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The contingent effects of innovative digital sales technologies on B2B firms' financial performance

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ABSTRACT

Business-to-business (B2B) firms make large investments to implement innovative digital sales technology (IDST) in the hope of increasing firm performance. While marketing research generally indicates that these investments should pay off, recent experiences from managerial practice suggest that such beneficial payoffs may not necessarily arise. To examine the effects of implementing IDSTs on B2B firm performance, we differentiate between customer-sensing and customer-linking IDSTs: while customer-sensing IDST has the primary purpose of identifying new sales opportunities (e.g., predictive analytics) early within the B2B sales funnel, the purpose of customer-linking IDST (e.g., augmented reality application) is to close sales opportunities. The results of a multi-data study involving 314 B2B firms confirm that implementing customer-sensing and customer-linking IDST can exhibit a complementary, positive effect on firm profit, but this effect strongly varies with the sales task environment in terms of firms' offering and demand complexity. In unfavorable conditions, extensive digitalization in B2B sales can even harm firm profit. These findings contribute to sales technology research and the literature on marketing capabilities and guide managers on how to ensure successful sales digitalization.

1. Introduction

In business-to-business (B2B) firms, implementation of digital technologies to improve sales processes seems to have emerged as a panacea for increasing firm performance (Singh et al., 2019; Verhoef et al., 2021), and firms heavily invest in innovative technology, such as machine learning, robotization, and artificial intelligence (AI) (Petersen et al., 2022). The World Economic Forum (WEF, World Economic Forum, 2018) indicates that such technologies can increase productivity by 30 %–70 %, pressuring managers to accelerate the digitalization of their own sales organizations (Lamberton & Stephen, 2016). However, although reports estimate that worldwide spending on digital technologies will reach $6.3 trillion by 2024 (IDC, 2021), an estimated 48 % of firms suffer negative returns on their investments (McKinsey & Company, 2017).

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Given the high potential of implementing such technologies but the often disappointing returns (Alavi & Habel, 2021), the question arises as to why some firms succeed in capturing value from these technologies while others fail.

We define innovative digital sales technologies (IDST) as new information technology (IT) applications with new technological functionalities for collecting, processing, and disseminating digital information[1]; functionalities that were previously technically infeasible or not economically viable with traditional sales technologies. IDSTs and these new functionalities can be diverse: For instance, big data scraper collect and make sense of previously unexploitable data, such as unstructured text data from websites; AI-based predictive lead scoring tools process historical data (as most established scoring tools), but also continuously learn from new information, improving lead scoring accuracy over time; Augmented-reality (AR) based digital prototypes realistically showcase relevant product features in the customers' real environment but without the need of physical representation. This makes product-centric selling presentations, typically used in B2B sales and traditionally conducted with tools like sales tablets, significantly more illustrative and customer-centric. Thus, IDSTs can change established sales processes and help the sales force identify and close new business opportunities (e.g., Verhoef et al., 2021), contributing to a B2B firm's essential selling capabilities. Our definition of IDST is thereby in line with the understanding of "new-age technologies" (Petersen et al., 2022, p. 571), "new digital technologies" (Verhoef & Bijmolt, 2019, p. 343), or "emerging digital technologies" (Verhoef et al., 2021, p. 890) repeatedly discussed in marketing literature.

Prior research has primarily shown that implementing sales technology, such as sales force automation tools (Hunter & Perreault, 2007), can boost firm performance by increasing sales productivity and lowering sales-related costs. They support the sales force, "helping salespeople to forge relationships with business customers" (Hunter & Perreault, 2007, p. 28), and "make repetitive (administrative) tasks more efficient" (p. 17). Most firms employ traditional sales technologies today[2] to support the workflows of their sales force, such as contact management systems, video-conferencing and collaboration software, or data visualization tools. However, at a time when up to 75 % of large-scale sales digitalization projects never reach their goals (Reeves & Whitaker, 2019), those findings contrast with managers' experience. We argue that examining this tension is important for marketing research and practice for three reasons.

