop technical implementation capabilities. The I–C boundary is blurred by organizations like I2 that perform consulting under an intermediary mandate. These boundary cases do not invalidate the framework but indicate that actor categories in emerging ecosystems are better understood as functional roles on a spectrum rather than as discrete organizational types. The taxonomy's ability to classify these hybrid configurations within actor-specific dimensions (e.g., SP D6: consulting function absorption) demonstrates that the classification approach can accommodate porosity without losing analytical structure.

5.7 Surprising Findings

Several findings were not anticipated by the theoretical framework and warrant explicit discussion.

First, the shadow AI pathway into formal adoption inverts the conventional framing of AI adoption as a strategic decision (Davenport & Ronanki, 2018). In the case of SME3, employees had adopted consumer-grade AI tools (Ronge et al., 2025) privately before any organizational decision had been made. The managing director's response was to adopt a formally governed enterprise solution to contain data security risk rather than to pursue operational improvement. This pathway is not theorized in the reviewed adoption literature (Ströbele et al., 2025; Bundesnetzagentur, 2025) and suggests that security and compliance positioning can be the primary value proposition for SPs serving this entry condition.

Second, the hidden cost finding's consistency across all four actor types is surprising: SPs, consultants, intermediaries, and SMEs all independently described the same dynamic, suggesting it is a stable ecosystem feature rather than an information problem that transparency alone could address.

Third, the SP–SME framing divergence, where SPs foreground AI as the value proposition while advanced SME adopters have absorbed AI into invisible operational infrastructure, was not anticipated by the literature. This inverts the assumption, implicit in much of the AI-BMI discourse, that AI-centrality indicates advanced business model maturity.

5.8 Theoretical Contributions

This thesis makes four theoretical contributions.

First, it contributes to the AI-driven BMI literature by moving beyond the focal-firm perspective that dominates existing work (Jorzik et al., 2024; Burström et al., 2021; Sjödin et al., 2023). By examining BMCs across four actor types simultaneously, the thesis demonstrates that AI-related BMCs differ systematically by ecosystem position and that the dominant configuration logic is risk-bounded incrementalism rather than transformative innovation. This extends Jorzik et al.'s (2024) distinction between active and evolutionary BMI by showing that even the most advanced SME configurations represent evolutionary BMI in practice.

Second, it contributes to ecosystem theory by providing one of the first empirical applications of Adner's (2017) ecosystem-as-structure framework and Jacobides et al.'s (2018) role-based coordination logic to an emerging AI ecosystem without a dominant orchestrator. The findings show that alignment failures in this setting are structural rather than behavioral. The "missing position" concept, a bottleneck caused not by absent capabilities but by incompatible role-attribute combinations, extends Adner's ecosystem-as-structure logic by showing how alignment failures can arise when a necessary position does not correspond to a viable business model.

Third, it contributes to the SME AI adoption literature by reframing adoption barriers as ecosystem-level bottlenecks. Ströbele et al. (2025) and Bundesnetzagentur (2025) identify barriers individually. The present thesis shows that these barriers are compound, co-occurring, and produced by the ecosystem configuration rather than by SME-internal limitations alone. The ecosystem-level explanation for the gap between potential and realized absorptive capacity (Müller et al., 2021; Cohen & Levinthal, 1990) represents a specific contribution: SMEs cannot convert recognized opportunities into productive implementations because the conversion depends on structurally absent ecosystem alignment.

Fourth, it contributes to taxonomy research by applying Nickerson et al.'s (2013) iterative method to classify actor-specific AI BMCs in an emerging empirical context. The Gioia methodology identifies themes; the taxonomies classify individual cases along defined dimensions, making within-actor variation visible and enabling cross-actor comparison. This demonstrates that the Nickerson et al. method is productive for multi-actor ecosystem analysis, not only for single-object classification.

5.9 Practical Implications

For SMEs, AI adoption decisions should be evaluated based on total cost of ownership (TCO), including internal employee time, data preparation, and organizational change, rather than subscription pricing alone. Data readiness should be treated as a business model precondition, not an IT afterthought. The shadow AI finding suggests that SMEs should proactively govern employee AI use rather than waiting for security incidents to force reactive adoption decisions (Davenport & Ronanki, 2018).

For SPs, making implementation effort and data requirements transparent at the pre-sales stage would reduce the ROI uncertainty that suppresses adoption scaling. The progressive absorption of consulting functions is a structural response to a coordination gap, but it carries neutrality risks that should be managed transparently. Providers should also clarify upstream dependency exposure so that SME clients can assess the cost and continuity risks embedded in their subscription.

For consultants, the inverse relationship between vendor neutrality and technical capability represents both a structural challenge and a competitive opportunity. Boutique consultancies that can credibly combine neutrality with technical depth would occupy the structural position the ecosystem currently lacks. Large consultancies should consider disclosing alliance relationships and certification portfolios to enable SMEs to evaluate whether recommendations reflect the optimal solution or the consultant's capability investments.

For intermediaries, a shift toward outcome-oriented metrics tracking whether SMEs advance to implementation would better align incentives with ecosystem needs, with the I2 model as a configuration worth exploring. For policymakers and public funders, the findings suggest that public funding for intermediary programs should be restructured around adoption outcomes rather than awareness outputs. The trilemma finding further suggests that policymakers should consider whether a neutral, technically competent, and financially accessible advisory function could be created or funded through public mechanisms, since the market alone does not produce this combination.

5.10 Proposed Ecosystem Framework

The empirical findings necessitate a revision of the literature-based conceptual value-flow framework presented in Section 2.5. Three modifications are warranted.

First, the framework must incorporate the upstream dependency layer. Hyperscalers, LLM providers, Cloud providers and ERP/CRM vendors were not part of the original four-actor framework but were unanimously identified by respondents across all four actor types as structurally determinative. The revised framework positions this upstream layer as a structural dependency condition rather than a fifth actor type, reflecting the boundary-condition interpretation supported by the data.

Second, the framework must reflect the empirical finding that actor boundaries are porous. The SP–C boundary is eroding through consulting function absorption; the I–C boundary is blurred by organizations performing consulting under intermediary mandates. The revised framework represents these boundaries as permeable rather than fixed, reflecting the hybrid configurations observed in practice.

