

Krome, Maximilian Julius

Article

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Ecosystem Selection Criteria and Implications: A Conjoint Experiment of Ecosystem Partners' Decision-Making

Maximilian Julius Krome 

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Abstract The business ecosystem literature suggests that orchestrators must attract partners by offering a competitive partner value proposition (PVP). Despite the importance of attracting sufficient partners, PVP elements have only been viewed through the orchestrator's lens. No study has addressed the decision process of partners or asked how they choose an ecosystem with which to cooperate. We address this gap through a choice-based conjoint analysis based on actual screening decisions of partner facilities in German sports aggregation ecosystems. We explore partner preferences and the attributes that constitute their decisions, documenting obstacles to ecosystem thinking, heterogeneous preferences among partners, and the need for a more differentiated view of ecosystem network effects. Our findings contribute to the understanding of partners' decision processes and have implications for orchestrators in developing competitive PVPs.

JEL CODES L100 · L110 · L224 · M100 · M110

Abbreviations

PVP	Partner value proposition
CVP	Customer value proposition
BE	Business ecosystem
Aggregator	The orchestrator/focal firm of a sports aggregation ecosystem
Partners	Ecosystem participants, contributors, and complementors
WTA	Winner-takes-all dynamics
MNL	Multinomial logit
HB	Hierarchical Bayes

✉ Maximilian Julius Krome
Fakultät VII Wirtschaft und Management, Technische Universität Berlin, Straße des
17. Juni 135, 10623 Berlin, Germany
E-Mail: maximilian.krome@icloud.com; krome@campus.tu-berlin.de

OLS	Ordinary Least Squares
CBC	Choice-based Conjoint

1 Introduction

Business ecosystems (BEs) have become a topic of scholarly interest throughout the global economy (Evans and Schmalensee 2016; Jacobides et al. 2024; Kapoor 2018; Rong et al. 2024). While multiple synonyms for BEs exist, including platform firms, two-sided markets, innovation and transaction ecosystems (Thomas and Autio, 2020), they describe a set of actors interacting to deliver a joint value proposition (Adner, 2017). Through the collaborative aspect, ecosystems enable value creation beyond the individual capacity of each participant (Boudreau, 2012; Dattee et al., 2023; Jacobides et al., 2018; Kapoor, 2018). BEs bring together different participant groups, such as partners and customers (McIntyre et al., 2021), and generally benefit from network effects; the more participants there are, the more attractive joining becomes, leading to potential winner-takes-all dynamics (WTA) (Armstrong, 2006; Eisenmann et al., 2006; Inoue, 2019; Pidun et al., 2020, 2022; Rochet & Tirole, 2003). While this effect is best documented for platform firms due to their definitory distinctiveness the logic holds true for the broader Business Ecosystem which benefits from a higher number of participants on the user or the partner side (Awano & Tsujimoto, 2022; Inoue, 2019; Krome & Pidun, 2023; Pidun et al., 2020, 2022).

While multiple synonyms for business ecosystems exist, including two-sided markets, digital and software platforms, and innovation and transaction ecosystems (Daymond et al., 2023; Martín-Peña et al., 2024; Wegner et al., 2024), we follow the logic of Thomas and Autio (2020) and understand the business ecosystem as a conglomeration of actors that create a clear value proposition targeted at a defined audience (Adner 2017).

Ecosystems attract users through an attractive customer value proposition (CVP). However, orchestrators must develop a partner value proposition (PVP) to attract and retain ecosystem partners (Cennamo, 2018; Krome & Pidun, 2023) that voluntarily cooperate (Rietveld et al., 2019). Taking Amazon and its marketplace universe as an example, the CVP clearly depends on the orchestrator's choice which verticals to offer on its platform and which quality range to allow for sale (Cennamo, 2018; Zhou & Song, 2018). Amazon must thus position itself somewhere between a one-stop shop and a specialist retailer while trading off lower quality range volume business with high-quality margins. Simultaneously, these decisions influence which and how many ecosystem partners to allow access to its platform. Fewer vendors make it easier for Amazon to control products offered and their quality while more partners make the shopping experience for customers more appealing (Boudreau, 2012). The ease of access contributes to an attractive PVP as do decisions how tightly Amazon controls partner activity, how it charges them for participation and how much stability partners are guaranteed (Dushnitsky et al., 2022; Zhou & Song, 2018).

Previous studies have explored different elements of a PVP such as how open and accessible an ecosystem should be (Boudreau, 2012; Mukhopadhyay et al., 2016;

Pereira et al., 2019), how to manage the degree of internal competition between ecosystem participants (Rysman, 2009), how to best distribute value to keep partners engaged (Iansiti & Levien, 2004; Martin et al., 2017; Tiwana, 2014), and how to generate a compelling offer to attract and retain ecosystem partners (Birkinshaw, 2019; Cennamo, 2018; Cusumano et al., 2019; Rietveld & Schilling, 2021). But despite the importance of partners in an ecosystem, few studies examined their strategic decision-making, such as the essential decision of whether to engage in an ecosystem, and in which one (Iansiti & Levien, 2004; Krome & Pidun, 2023). To the best of our knowledge, no study addresses how partners approach this strategic decision for or against a potential ecosystem for cooperation. Understanding how partners evaluate and trade off different PVP elements is essential, as it allows us to deduce how orchestrators can further improve their PVP offerings.

Thus, the following research questions guide this study: How do ecosystem partners decide which ecosystems to cooperate with? Which factors are relevant to decision-making?

To assess how partners consider whether and with which ecosystems to cooperate, we compare decision-making across (potential) partners of sports aggregation ecosystems. Such an ecosystem comprises three participants: a sports aggregator (orchestrator), independent physical sports facilities (partners), and individual users (customers) of sports facilities. The aggregator builds a partner base of sports facilities that allow external users to access their facilities in return for usage fees. The aggregator provides this service to customers who pay a monthly subscription fee for flexible usage of the aggregator's network of partner facilities¹. The partners—-independent sports facilities—consider whether they want to participate in this ecosystem and, if so, with which one of the multiple providers. We used a conjoint analysis of actual 1410 screening decisions made by 141 real sports facilities in Germany to analyze this decision. Conjoint analyses more accurately represent the actual decision behavior and underlying preference structures than post-hoc approaches such as interviews or questionnaires (Shepherd & Zacharakis, 1999, 2018). They measure decision preferences conjointly by making tradeoffs between criteria. This experiment allows us to better understand the decision attributes of partners and provides the first comparative evaluation of different PVP elements.

The contributions of this study are as follows. First, we identify the set of attributes that partners consider in sports aggregation ecosystems and highlight that the importance of an attractive PVP is ecosystem-dependent. Second, we show that partners may not have adopted ecosystem thinking when engaging and may see ecosystems rather as a source of incremental revenue. Third, we empirically document that partners are not homogeneous but that heterogeneous preferences may require orchestrators to develop a more differentiated PVP. Fourth, our data challenge the universality of WTA assumptions and highlight the need to differentiate between network effects on the global and local scales.

The remainder of this paper is organized as follows: Section 2 presents the theoretical background of this study. Section 3 explains the research design and sample.

¹ These customers can be private individuals (B2C) or companies that offer the service as a subsidized benefit to their employees (B2B).

Section 4 presents the study's results, which we discuss in Section 5. Finally, Section 6 concludes the paper and highlights areas for future research.

2 Theoretical Background

Transferred from the field of biology, the *ecosystem* term refers to a group of independent firms that interact and depend on each other's activities (Moore, 1999). These firms are not directed through hierarchical structures or open market mechanisms (Rietveld et al., 2019) but instead voluntarily coalesce to create a value proposition (Adner, 2017; Jacobides et al., 2024). Ecosystems bring together two or more distinct participant groups (McIntyre et al., 2021), and the ability to attract (and retain) participants is an essential success factor. Not only are the right participants required to contribute their capabilities to the value proposition, but the more participants, the more opportunities they have to interact (Eisenmann et al., 2006).

This phenomenon describes the network effects² inherent to ecosystems, where an increase in one participant group creates value for other participant groups (Evans, 2003; Rochet & Tirole, 2003). Network economists argue that network effects are the main drivers of ecosystem value and success (Armstrong, 2006; Cennamo & Santaló, 2013). The logic that more participants continuously increase the attractiveness of the ecosystem leads to WTA dynamics (M. L. Katz & Shapiro, 1992), suggesting that the selected ecosystem will become so popular that it can dominate a market (Cennamo, 2018; Gawer & Cusumano, 2008).

Thus, attracting participants is a central necessity, but not straightforward (Dushnitsky et al., 2022). Orchestrators aim to align participants of multiple groups that pursue economic self-interest and differ in their characteristics (Adner, 2017; Foss et al., 2023; McIntyre et al., 2021; Rietveld et al., 2019)³. Adner (2017) argues that alignment in which all actors are content with their positions is a major challenge for an ecosystem. This necessity of aligning and balancing different interests between participants contrasts ecosystem strategy with traditional strategy, in which the firm focuses on creating a competitive advantage (Adner, 2006, 2017; Sulich & Soloduchko-Pelc, 2024). While firms previously attracted customers by providing a competitive and superior CVP, ecosystem orchestrators now face the additional challenge of attracting the right partners to do so. In addition to the CVP, orchestrators must provide a PVP that makes the ecosystem relatively more attractive than competing ecosystems in attracting the best partners (Cennamo, 2018; Krome & Pidun, 2023).

² Network effects can arise between participants in their own group ("direct" or "same-side" network effects), such as in the number of users on a social media platform. Alternatively, they can arise between different groups ("indirect" or "cross-side"), when the increase of participants in one group creates value for participants of other groups, such as app developers and app users (Hagiu & Spulber, 2013; Rochet & Tirole, 2003; Zhu & Iansiti, 2019).

³ The research stream focusing on the "chicken-and-egg-problem" deals with the question of how to attract different participants groups, and especially what benefits to offer to one group such that they start creating value for another (Karhu et al. 2020; Parker and van Alstyne 2014; Rochet and Tirole 2003).

The literature already provides insights into the potential factors that contribute to an attractive PVP (Hilbolling et al., 2020; Krome & Pidun, 2023; Rietveld & Schilling, 2021; Rong et al., 2020). Partners are fundamentally economically incentivized (Rietveld et al., 2019); accordingly, their interest in ecosystem participation depends on their ability to generate revenue. BEs address these challenges by providing reach, branding power, and scalability to tap into new revenue pools (Cusumano et al., 2019). The ability to orchestrate innovation enables BEs to monetize hitherto untapped models, such as the sharing economy (Chen et al., 2019) or notoriously volatile industries with high levels of uncertainty (Rong et al., 2013). In addition to accessing new markets, partners can benefit from previously unreached markets; for example, Jin and Hurd (2018) show that BEs can solve intercultural challenges and thus provide an effective channel for internationalization. Moreover, BEs have shifted the focus of competition away from individual competitive (asset) advantages aimed at gaining market share toward growing the overall market size, implying increased value potential for all participants (Birkinshaw, 2019; Cennamo, 2018).

Apart from the initial motivation to engage in the first place, several other factors can make ecosystems more appealing. As partners often decide between competing ecosystems, orchestrators must ensure that they attract partners by creating a more attractive PVP than their competitors (Cennamo, 2018; Gawer & Cusumano, 2002; Iansiti & Levien, 2004). The general conditions under which partners join and collaborate within the ecosystem are broadly termed “governance,” and include mechanisms for control, pricing, and pie-sharing (Altman et al., 2022; Tiwana, 2014), as well as mechanisms to incentivize collaboration and deepen cooperation among ecosystem participants (Martin et al., 2017). Authors agree that ecosystem governance is “*about ‘pleasing all sides’ [...] as much [as] it is about platform profit-seeking*” (Boudreau & Hagiu, 2009, p. 186), indicating that again a balance of different factors is needed.

As the first significant governance decision, the orchestrator determines *who* can contribute to the ecosystem and *what* can be contributed. Openness is a key control mechanism for orchestrators to regulate who can affiliate with the ecosystem (Boudreau, 2012; Pereira et al., 2019). This access control allows the regulation of the number of participants and the quality of the offer. When access is easy, the number of participants increases, making coordination and quality assurance for the orchestrator more difficult (Gulati et al., 2012; Mukhopadhyay et al., 2016). Access to ecosystems is important for two reasons. First, partners expect their ecosystems to provide sufficient customers of the right types (G. Parker et al., 2016). Second, access regulates the number of (competing) partners an orchestrator allows. Although a higher number of ecosystem partners increases the value of the overall platform, partners do not value direct competitors that potentially compete for the same customer attention (Cennamo, 2021; Halaburda et al., 2018).

Besides deciding who contributes to the ecosystem, the orchestrator should ensure that partners can monetize the value proposition and successfully satisfy their revenue ambitions. Consequently, partners value orchestrators’ actions that actively support them in facilitating transactions. The literature provides various examples of orchestrator efforts such as active marketing support and promotion (Benlian et al., 2015; Cennamo & Santaló, 2019; Rietveld et al., 2019), co-branding cam-

paigns (Wareham et al., 2014), priority listing (T. L. Huber et al., 2017), and quality assurance and rating systems (Pereira et al., 2019; Rietveld et al., 2020).