First, the range and effectiveness of functionalities of sales technologies have substantially increased in recent years (Huang & Rust, 2018; Singh et al., 2019). IDSTs have the potential to substantially improve firms' sales effectiveness and efficiency (Singh et al., 2019). By implementing them and improving their selling capabilities, firms may differentiate themselves from competitors. However, their implementation can also entail considerable costs for firms, which may reduce or nullify such benefits. While IDSTs promise new and superior functionalities compared to traditional sales technologies and are increasingly prevalent in practice (Grewal et al., 2020), their impact on firm performance is still not fully understood.

Second, prior research has often focused on single sales technologies, such as AI sales coaches (Luo et al., 2021), social media analysis (Schendzielarz et al., 2022), or big data analytics (Lam et al., 2017). While this focus helps examine the impact of a specific technology, it neglects the potential interdependence of IDSTs, and a differentiated view may uncover valuable results on sales technology (Hunter, 2019).

Third, the complexity of a firm's business model and offering and the complexity of customer demand are among the most dominant challenges for B2B firms (Schmitz & Ganesan, 2014). Yet, previous research has scarcely examined how these contextual factors shape the effects of implementing IDSTs in B2B firms (Table 1). Accounting for heterogeneous effects across different B2B environments is crucial for marketing research and practice to fully understand the financial consequences of implementing IDSTs (e.g., Habel et al., 2023a).

For this purpose, we developed a conceptual framework, drawing from research on marketing capabilities (Day, 1994) and task–technology fit theory (Goodhue & Thompson, 1995). Initially, we employed the marketing capability framework to distinguish between *customer-sensing IDST* and *customer-linking IDST* and inform this distinction by interviewing 22 B2B sales executives. Customer-sensing IDST has the primary purpose of supporting the sales force in identifying attractive leads early in the B2B sales funnel by generating higher quality (more comprehensive) customer knowledge than traditional sales technology. Customer-linking IDST, on the other hand, has the primary purpose of supporting the sales force in converting leads late in the B2B sales funnel by means of higher quality (more tailored) customer communication (as compared to traditional sales technology). Empirical evidence speaks to the point that implementing technologies that we define as customer-sensing IDST will likely benefit firm profit (e.g., D'Haen et al., 2016). Importantly, we add to this notion, arguing that customer-sensing and customer-linking IDST can have a complementary (i.e., positive interactive effect; Homburg & Wielgos, 2022) effect on firm profit: Customer-linking IDST likely strengthens the impact of customer-sensing IDST on firm profit (H1), as it can help the sales force to convert a higher share of attractive leads identified by customer-sensing IDST by closely tailoring the communication with customers to their needs. However, drawing on task–technology fit theory, we argue that this complementary effect of IDSTs may not unconditionally occur but likely depends on the firm's *offering complexity* (H2) and *demand complexity* (H3).

To examine this framework, we conducted a key-informant study in 2019 with experienced sales executives and matched their responses to objective profit records of 314 B2B firms. We analyzed the data through regressions and took several steps to ensure the causal identification of the effects, such as including a broad set of control variables, a Heckman selection correction (based on a random sample of 10,000 B2B firms and objective records on firms' digital infrastructure), and Gaussian copulas. Results show that IDSTs have a complementary effect on firm profit: Customer-linking IDST indeed can strengthen

[1] In line with prior sales technology differentiations (Hunter & Perreault, 2007) and recent conceptualizations of digital sales technologies (e.g., Singh et al., 2019).
[2] For instance, in our 2019 survey, 83% of managers indicated that their sales organization employs traditional sales technology such as CRM systems (see empirical study).

Table 1
Comparison of research on the firm performance impact of IDSTs.