Third, the framework must incorporate the non-monetary value flows that the empirical findings revealed as essential. Data flows, employee time, domain knowledge, trust, referral legitimacy, and risk transfers operate alongside monetary flows and are often preconditions for monetary exchanges to occur. The revised framework (see Figure 3) traces all four flow types, monetary, data, capability/service, and risk, across the six bilateral relationships (SP↔SME, C↔SME, I↔SME, SP↔C, I↔SP, I↔C), with bottleneck indicators (see Table 13) marking where flows are blocked, misaligned, or underdeveloped.

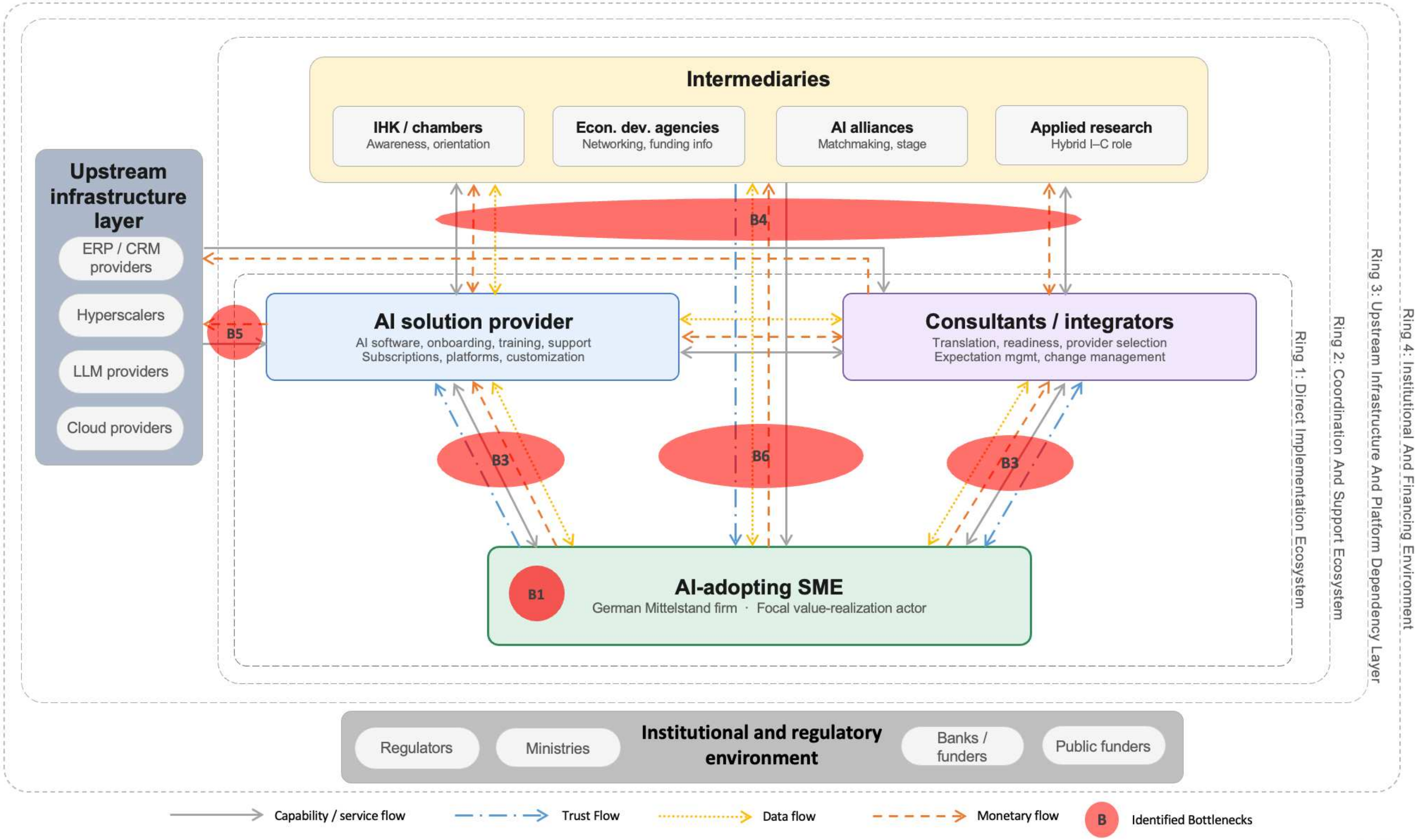

Figure 3: Empirical ecosystem framework for AI adoption in German SMEs

Table 13: Empirical bottleneck zones in the German SME AI ecosystem

ID	Bottleneck zone	Description	Sub-components	Empirical source
B1	SME internal readiness	AI adoption is gated by internal preconditions that compound each other: poor data quality, fragmented IT infrastructure, insufficient employee time, absent management sponsorship, unquantifiable ROI, and uncontrolled shadow AI use. Data readiness is the single most frequently cited barrier across all four actor types.	Data readiness and quality	SME1, SME2, SME5, SP4, C1, C2, C3, C4
			Legacy IT and ERP/CRM gaps	SME2, SME4, SP4, C2, C3
			Employee time and operational overload	SME2, SME5, C1, C3
			Missing internal sponsor / key-person dependency	SME2, SME5, C1, C2, I3
			ROI uncertainty and business case gap	SME1, SME2, SME3, SP3, C1, C4
			Shadow AI and governance pressure	SME1, SME2, SME3, SP2, C4
			Employee resistance and job-loss fears	SME1, SME4, SME5, I4
BN2	SP-SME implementation gap	The transition from available AI software to operational AI use in the SME is where value most frequently fails to materialize. Data preparation effort is systematically underestimated, system integration is technically complex, and expectations between what is sold and what is delivered diverge. Vendor lock-in compounds the problem over time.	Hidden data preparation cost	SME1, SME5, SP4, C1, C2, C3
			Integration difficulty (ERP/CRM interfaces)	SME1, SME4, SP3, SP4, C3
			Expectation gap (promised vs. delivered value)	SME1, SME2, C1, SP4
			Vendor lock-in and switching costs	SME1, SME2, SP1, SP2, SP4, C1
			Data sensitivity and privacy concerns	SME1, SME3, SME5, SP2, SP4
			Upfront cost barrier (onboarding fees)	SME2, SP4, C2
BN3	C-SME advisory undervaluation	The actor best positioned to help SMEs navigate the ecosystem is structurally underutilized. SMEs benchmark consultant daily rates against internal employee costs and perceive advisory as unaffordable. The intangible nature of advisory value (objectivity, expectation management, provider selection) makes it difficult to justify. Success-based pricing was tried and failed due to causality attribution problems.	Advisory value undervalued relative to internal labor cost	C2, C4, C6
			Neutrality–technical depth–affordability tension	C1, C2, C6, SME2
			Causality attribution failure (success-based pricing abandoned)	C1, C2, SP4, SME5