In addition to facilitating transactions, ecosystems can strengthen their PVPs by providing further resources to underline the partnership approach and envisioned level of cooperation. Orchestrators offer a common platform or basic services (Iansiti & Levien, 2004), but they can further attract partners by empowering them to create value and enhance their offerings. For example, orchestrators support by sharing business intelligence in the form of market reports (T. L. Huber et al., 2017), creating space for collaboration through software documentation (Benlian et al., 2015), development kits (Eaton et al., 2015), complementor conferences (Foerderer, 2020), forums (Boudreau & Hagi, 2009), and other support such as business plans (Hukal et al., 2020) or financing lines (Wareham et al., 2014).

Finally, ecosystems set pricing mechanisms to provide incentives and split value in the ecosystem. The orchestrator can subsidize partners to attract participants to the ecosystem and kickstart network effects (Armstrong, 2006; Caillaud & Jullien, 2003; G. G. Parker & Van Alstyne, 2005). In addition, ecosystems can implement transaction or membership fees to split the value and risks between the participants and orchestrators (Tiwana, 2014). Eventually, partners react sensibly to changes in pricing structures, and scholars agree that partners are attracted to well-governed ecosystems that protect their margins (Gawer, 2014). If partners risk becoming unprofitable, they are more likely to leave the ecosystem (Zhang & Liang, 2011).

In summary, the literature thematizes the different constituents of an attractive PVP, including economic factors such as revenue and softer contributors such as ongoing support and provision of resources. Generally, a strong PVP draws from generating revenue, accessing favored customer types, and providing sufficient ecosystem resources to engage in innovation, value delivery, and collaborative activities with other participants. The partners are likely to choose the most promising ecosystem for long-term success (Evans & Schmalensee, 2016). The literature suggests that ecosystem size plays a role: the larger the existing base, the more benefits, such as increased visibility, ecosystem credibility, access to resources, and collaboration opportunities, and a more extensive customer and revenue base with the potential for network effects (Gawer & Cusumano, 2014; Iansiti & Levien, 2004; Ritala et al., 2014). Market positioning is essential, as the willingness to join an ecosystem increases exponentially with its existing base (Boudreau, 2012) and may even supersede other advantages, such as superior product quality vis-à-vis a comparable competitor (Zhu & Iansiti, 2012, 2019).

While existing research highlights the different PVP elements that are assumed to appeal to partners, such studies concentrate on how the orchestrator can operationalize these elements. Few studies considered the perspective of potential partners or even assumed their perspective regarding how partners evaluate PVP elements or select their ecosystems for cooperation (Altman, 2017). This is essential for two reasons. First, partners act strategically and independently; therefore, it is necessary to assume their perspectives to understand their strategic choices. Second, while the constituent PVP elements are known, there is no research on how partners evaluate or potentially trade-off between these elements. Given the importance of attracting the right partners for ecosystem success, a thorough understanding of how partners

select their ecosystem for cooperation will not only shed light on their strategic thinking but also allows us to evaluate how orchestrators can further improve their PVP offerings.

3 Methodology

In the following paragraphs, we briefly describe the empirical setting, highlighting why sports aggregation ecosystems are an ideal setting for our research. Then, we explain the research design and survey administration process. A flow diagram (Fig. 1) visualizes the steps followed.

3.1 Empirical Context

We conduct our experiment in the German sports aggregation market, which provides an appropriate setting for our research questions. Only the collaboration of three independent participants—the aggregator, individual users of sports facilities, and physical sports facilities—can realize this value proposition. The aggregator signs up a network of partner sports facilities that allow external users access in return for “per-check-in” compensation. Conversely, the aggregator attracts users by providing access to an appealing partner network for monthly subscription fees. As such, partners gain access to the aggregator’s additional user pool, and users benefit from a flexible offer, irrespective of their geographical location. This context is especially suitable for our question because of the competitive dynamics: multiple ecosystems⁴ coexist, and accordingly, aggregators actively compete for partners. Active aggregators differ in their attributes and, consequently, in their PVPs. In turn, sports facilities in the German market are confronted with whether to engage in a sports aggregation ecosystem, and if so, with which aggregator to cooperate.

3.2 Research Design

In our main study, we conduct an experimental conjoint analysis (Louviere et al., 2000) to investigate partners’ decision-making behaviors. Conjoint analysis is a type of discrete choice modeling that appeals to random utility theory (Louviere et al., 2000; Manski, 1977) purporting that individuals choose from sets of alternatives by maximizing their perceived utility (Albaladejo-Pina & Díaz-Delfa, 2009). McFadden (1974) pioneered the first multinomial logit model (MNL), but Louviere and Woodworth (1983) later developed choice modeling and first experimental designs. This technique involves participants making a series of decisions between alternatives in a choice set. The decisions allow the decomposition of the participant’s preference structure, unveiling how the decision maker trades off the importance of competing attributes that define the alternatives. This approach uncovers the under-

⁴ The most prominent ecosystems in the market include: Urban Sports Club, Hansefit, EGYM Wellpass, Gympass, and Gympool.

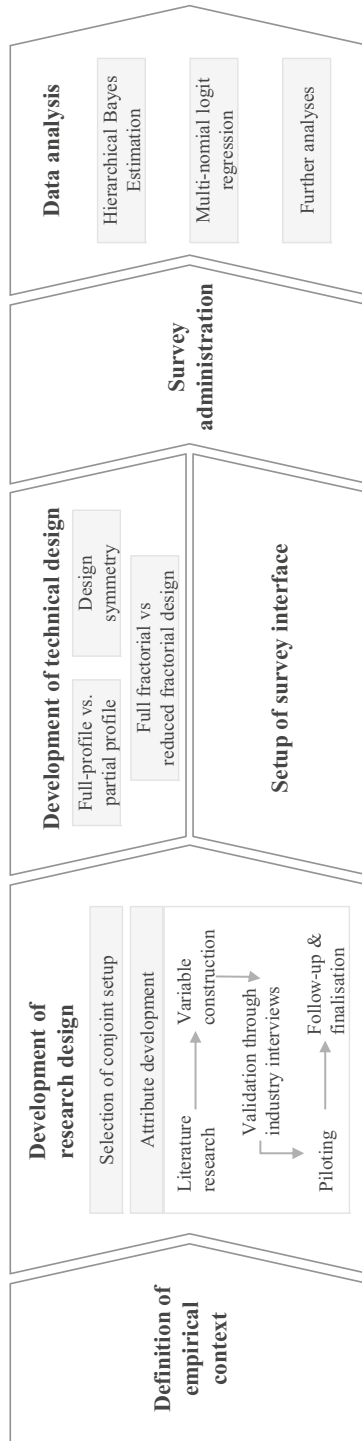


Fig. 1 Flow diagram of methodology

lying preferences as multiple decision criteria are analyzed conjointly and multivariately, reflecting the actual decision behavior more accurately.

Conjoint choice experiments are a standard procedure for analyzing preferences across disciplines (Kraus et al., 2017), such as marketing or transportation (Eggers & Sattler, 2011), hospitality and tourism products (Crouch & Louviere, 2001), environmental management, retailing and leisure (Adamowicz et al., 1998), and, nowadays, the field of venture capital or private equity (Ademi et al., 2023; Block et al., 2019; Wuebker et al., 2015). However, with a few exceptions, such choice experiments have not been applied to managerial decision-making (Kraus et al., 2017).

Post-hoc approaches, such as interviews or questionnaires, are limited because they collect information about a decision after it has been made (Shepherd & Zacharakis, 1999). Conjoint, however, overcomes this limitation as it collects information as the decision is made, which limits self-reporting and recall biases. Addressing the inherent doubt of external validity, previous research (e.g. Adamowicz et al., 1998; Shepherd & Zacharakis, 2018) supports conjoint studies, as their data strongly correlate with real-world decision behaviors.

3.2.1 *Choice-Based-Conjoint*

We use a choice-based conjoint analysis (CBC) in which objects (aggregators⁵) characterized by different attributes are evaluated by participants (decision makers of partner facilities⁶). Participants are asked to deterministically decide between multiple hypothetical orchestrator profiles that differ in the characteristics of their defined attributes but are assumed to be equal for everything else.

Before making the series of choices, we provided all participants with background information on the study, the attribute characteristics of the choices to be made, and the decision tasks. To ensure that all participants understood the decision tasks similarly, we summarized our understanding of orchestrator characteristics in the introduction. Participants were told that they would be confronted with a choice of multiple aggregators, between which they could decide on potential cooperation for their sports facility.

After each choice task, the participants had to indicate whether the alternatives displayed were attractive or unattractive for cooperation. This “dual-response” replaces the traditional “None” option and aims at better reflecting the participants’ real choice environment (Johnson & Orme, 2003).

3.2.2 *Identification and Derivation of Attributes*

Because alternative profiles for the choice experiment are constructed from combinations of attributes and levels, a critical aspect is finding appropriate attributes and respective levels to do so (Hoyos, 2010; Kim & Perdue, 2013). Simultaneously,

⁵ The orchestrator of the sports aggregation ecosystem builds a partner base of sports facilities to attract users.

⁶ The individual (potential) partners of the ecosystem offer access to their facilities to individual end users through the aggregator.

the design must be concise, as the size and complexity of the experiment increase exponentially with an increase in the number of attributes or levels per attribute (Crouch & Louviere, 2004; Hensher et al., 2005).

We proceed in three steps to identify a set of decision criteria used by facility owners. First, we derive a list of possible criteria from existing ecosystem research. Second, we translate these criteria into relevant variables visible in the sports aggregation market and actually used by both aggregators to differentiate and sports facilities when selecting an ecosystem. Third, we conduct six interviews with industry experts and sales functions of aggregators to identify potentially missing criteria and narrow the list to a conclusive set. Shepherd and Zacharakis (2018) highlight that conjoint experiments should reflect the participants' real-world environments to guarantee external validity. As such, after piloting the study, we followed up with industry respondents who confirmed that our final attribute list contained the relevant attributes used for decision-making in sports aggregation ecosystems and reflected the actual decision environment.

The identified attributes are (1) *partner network of the aggregator*, (2) *breadth of product offering*, (3) *channel*, (4) *handling/support*, (5) *risk sharing*, (6) *revenue potential*, and (7) *market position*. These criteria are generally in line with factors mentioned in ecosystem research that contribute to the attractiveness of an ecosystem from the partner's perspective⁷ (Sect. 2, "PVP"). Table 1 summarizes the attributes and outlines the operationalization, including the levels and descriptions.

3.3 Technical Design Information

Because (potential) partners consider their cooperation decisions holistically, we employed a full-profile CBC, which means that all attributes regarding the decision are presented to participants at once. Because all possible combinations of attribute levels result in too many decision tasks⁸ for one participant, CBC is usually paired with a "reduced conjoint design" (Chrzan & Orme, 2000). Furthermore, the design is "asymmetric" because the number of levels differs across the attributes⁹.

The study generated 300 designs¹⁰, each consisting of seven attributes whose levels were randomly assigned to three different aggregator profiles. Participants were asked to select one of the three profiles across 12 choice tasks. While ten of these tasks were randomly assigned, two were held constant across participants to allow for testing of test-retest reliability. Figure 2 shows an example of the choice tasks faced by the participants in various manifestations.

CBC designs can suffer from different types of order effects (Chrzan, 1994), which can be accounted for in addition to randomly assigning participants to experimental designs. To mitigate the impact of the (1) *order of attributes* effect, the

⁷ Table 2 provides an overview of exemplary literary sources for each topic.

⁸ Our setup contains 432 combinations.

⁹ An asymmetric design is aided by a balanced-overlap approach, which is a common design strategy for CBC studies (e.g. Chrzan & Orme, 2000).

¹⁰ The generated 300 possibilities are less than the possible 432 combinations due to the balanced-overlap approach, which aims to reduce computational effort in conjoint studies (Chrzan & Orme, 2000).

attribute order within a choice task was randomized across participants and only kept the same for any one participant. We avoided the impact of (2) *order of options in a choice task* effect because the three options within any given choice task were randomly ordered. Finally, we addressed the (3) *order of choice tasks* effect as the choice tasks were randomly ordered in each design.

Before conducting the survey, we tested the design with four potential respondents and four researchers to ensure the study logic, clarity of the tasks, validity of attributes, and the challenge of the complexity and number of choice tasks to complete.

3.4 Administration of Survey, Data, and Sample

We used the SSI Web survey to conduct the CBC survey. For ease of use, immediacy, time-saving, and higher response rates, web-based surveys provide an appropriate means of collecting data (Caussade et al., 2005). The final questionnaire contained three sections: (1) background information about the study, (2) respondents' demographic data, and (3) 12 choice sets.