Authors (year)	Data and research setting	Technology-related construct	Examined technology	Examined moderators	Differentiated technology view	Contingency account		Ambivalent effects on firm performance
					Customer-sensing and customer-linking IDST	Complementary technology effects	Internal and external firm environment	
Homburg & Wielgos (2022)	• 273 firms (382 managers, B2C/B2B) • Survey & objective data	Digital marketing capabilities	Social media, mobile, content marketing, SEM, web analytics, email	Environmental dynamism, market orientation	✗	(✗)[b]	✓	✓
Wielgos et al., (2021)	• 224 firms (387 managers, B2C/B2B) • 3,212 customers • Survey & objective data	Digital business capability	No specific technology	Technological dynamism, structural flux, B2B vs. B2C	✗	✗	✓	✓
Lawrence et al., (2019)	• 3,653 customers (B2B) • 237 salesperson–customer experiments (B2B) • Objective data	Online activities	Web shop	Customer-salespersoncontact	✗	✗	✗	✗
Vieira et al., (2019)	• 132 weeks longitudinal data (B2B) • Objective data	Technology investments	Digital communication tools	–	✗	✓	✗	✗
Davis-Sramek et al., (2010)	• 152 executives (B2B) • Survey data	E-commerce use; supply chain analytic IT	E-commerce; analytic IT	Environmental unpredictability	✗	✗	External	✗
Krasnikov et al., (2009)	• 125 bank information outputs (B2B) • Objective data • B2B	Technology implementation	CRM system	Commitment, time of adoption, firm size	✗	✗	Internal	✓
Rapp et al., (2010)	• 215 executives	CRM technology capability	CRM system	Environmental dynamism	✗	✗	External	✗
Becker et al., (2009)	• 90 key informants (B2C) • Survey data	Technology implementation	CRM system	Employee/ management support	✗	✗	Internal	✗
Jayachandran et al., (2005)	• 172 executives • Survey data• B2C/B2B	Technology use (moderator)	CRM system	CRM technology use	✗	✗	Internal	✗
Saini & Johnson (2005)	• 122 executives (B2C) • Survey data	E-commerce capabilities	E-commerce	Market orientation	✗	✗	Internal	✗
Reinartz et al., (2004)	• 211 executives (B2C) • Survey & objective data	IT investments/availability (moderator)	CRM system	CRM organizational alignment, technology	✗	✗	✗	(✓)[a]
This study	• 22 in-depth interviews with sales executives • 597 sales executives • Survey & objective data • B2B	Customer-sensing IDST; customer-linking IDST	**IDSTs** (e.g., virtual reality (VR)/ augmented reality (AR), predictive analytics)	Offering complexity, demand complexity	✓	✓	✓	✓

[a] Results show an unexpected, negative interactive effect of CRM technology. References for studies not discussed in the main text appear in Web Appendix H. [b] Homburg and Wielgos (2022) investigate complementary and substitutive effects of digital marketing capabilities with classic (non-technology-enabled) marketing capabilities. B2C = business-to-consumer.

the firm profit impact of customer-sensing IDST. This complementary effect becomes stronger with increasing offering complexity but weaker with increasing demand complexity.

Our study contributes to marketing research in three ways: First, it introduces a novel theory-based differentiation of IDSTs, which we also validate through qualitative interviews: IDSTs related to firms' customer-sensing and customer-linking capabilities. The results show that this distinction is empirically meaningful because firm performance strongly depends on whether B2B firms implement higher levels of customer-sensing IDST only or supplement it with higher levels of customer-linking IDST. Second, research on sales technologies emphasizes beneficial effects on sales and firm performance. Our results provide more nuance to this literature by showing that the implementation of IDSTs can also reduce firm profits and thus exert ambivalent effects (Table 1). Here, we contribute to explaining why many B2B firms benefit to a significantly lesser extent from implementing IDSTs than initially expected. Third, we uncover the moderating role of offering and demand complexity. These contextual factors determine the key tasks the sales force needs to accomplish. Customer-linking IDST needs to fit with these tasks to be able to strengthen the firm profit effect of customer-sensing IDST; otherwise, the costs of implementing IDSTs may exceed the incremental revenue gains.