ID	Bottleneck zone	Description	Sub-components	Empirical source
BN4	Intermediary coordination failure	Intermediaries produce awareness and orientation but fail to bridge the gap to implementation. Their neutrality mandate prevents specific provider recommendations. Their funder-imposed KPIs reward activity metrics (events held, companies reached) rather than adoption outcomes. The result is a formal coordination mechanism that does not coordinate.	Awareness without implementation	SME2, SME4, SME5, SP2, SP4, C1, C2
			Too generic for industry-specific SME needs	SME2, SME4, SME5, SP2, SP4, C1, C2
			Neutrality prevents provider recommendations	I1, I2, I3, I4
			Activity KPIs rather than adoption KPIs	I1, I3, I4
			Loss of visibility after referral	I1, I3, I4
BN5	Upstream dependency and pass through	Actors invisible to the SME, hyperscalers, LLM providers, cloud vendors, and ERP/CRM platforms, determine what solution providers can offer and at what price. Unilateral upstream pricing or interface changes cascade downstream, altering SP business models and SME costs. SMEs are typically unaware of their second-tier dependency exposure.	API and LLM pricing power	SP4, SME4, SME5, C1
			Cloud and compute dependency	SP2, SP3, SP4
			ERP/CRM interface instability	SP4, C3, SP3, C5
			Invisible cost and risk pass-through to SME	SME4, SME5
			Consultant capability lock-in through platform alliances	C6, C3, C5
BN6	Missing competent-affordable-neutral position	No current ecosystem actor simultaneously provides the three qualities SMEs need most: technical competence (understanding AI implementation), financial affordability (fitting SME budgets), and commercial neutrality (recommending what fits, not what pays commission). Large consultancies are competent but expensive and alliance biased. Boutique consultants are neutral and affordable but lack deep technical capability. Solution providers are competent but commercially interested. Intermediaries are neutral but lack both technical depth and implementation capacity. This structural gap is the thesis's central ecosystem-level finding.	Large consultancies: competent but expensive and alliance-biased	C6, C2, C1
			Boutique consultants: neutral and affordable but technically limited	C1, C2, SME2
			Solution providers: competent but commercially interested	C6, C2, SME2
			Intermediaries: neutral but lacking technical depth	I1, I2, I3, I4
			Informal referrals outperform institutional matchmaking	SP2, SP4, C2, SME5

6. Conclusion

6.1 Restating the Research Problem

This thesis set out to investigate how value creation, capture, and delivery are configured across actors in the German SME AI ecosystem and how value flows and bottlenecks shape value realization. The research problem was motivated by the observation that AI tools are increasingly available to German SMEs, yet availability alone does not translate into productive use.

The central finding is that AI value realization in the German SME ecosystem is constrained not by technological immaturity or SME unwillingness but by structural misalignment between the BMCs of the actors whose coordination the value proposition demands.

6.2 Answering RQ1

The findings show that configurations differ systematically across actor types. SMEs adopt AI predominantly as internal operational infrastructure or peripheral productivity support, capturing value through cost avoidance, margin protection, and operational efficiency. In the most advanced case observed (SME5), AI has become invisible to the customer: the value proposition is reliability, not technology, and AI functions as the internal mechanism that makes this commitment operationally feasible. This represents evolutionary rather than active BMI in Jorzik et al.'s (2024) terms and suggests that the dominant AI-BMI logic in the German SME context is risk-bounded incrementalism rather than transformative innovation.

SPs have converged on hybrid architectures that combine standardized AI cores with bounded customization and implementation layers. The SP taxonomy identifies three distinct offering architectures: vertical end-to-end, horizontal platform, and consulting-implementation hybrid, revealing supply-side variation that firm-centric studies do not capture.

Consultants operate along a spectrum defined by the inverse relationship between vendor neutrality and technical depth. Large consultancies offer implementation capability but carry alliance-driven recommendation biases; boutique consultancies maintain independence but may lack the technical scale to evaluate complex offerings.

Intermediaries reveal at least four functionally distinct configurations, from awareness-only event providers to applied research organizations that perform consulting and prototyping, challenging the assumption that intermediaries constitute a single coherent actor type. The I2 boundary case, where an applied research institute explicitly describes its function as consulting rather than coordination, demonstrates that the intermediary category as theorized in the ecosystem literature does not hold as an empirically uniform role.

6.3 Answering RQ2

The findings show that value flows in the ecosystem are multi-currency and asymmetric. SMEs contribute not only subscription fees but also operational data, employee time, domain knowledge, process exposure, and reference legitimacy. These non-monetary flows are essential preconditions for AI value creation but are systematically undervalued: they appear in no invoice, are excluded from business cases, and are not reflected in the ROI calculations that SMEs attempt to construct.

The bottleneck architecture is compound rather than sequential. Data readiness, internal capability gaps, ROI uncertainty, and time constraints co-occur and reinforce each other. The most consequential bottleneck is structural: SMEs require advisory support that is simultaneously competent, affordable, and neutral, but no current actor provides this combination. This "missing position" represents a coordination failure that no single actor's business model adjustment can resolve.

6.4 Limitations

The qualitative design with 19 interviews supports analytical but not statistical generalization. Purposive and snowball sampling may overrepresent visible actors (Parker et al., 2019). The intermediary sample is regionally concentrated in southern Germany, one of the country's strongest intermediary ecosystems; intermediary marginality may be more pronounced in regions with weaker support structures, meaning the findings likely understate rather than overstate the coordination gap. The consultant sample skews toward large firms (four of six), limiting robustness of claims about boutique configurations.