Through a German Industry Association (DSSV), we identified fitness facilities that were willing to assist in distributing the survey through an affiliated specialist journal. The survey was administered in February 2023 through a newsletter directed

Table 1 Differentiation potential observed along strategic variables

Attribute	Attribute levels	Attribute description
Partner network of the aggregator (3 levels, nominal)	1. Nationwide, relatively less dense 2. Nationwide, urban centers 3. Relatively small and regional	Describes the existing geographical footprint of the network of partner facilities of the aggregator
Breadth of product offering (2 levels, ordinal)	1. Broad offering 2. Concentrated offering	Describes the breadth of sport types currently on offer for the aggregator
Channel of the aggregator (3 levels, nominal)	1. B2C 2. B2B 3. B2B & B2C	Describes which end user the aggregator channels to the facilities: B2C are private individuals and B2B are the employees of corporate clients
Handling/support of the aggregator (2 levels, nominal)	1. Aggregator supports 2. No support	Degree to which aggregator supports participating partners, e.g., marketing, sales, administration
Risk sharing (2 levels, nominal)	1. Potential/risk shared with aggregator 2. Potential/risk with aggregator	Describes who carries both downside risk and potential upside of fluctuating demand
Revenue potential (3 levels, ordinal)	1. Same or more as existing user 2. 70–100% of existing user 3. Less than 70% of existing user	Amount of revenue generated per aggregator user compared to existing users of partner's facility
Market position of the aggregator (2 levels, ordinal)	1. Top 3 2. Not top 3	Describes how well-positioned the aggregator is in the overall market

at 8000 facility owners and managers. There were two reminders over the course of eight weeks. A total of 2258 respondents took part in the request to participate in the study, of which 249 began with the choice task section. After cleaning our sample for responses that did not complete all 12 CBC tasks, we retained 141 complete responses¹¹. The descriptive statistics for our sample are summarized in Table 3 and 4.

We then apply a Hierarchical Bayes (HB) procedure to calculate the part-worth utilities for all attribute levels. Historically, conjoint analysis researchers used metric approaches and ordinary least squares (OLS) regression models to estimate part-worth utilities. However, HB models, first introduced in 1995 (Allenby & Ginter, 1995; Lenk et al., 1996), gained popularity with the rise of CBC designs. In addition to OLS, the HB models employ two levels: a lower individual level (beta) and an upper population level (alpha). This property allows the model to compensate for missing information at the individual level by “borrowing” information from the overall population¹². This is advantageous because the estimation of individual part-worth utilities deals with preference heterogeneity problems, which is essential in fractional factorial designs where OLS approaches may result in less precise

Table 2 Study attributes and relevant references to the ecosystem literature

Attribute	Literature references (non-exhaustive)
Partner network of the aggregator	Discussion of network effects: Eisenmann et al., 2006; Armstrong, 2006; Cennamo and Santalo, 2013; Zhu and Iansiti, 2019; Rochet and Tirole 2003; Hagiu and Spulber, 2013; Katz and Shapiro, 1992
Breadth of product offering	Discussion of openness for the channel (customer) and product offer (partner): Boudreau, 2012; Pereira et al., 2019; Gulati et al., 2012; Mukhopadhyay et al., 2016; Parker et al., 2016; Rysman, 2009; Cennamo, 2021; Halaburda et al., 2018
Channel of the aggregator	
Handling/support of the aggregator	Examples of concrete resources: Cennamo and Santalo, 2019; Benlian et al. 2015; Rietveld et al. 2019; (marketing support and promotion), Huber et al., 2017 (market reports), Boudreau and Hagiu, 2009 (partner forums), Hukal et al., 2020 (business plans), Wareham et al., 2014 (financing lines)
Risk sharing	General governance discussion and ‘pie-sharing’ mechanisms: Tiwana, 2014; Martin et al., 2017; Gawer and Cusumano, 2002; Cennamo, 2018; Iansiti and Levien, 2004
Revenue potential	Discussion of revenue potential, ecosystem benefits, and partner attractiveness: Birkinshaw, 2019; Cennamo, 2018; Chen et al., 2019; Rong et al., 2013; Jin and Hurd, 2018; Cusumano et al., 2019; Rietveld et al., 2019; Gawer, 2014; Zhang and Liang, 2011
Market position of the aggregator	Discussion of network effects and dominant positioning: Ritala et al., 2014; Gawer and Cusumano, 2014; Katz and Shapiro, 1992; Cennamo and Santalo, 2013; Iansiti and Levien, 2004; Evans and Schmalensee, 2016

¹¹ The individual 141 responses came mostly from non-chain facilities ($n=131$), suggesting independent decision-making, while 10 respondents represented chains. Overall, the 141 individual participants represented 235 facilities for whom the decision data were applicable.

¹² Please see Sawtooth Software (2021) for a more detailed description of the Hierarchical Bayes procedure.

Breadth of product offering	Concentrated offering	Broad offering	Concentrated offering
Amount earned with an aggregator customer	Less than 70% of revenue of existing customer	More than or same revenue as existing customer	Between 70 – 100% of revenue of existing customer
Market position of aggregator	Non-top 3	Top 3	Top 3
Channel of the aggregator	Both, B2C and B2B	B2B (corporate clients)	B2C (private customers)
Handling/support of the aggregator	Aggregator supports	Aggregator does not support	Aggregator does not support
Partner network of the aggregator	Nationwide, relatively less dense	Nationwide, relatively less dense	Nationwide, urban focus
Sharing of utilization risk	Potential/risk shared with aggregator	Potential/risk carried by aggregator	Potential/risk carried by aggregator
	<input type="button" value="Select"/>	<input type="button" value="Select"/>	<input type="button" value="Select"/>

Given the choices, would you decide to cooperate with an aggregator?

Fig. 2 Sample choice task from web-based survey

estimates (Lenk et al., 1996; Rossi et al., 2006). We follow the common approach of applying the HB procedure to calculate the MNL model parameters (Johnson, 2000; Sawtooth Software, Inc., 2021; Train, 2009). HB is the most sophisticated method for estimating discrete choices in experiments. In addition, Table 5 presents the results of a simple MNL estimation of part-worth utilities to validate the HB robustness and for readers who are less acquainted with this method.

4 Results

4.1 Main Results

Our results are based on the responses of 141 participants who completed the survey fully, resulting in 1410 choice tasks. The main results of our conjoint experiment are displayed in Tables 5 and 6, which present the analysis of the utility parameters for

Table 3 Descriptive statistics

Sample characteristics	<i>N</i>	%
<i>Type of facility</i>		
Individual facility	94	67
Chain	10	7
Micro facility	29	21
EMS facility	8	6
<i>Number of facilities represented</i>	235	
<i>Location of facility</i>		
Small town	39	28
Small city	38	27
Medium-size city	18	13
Large city	46	33
<i>Strategic orientation</i>		
Rather short-term	26	18
Rather long-term	110	78
Other	5	4
<i>Target customer group</i>		
Broad target group	74	52
Specific/selected target group	67	48
<i>Competitors in proximity</i>		
<2	27	19
2–5	53	38
5–10	44	31
>10	17	12
<i>Competitive intensity</i>		
Low	35	25
Medium	81	57
High	25	18
<i>Utilization of facility</i>		
Low	16	11
Medium	100	71
High	25	18
<i>Growth trajectory</i>		
Decreasing member numbers	7	5
Stable	54	38
Increasing member numbers	80	57
<i>Profitability</i>		
Low	30	21
Medium	86	61
High	25	18
<i>Existing cooperation with aggregator</i>		
Yes, with one	48	34
Yes, with multiple	46	33
No, with none	47	33

Table 4 Descriptive statistics

Sample characteristics	N	Mean	SD	Min	Max	Description
Type of facility	141	1.65	0.99	1	4	Type of facility where respondent is employed (categorical: 1 = individual facility, 2 = chain, 3 = micro facility, 4 = EMS facility)
Number of facilities represented	141/237	1.68	2.26	1	22	Number of facilities which individual respondent represents (interval)
Location of facility	141	2.50	1.21	1	4	Type of environment in which facility is located (categorical: 1 = small town, 2 = small city, 3 = medium-size city, 4 = large city)
Strategic orientation	141	1.85	0.45	1	3	Time horizon for which strategic decision are made (categorical: 1 = rather short-term, 2 = rather long-term, 3 = other)
Target customer group	141	1.48	0.50	1	2	Target customer segment of the facility (categorical: 1 = broad target group, 2 = specific/selected target group)
Competitors in proximity	141	2.36	0.93	1	4	Number of competitors in direct proximity (10 min drive) (categorical: 1 = > 2, 2 = 2–5, 3 = 5–10, 4 = > 10)
Competitive intensity	141	1.93	0.65	1	3	Degree of perceived competitive intensity for facility (categorical: 1 = low, 2 = medium, 3 = high)
Utilization of facility	141	2.06	0.54	1	3	Current capacity utilization of facility (categorical: 1 = low, 2 = medium, 3 = high)
Growth trajectory	141	2.52	0.59	1	3	Current growth trajectory of the facility (categorical: 1 = decreasing member numbers, 2 = stable development, 3 = increasing member numbers)
Profitability	141	2.04	0.63	1	3	Current state of profitability of facility (categorical: 1 = low, 2 = medium, 3 = high)
Existing cooperation with aggregator	141	1.99	0.82	1	3	Facility's current experience with aggregators and status of cooperation (categorical: 1 = existing cooperation with one aggregator, 2 = existing cooperation with multiple aggregators, 3 = no existing cooperation)

each attribute level and the relative importance¹³ of the seven attributes in explaining the observed choices, respectively. The part-worth (utilities) are HB estimates that detail the average effect of any attribute level on the decision with which aggregator to cooperate. While positive values indicate higher desirability of an attribute level, negative values indicate lower desirability. Part-worth utilities are interval data scaled to zero within each attribute; thus, utilities are not directly comparable across attributes.

The preferences for the *partner network* attribute indicate that “relatively small and regional” networks provide the highest utility and are preferred over other network types, with “nationwide, urban centers” contributing the lowest utility. Similarly, the results for the *channel* attribute show that the “B2C” user segment contributes the lowest value to overall utility, whereas the “B2B” segment offers the highest part-worth utility. The attribute *revenue potential* reflects that making considerably less per aggregator customer compared to existing customers is the least preferred, and the highest potential is preferred. The level at which facilities earn an amount comparable to or slightly below what they make with current users seems relatively indifferent. The preferences for attribute levels related to the *support of the aggregator*, *risk sharing*, and *market position* follow a common logic; that is, aggregators that offer support, carry the risk exclusively, and have a good market position positively impact cooperation decisions. The preference for the last attribute, *breadth of product offering*, indicates that partners prefer concentrated offerings over broad offerings.

Utilities indicate preferences for a given attribute. In comparison, the relative importance values of the seven attributes (Table 6) indicate how strongly a change in the level of any attribute affects the total utility of an aggregator’s offering. The higher the value, the higher is the contribution of the respective attribute to the aggregator’s total utility value. To enable a better comparison, the values were normalized such that the sum of all importance values yielded 100% (e.g. Block et al., 2019). Overall, we can see that three attributes strongly influence the decisions. *Revenue potential* (31%), *channel* (21%), and *partner network* (18%) account for approximately 70% of the overall decision. Among the remaining attributes, *support of the aggregator* contributes ~10% of the overall decision, with the remainder accounting for ~6–7%. We use a two-sided Wilcoxon test for paired samples to assess whether the differences between the relative importance values are statistically significant. The approach is a non-parametric test used to analyze differences between measures of the same sample. It serves as an alternative to the Student’s t-test when the population cannot be assumed to be distributed normally but the data can be ranked (Neumann et al., 2020). The test shows that the relative importance values for the four most important attributes differ significantly whereas the difference between the values is insignificant for the least important attributes. This indicates that, with decreasing importance for the overall decision, the distinctiveness between attributes also decreases.

¹³ The relative importance value is calculated per attribute by taking the range between the highest and lowest part-worth utility within each attribute and scaling this value to 100 (%) across attributes (Orme, 2010).

Table 5 Results of the Hierarchical Bayes (HB) and multinomial logit (MNL) estimation for decision to cooperate with aggregator. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

	Hierarchical Bayes model			Multinomial logistic regression		
	Coefficient ^a	Standard error	Standard deviation	95% interval of posterior distribution ^b	Coefficient	Standard error
<i>Partner network of the aggregator</i>						
Nation-wide, relatively less dense	-0.14804	0.00121	0.10841	-0.15042	-0.03289	0.040
Nationwide, urban centers	-0.26840	0.00136	0.12173	-0.27107	-0.16477***	0.041
Relatively small and regional	0.41644	0.00174	0.15606	0.41302	0.19766***	0.039
<i>Breadth of product offering</i>						
Broad offering	-0.00688	0.00088	0.07872	-0.00860	-0.01327	0.028
Concentrated offering	0.00688	0.00088	0.07872	0.00515	0.01327	0.028
<i>Channel of the aggregator</i>						
B2C	-0.53470	0.00148	0.13204	-0.53759	-0.18568***	0.040
B2B	0.27359	0.00176	0.15720	0.27014	0.11539**	0.039
B2B & B2C	0.26111	0.00125	0.11211	0.25865	0.07028*	0.039
<i>Handling/support of the aggregator</i>						
Aggregator supports	0.37959	0.00091	0.08162	0.37780	0.14884***	0.028
No support	-0.37959	0.00091	0.08162	-0.38137	-0.14884***	0.028
<i>Risk sharing</i>						
Potential/risk shared with aggregator	-0.14421	0.00086	0.07726	-0.14590	-0.06138**	0.028
Potential/risk with aggregator	0.14421	0.00086	0.07726	0.14252	0.06138**	0.028
<i>Revenue potential</i>						
Same or more as existing user	1.33596	0.00199	0.17841	1.33205	0.54376***	0.039
70–100% of existing user	0.14492	0.00132	0.11798	0.14233	0.02753	0.040
Less than 70% of existing user	-1.48088	0.00205	0.18302	-1.48489	-0.57130***	0.044

Table 5 (Continued)

	Hierarchical Bayes model		95% interval of posterior distribution ^b		Multinomial logistic regression	
	Coefficient ^a	Standard error	Standard deviation		Coefficient	Standard error
<i>Market position of the aggregator</i>						
Top 3	0.23535	0.00086	0.07660	0.23702	0.09102***	0.028
Not top 3	-0.23535	0.00086	0.07660	-0.23367	-0.09102***	0.028
Number of observations	1410				1410	
RLH value ^c	0.649					
Log-likelihood					-1684.200	

^aThe coefficient estimates are equal to the means of the saved draws of the posterior population after convergence. As suggested by Train (2009), only every fifth out of the total of 40,000 draws was kept and used for calculation to reduce the correlation among draws from Gibbs sampling. Reported are the standard deviation of model coefficients' values per attribute level in the subsequent column. Coefficient estimates are interval scaled and zero centered within attributes.