2. Conceptualization of customer-sensing and customer-linking IDST

In the following, we conceptualize our focal constructs, customer-sensing IDST and customer-linking IDST, on the basis of the marketing capabilities framework. We also conducted 22 in-depth interviews with senior managers from across B2B industries to inform our conceptualization.

2.1. Marketing capabilities for B2B sales organizations

Firms' financial performance depends largely on their capabilities to successfully market products to customers. Research has yielded a variety of marketing capabilities valuable for the firm, such as market-sensing, customer-linking, brand management, and strategic marketing planning and coordination (Moorman & Day, 2016). In line with prior research, we focus on two of the most essential marketing capabilities for building a market-oriented[3] B2B sales organization: market-sensing and customer-linking (Day, 1994; Rindfleisch & Moorman, 2003).

Firms with distinctive market-sensing capabilities have an improved ability to identify sales opportunities with prospective and existing customers. Sensing capabilities create competitive advantages for firms by generating knowledge on markets, competitors, and customers (Day, 1994). In the B2B sales context of our study, this knowledge generation is reflected in firms' acquisition of customer information, generation and qualification of leads, and the prioritization of customers (Ingram et al., 2019; Johnson & Marshall, 2016). To emphasize this key relevance in generating customer knowledge and sales opportunities, in our paper, we refer to customer-sensing hereinafter.

Firms with distinctive customer-linking capabilities have an improved ability to exploit business potential by closing sales. These capabilities reflect firms' communicative activities to customers to sell offerings (Ritter, 2020), such as sales presentations or individualizing proposals for customers (Ingram et al., 2019; Johnson & Marshall, 2016).

Further, scholars have shown that different marketing capabilities can complement each other's effects on firm performance (e.g., Morgan, Katsikeas, & Vorhies, 2012). This means that "the returns to one capability are affected by the presence of another" (Morgan, Slotegraaf, and Vorhies 2009, p. 286). For example, firms need both, capabilities to identify new business potential (e.g., identify and qualify leads) and the capability to capitalize on them (e.g., converting leads) to outperform competitors (e.g., Zahra & George, 2002).

2.2. Preliminary interviews

To provide first insights into how IDSTs can help build such customer-sensing and customer-linking capabilities and to better understand their proliferation in B2B sales practice, we interviewed 22 top-level sales executives from across industries (Appendix A shows a sample overview and the interview guide; Web Appendix A outlines our procedure). In the semi-structured in-depth interviews (average duration of 63 min), we asked respondents to provide real-life examples, elaborate on how they contribute to B2B sales tasks, and to discuss potential conditions for a positive firm performance impact. Table 2 illustrates exemplary quotes on how B2B firms apply IDSTs. The results show the high managerial relevance of IDSTs for B2B sales and support a classification of IDSTs according to their primary purpose, offering first insights into the content validity of the constructs we define subsequently.

2.3. Defining customer-sensing and customer-linking IDST

Drawing on marketing capabilities theory and supported by our interview insights, we differentiate firms' implementation of IDSTs in two key areas covering the B2B sales funnel: customer-sensing and customer-linking (see Table 3). Notably, we assume IDSTs to support the sales force and not replace it, particularly in a B2B context. As Alavi and Habel (2021, p. 84)

[3] Market orientation reflects a firm's "superior skills in understanding and satisfying customers" (Day, 1994, p. 37) and is related to superior firm performance (Jaworski & Kohli, 1993).

Table 2
Interview quotes on exemplary applications of IDSTs in B2B sales organizations.