The research is cross-sectional and captures a rapidly evolving ecosystem. The upstream dependency layer was identified through focal actor accounts; no direct interviews were conducted with hyperscalers, LLM providers, or ERP vendors, meaning the upstream analysis reflects downstream perceptions. Translation from German to English using machine translation, reviewed by the researcher as a native German speaker with both versions accessible during coding, introduces a risk that nuances may have been altered, though the bilingual approach mitigates this. The hybrid coding procedure, while bounded and subject to full researcher control, warrants transparency as a methodological choice.

The taxonomies are an initial empirical classification, not a universal taxonomy. Several characteristics are supported by single cases and require validation with larger samples. Actor boundaries proved empirically porous, particularly at the SP–C and I–C intersections, indicating that actor types should be understood as functional roles rather than discrete categories.

6.5 Future Research

First, the actor-specific taxonomies are grounded in 19 qualitative cases. A quantitative survey study could test whether the taxonomy dimensions hold across a broader population and reveal whether the within-actor variation observed, such as the three SP archetypes or the four intermediary configurations, is statistically robust.

Second, the upstream dependency layer was identified inductively but not studied directly. A dedicated study interviewing hyperscalers, LLM providers, and ERP/CRM vendor representatives alongside downstream actors would clarify whether upstream providers constitute a fifth actor type and whether downstream perceptions of upstream influence align with upstream self-characterizations.

Third, this thesis captures a cross-sectional snapshot of an emerging ecosystem. A longitudinal multiple-case study tracking the same SMEs and their ecosystem partners over 12 to 24 months would reveal how BMCs evolve as the ecosystem matures, whether the compound bottleneck structure dissolves or solidifies over time, and whether the SP–C boundary collapse produces stable hybrid configurations or creates new coordination problems.

Fourth, the "competent, affordable, and neutral" trilemma identifies a structural gap but does not test solutions. An action research or design science study developing and piloting a neutral AI advisory model for SMEs, whether publicly funded, cooperative, university-based, or hybrid, would address the most practically consequential finding of this thesis. Comparing different advisory models across institutional forms would clarify which configurations come closest to bridging the trilemma and under what conditions.

Finally, a cross-country comparative study applying the same multi-actor taxonomy approach to SME AI ecosystems in comparable European economies would test whether the alignment failures identified here are specific to the German Mittelstand context or generalizable to other SME-intensive economies.

6.6 Closing Reflection

This thesis contributes a multi-actor, taxonomy-based analysis of how AI-enabled value creation, capture, and delivery are configured and constrained in the German SME AI ecosystem. It moves beyond the focal-firm perspective by examining BMCs across four actor types simultaneously and classifying them through taxonomies grounded in Nickerson et al.'s (2013) method. It extends ecosystem theory by applying Adner's (2017) and Jacobides et al.'s (2018) frameworks to an emerging, non-platform-centric AI ecosystem and identifying a new form of bottleneck, the "missing position", where the required combination of role attributes does not correspond to any viable business model. It reframes SME adoption barriers as ecosystem-level bottlenecks, showing that the gap between potential and realized absorptive capacity is the product of structural misalignment across the actors on whom the SME's adoption depends.

The challenge this thesis identifies is not how to make AI available to German SMEs. AI is available. The challenge is how to align ecosystem roles, value flows, and responsibilities so that the capabilities already present in the ecosystem can combine into value that SMEs can realize. Until that alignment is achieved, the gap between AI's recognized potential and its productive implementation in the German Mittelstand will persist, not for lack of technology, but for lack of coordination.

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8. Appendix

Table 14: Overview of interviews and interview partners

Actor Type	Interview No.	Interview Code	Position in Company	Date of Interview	Interview Duration
AI-Adopting SME	1	SME1	Managing Director	25.04.2026	1:01h
	2	SME2	Managing Director	26.04.2026	0:30h
	3	SME3	Assistant to CEO	24.04.2026	1:27h
	4	SME4	Member Board of Management & Project Manager AI Activities	26.04.2026	1:01h
	5	SME5	Managing Director	27.04.2026	1:30h
Consultants	6	C1	Managing Partner	29.04.2026	0:49h
	7	C2	Founder & Managing Partner	06.05.2026	0:42h
	8	C3	Junior Consultant	04.05.2026	0:47h
	9	C4	Senior Manager	04.05.2026	0:57h
	10	C5	Senior Manager	30.04.2026	1:01h
	11	C6	Partner	08.05.2026	0:25h
Intermediaries	12	I1	I1.1 Head of Industry & AI Community I1.2 Project Manager Industry & Digitalization	05.05.2026	1:20h
	13	I2	Senior Researcher & Consultant	07.05.2026	1:12h
	14	I3	Consultant	07.05.2026	0:44h
	15	I4	Community Manager	08.05.2026	1:27h
Solution Provider	16	SP1	Agent - Sales & Business Development	27.04.2026	0:45h
	17	SP2	Sales & Business Development	04.05.2026	0:57h
	18	SP3	Senior Solution Consultant	08.05.2026	0:37
	19	SP4	Co-Founder & Head of Sales	08.05.2026	0:57h

Table 15: Overview of interviewee companies

Actor Type	Interview No.	Interview Code	Company Description
AI-Adopting SME	1	SME1	Family-owned SME active in specialized component trading for a premium consumer-goods segment. The company serves both business customers and private customers through personal sales and digital ordering channels.
	2	SME2	Family-owned regional trading company supplying materials to business customers in a traditional construction-related sector. The company operates mainly through long-standing customer relationships and short-term delivery capability.
	3	SME3	Medium-sized industrial manufacturer producing specialized technical components for business customers in machinery-related industries. The company operates internationally and is gradually expanding its digital and AI capabilities.