^bThe 95% interval is calculated based on the posterior distribution population means per level used to calculate the coefficients. The interval gives an indication how reliable the coefficient estimates are across all draws of the modelling process.

^cRoot likelihood (RLH) measures the goodness of fit of the model in realistically depicting and predicting respondents' choices. RLH is calculated by taking the *n*th root of the likelihood where *n* reflects the total number of choices of respondents across tasks. 1 is the best possible value and the worst value is 1 divided by the number of concepts available per choice task (1/*j* with *j* being the number of alternative concepts per choice task) (Sawtooth Software, 2021).

Table 6 Average relative importance values of attributes based on Hierarchical Bayes model

Attribute	Average Importances	Standard deviation	z-value
Revenue potential	31.4571	16.7324	-4.992***
Channel of the aggregator	20.6775	12.6541	-1.705*
Partner network of the aggregator	18.1590	14.3029	-5.879***
Handling/support of the aggregator	9.3497	7.5778	-2.178**
Risk sharing	6.9787	5.5345	-0.020
Market position of the aggregator	6.9468	6.3559	-1.573
Breadth of product offering	6.4312	5.8760	
Total	100.0		

Z-value: A two-sided Wilcoxon test for paired samples shows that the difference between the relative importance values of these two attributes is significant. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

4.2 Differences Across Segments

Tables 7 and 8 contain the results of dedicated models for the selected segments of partner facilities for which we performed a subsample analysis. This analysis allows us to discern differences among partners and is motivated by the input gathered in the industry interviews. The input suggested that the facilities' decision rationale and customer behavior may differ based on the physical location. Furthermore, respondents indicated that the rationale for joining an ecosystem may be driven by the competitive pressure experienced. Finally, whether a facility already cooperates with an aggregator may strongly influence decision behavior. Accordingly, we performed subsample analyses using three categorical variables: (a) facility location, (b) competitors in proximity, and (c) existing aggregator cooperation.

Running a separate model for each sub-segment indicates whether the preferences are lower or higher for each sub-segment. However, a comparison could not discern whether these differences across segments are statistically significant. To address this issue, we estimate separate regressions that test different subsegments. The coefficients are the interaction terms that indicate whether the value of one segment differs significantly from that of the respective reference group. For example, Model 1 (Table 7) compares the preferences of facilities in different locations with the reference group of facilities in large cities. We estimate these regressions for part-worth utilities (Table 5) and the relative importance of the decision criteria (Table 6) across the selected segments. Below, we briefly describe the models used for each segment.

4.2.1 Location of Facility

Model 1 in Table 7 compares respondents' preferences across different locations against the reference group of facilities from large cities. The results show significant differences in preferences, mainly regarding the *partner network* of the aggregator and, to some extent, the *market position*. Regarding the network, we can see that facilities in small towns and medium-sized cities show a significantly lower preference for "large, nationwide networks" and a significantly positive pref-

Table 7 Model 1–3. Results of the conjoint analysis with comparison across respondent groups. This table shows the results of a regression, where the dependent variable is the preference of the decision maker and the independent variables are the respective category of partner facility. Each attribute level is interacted with the respective partner category. For example, in Model 1 every attribute level is interacted with a dummy variable that takes a value of 1 if the respective decision maker (partner) is situated in the given location and, and 0 if not. Focusing on interaction effects allows to identify differences. For example, Model 1 shows that partners from ‘small towns’ derive significantly lower utility from ‘nationwide, urban center’ networks compared to partners from large cities.

Model	(1)			(2)			(3)		
	Location of facility			Competitors in proximity			Existing aggregator cooperation		
	Small town	Small city	Medium-size city	2–5	5–10	> 10	Yes, with one	Yes, with more than one	R-squared
Partner network of the aggregator	Reference group: large city			Reference group: <2			Reference group: No existing cooperation		
Nation-wide, relatively less dense	-20.713 [15.070]	1.7333 [14.427]	8.5837 [18.028]	-3.8634 [15.622]	-10.829 [16.914]	-9.7690 [21.473]	-21.087 [13.721]	-33.968** [14.320]	0.1498
Nationwide, urban centers	-39.314*** [13.927]	-21.555 [13.334]	-44.676*** [16.661]	-8.6688 [14.438]	-3.3397 [15.632]	-25.384 [19.845]	35.093*** [12.681]	44.305*** [13.235]	0.2825
Relatively small and regional	51.316** [20.518]	29.215 [19.644]	66.119*** [24.545]	27.998 [21.269]	19.318 [23.029]	48.716* [29.236]	-51.518*** [18.681]	-77.642*** [19.497]	0.2839
Breadth of product offering									
Broad offering	-1.1457 [6.6651]	-3.4230 [6.3811]	9.1340 [7.9733]	-2.7589 [6.9092]	-10.363 [7.4808]	9.4396 [9.4970]	0.8305 [6.0685]	-0.2033 [6.3336]	0.1947
Concentrated offering	1.1457 [6.6651]	3.4230 [6.3811]	-9.1340 [7.9733]	2.7589 [6.9092]	10.363 [7.4808]	-9.4396 [9.4970]	-0.8305 [6.0685]	0.2033 [6.3336]	0.1947

Table 7 (Continued)

Model	(1)			(2)			(3)		
	Location of facility			Competitors in proximity			Existing aggregator cooperation		
	Small town	Small city	Medium-size city	2–5	5–10	> 10	Yes, with one	Yes, with more than one	R-squared
Channel of the aggregator									
B2C	-20.713 [15.070]	1.7333 [14.427]	8.5837 [18.028]	-3.8634 [15.622]	-10.829 [16.914]	-9.7690 [21.473]	-21.087 [13.721]	-33.968** [14.320]	0.1498
B2B	20.866 [21.941]	-3.1785 [21.006]	-9.7060 [26.247]	-13.645 [22.744]	10.306 [24.626]	9.6691 [31.263]	43.375** [19.977]	48.026** [20.850]	0.1787
B2B & B2C	-0.1525 [11.146]	1.4451 [10.671]	1.1223 [13.334]	17.508 [11.555]	0.5231 [12.511]	0.0999 [15.883]	-22.288** [10.149]	-14.057 [10.592]	0.2190
Handling/support of the aggregator									
Aggregator supports	2.9067 [8.4084]	11.318 [8.0501]	6.1694 [10.058]	8.2704 [8.7164]	10.594 [9.4375]	26.307** [11.981]	0.4683 [7.6558]	-5.9449 [7.9902]	0.1443
No support	-2.9067 [8.4084]	-11.318 [8.0501]	-6.1694 [10.058]	-8.2704 [8.7164]	-10.594 [9.4375]	-26.307** [11.981]	-0.4683 [7.6558]	5.9449 [7.9902]	0.1443
Risk sharing									
Potential/risk shared with aggregator	4.6601 [7.7380]	0.0076 [7.4083]	-1.9726 [9.2569]	-10.883 [8.0215]	-14.895* [8.6851]	7.9024 [11.025]	5.0972 [7.0454]	-4.5039 [7.3532]	0.1599
Potential/risk with aggregator	-4.6601 [7.7380]	-0.0076 [7.4083]	1.9726 [9.2569]	10.883 [8.0215]	14.895* [8.6851]	-7.9024 [11.025]	-5.0972 [7.0454]	4.5039 [7.3532]	0.1599

Table 7 (Continued)

Model	(1)		(2)				(3)		R-squared
	Location of facility		Competitors in proximity		Existing aggregator cooperation				
	Small town	Small city	Medium-size city	2–5	5–10	> 10	Yes, with one	Yes, with more than one	
Revenue potential									
Same or more as existing user	13.285 [22.078]	16.142 [21.137]	1.5849 [26.411]	20.485 [22.886]	43.395* [24.780]	-1.3245 [31.459]	7.2388 [20.101]	20.509 [20.980]	0.1665
70–100% of existing user	-21.767 [13.532]	-18.526 [12.955]	-9.1207 [16.188]	12.368 [14.028]	9.1124 [15.188]	1.6907 [19.282]	6.5005 [12.321]	20.367 [12.859]	0.1032
Less than 70% of existing user	8.4814 [21.725]	2.3838 [20.799]	7.5358 [25.990]	-32.853 [22.521]	-52.508** [24.384]	-0.3662 [30.956]	-13.739 [19.780]	-40.877* [20.645]	0.1444
Market position of the aggregator									
Top 3	-12.683* [6.9241]	-12.801* [6.6291]	-8.8981 [8.2832]	-1.8123 [7.1777]	-19.047** [7.7716]	-13.001 [9.8661]	9.4166 6.3043	12.831* 6.5798	0.2308
Not top 3	12.683* [6.9241]	12.801* [6.6291]	8.8981 [8.2832]	1.8123 [7.1777]	19.047** [7.7716]	13.001 [9.8661]	-9.4166 6.3043	-12.831* 6.5798	0.2308
N (decisions)	460	380	180	270	440	170	470	460	
N (respondents)	46	38	18	27	44	17	47	46	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

erence for “small and regional” networks compared to facilities in large cities. The attribute level of “nationwide and relatively less dense” networks is not significantly impacted. Further, facilities in small towns and cities show a lower preference for “top 3” aggregators and a higher preference for “non-top 3” aggregators compared to large city facilities, albeit significant only at 10%.

Model 4 in Table 8 shows the differences in relative attribute importance across segments and indicates that facilities in small towns and medium-sized cities attach significantly higher importance to the aggregator’s *partner network* than facilities in large cities.

4.2.2 Competitors in Proximity

Model 2 in Table 7 compares the respondents’ preferences across competitive intensities measured by the number of competitors in direct proximity. We compare facilities with higher numbers to the reference group of “<2.” The results show that facilities with high competitive pressure (“>10”) have a significantly higher preference for aggregator support and dislike the lack thereof compared to the reference group. Also, there is a tendency to prefer “non-top 3” aggregators over “top 3” aggregators, significant at the 5% level. Regarding the importance of different attributes for decision-making (Model 5, Table 8), the results indicate that the importance of the aggregator *market position* decreases significantly at the 5% and 10% level for facilities with “5–10” and “>10” competitors in proximity, respectively.

4.2.3 Existing Aggregator Cooperation

Model 3 in Table 7 compares the preferences of facilities with existing aggregator cooperation with those of the reference group without existing cooperation. The results show that the groups differ significantly in their preferences regarding the attributes of the *partner network*, *channel*, and *market position* to a lesser extent. Regarding the *network*, facilities with existing cooperation—one or more aggregators—show a significantly higher preference for nationwide networks focusing on cities. In turn, they attach significantly lower value to small and regional networks. Regarding the *channel*, aggregators with existing cooperations derive significantly more utility from the B2B channel and lower value from the mixed “B2B & B2C” and “B2C” for aggregators with one and those with more than one existing cooperation, respectively. The *market position* indicates that partners cooperating with multiple aggregators derive higher value from “top 3” aggregators, albeit only significantly at the 10% level.

A comparison of the importance values assigned to the decision criteria indicated three differences. First, facilities with multiple existing cooperations attach significantly lower weight to aggregator *partner network*. Second, facilities with existing cooperations (one or multiple) attach lower weight to the aggregator’s *product offering*. Third, the *revenue potential* increases significantly in importance for facilities with multiple existing cooperations at the 1% level.

Table 8 Model 4–6. Results of the conjoint analysis with comparison across respondent groups. This table shows the results of a regression, where the dependent variable is the individual importance the decision maker attaches to an attribute and the independent variables are the respective category of partner facility. Each attribute level is interacted with the respective partner category. For example, in Model 4 every attribute level is interacted with a dummy variable that takes a value of 1 if the respective decision maker (partner) is situated in the given location and 0 if not. Focusing on interaction effects allows to identify differences. Model 1 shows that partners from ‘small towns’ attach significantly more importance to the partner network attribute compared to partners from large cities.