Customer-sensing (Primary purpose: identification of attractive leads)	**Customer-linking** (Primary purpose: converting leads)
Predictive analytics: "We do this for lead scoring. And this is all about prediction. Using Salesforce Einstein, one can recognize the most valuable leads and how to best approach them. [Salesforce Einstein] analyzes the type of lead, its origin, all prior interactions with our firm, and what content he has already looked at…and then it recommends the best opportunity to convert him from a lead to a customer." (#1)	**Virtual reality (VR) applications:** "To make it more eye-catching, at [past employer company], we had that virtual [name]-World, where business customers could dive into. For instance, the customer could say: 'I have this waterworks, and I need a new agitator for our clarification tank.' He could jump right into this virtual world and see how the agitator would be implemented in his particular facility." (#3)
Cloud analytics/Internet of Things (IoT) technology: "Take Thyssenkrupp as an example, who are always particularly far ahead, especially in the pre-sales area. They collect a lot of data on elevator usage patterns and are thus able to predict when the elevator will fail and when the customer will have a need for maintenance. That way, they can sell more service contracts." (#4)	**Proposal generators:** "We have special configurators with which we can carry out automated [industrial solution] planning and offer generation, …this tool can be used not only by a specialist consultant, who has to create fairly complex proposals, but it is much simpler to use … and we make those tools available to our customers… this allows the customer to participate in the planning process". (#12).
Machine learning algorithms: "Automated collection and clustering of unstructured data, for example, NoSql Big Data to tease out customer needs or a news analysis. The important thing is to train systems with machine learning algorithms to provide our salespeople with relevant targets." (#16)	**Sales presentation apps:** "With recent sales apps, I can digitalize my sales force. That's a pressing topic for me, and one that I'm currently still pushing forward at COMPANY…. The app compiles individualized sales presentations for certain customers, drawing from a huge slide deck. But these sales apps are not yet widely established." (#21)

put it: "The potential of new sales tools to substitute individual salespeople in the stages of the personal selling process may be available in some industries and for some business models, but very limited in others, such as contexts with high selling complexity or industrial settings.".

First, we define *customer-sensing IDST* as new IT applications whose new technological functionalities can support the sales force in identifying more attractive leads with higher conversion probability by generating more comprehensive customer knowledge (as compared to traditional sales technologies). As B2B firms implement higher levels of customer-sensing IDST, they increasingly use innovative analytics technology to collect and process customer information, use it to generate leads (~sales opportunities with existing and prospective customers), and make data-based recommendations for prioritizing customers. Such data may encompass representative information on customers' industry, business models, needs, and individual purchase likelihoods. These technologies exhibit functionalities beyond those of traditional sales technologies: They provide access to new sources of information (e.g., unstructured data; D'Haen et al., 2016), offer means to process (analyze) big data, or are increasingly able to learn from new customer information (e.g., Singh et al., 2019; Lam et al., 2017).[4]

Second, we define *customer-linking IDST* as new IT applications whose new technological functionalities can support the sales force in converting leads by more closely tailoring the communication with customers (as compared to traditional sales technologies). As B2B firms implement higher levels of customer-linking IDST, they increasingly use innovative communication technology to select and present relevant product information and tailor proposals to customer needs. These technologies exhibit functionalities beyond those of traditional sales technologies, offering greater richness and personalization in disseminating information to customers (e.g., Harz,Hohenberg,& Homburg, 2022; Appel et al., 2020).

These definitions capture different manifestations of technologies: technologies with a specific emphasis on either customer-sensing (e.g., AI-based predictive lead scoring) or customer-linking (e.g., VR showcase for product features); technologies designed for both customer-sensing and customer-linking (e.g., AI-based virtual agents that draw from existing customer knowledge and communicate autonomously with customers; Kannan & Bernoff, 2019); established technologies (e.g., CRM systems[5]) upgraded with innovative technology add-ons, such as an IoT interface or an AI-language model (e.g., AutoGPT; Marks, 2023). Hence, instead of focusing on specific technologies, we consider the extent to which firms have implemented IDSTs with the purpose of identifying attractive sales opportunities (customer-sensing) or close sales opportunities (customer-linking) in our concepts and measures (see section 4.2 and Zablah et al., [2012] for a similar approach). Note that we do not cover innovative communication technologies focused on relationship maintenance, like chatbots for service disruption support, in this study (see limitations).