Actor Type	Interview No.	Interview Code	Company Description
	4	SME4	Medium-sized machinery and plant engineering company producing industrial equipment for processing and handling materials. The company combines machine sales with service and spare-parts activities.
	5	SME5	Family-owned regional logistics SME providing transport and logistics services to industrial business customers. The company operates its own fleet and focuses on reliability, flexibility, and regional customer proximity.
Consultants	6	C1	Small management consultancy supporting industrial SMEs in process optimization, sales, service, and transformation projects. The firm works with a small internal team and selected external specialists.
	7	C2	Boutique consultancy supporting SMEs in digital transformation, process improvement, provider selection, implementation support, and change management. AI-related advisory work has recently become a growing part of its activities.
	8	C3	Large technology and transformation consultancy supporting enterprise software and system-transformation projects for medium-sized and large organizations.
	9	C4	Large technology and transformation consultancy supporting enterprise software and system-transformation projects for medium-sized and large organizations.
	10	C5	Large technology and transformation consultancy supporting enterprise software and system-transformation projects for medium-sized and large organizations.
	11	C6	Large technology and transformation consultancy supporting enterprise software and system-transformation projects for medium-sized and large organizations.
Intermediaries	12	I1	Publicly funded regional economic development organization supporting companies, start-ups, public institutions, and municipalities through networking, knowledge transfer, and innovation-related initiatives.
	13	I2	Applied research organization supporting companies and public institutions in digital transformation, innovation, and technology-related implementation projects.
	14	I3	Regional business association supporting companies through advisory services, networking, training, information events, and representation of business interests.
	15	I4	Regional innovation intermediary connecting businesses, research organizations, public-sector actors, and technology stakeholders to support AI-related knowledge transfer and collaboration.
Solution Provider	16	SP1	German AI solution provider offering sensor-based monitoring and analytics software for industrial equipment and maintenance-related use cases.
	17	SP2	German software provider offering a secure enterprise platform for accessing and managing generative AI tools across organizations.
	18	SP3	German AI solution provider offering software and implementation support for industrial companies, with a focus on AI-enabled process automation and enterprise use cases.
	19	SP4	German AI solution provider offering software solutions for forecasting, process automation, and decision support in trade- and logistics-related business processes.

Table 16: Gioia Coding Output

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
Everything is focused on the subscription.	Packaging AI into scalable recurring-revenue models	AI Business Model Configurations	RQ1, RQ2	AI Solution Provider	SP1; SP2; SP4; SME1; SME5
The platform is standardized.	Packaging AI into scalable recurring-revenue models	AI Business Model Configurations	RQ1	AI Solution Provider	SP1; SP2; SP4
We don't build something for each customer.	Standardizing the AI core while limiting customization	AI Business Model Configurations	RQ1	AI Solution Provider	SP2; SP4
We have a core and adapt it.	Standardizing the AI core while limiting customization	AI Business Model Configurations	RQ1	AI Solution Provider	SP4; SP1
Customizing is 30 to 40 percent of the initial project.	Balancing scalability with customer-specific adaptation	AI Business Model Configurations	RQ1	AI Solution Provider; SME Adopter	SP4; SME1; SME5
There is still an implementation effort.	Combining productized AI with implementation services	AI Business Model Configurations	RQ1, RQ2	AI Solution Provider; Consultant/Integrator	SP3; SP4; SME1; SME5; C3; C5
One-time implementation fees at the beginning.	Combining productized AI with implementation services	AI Business Model Configurations	RQ1, RQ2	AI Solution Provider; SME Adopter	SME1; SME5; SP4; SP1
Support is included in the subscription.	Embedding ongoing support into AI delivery models	AI Business Model Configurations	RQ1	AI Solution Provider	SP4; SME1; SME5; SP1
Not a six-figure commitment.	Lowering adoption thresholds through modular entry models	AI Business Model Configurations	RQ1, RQ2	AI Solution Provider; SME Adopter	SP2
Start small and only move up when they are satisfied.	Lowering adoption thresholds through staged adoption	AI Business Model Configurations	RQ1, RQ2	AI Solution Provider; SME Adopter	SP1; SME2
Everything from a single source.	Blurring consulting, implementation, and technology provision	AI Business Model Configurations	RQ1	AI Solution Provider; Consultant/Integrator	SME1; SME4; C6

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
Solution provider and consultant are one team for us.	Blurring consulting, implementation, and technology provision	AI Business Model Configurations	RQ1	SME Adopter; AI Solution Provider	SME4
We deliver the technology.	Differentiating technology provision from change enablement	AI Business Model Configurations	RQ1	AI Solution Provider	SP2; SP3; SP4
We cover the entire spectrum, strategy to implementation.	Full-service consulting as AI transformation architecture	AI Business Model Configurations	RQ1	Consultant/Integrator	C5; C6; C3
We don’t program, but we control project management and quality assurance.	Consultant as orchestrator rather than technology builder	AI Business Model Configurations	RQ1	Consultant/Integrator	C1; C2
AI readiness assessment.	Productizing consulting into standardized SME entry packages	AI Business Model Configurations	RQ1	Consultant/Integrator	C2; C6
Use case identification: where does AI have the greatest leverage?	Translating AI potential into business-model-relevant use cases	AI Business Model Configurations	RQ1	Consultant/Integrator; SME Adopter	C1; C2; C6; I2; I3
The use case has to be specific.	Concrete use cases as the basis for AI value creation	AI Business Model Configurations	RQ1	Cross-actor	C1; C2; I2; I3; SME2; SP4
Concrete use cases make AI tangible.	Concrete use cases as the basis for AI value creation	AI Business Model Configurations	RQ1	Cross-actor	I1; I2; I3; I4; C2; SME2
AI is not the value proposition; the customer buys reliability.	AI as hidden operational capability rather than market-facing offer	AI Business Model Configurations	RQ1	SME Adopter	SME5; SME3; SME1
The customer doesn’t notice AI directly, but indirectly through	AI as hidden operational capability rather than market-facing offer	AI Business Model Configurations	RQ1	SME Adopter	SME5