Model	(4)			(5)			(6)			R-squared		
	Location of facility			Competitors in proximity			Existing aggregator cooperation					
	Small town	Small city	Medium-size city	2–5	5–10	> 10	Yes, with one	Yes, with more than one				
Partner network of the aggregator	Reference group: large city	7.547** [3.499]	2.543 [3.35]	8.835** [4.186]	Reference group: <2	-0.004 [3.628]	-0.163 [3.928]	3.026 [4.986]	Reference group: No existing cooperation	-4.902 [3.186]	-8.577** [3.325]	0.1499
Breadth of product offering		-1.224 [1.29]	-0.584 [1.235]	-0.526 [1.543]	0.996 [1.337]	0.235 [1.448]	1.709 [1.838]			-2.587** [1.175]	-2.941** [1.226]	0.1534
Channel of the aggregator		3.044 [2.981]	0.807 [2.854]	-0.111 [3.566]	-0.832 [3.09]	-4.455 [3.345]	-2.655 [4.247]			4.397 [2.714]	5.352* [2.832]	0.2166
Handling/support of the aggregator		-0.289 [1.824]	1.698 [1.747]	-0.099 [2.182]	-0.218 [1.891]	0.108 [2.048]	3.445 [2.599]			-1.354 [1.661]	-2.536 [1.734]	0.2057
Risk sharing		-1.179 [1.432]	-2.012 [1.371]	-1.476 [1.713]	-0.179 [1.485]	0.602 [1.608]	-1.844 [2.041]			-0.794 [1.304]	-1.765 [1.361]	0.1330
Revenue potential		-5.281 [3.852]	-0.408 [3.688]	-4.863 [4.608]	1.769 [3.993]	7.423* [4.324]	0.198 [5.489]			5.654 [3.507]	10.337*** [3.661]	0.2211
Market position of the aggregator		-2.618* [1.564]	-2.044 [1.497]	-1.762 [1.871]	-1.524 [1.621]	-3.750** [1.755]	-3.880* [2.228]			-0.413 [1.424]	0.129 [1.486]	0.1773

Table 8 (Continued)

Model	(4)		(5)			(6)		R-squared				
	Location of facility		Competitors in proximity			Existing aggregator cooperation						
	Small town	Small city	Medium-size city	2–5	5–10	> 10	Yes, with one	Yes, with more than one				
<i>N</i> (decisions)	460	390	380	180	270	270	530	440	170	470	480	460
<i>N</i> (respondents)	46	39	38	18	27	27	53	44	17	47	48	46

**** $p < 0.01$; *** $p < 0.05$; * $p < 0.1$

5 Discussion

Our analysis of the CBC responses of 141 respondents offers insights into their decision structures. The data presented shed light on the perspectives of ecosystem partners regarding the individual constituents of an ecosystem PVP. In the following sections, we highlight the surprising results in relation to existing research and interpret the findings.

5.1 Facilities See Aggregators Mainly as a Revenue Source and Have Not Adopted “Ecosystem Thinking”

The main results carry two implications suggesting that (i) partners see the ecosystem as a source of revenue rather than a long-term partnership when cooperating with an aggregator and that (ii) partner facilities have not (yet) adjusted to “ecosystem thinking”.

Regarding (i), *revenue potential* is implicitly discussed in the literature as a motivator (Cennamo, 2018; Jin & Hurd, 2018; Rietveld et al., 2019), but constitutes only one element of an attractive PVP. However, our results indicate that *revenue potential* dominates cooperation decisions, dwarfing other partnership aspects in sports aggregation ecosystems. The attribute importances (Table 6) support this interpretation. The *revenue potential*¹⁴ is the single most influential attribute in the overall decision. The second most important attribute is *channel* (~21%), suggesting that partners thoroughly consider the type of customer they can access through the aggregator. When combined, both attributes accounted for more than 50% of the overall decision. The part-worth utilities of the *revenue potential* indicate a clear preference for high revenue per aggregator customer, dislike for the lowest revenue per customer, and almost indifference for comparable revenue potential. This finding suggests that generating a comparable revenue per aggregator customer compared to existing customers leaves the partner indifferent toward cooperation, lower revenue has an evident influence on cooperation, and the potential to generate more revenue per customer through the aggregator highly motivates partners to participate in the ecosystem. Additionally, the *channel* attribute shows the strongest preference for the B2B channel, in which the aggregator sources customers to their partners through corporate clients. B2C, on the other hand, yields negative utility and is the least preferred. As partner facilities are primarily active in the B2C business, partners aim to avoid customer segments with a high risk of cannibalizing their existing (B2C) business while aiming for the segment that provides them with the highest degree of incrementality (B2B).

These results indicate that partners see the sports aggregation ecosystem as a source of incremental revenue more than as a partnership vehicle, in which partners collaborate and engage with their orchestrators to improve their ecosystem’s overall offering and success. Where revenue dominates the decision, other attributes such

¹⁴ For clarification: revenue potential refers to the revenue that a partner (sports facility) can generate per additional customer sourced through the aggregator platform compared to the revenue the partner makes per existing customer.

as *risk sharing* and *handling/support*, which typically reflect partnership thinking (Benlian et al., 2015; Eaton et al., 2015; T. L. Huber et al., 2017; Wareham et al., 2014), score comparatively low, at 7% and 6%, respectively. Furthermore, preferences regarding *risk sharing* indicate that partners prefer the aggregator to carry all the risks. This suggests that partners do not see value in a closer cooperative relationship or do not want to commit to it if it requires risk sharing.

This aspect is particularly interesting given that ecosystem participation does not only serve as an opportunity to increase partner performance (Barney et al., 2023; Fernández-Portillo et al., 2024) but may allow to reduce partners' risk via diversification and increased resilience. For example, orchestrators can provide non-financial benefits to partners such as learning opportunities, support in supply chain and operations management, access to financing lines, and even provide support in crises such as COVID-19 to ensure long-term viability of the partnerships (Krome et al., 2025; Wareham et al., 2014).

Apart from seeing the ecosystem as a source of incremental revenue rather than a long-term partnership, the results imply that (ii) partners in sports aggregation ecosystems think mainly about bilateral relationships. As ecosystems are fundamentally more complex than the aggregation of individual bilateral relationships, this suggests that partners have not yet adapted to “ecosystem thinking” (Adner, 2017). For example, the utilities indicate that partners prefer a concentrated aggregator offering to a broad one. As the product offering directly results from openness (Sect. 2), that is, to whom the aggregator grants access to the ecosystem, this implies two things. First, partners do not consider the overall value proposition of the ecosystem but instead focus on their individual relationship with the customer; that is, they do not ask, “What is the larger value proposition that the ecosystem provides for my customer?” Thus, partners do not value diversity in product offers to attract users to the platform (e.g. Boudreau, 2012). Second, a concentrated offer implies a higher density of direct (substitutable) competitors and, consequently, the risk of increasing internal competition. The literature describes this as “crowding out,” which partners generally avoid (Cennamo, 2021; Halaburda et al., 2018; Rysman, 2009). Our results imply that partners either do not care about this internal competitive pressure or do not think in terms of the ecosystem to recognize it as a threat. Beyond the risk of internal competition that increases with a higher density of direct competitors, a growing size of the network may imply more complexity in itself. To ensure that the network remains viable, quality is controlled and favored behavior is ensured, the orchestrator needs to actively manage and govern the ecosystem (Pidun et al., 2021). Since the ecosystem logic is relatively new it may be the case that the risk governance of the partners considering ecosystem participation lags behind and that especially network risk is a vital factor to consider (Stein & Wiedemann, 2016).

In general, the *breadth of the product offering* scores ~6% in terms of relative importance and is the least important attribute. This further underlines the fact that partners do not attribute importance to considerations such as the overall ecosystem value proposition, the resulting CVP, or implications for internal dynamics, such as preferring a concentrated offer despite the risk of higher internal competition. Potentially, partners do not (strategically) consider this factor or sacrifice any dislike for higher revenue potential.

A possible explanation for both interpretations, i) the high focus on incremental revenue over other ecosystem benefits and ii) the low consideration of ecosystem thinking, may be that partners are not aware of these potential benefits before joining; that is, they generally understand ecosystems as a sales channel and are unaware of partnership benefits, such as resource sharing.

If this were the case, then the focus on revenue should decrease over time, and the importance of attributes reflecting partnership aspects and ecosystem thinking should increase. Our subsample analysis allowed us to test this hypothesis. The results discussed in Sect. 4.2 (Table 8) compare partners with and without aggregator experience. Contrary to expectations, the attribute importances of *risk sharing* and *handling/support* did not change significantly over time. Moreover, the importance of the *partner network* and *product offering* decreases significantly for partners with multiple aggregator cooperation and those with one aggregator cooperation, respectively. In turn, facilities with multiple aggregator cooperations show an increase in the importance of the *channel* reflecting incrementality and a significant increase in the importance of *revenue potential* for their decisions.

Consequently, the subsample analysis suggests that the effects observed in the main results have increased over time. Partners do not learn to appreciate ecosystem values over time if they are unaware of them. Instead, the more experience partners have with ecosystems, the more important aspects of incremental revenue become and the lower the importance they attach to ecosystem thinking and partnership attributes. While the data does not allow us to make inferences about this phenomenon in other sectors the conclusion does not contradict the broader literature which highlights that ecosystem partners retain economic and legal independence (Lingens & Huber, 2023). While participants manage the tension between ecosystem-wide and individual value, Oskam et al. (2021) suggest that eventually partners will prioritize their benefit and leave an ecosystem as soon as the alignment in their favor fails.

5.2 WTA Effects Must Be Viewed in a Differentiated Manner

The literature places immense emphasis on the dominating role of network effects and the resulting WTA dynamics (Cennamo & Santaló, 2013; Eisenmann et al., 2006; Evans, 2003; M. L. Katz & Shapiro, 1992), network economists underline their logic (Armstrong, 2006; Rochet & Tirole, 2003), and researchers explicitly focus on how to instrumentalize them (Amelio & Jullien, 2012; Bakos & Halaburda, 2020; Gawer & Cusumano, 2008; Rochet & Tirole, 2003). However, our data from sports aggregation ecosystems suggest that considerations around WTA dynamics—mainly reflected through *partner network* and *market position*, in our setting (see Sect. 2)—should be viewed in a more differentiated manner.

The relative importance values indicate that size effects are not the dominant decision driver. The aggregator's *market position* shows a relative importance of ~7%, indicating that partners attribute comparably little importance to the aggregator's current standing when choosing an ecosystem to join. This contrasts with existing research that highlights the benefits of joining the dominant ecosystem for visibility, credibility, customer access, and others benefits (Ritala et al., 2014; Zhu & Iansiti, 2012, 2019). Similarly, while the *partner network* attribute scores among the top

attributes, *revenue potential* and *channel* are ultimately more important. Both indications challenge the WTA dynamics as the single most important decision driver.

Furthermore, partners prefer “small and regional” networks over “nationwide” networks. This contradicts the WTA literature, which suggests that more extensive networks are beneficial and increasingly attractive to partners (Boudreau, 2012; Evans & Schmalensee, 2016; Gawer & Cusumano, 2008; Iansiti & Levien, 2004; Ritala et al., 2014). While this finding does not indicate that partners are opposed to dominant ecosystems, the results suggest that partners value some benefits of regionality, such as a close relationship with the aggregator, more highly than the overall size benefits of the ecosystem. One possible explanation could be that partners consider the aggregator network as something carrying inherent risk that needs to be managed (Stein & Wiedemann, 2016). The governance literature (e.g. Hilbolling et al., 2020; Pidun et al., 2021; Rietveld & Schilling, 2021) suggests that larger networks increase complexity for the orchestrator to effectively control partner behavior and ensure desired outputs and quality thereby increasing the viability risk of the network. Another possible explanation for these results may be a local bias, as Huotari et al. (2017) document on the consumer side, which purports that regional preferences exist that may favor “local champions” or “regional winners” and avoid WTA dynamics on an overarching scale (Zhu et al., 2021). Specifically, in our setting, this would imply that WTA effects are not dominant at the national level but rather within regional clusters, where partners prefer aggregators that can provide the strongest local network with the most extensive local customer base.

This possibility implies heterogeneity within our sample, which can be tested by segmentation along the location of the partner facility. The results (Sect. 4.2 and Table 8) show some differences. While the importance of *market position* does not change significantly across facility locations, partners from smaller, less urban locations (e.g. small towns and medium-sized cities) place significantly higher importance on the *network* attribute than partners from large cities; that is, the network assumes a higher relevance for the overall decision outcome. At the same time, the utilities indicate that these partners (i.e., small towns and medium-sized cities) derive significantly higher value from “small and regional networks” and significantly less value from “nationwide networks with a focus on urban areas”. Hence, facilities that care about the network do not prefer the largest network in absolute size, but rather a regional presence, which may well reflect a local champion. A similar interpretation stems from the *market position* attribute. Partners from small locations show a lower preference for “top 3” aggregators and a higher preference for “non-top 3”, indicating that not the globally best-known aggregator is appealing, but rather a relatively smaller ecosystem that can better match the partners’ regional requirements. These differences along location parameters explain the main results, indicating that regional biases and preferences play a considerable role. In sports aggregation ecosystems, the overall network size and global WTA dynamics seem to be less important than the network strength and position in the respective region of the partner. Partners may value the benefits of regionality, such as close relationships, a strong local network, and a user base, over the advantages derived from a large ecosystem on a global scale (e.g. Zhu et al., 2021).

We can draw multiple conclusions. First, our main results indicate that the WTA dynamics are not the dominant decision criterion in our setting. Second, network effects are not dominant globally; however, the partner base is heterogeneous and shows evidence of local preferences. As such, WTA approaches may still be highly relevant at the regional cluster level rather than on an overall national scale. Finally, the heterogeneity observed in partner preferences suggests that orchestrators may fail to develop a singular PVP. Instead, they may need a more nuanced value proposition to attract and retain the overall targeted partner composition because elements that successfully attract one partner may deter the other. Cennamo and Santaló (2013) investigate differentiated consumer preferences and implications for orchestrators in developing their CVP. Our results suggest that a similar differentiation approach may be beneficial to the partner side.

6 Conclusion

6.1 Contributions to the BE Literature

Ecosystems bring together different actors to realize a value proposition beyond each contributor's individual capacity. Attracting participants is essential for such value propositions to materialize and network effects to begin. The literature highlights that a PVP is required, beyond a strong CVP. Researchers addressed the constituent elements of such a PVP and analyzed how orchestrators can operationalize them. However, despite the importance of attracting partners and understanding how partners perceive a PVP, this study is the first to assess the decision criteria of partners considering their cooperation with an ecosystem. Using analysis, we applied an experimental methodology to assess the decision structures of different types of partners in the German sports aggregation ecosystem.

This study contributes to existing literature in several ways. First, our study highlights that the factors of an attractive PVP are ecosystem-dependent, such that there is no universal answer to what constitutes a good PVP. We derive a set of relevant criteria for partners in German sports aggregation ecosystems to choose their orchestrators for cooperation. The fact that we required industry interviews to operationalize the factors found in the literature highlights the importance of considering the corresponding ecosystem context.

Second, we find evidence that partner engagement in an ecosystem does not guarantee “ecosystem thinking”. Instead, partners may consider the ecosystem mainly as an additional source of revenue. *Revenue potential* dominates the decision of which ecosystem to cooperate with. Where *revenue potential* and the final customer *channel* account for more than 50% of the decision outcome, traditional ecosystem attributes such as *risk sharing* or the *handling/support* of the aggregator are comparably less important. Moreover, our results indicate that partners continue to think in bilateral relationships; that is, towards their orchestrators or individual customers. For example, partners attach little importance to the ecosystem's *breadth of product offering*, indicating that they do not consider the ecosystem's overall value proposition or its related impact on internal competitive dynamics. Interestingly, these

indications increase with growing aggregator experience, implying that partners do not learn to value the benefits of the overall ecosystem over time. Instead, their focus further shifts from partnership aspects to a more exclusive focus on their own (incremental) revenue generation.

Third, our data indicate that partners should not be seen as a homogeneous base but may have heterogeneous preferences. Our subsample analyses show significant differences in preferences across segments, suggesting that a single orchestrator PVP likely does not appeal equally to all partners. On the one hand, this implies an opportunity for orchestrators to differentiate their positioning through a tailored PVP that targets specific sets of partners in their ecosystem. However, orchestrators must account for heterogeneous preferences when developing a strong PVP. Similar to differentiating CVPs, orchestrators may need to create more differentiated offerings for their partners.

Finally, we find that network effects need to be viewed in a differentiated manner, and one should be careful when assuming WTA dynamics as the dominant decision driver. In our setting, partners do not attach high importance to the attributes of the existing *partner network* (size) or the *market position* of the aggregator. *Revenue potential* and *channel* are more important, suggesting that WTA considerations do not drive cooperative decisions. Moreover, one must distinguish between global and local network effects, with some ecosystems benefitting from either one or the other. Our main results indicate that partners prefer “small regional networks”, questioning the universal benefits of nationwide partner networks. The subsample analysis shows that this result is driven by particular partner segments that not only attach higher importance to the network itself, but actually prefer a smaller, local player. Contrary to the literature asserting that more extensive networks are increasingly attractive, our results indicate that partners may prefer a local winner to the largest or best-positioned ecosystem on a global scale.

6.2 Limitations and Future Research

Our study has some limitations that may serve as a starting point for future research on the decision structures of ecosystem partners and the resulting implications for PVPs.

First and foremost, our study is geographically limited by our empirical context which is defined by competing ecosystems in the German market. This may limit the transferability of the results as the geographical context may make a difference (Krome et al., 2025). For example, the aggregation business model in the US differs in terms of value proposition for both customers and partners from the one observed in Germany suggesting that the specific interaction of ecosystem partners with the orchestrator may differ as well (fitness MANAGEMENT, 2019). Moreover, while the Polish market operates under the same value model as in Germany, the market dynamics are not comparable. As one aggregator grew to dominate the market thereby exerting immense pressure on the ecosystem partners one can assume that the sentiment of respondents towards the ecosystem reflected in the survey responses may differ fundamentally (fitness MANAGEMENT, 2019; Krome et al., 2025).

Second, our study does not include additional demographic factors on the respondents themselves (e.g. age, gender, tenure in the industry) that may influence the results. Whilst we collected moderating variables on the (potential) ecosystem partner represented, a deeper look into the respondents' population could explore how demographic influences (e.g. gender effect) shape the results. Similarly, internal firm characteristics such as management maturity or degree of digitalization could explain the readiness and understanding of the ecosystem concept as a new organizational form.

Third, our study is part of a growing body of experimental research applying conjoint methodology, for which one must be aware of the potential differences between experiments and reality. CBC experiments better depict decision settings in real market behavior than other methods, such as rating-based experiments (Elrod et al., 1992; Franke et al., 2008; J. Huber et al., 2002). Nevertheless, the possibility persists that the study design overestimates some criteria and underestimates others. The attribute-task compatibility effect (Nowlis & Simonson, 1997) provides an example in which specific attributes are overemphasized in choice-based settings, while others are underrepresented. Future research could thus extend the emerging experimental research body by applying multi-method approaches tailored to capture the effects of a particular design setting and validating our results using other methods, such as rating-based approaches.

To the best of our knowledge, this study is the first to apply a CBC approach in a business ecosystem context. As such, we relied heavily on the existing literature and validating industry interviews to derive the attributes for the decision task. Other studies could replicate this approach in different ecosystem settings. The benefits are two-fold. First, further research in this field could validate and extend the relevance of the applied decision attributes. Second, insights from different ecosystems would indicate the extent to which individual ecosystems are comparable and generalizable to the general BE literature.

Fourth, we find that partners in German sports aggregation ecosystems regard ecosystems mainly as a source of additional revenue and not as long-term partnerships. Future research could build on this insight and investigate whether similar outcomes can be observed in different ecosystem contexts. Future research could test for possible correlations with ecosystem performance and health, if indications differ across ecosystems. If multiple contexts indicate that partners see ecosystems mainly as a revenue source, researchers could further differentiate the extent to which this is driven by ecosystem type. Moreover, future research could conduct event studies to test whether contextual factors—our industry involves physical interaction limited throughout the COVID pandemic—influence outcomes.

Fifth, given our approach to derive factors from the existing literature our attributes are influenced by the performance side of ecosystem evaluation. Beyond this, there are newer studies looking beyond the measurable performance impact to assessing ecosystem benefits stemming from diversification, increased crisis resilience and the ability to more swiftly adapt to changing environments (Koster et al., 2023; Krauze, 2025; Toufaily & Zalan, 2023). Future research could isolate these factors and try to evaluate partners' understanding and appreciation of these when deciding on ecosystem participation.

Finally, we require a differentiated perspective on WTA dynamics, in which the difference between local and global network effects seems especially important (e.g. Zhu et al., 2021). Prior research focused on the customer side to test ecosystem positioning, differentiation, and local customer preferences (Cennamo & Santaló, 2013). Future research could apply the logic to the partner side and test how visible effects such as a local bias interact with logical size advantages of dominant ecosystems. As a next step, the research could address how to effectively integrate such local differences into a strong PVP and evaluate how differentiated orchestrators need to develop their PVP.

6.3 Managerial Implications

Despite these limitations, this study offers interesting insights for practitioners and ecosystem participants. Regarding partners, our findings show that local preferences are a valid and real phenomenon in strategic decision-making. While this does not negate the influence of network effects, it suggests that partners can take a more nuanced approach toward local champions rather than a default preference for the largest or best-positioned ecosystem on a global scale. Furthermore, partners should be aware that ecosystems hold benefits beyond pure revenue potential, such as opportunities for learning, (product) innovation, or other perks (Sect. 2), which should not be overlooked in decision-making. Apart from considering these benefits in their ecosystem choices, partners should actively leverage them as participants in their respective ecosystems to realize their full potential (Inoue, 2019). Where it seems that a main challenge for partners may remain to treat an ecosystem as more than a distribution channel, it may be necessary to progress the institutional logic on the partner side as well. Altman and Tushman (2017) discuss the changes in institutional requirements from an orchestrator perspective, such as an increased outward focus on openness or different leadership capabilities. Transferring this logic to the participant side, partners may equally need to adjust the skillset and mentality to really appreciate and leverage ecosystem benefits whilst extending their collaboration and understanding beyond the bilateral relationship with the orchestrator.

Our results have various implications for orchestrators. Our research shows that not all partners join ecosystems prepared and educated. A lack of ecosystem thinking among partners may hinder the full development of ecosystem benefits and reduce incentives to pure revenue potential. As such, orchestrators may face an educational need to prepare their partners for sustainable and productive cooperation. Requirements may stretch beyond the pure construction of an appealing value proposition for the partner which details how interactions are governed, and value is split. Rather, orchestrators would have to equip partners to understand the ecosystem and the inherent value potential from contributing and interacting. For example, orchestrators could provide structured onboarding and training or create internal learning platforms that allow partners to understand the benefits and workings of the overarching value proposition (Gomes et al., 2023). Orchestrators sometimes provide additional benefits to retain partners in the ecosystem (Krome et al., 2025). They may benefit from promoting these non-financial benefits in their value proposition to partners before they even join the ecosystem. Examples include mutual learning opportuni-

ties for partners, forums for strategic alignment such as industry roundtables, best practice-sharing for non-competing partners, co-development of partner business models, and operational support through (ecosystem) scale benefits.

Moreover, our findings suggest that orchestrators cannot assume that potential ecosystem partners have homogeneous preferences. To compete actively for the right partners, orchestrators may need to diverge from offering a universal PVP. Rather, orchestrators should differentiate their partner offerings and evaluate how they can best target their preferred partner groups. This finding also implies that the fate of competing ecosystems is not necessarily determined by first-mover advantages, which lead to inevitable WTA outcomes (Eisenmann et al., 2006; Hagiú, 2009). Instead, heterogeneous preferences will always allow orchestrators to differentiate into niche offerings not only on the consumer side, but also on the partner side.

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Data availability The data underlying this survey will be shared upon request.

Conflict of interest M.J. Krome declares that he has no competing interests.

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References

- Adamowicz, W., P. Boxall, M. Williams, and J. Louviere. 1998. Stated preference approaches for measuring passive use values: choice experiments and contingent valuation. *American Journal of Agricultural Economics* 80(1):64–75. <https://doi.org/10.2307/3180269>.
- Ademi, P., M.C. Schuhmacher, and A.L. Zacharakis. 2023. Evaluating Affordance-based opportunities: a conjoint experiment of corporate venture capital managers' decision-making. *Entrepreneurship Theory and Practice* 47(6):2293–2322. <https://doi.org/10.1177/10422587221134788>.
- Adner, R. 2006. Match Your Innovation Strategy to Your Innovation Ecosystem. Harvard Business Review. <https://hbr.org/2006/04/match-your-innovation-strategy-to-your-innovation-ecosystem>.
- Adner, R. 2017. Ecosystem as structure: an actionable construct for strategy. *Journal of Management* 43(1):39–58. <https://doi.org/10.1177/0149206316678451>.
- Albaladejo-Pina, I.P., and M.T. Díaz-Delfa. 2009. Tourist preferences for rural house stays: Evidence from discrete choice modelling in Spain. *Tourism Management* 30(6):805–811. <https://doi.org/10.1016/j.tourman.2009.01.001>.
- Allenby, G.M., and J.L. Ginter. 1995. Using extremes to design products and segment markets. *Journal of Marketing Research* 32(4):392. <https://doi.org/10.2307/3152175>.
- Altman, E.J. 2017. Dependencies, complementor evolution, response strategies: joining a multi-sided platform ecosystem. *Academy of Management Proceedings* 2017(1):15484. <https://doi.org/10.5465/AMBPP.2017.15484abstract>.
- Altman, E.J., and M.L. Tushman. 2017. Platforms, open/user innovation, and ecosystems: a strategic leadership perspective. In *Advances in strategic management*, Vol. 37, ed. J. Furman, A. Gawer, B.S. Silverman, and S. Stern, 177–207. Emerald Publishing. <https://doi.org/10.1108/S0742-332220170000037007>.