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
punctuality and fewer cancellations.					
AI is responsible internally for efficiency and margin.	AI as margin-protecting operational infrastructure	AI Business Model Configurations	RQ1	SME Adopter	SME5; SME1; SME3; SME4
Guaranteed delivery windows as a premium service.	AI-enabled process improvements becoming new service offerings	AI Business Model Configurations	RQ1	SME Adopter	SME5
Automated follow-up of spare-parts offers.	AI-enabled revenue activation in existing business models	AI Business Model Configurations	RQ1	SME Adopter	SME4
Demand forecasting tools.	AI-enabled optimization of purchasing, inventory, and capacity	AI Business Model Configurations	RQ1	SME Adopter; AI Solution Provider	SME1; SME2; SP4
Route optimization and predictive maintenance.	AI-enabled optimization of logistics and asset utilization	AI Business Model Configurations	RQ1	SME Adopter; AI Solution Provider	SME5; SP1
Automated quotation creation.	AI-enabled automation of sales and administrative workflows	AI Business Model Configurations	RQ1	SME Adopter; AI Solution Provider	SME1; SP4
ChatGPT for emails, summaries, translations.	Low-threshold generative AI as office productivity layer	AI Business Model Configurations	RQ1	SME Adopter	SME1; SME2; SME3; SME5
Employees use AI privately.	Bottom-up shadow AI use triggers formal, secure AI adoption	Adoption Barriers and Bottlenecks	RQ1, RQ2	SME Adopter	SME1; SME2; SME3; C4
Company email addresses were already stored with OpenAI.	Bottom-up shadow AI use triggers formal, secure AI adoption	Adoption Barriers and Bottlenecks	RQ1, RQ2	SME Adopter	SME3
We didn’t want to block AI like banning the internet.	Bottom-up shadow AI use triggers formal, secure AI adoption	Adoption Barriers and Bottlenecks	RQ1, RQ2	SME Adopter	SME3

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
We needed a safe solution so employees stop using open websites.	Bottom-up shadow AI use triggers formal, secure AI adoption	Adoption Barriers and Bottlenecks	RQ1, RQ2	SME Adopter; AI Solution Provider	SME3; SP2
SMEs pay with money, data, time, and domain knowledge.	Multidirectional value exchange beyond monetary payment	Ecosystem Value Flows	RQ2	SME Adopter	SME1; SME3; SME4; SME5; C1; C2
Operational data for training.	Data as input currency for AI value creation	Ecosystem Value Flows	RQ2	SME Adopter; AI Solution Provider	SME1; SME5; SP4; SP1
Customer feedback on model quality.	Feedback loops as non-monetary value flows	Ecosystem Value Flows	RQ2	SME Adopter; AI Solution Provider	SME1; SME5; SP1; SP2; SP4
Reference customers, reviews, case studies.	Reputation and reference value as ecosystem currency	Ecosystem Value Flows	RQ2	SME Adopter; AI Solution Provider	SME3; SP1; SP2; SP4; I1
Personal relationship is crucial.	Trust as precondition for sensitive data and adoption decisions	Ecosystem Value Flows	RQ2	Cross-actor	SME1; SME2; SME5; C1; C2
Trust is mainly created in the direct provider relationship.	Trust-building as bilateral value flow	Ecosystem Value Flows	RQ2	SME Adopter; AI Solution Provider	SME1; SME3; SME4; SME5
Access to SMEs, stage at events, visibility.	Visibility and market access as intermediary-provided value	Ecosystem Value Flows	RQ2	Intermediary; AI Solution Provider; Consultant/Integrator	I1; I3; I4; SP1; SP4; C1; C2
Providers give specialist lectures, demos, sponsorships.	Content-for-access exchange between providers and intermediaries	Ecosystem Value Flows	RQ2	AI Solution Provider; Intermediary	I1; I3; I4; SP1; SP4
Consultants get demo access, training, and technical introductions.	Technology knowledge transfer from providers to consultants	Ecosystem Value Flows	RQ2	AI Solution Provider; Consultant/Integrator	C1; C2; C3; C6; SP2

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
We give providers SME requirements and market feedback.	Consultants as translators of SME needs to providers	Ecosystem Value Flows	RQ2	Consultant/Integrator; AI Solution Provider	C1; C2; SP1; SP2
The consultant came through a personal network.	Informal referrals as high-value ecosystem flow	Ecosystem Value Flows	RQ2	Cross-actor	SME5; C1; C2; SP4
Word of mouth is our most important sales channel.	Recommendations as non-monetary acquisition currency	Ecosystem Value Flows	RQ2	AI Solution Provider; Consultant/Integrator; SME Adopter	SP2; SP4; C2; SME5
Point out funding programs.	Funding information as intermediary value flow	Ecosystem Value Flows	RQ2	Intermediary; SME Adopter	I1; I2; I3; I4; SME2; SME4
The bank requires a business plan and risk assessment.	Financing approval as conditional monetary flow	Ecosystem Value Flows	RQ2	SME Adopter; Upstream Platform	SME2
We pay API costs and pass them on.	Upstream infrastructure costs flowing downstream	Ecosystem Value Flows	RQ2	Upstream Platform; AI Solution Provider; SME Adopter	SP2; SP4; SME4; SME5; C1
License revenues as reseller.	Platform alliances as consultant revenue stream	Ecosystem Value Flows	RQ2	Consultant/Integrator; Upstream Platform	C5; C6
Thought leadership as a free value flow into the market.	Knowledge assets as market-shaping value flows	Ecosystem Value Flows	RQ2	Consultant/Integrator	C6; I4
Customer time is a real cost factor.	Employee time as hidden implementation cost	Ecosystem Value Flows	RQ2	SME Adopter	SME1; SME5; C1; C2; C3
The data is there, but chaotic.	Data readiness as prerequisite for AI value realization	Adoption Barriers and Bottlenecks	RQ2	SME Adopter	SME1; SME2; SME5; SP4; C1; C3; C4

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
Data preparation is the biggest issue.	Data readiness as prerequisite for AI value realization	Adoption Barriers and Bottlenecks	RQ2	SME Adopter; AI Solution Provider; Consultant/Integrator	SME1; SME5; SP4; C1; C2; C3
Garbage in, garbage out.	Poor data quality undermining AI outputs	Adoption Barriers and Bottlenecks	RQ2	Cross-actor	SME5; C1; C4; SP4
Interfaces to the CRM system and ERP system.	Integration into legacy systems as bottleneck	Adoption Barriers and Bottlenecks	RQ2	SME Adopter; AI Solution Provider	SME1; SME4; SP3; SP4; C3
Our ERP is outdated.	Legacy IT infrastructure constraining AI adoption	Adoption Barriers and Bottlenecks	RQ2	SME Adopter	SME2; SME4; SP4; C2; C3
Orders come by phone, fax, email and Excel.	Fragmented process data limiting AI learnability	Adoption Barriers and Bottlenecks	RQ2	SME Adopter	SME2; SME1
Customer data is rather a difficult topic.	Data sensitivity and privacy concerns slowing implementation	Adoption Barriers and Bottlenecks	RQ2	SME Adopter; AI Solution Provider	SME1; SME3; SME5; SP2; SP4
Customers lack the skills and time.	SME capability gaps as adoption bottleneck	Adoption Barriers and Bottlenecks	RQ1, RQ2	SME Adopter	SME2; I3; I4; SP1; SP2; C1; C2
We simply don't have the time.	Operational overload preventing transformation work	Adoption Barriers and Bottlenecks	RQ2	SME Adopter	SME2; SME5; C1; C3
95 percent would have to be external.	Dependence on external implementation capacity	Adoption Barriers and Bottlenecks	RQ1, RQ2	SME Adopter; Consultant/Integrator; AI Solution Provider	SME2; SME1; SME5
There is no internal sponsor.	Missing internal ownership as implementation bottleneck	Adoption Barriers and Bottlenecks	RQ2	SME Adopter	I3; C2; SME2

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
One person drives the topic; if unavailable, everything stops.	Key-person dependency in SME AI adoption	Adoption Barriers and Bottlenecks	RQ2	SME Adopter	C1; SME2; SME5
Employees are afraid of losing their jobs.	Workforce acceptance and job-loss fears as adoption barrier	Adoption Barriers and Bottlenecks	RQ2	SME Adopter	SME1; SME4; SME5; I4
Older employees have extreme mistrust.	Generational differences in AI acceptance	Adoption Barriers and Bottlenecks	RQ2	SME Adopter	SME4; SME5
We don't know how to calculate the ROI.	ROI uncertainty blocking AI investment	Adoption Barriers and Bottlenecks	RQ2	SME Adopter	SME2; SME1; SME3; SP3; C1
Providers promise 20 to 30 percent savings, but related to what?	Distrust of provider ROI claims	Adoption Barriers and Bottlenecks	RQ2	SME Adopter	SME2; SME1; C1
Success-based pricing was a disaster.	Difficulty assigning causality for AI outcomes	Adoption Barriers and Bottlenecks	RQ2	Consultant/Integrator; AI Solution Provider	C1; C2; SP4; SME5
AI is a must, but the business case is unclear.	Strategic necessity without measurable short-term return	Adoption Barriers and Bottlenecks	RQ1, RQ2	SME Adopter; Consultant/Integrator	SME2; SME3; C4; SP3
The onboarding fee is a hurdle.	Upfront cost barriers in SME adoption	Adoption Barriers and Bottlenecks	RQ2	SME Adopter; AI Solution Provider	SP4; SME2; C2
SMEs compare consultant costs with employee costs.	Consulting value is undervalued relative to internal labor	Adoption Barriers and Bottlenecks	RQ2	SME Adopter; Consultant/Integrator	C2; C4; C6
Funding applications are too bureaucratic.	Public support exists but is hard to access	Adoption Barriers and Bottlenecks	RQ2	SME Adopter; Intermediary	SME2; SME5; I2; I3; I4
Banks are skeptical.	Financing constraints block AI investment	Adoption Barriers and Bottlenecks	RQ2	SME Adopter; Upstream Platform	SME2

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
GDPR and AI Act create uncertainty.	Regulation-induced hesitation	Adoption Barriers and Bottlenecks	RQ2	Cross-actor	SME1; SME2; SME3; SME4; SME5; I3; C1; C2; C6; SP1; SP2; SP4
Regulation also creates trust.	Compliance as both barrier and legitimacy mechanism	Adoption Barriers and Bottlenecks	RQ2	Cross-actor	SME1; SME3; SP2; SP4; I4
We need orientation first.	Intermediaries as early-stage sense-making actors	Ecosystem Roles and Co-ordination	RQ1, RQ2	Intermediary; SME Adopter	I1; I2; I3; I4; SME2; C2
We do not implement; we orient.	Intermediary role as awareness builder rather than executor	Ecosystem Roles and Co-ordination	RQ1	Intermediary	I1; I2; I3; I4
Duty of neutrality.	Neutrality as role constraint and trust mechanism	Ecosystem Roles and Co-ordination	RQ1, RQ2	Intermediary	I1; I2; I3; I4
We do not recommend specific providers by name.	Neutrality limiting actionable matchmaking	Ecosystem Roles and Co-ordination	RQ1, RQ2	Intermediary	I1; I2; I3
Providers want to turn events into sales events.	Tension between neutral ecosystem facilitation and provider sales	Ecosystem Roles and Co-ordination	RQ2	Intermediary; AI Solution Provider	I1; I3; I4
Practical examples are stronger than lectures.	Peer use cases as intermediary sensemaking mechanism	Ecosystem Roles and Co-ordination	RQ1, RQ2	Intermediary; SME Adopter	I1; I3; I4
The IHK events are too general.	Generic intermediary offerings failing industry-specific needs	Ecosystem Roles and Co-ordination	RQ2	SME Adopter; Intermediary	SME2; SME4; SME5; SP2; SP4; C1; C2
Intermediaries are not relevant as acquisition channels.	Weak provider-side value of general intermediaries	Ecosystem Roles and Co-ordination	RQ2	AI Solution Provider; Intermediary	SP1; SP2; SP4; C6