- Altman, E.J., F. Nagle, and M.L. Tushman. 2022. The translucent hand of managed ecosystems: engaging communities for value creation and capture. *Academy of Management Annals* 16(1):70–101. <https://doi.org/10.5465/annals.2020.0244>.
- Amelio, A., and B. Jullien. 2012. Tying and freebies in two-sided markets. *International Journal of Industrial Organization* 30(5):436–446. <https://doi.org/10.1016/j.ijindorg.2012.03.002>.
- Armstrong, M. 2006. Competition in two-sided markets. *The RAND Journal of Economics* 37(3):668–691. <https://doi.org/10.1111/j.1756-2171.2006.tb00037.x>.
- Awano, H., and M. Tsujimoto. 2022. Mechanisms for business ecosystem members to capture value through the strong network effect. *Sustainability* 14(18):11595. <https://doi.org/10.3390/su141811595>.
- Bakos, Y., and H. Halaburda. 2020. Platform competition with multihoming on both sides: subsidize or not? *Management Science* 66(12):5599–5607. <https://doi.org/10.1287/mnsc.2020.3636>.
- Barney, J.B., T.B. Mackey, and A. Mackey. 2023. Why has it been so hard to define competitive advantage? *Strategic Management Review* 4(1):1–13. <https://doi.org/10.1561/111.00000050>.
- Benlian, A., D. Hilkert, and T. Hess. 2015. How open is this platform? The meaning and measurement of platform openness from the complementers' perspective. *Journal of Information Technology* 30(3):209–228. <https://doi.org/10.1057/jit.2015.6>.
- Birkinshaw, J. 2019. Ecosystem businesses are changing the rules of strategy. Harvard Business Review. <https://hbr.org/2019/08/ecosystem-businesses-are-changing-the-rules-of-strategy>.
- Block, J., C. Fisch, S. Vismara, and R. Andres. 2019. Private equity investment criteria: an experimental conjoint analysis of venture capital, business angels, and family offices. *Journal of Corporate Finance* 58:329–352. <https://doi.org/10.1016/j.jcorpfin.2019.05.009>.
- Boudreau, K.J. 2012. Let a thousand flowers bloom? An early look at large numbers of software app developers and patterns of innovation. *Organization Science* 23(5):1409–1427. <https://doi.org/10.1287/orsc.1110.0678>.
- Boudreau, K.J., and A. Hagiu. 2009. Platform rules: multi-sided platforms as regulators. In *Platforms, markets and innovation*, ed. A. Gawer. Edward Elgar. <https://doi.org/10.4337/9781849803311.00014>.
- Caillaud, B., and B. Jullien. 2003. Chicken & egg: competition among intermediation service providers. *The RAND Journal of Economics* 34(2):309. <https://doi.org/10.2307/1593720>.
- Caussade, S., J.D.D. Ortúzar, L.I. Rizzi, and D.A. Hensher. 2005. Assessing the influence of design dimensions on stated choice experiment estimates. *Transportation Research Part B: Methodological* 39(7):621–640. <https://doi.org/10.1016/j.trb.2004.07.006>.
- Cennamo, C. 2018. Building the value of next-generation platforms: the paradox of diminishing returns. *Journal of Management* 44(8):3038–3069. <https://doi.org/10.1177/0149206316658350>.
- Cennamo, C. 2021. Competing in digital markets: a platform-based perspective. *Academy of Management Perspectives* 35(2):265–291. <https://doi.org/10.5465/amp.2016.0048>.
- Cennamo, C., and J. Santaló. 2013. Platform competition: strategic trade-offs in platform markets. *Strategic Management Journal* 34(11):1331–1350. <https://doi.org/10.1002/smj.2066>.
- Cennamo, C., and J. Santaló. 2019. Generativity tension and value creation in platform ecosystems. *Organization Science* 30(3):617–641. <https://doi.org/10.1287/orsc.2018.1270>.
- Chen, D., N. You, and F. Lv. 2019. Study on sharing characteristics and sustainable development performance: mediating role of the ecosystem strategy. *Sustainability* 11(23):6847. <https://doi.org/10.3390/su11236847>.
- Chrzan, K. 1994. Three kinds of order effects in choice-based conjoint analysis. *Marketing Letters* 5(2):165–172. <https://doi.org/10.1007/BF00994106>.
- Chrzan, K., and B. Orme. 2000. An overview and comparison of design strategies for choice-based conjoint analysis. In *Sawtooth Software Conference Proceedings*, 161–177.
- Crouch, G.I., and J.J. Louviere. 2001. A review of choice modelling research in tourism, hospitality and leisure. In *Consumer psychology of tourism, hospitality and leisure*, 1st edn., Vol. 2, ed. J.A. Mazanec, G.I. Crouch, J. R. Brent Richie, and A.G. Woodside, 67–86. CABI. <https://doi.org/10.1079/9780851995359.0067>.
- Crouch, G.I., and J.J. Louviere. 2004. The determinants of convention site selection: a logistic choice model from experimental data. *Journal of Travel Research* 43(2):118–130. <https://doi.org/10.1177/0047287504268233>.
- Cusumano, M.A., A. Gawer, and D.B. Yoffie. 2019. *The business of platforms: Strategy in the age of digital competition, innovation, and power*, 1st edn. Harper Business.
- Dattee, B.A., L.D.W. Thomas, and E. Autio. 2023. The limits of innovation ecosystem strategy: a demand-side view. *Academy of Management Proceedings* 2023(1):15268. <https://doi.org/10.5465/AMPROC.2023.15268abstract>.

- Daymond, J., E. Knight, M. Rumyantseva, and S. Maguire. 2023. Managing ecosystem emergence and evolution: strategies for ecosystem architects. *Strategic Management Journal* <https://doi.org/10.1002/smj.3449>.
- Dushnitsky, G., E. Piva, and C. Rossi-Lamastra. 2022. Investigating the mix of strategic choices and performance of transaction platforms: evidence from the crowdfunding setting. *Strategic Management Journal* 43(3):563–598. <https://doi.org/10.1002/smj.3163>.
- Eaton, B., S. Elaluf-Calderwood, C. Sørensen, and Y. Yoo. 2015. Distributed tuning of boundary resources: the case of apple's IOS service system. *MIS Quarterly* 39(1):217–243. <https://doi.org/10.25300/MISQ/2015/39.1.10>.
- Eggers, F., and H. Sattler. 2011. Preference measurement with conjoint analysis. Overview of state-of-the-art approaches and recent developments. *GfK Marketing Intelligence Review* 3(1):36–47. <https://doi.org/10.2478/gfkmir-2014-0054>.
- Eisenmann, T., G.G. Parker, and M.W. Van Alstyne. 2006. Strategies for Two-Sided Markets. Harvard Business Review. <https://hbr.org/2006/10/strategies-for-two-sided-markets>.
- Elrod, T., J.J. Louviere, and K.S. Davey. 1992. An empirical comparison of ratings-based and choice-based conjoint models. *Journal of Marketing Research* 29(3):368. <https://doi.org/10.2307/3172746>.
- Evans, D.S. 2003. Some empirical aspects of multi-sided platform industries. *Review of Network Economics* <https://doi.org/10.2202/1446-9022.1026>.
- Evans, D.S., and R. Schmalensee. 2016. *Matchmakers: the new economics of multisided platforms*. Harvard Business Review Press.
- Fernández-Portillo, A., N. Ramos-Vecino, A. Ramos-Mariño, and G. Cachón-Rodríguez. 2024. How the digital business ecosystem affects stakeholder satisfaction: Its impact on business performance. *Review of Managerial Science* 18(9):2643–2662. <https://doi.org/10.1007/s11846-023-00720-2>.
- fitness MANAGEMENT. 2019. Reisen, shopping, fitness: Online-Vermittler helfen beim Sparen. fitness MANAGEMENT – Fachverlag der Fitness- und Gesundheitsbranche. <https://www.fitnessmanagement.de/vergleichen-buchen-sparen/>.
- Foerderer, J. 2020. Interfirm exchange and innovation in platform ecosystems: evidence from apple's worldwide developers conference. *Management Science* 66(10):4772–4787. <https://doi.org/10.1287/mnsc.2019.3425>.
- Foss, N.J., J. Schmidt, and D.J. Teece. 2023. Ecosystem leadership as a dynamic capability. *Long Range Planning* 56(1):102270. <https://doi.org/10.1016/j.lrp.2022.102270>.
- Franke, N., M. Gruber, D. Harhoff, and J. Henkel. 2008. Venture capitalists' evaluations of start-up teams: trade-offs, knock-out criteria, and the impact of VC experience. *Entrepreneurship Theory and Practice* 32(3):459–483. <https://doi.org/10.1111/j.1540-6520.2008.00236.x>.
- Gawer, A. 2014. Bridging differing perspectives on technological platforms: toward an integrative framework. *Research Policy* 43(7):1239–1249. <https://doi.org/10.1016/j.respol.2014.03.006>.
- Gawer, A., and M.A. Cusumano. 2002. *Platform leadership: how intel, Microsoft, and Cisco drive industry innovation*. Harvard Business School Press.
- Gawer, A., and M.A. Cusumano. 2008. How companies become platform leaders. *MIT Sloan Management Review* 49:28–35.
- Gawer, A., and M.A. Cusumano. 2014. Industry platforms and ecosystem innovation. *Journal of Product Innovation Management* 31(3):417–433. <https://doi.org/10.1111/jpim.12105>.
- Gomes, L.A.D.V., F.E. Farago, A.L.F. Facin, X.A. Flechas, and L.E.N. Silva. 2023. From open business model to ecosystem business model: a processes view. *Technological Forecasting and Social Change* 194:122668. <https://doi.org/10.1016/j.techfore.2023.122668>.
- Gulati, R., P. Puranam, and M. Tushman. 2012. Meta-organization design: rethinking design in interorganizational and community contexts. *Strategic Management Journal* 33(6):571–586. <https://doi.org/10.1002/smj.1975>.
- Hagiu, A. 2009. Two-sided platforms: product variety and pricing structures. *Journal of Economics & Management Strategy* 18(4):1011–1043. <https://doi.org/10.1111/j.1530-9134.2009.00236.x>.
- Hagiu, A., and D. Spulber. 2013. First-party content and coordination in two-sided markets. *Management Science* 59(4):933–949. <https://doi.org/10.1287/mnsc.1120.1577>.
- Halaburda, H., Jan M. Piskorski, and P. Yıldırım. 2018. Competing by restricting choice: the case of matching platforms. *Management Science* 64(8):3574–3594. <https://doi.org/10.1287/mnsc.2017.2797>.
- Hensher, D.A., J.M. Rose, and W.H. Greene. 2005. *Applied choice analysis: a primer*. Cambridge University Press.
- Hilbolling, S., H. Berends, F. Deken, and P. Tuertscher. 2020. Complementors as connectors: managing open innovation around digital product platforms. *R&D Management* 50(1):18–30. <https://doi.org/10.1111/radm.12371>.