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
Associations closer to the industry are more relevant.	Industry-specific intermediaries outperform generic ones	Ecosystem Roles and Co-ordination	RQ1, RQ2	Intermediary; AI Solution Provider; SME Adopter	SME5; SP4; I4
There is no overarching AI eco-system management.	Fragmentation of ecosystem coordination	Ecosystem Roles and Co-ordination	RQ1, RQ2	Intermediary; Cross-actor	I1; I3; I4
Too many parallel structures.	Fragmented support landscape confusing SMEs	Ecosystem Roles and Co-ordination	RQ2	Intermediary; SME Adopter	I1; I3; C1
Consultants translate between business and technology.	Consultant as boundary-spanning translator	Ecosystem Roles and Co-ordination	RQ1, RQ2	Consultant/Integrator	C1; C2; C6; SME5
Solution providers also advise.	Role blurring between provider and consultant	Ecosystem Roles and Co-ordination	RQ1	AI Solution Provider; Consultant/Integrator	SME1; SME4; SP1; SP3; C1; C2
Fraunhofer sits between research and consulting.	Hybrid intermediary/research/consulting role	Ecosystem Roles and Co-ordination	RQ1	Intermediary; Consultant/Integrator	I1; I2; C1; C5
Research institutes need SMEs for funding projects.	Research as ecosystem actor with its own incentives	Ecosystem Roles and Co-ordination	RQ1, RQ2	Intermediary; SME Adopter	I1; I2; I4
We measure activity, not impact.	Intermediary impact measurement gap	Ecosystem Roles and Co-ordination	RQ2	Intermediary	I3; I1; I4
We measure awareness, but not adoption.	Intermediary impact measurement gap	Ecosystem Roles and Co-ordination	RQ2	Intermediary	I3
Number of events and participants.	Activity-based intermediary KPIs	Ecosystem Roles and Co-ordination	RQ2	Intermediary	I1; I3; I4
Implementation outcomes disappear after handover.	Loss of visibility after intermediary referral	Ecosystem Roles and Co-ordination	RQ2	Intermediary	I1; I3; I4

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
Sponsor KPIs reward reach rather than depth.	Funding metrics shaping intermediary behavior	Ecosystem Roles and Coordination	RQ2	Intermediary; Upstream Platform	I1; I3; I4
The second level behind us is missing.	Upstream platform dependence	Structural Dependencies and Power Asymmetries	RQ1, RQ2	Upstream Platform; AI Solution Provider	SP2; SP3; SP4; SME4; SME5; C1; C3; C5; C6
Hyperscalers and LLM providers determine what we can offer and at what price.	Upstream platform dependence	Structural Dependencies and Power Asymmetries	RQ1, RQ2	Upstream Platform; AI Solution Provider	SP2; SP3; SP4; C1; C6
If OpenAI doubles API prices, it changes our business model.	Upstream pricing power and downstream pass-through	Structural Dependencies and Power Asymmetries	RQ2	Upstream Platform; AI Solution Provider; SME Adopter	SP4; SME4; SME5; C1
SAP, Microsoft Dynamics, SAGE interfaces are critical.	ERP/CRM vendors as hidden integration gatekeepers	Structural Dependencies and Power Asymmetries	RQ1, RQ2	Upstream Platform; AI Solution Provider	SP3; SP4; C3; C5
If ERP providers change their interfaces, we have a problem.	Interface dependency and loss of control	Structural Dependencies and Power Asymmetries	RQ2	Upstream Platform; AI Solution Provider	SP4; C3
Our provider buys cloud and AI models; we don't know who is behind it.	SMEs exposed to invisible upstream dependencies	Structural Dependencies and Power Asymmetries	RQ2	SME Adopter; Upstream Platform	SME4; SME5
Consultant alliances influence what is recommended.	Certification and alliance portfolios shaping solution choice	Structural Dependencies and Power Asymmetries	RQ1, RQ2	Consultant/Integrator; Upstream Platform	C3; C5; C6; C4
If I have 50 Azure consultants and 3 AWS consultants, the recommendation tends one way.	Capability lock-in through consultant specialization	Structural Dependencies and Power Asymmetries	RQ1, RQ2	Consultant/Integrator; Upstream Platform	C6

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
Vendor lock-in.	Dependency on provider-specific systems and knowledge	Structural Dependencies and Power Asymmetries	RQ2	SME Adopter; AI Solution Provider	SME1; SME2; SP1; SP2; SP4; C1
Afraid of dependencies.	SME concern over external lock-in and loss of control	Structural Dependencies and Power Asymmetries	RQ2	SME Adopter	SME1; SME2; SME5
The trained model belongs to us, but it is a grey area.	Ambiguous ownership of learned models and derived knowledge	Structural Dependencies and Power Asymmetries	RQ2	SME Adopter; AI Solution Provider	SME1; SP4
Risk lies with the customer.	Asymmetric allocation of business risk	Structural Dependencies and Power Asymmetries	RQ2	SME Adopter; AI Solution Provider; Consultant/Integrator	SP1; SP2; SP4; C1; C2; C4; C5
We bear platform risk, but not performance promises.	Technical risk separated from business-outcome risk	Structural Dependencies and Power Asymmetries	RQ2	AI Solution Provider	SP2; SP4
Reputational risk is bidirectional.	Contractual risk and reputational risk diverge	Structural Dependencies and Power Asymmetries	RQ2	Cross-actor	SP3; SP4; C2
Competent, affordable, and neutral at the same time.	Structural mismatch between SME needs and support-market offerings	Structural Dependencies and Power Asymmetries	RQ1, RQ2	SME Adopter; Consultant/Integrator; AI Solution Provider	C6; C2; SME2
Large consultancies are too expensive, boutiques lack technical depth, providers have conflicts of interest.	Structural support gap in SME AI ecosystem	Structural Dependencies and Power Asymmetries	RQ1, RQ2	Cross-actor	C6; C2; C1; SME2
Regulation and funding sit outside the ecosystem but govern what happens inside.	Institutional dependency shaping adoption feasibility	Structural Dependencies and Power Asymmetries	RQ2	Upstream Platform; Cross-actor	SME2; SME3; SME4; SME5; I2; I3; I4; C1; C2; C6

First-Order Code (informant language)	Second-Order Code (researcher theme)	Aggregate Dimension	Relevant to RQ	Actor Type(s)	Interview ID(s)
Government, regulator, bank and funding bodies are missing actors.	Institutional actors as structural ecosystem constraints	Structural Dependencies and Power Asymmetries	RQ1, RQ2	Upstream Platform; SME Adopter	SME2; SME3; SME4; I2; I3; I4; C1; C2; C6