- Hoyos, D. 2010. The state of the art of environmental valuation with discrete choice experiments. *Ecological Economics* 69(8):1595–1603. <https://doi.org/10.1016/j.ecolecon.2010.04.011>.
- Huber, J., D. Ariely, and G. Fischer. 2002. Expressing preferences in a principal-agent task: a comparison of choice, rating, and matching. *Organizational Behavior and Human Decision Processes* 87(1):66–90. <https://doi.org/10.1006/obhd.2001.2955>.
- Huber, T.L., T. Kude, and J. Dibbern. 2017. Governance practices in platform ecosystems: navigating tensions between cocreated value and governance costs. *Information Systems Research* 28(3):563–584. <https://doi.org/10.1287/isre.2017.0701>.
- Hukal, P., O. Henfridsson, M. Shaikh, and G. Parker. 2020. Platform signaling for generating platform content. *MIS Quarterly* 44:1177–1205. <https://doi.org/10.25300/MISQ/2020/15190>.
- Huotari, P., K. Järvi, S. Kortelainen, and J. Huhtamäki. 2017. Winner does not take all: selective attention and local bias in platform-based markets. *Technological Forecasting and Social Change* 114:313–326. <https://doi.org/10.1016/j.techfore.2016.08.028>.
- Iansiti, M., and R. Levien. 2004. *The keystone advantage: What the new dynamics of business ecosystems mean for strategy, innovation, and sustainability*. Harvard Business School Press.
- Innovation Ecosystems in Management: An Organizing Typology. (2020). In L. D. W. Thomas & E. Autio, *Oxford Research Encyclopedia of Business and Management*. Oxford University Press. <https://doi.org/10.1093/acrefore/9780190224851.013.203>
- Inoue, Y. 2019. Winner-takes-all or co-evolution among platform ecosystems: a look at the competitive and symbiotic actions of complementors. *Sustainability* 11(3):726. <https://doi.org/10.3390/su11030726>.
- Jacobides, M.G., C. Cennamo, and A. Gawer. 2018. Towards a theory of ecosystems. *Strategic Management Journal* 39(8):2255–2276. <https://doi.org/10.1002/smj.2904>.
- Jacobides, M.G., C. Cennamo, and A. Gawer. 2024. Externalities and complementarities in platforms and ecosystems: from structural solutions to endogenous failures. *Research Policy* 53(1):104906. <https://doi.org/10.1016/j.respol.2023.104906>.
- Jin, H., and F. Hurd. 2018. Exploring the impact of digital platforms on SME internationalization: New Zealand SMEs use of the Alibaba platform for Chinese market entry. *Journal of Asia-Pacific Business* 19(2):72–95. <https://doi.org/10.1080/10599231.2018.1453743>.
- Johnson, R. 2000. *Understanding HB: an intuitive approach*. Sawtooth Software Research Paper Series.
- Johnson, R., and B. Orme. 2003. *Getting the most from CBC*. Sawtooth Software Research Paper Series.
- Kapoor, R. 2018. Ecosystems: broadening the locus of value creation. *Journal of Organization Design* 7(1):12. <https://doi.org/10.1186/s41469-018-0035-4>.
- Katz, M.L., and C. Shapiro. 1992. Product introduction with network externalities. *Journal of Industrial Economics* 40(1):55–83.
- Kim, D., and R.R. Perdue. 2013. The effects of cognitive, affective, and sensory attributes on hotel choice. *International Journal of Hospitality Management* 35:246–257. <https://doi.org/10.1016/j.ijhm.2013.05.012>.
- Koster, A., N. Lang, U. Pidun, and G. Wiest. 2023. In uncertain times, double down on business ecosystems. <https://www.bcg.com/publications/2023/build-business-ecosystem-resilience-in-uncertain-times>.
- Kraus, S., C. Mitter, F. Eggers, and P. Stieg. 2017. Drivers of internationalization success: a conjoint choice experiment on German SME managers. *Review of Managerial Science* 11(3):691–716. <https://doi.org/10.1007/s11846-016-0201-4>.
- Krauze, B. 2025. An analysis of resilience in digital business ecosystems. In *Research challenges in information science*, Vol. 548, ed. J. Grabis, T.E.J. Vos, M.J. Escalona, and O. Pastor, 162–171. Switzerland: Springer. https://doi.org/10.1007/978-3-031-92471-2_13.
- Krome, M.J., and U. Pidun. 2023. Conceptualization of research themes and directions in business ecosystem strategies: a systematic literature review. *Management Review Quarterly* 73(2):873–920. <https://doi.org/10.1007/s11301-022-00306-4>.
- Krome, M.J., U. Pidun, and Zu D. Knyphausen-Aufseß. 2025. Investigating the strategic choices of business ecosystem orchestrators: evidence from sports aggregation ecosystems. *Review of Managerial Science* <https://doi.org/10.1007/s11846-025-00857-2>.
- Lenk, P.J., W.S. DeSarbo, P.E. Green, and M.R. Young. 1996. Hierarchical Bayes conjoint analysis: recovery of partworth heterogeneity from reduced experimental designs. *Marketing Science* 15(2):173–191. <https://doi.org/10.1287/mksc.15.2.173>.
- Lingens, B., and F. Huber. 2023. Heading the orchestra of innovation: how firms align partners in ecosystems. *Innovation* 25(3):257–281. <https://doi.org/10.1080/14479338.2021.2016418>.

- Louviere, J.J., and G. Woodworth. 1983. Design and analysis of simulated consumer choice or allocation experiments: an approach based on aggregate data. *Journal of Marketing Research* 20(4):350. <https://doi.org/10.2307/3151440>.
- Louviere, J.J., D.A. Hensher, J.D. Swait, and W. Adamowicz. 2000. *Stated choice methods: analysis and applications*, 1st edn. Cambridge University Press. <https://doi.org/10.1017/CBO9780511753831>.
- Manski, C.F. 1977. The structure of random utility models. *Theory and Decision* 8(3):229–254. <https://doi.org/10.1007/BF00133443>.
- Martin, C.J., P. Upham, and R. Klapper. 2017. Democratising platform governance in the sharing economy: an analytical framework and initial empirical insights. *Journal of Cleaner Production* 166:1395–1406. <https://doi.org/10.1016/j.jclepro.2017.08.123>.
- Martín-Peña, M.-L., P.C. Lorenzo, and N. Meyer. 2024. Digital platforms and business ecosystems: a multidisciplinary approach for new and sustainable business models. *Review of Managerial Science* 18(9):2465–2482. <https://doi.org/10.1007/s11846-024-00772-y>.
- McFadden, D. 1974. Conditional Logit analysis of qualitative choice behavior. In *Frontiers in econometrics*, 105–142. Academic Press.
- McIntyre, D., A. Srinivasan, A. Afuah, A. Gawer, and T. Kretschmer. 2021. Multisided platforms as new organizational forms. *Academy of Management Perspectives* 35(4):566–583. <https://doi.org/10.5465/amp.2018.0018>.
- Moore, J. 1999. Predators and prey: a new ecology of competition. *Harvard Business Review* 71:75–86.
- Mukhopadhyay, S., M. De Reuver, and H. Bouwman. 2016. Effectiveness of control mechanisms in mobile platform ecosystem. *Telematics and Informatics* 33(3):848–859. <https://doi.org/10.1016/j.tele.2015.12.008>.
- Neumann, N.M., A. Plastino, J.A. Pinto Junior, and A.A. Freitas. 2020. Is p -value 0.05 enough? A study on the statistical evaluation of classifiers. *The Knowledge Engineering Review* <https://doi.org/10.1017/s0269888920000417>.
- Nowlis, S.M., and I. Simonson. 1997. Attribute-task compatibility as a determinant of consumer preference reversals. *Journal of Marketing Research* 34(2):205. <https://doi.org/10.2307/3151859>.
- Orme, B.K. 2010. *Getting started with conjoint analysis: strategies for product design and pricing research*, 2nd edn. Research Publ.
- Oskam, I., B. Bossink, and A.-P. De Man. 2021. Valuing value in innovation ecosystems: how cross-sector actors overcome tensions in collaborative sustainable business model development. *Business & Society* 60(5):1059–1091. <https://doi.org/10.1177/0007650320907145>.
- Parker, G.G., and M.W. Van Alstyne. 2005. Two-sided network effects: a theory of information product design. *Management Science* 51(10):1494–1504. <https://doi.org/10.1287/mnsc.1050.0400>.
- Parker, G., M. Van Alstyne, and S.P. Choudary. 2016. *Platform revolution: how networked markets are transforming the economy and how to make them work for you*, 1st edn. W. W. Norton.
- Pereira, J., M.M. Tavalaei, and H. Ozalp. 2019. Blockchain-based platforms: Decentralized infrastructures and its boundary conditions. *Technological Forecasting and Social Change* 146:94–102. <https://doi.org/10.1016/j.techfore.2019.04.030>.
- Pidun, U., M. Reeves, and M. Schüssler. 2020. Why do most business ecosystems fail? <https://www.bcg.com/publications/2020/why-do-most-business-ecosystems-fail>.
- Pidun, U., M. Reeves, and N. Knust. 2021. How do you manage a business ecosystem? <https://www.bcg.com/publications/2021/how-to-manage-business-ecosystem>.
- Pidun, U., M. Reeves, and B. Zoletnik. 2022. What is your business ecosystem strategy? <https://www.bcg.com/publications/2022/what-is-your-business-ecosystem-strategy>.
- Rietveld, J., and M.A. Schilling. 2021. Platform competition: a systematic and interdisciplinary review of the literature. *Journal of Management* 47(6):1528–1563. <https://doi.org/10.1177/0149206320969791>.
- Rietveld, J., M.A. Schilling, and C. Bellavitis. 2019. Platform strategy: managing ecosystem value through selective promotion of complements. *Organization Science* 30(6):1232–1251. <https://doi.org/10.1287/orsc.2019.1290>.
- Rietveld, J., J.N. Ploog, and D.B. Nieborg. 2020. The coevolution of platform dominance and governance strategies: effects on complements performance outcomes. *Academy of Management Discoveries* <https://doi.org/10.5465/amd.2019.0064>.
- Ritala, P., A. Golnam, and A. Wegmann. 2014. Coopetition-based business models: the case of Amazon.com. *Industrial Marketing Management* 43(2):236–249. <https://doi.org/10.1016/j.indmarman.2013.11.005>.
- Rochet, J.-C., and J. Tirole. 2003. Platform competition in two-sided markets. *Journal of the European Economic Association* 1(4):990–1029. <https://doi.org/10.1162/15424760322493212>.

- Rong, K., Y. Shi, and J. Yu. 2013. Nurturing business ecosystems to deal with industry uncertainties. *Industrial Management & Data Systems* 113(3):385–402. <https://doi.org/10.1108/02635571311312677>.
- Rong, K., Y. Lin, J. Yu, and Y. Zhang. 2020. Manufacturing strategies for the ecosystem-based manufacturing system in the context of 3D printing. *International Journal of Production Research* 58(8):2315–2334. <https://doi.org/10.1080/00207543.2019.1627436>.
- Rong, K., Y. Lin, W. Du, and S. Yang. 2024. Business ecosystem-oriented business model in the digital era. *Technology Analysis & Strategic Management* 36(10):3082–3099. <https://doi.org/10.1080/09537325.2023.2191743>.
- Rossi, P.E., G.M. Allenby, and R.E. McCulloch. 2006. *Bayesian statistics and marketing*. Wiley. <https://doi.org/10.1002/0470863692>.
- Rysman, M. 2009. The economics of two-sided markets. *Journal of Economic Perspectives* 23(3):125–143. <https://doi.org/10.1257/jep.23.3.125>.
- Sawtooth Software. 2021. The CBC/HB System for Hierarchical Bayes Estimation V5.6. Sawtooth Software. <https://content.sawtoothsoftware.com/assets/0f7f7cfd-468b-43fa-a775-77d2bfba1ef6>.
- Shepherd, D.A., and A. Zacharakis. 1999. Conjoint analysis: a new methodological approach for researching the decision policies of venture capitalists. *Venture Capital* 1(3):197–217. <https://doi.org/10.1080/136910699295866>.
- Shepherd, D.A., and A. Zacharakis. 2018. Chapter 6 conjoint analysis: a window of opportunity for entrepreneurship research. In *Advances in entrepreneurship, firm emergence and growth*, Vol. 20, ed. J.A. Katz, A.C. Corbett, 149–183. Emerald. <https://doi.org/10.1108/S1074-75402018000020011>.
- Stein, V., and A. Wiedemann. 2016. Risk governance: conceptualization, tasks, and research agenda. *Journal of Business Economics* 86(8):813–836. <https://doi.org/10.1007/s11573-016-0826-4>.
- Sulich, A., and L. Soloduch-Pelc. 2024. Strategic management and business ecosystem scientific relations—Key areas review. *International Journal of Innovation Studies* 8(3):287–296. <https://doi.org/10.1016/j.ijis.2024.04.005>.
- Tiwana, A. 2014. *Platform ecosystems: aligning architecture, governance, and strategy*. MK.
- Toufaily, E., and T. Zalan. 2023. Ecosystem well-being and resilience: lessons from crisis management in service organizations. *Journal of Business-to-Business Marketing* 30(4):349–370. <https://doi.org/10.1080/1051712X.2023.2289875>.
- Train, K. 2009. *Discrete choice methods with simulation*, 2nd edn. Cambridge University Press.
- Wareham, J., P.B. Fox, and J.L. Cano Giner. 2014. Technology ecosystem governance. *Organization Science* 25(4):1195–1215. <https://doi.org/10.1287/orsc.2014.0895>.
- Wegner, D., A.B. Da Silveira, D. Marconatto, and M. Mitrega. 2024. A systematic review of collaborative digital platforms: structuring the domain and research agenda. *Review of Managerial Science* 18(9):2663–2695. <https://doi.org/10.1007/s11846-023-00695-0>.
- Wuebker, R., N. Hampl, and R. Wüstenhagen. 2015. The strength of strong ties in an emerging industry: experimental evidence of the effects of status hierarchies and personal ties in venture capitalist decision making. *Strategic Entrepreneurship Journal* 9(2):167–187. <https://doi.org/10.1002/sej.1188>.
- Zhang, J., and X.-J. Liang. 2011. Business ecosystem strategies of mobile network operators in the 3G era: the case of China mobile. *Telecommunications Policy* 35(2):156–171. <https://doi.org/10.1016/j.telpol.2010.12.009>.
- Zhou, G., and P. Song. 2018. Third-party apps (TPAs) and software platform performance: the moderating role of competitive entry. *Information & Management* 55(7):901–911. <https://doi.org/10.1016/j.im.2018.04.004>.
- Zhu, F., and M. Iansiti. 2012. Entry into platform-based markets. *Strategic Management Journal* 33(1):88–106. <https://doi.org/10.1002/smj.941>.
- Zhu, F., and M. Iansiti. 2019. Why some platforms thrive and others don't. Harvard Business Review. <https://hbr.org/2019/01/why-some-platforms-thrive-and-others-dont>.
- Zhu, F., X. Li, E. Valavi, and M. Iansiti. 2021. Network interconnectivity and entry into platform markets. *Information Systems Research* 32(3):1009–1024. <https://doi.org/10.1287/isre.2021.1010>.