Our definitions of customer-sensing and customer-linking IDST align with broader, recently developed concepts (see Web Appendix B for a delimitation table). Both IDST types are innovative digital technologies (Petersen et al., 2022) and important drivers of a company's digitalization and digital transformation (altering business processes and changing the business logic of a firm; Verhoef et al., 2021). They likely contribute to firms' broader digital business (esp. marketing) capabilities (Homburg & Wielgos, 2022; Wielgos et al., 2021) whose performance potential depends on environmental characteristics

[4] With "implementation" of IDST, we refer to firms' investment in and provision of such technologies to the sales force for related activities. This aligns with research on firm-level investment outcomes (Anderson et al., 2006) and technology implementation (Krasnikov et al., 2009). Increasing implementation implies that technologies may have a more pervasive influence on related activities but must not reflect individuals' technology usage or adoption. Thus, we examine task–technology fit (promoting adoption; Goodhue & Thompson, 1995) and control for sales forces' IDST knowledge as an indicator of their competence (promoting adoption; Marcolin et al., 2000) in our model.

[5] An executive (#7) noted in this regard: "Based on our CRM system, an advanced plugin automatically generates offerings for specific customers … exactly what the customer wants, what I want to discuss with the customer.".

Table 3
Comparison of customer-sensing and customer-linking IDST in B2B sales firms.

Concept	**Innovative Digital Sales Technology (IDST)**	
Definition	New IT applications with new technological functionalities for collecting, processing, and disseminating digital information	
Concept	**Customer-sensing IDST**	**Customer-linking IDST**
Purpose in B2B sales funnel	Support sales force in lead identification	Support sales force in lead conversion
Functional advantage (as compared to traditional sales technologies)	Higher-quality (more comprehensive) customer knowledge yields attractive leads with higher conversion probability	Higher quality (more informative, more tailored) communication with customers promotes higher lead conversion rates
Exemplary technologies with respective focus[a]	AI-predictive analytics add-on for CRM, big data analytics, Cloud based analytics (e.g., internet of things)	Digital prototypes (e.g., augmented or virtual reality applications), proposal generators, new communication platforms (e.g., virtual agents)
Application examples	• SaaS company offering simulation software for mobility concepts uses a **lead scoring tool (eloqua) for identification** and **qualification** of sales opportunities with high purchase probability[b] • Endress + Hauser, a leading supplier of process and laboratory measurement technology has implemented an **industrial IoT platform called Netilion** to collect and retrieve usage data from customers and an **AI-based cloud solution** by Salesforce (2022) to qualify new, attractive leads based on this data	• Manufacturer of industrial burners and combustion systems uses **tailored 3D CAD and virtual product representations** for selected customers at trade fair presentations and sales encounters[b] • Atlas Copco, an industrial tool manufacturer uses Showpad eOS, an **automatic content generator** that preselects and presents **relevant product information to customers** (via 360° showrooms tailored presentations, AR applications). "Customers feel like they're getting the information they need quickly and easily, right in the palm of their hand." Leea Huffine, Marketing Manager, Atlas Copco (Showpad, 2023, Atlas Copco Reference)

[a] Examples of specific technologies emphasize on but may not contribute exclusively to the respective purpose. [b] Examples come from key-informant survey (chapter 4) and open answer fields in which respondents described current sales digitalization. They stem from respondents who indicated a higher (>4) extent of customer-sensing or customer-linking IDST, measured on a 7-point Likert scale.

and "complementarities among these capabilities" (Wielgos et al., 2021, p. 9). However, they differ from such broader concepts in their specific focus on sales organizations and by their differentiated purpose in the B2B sales funnel.

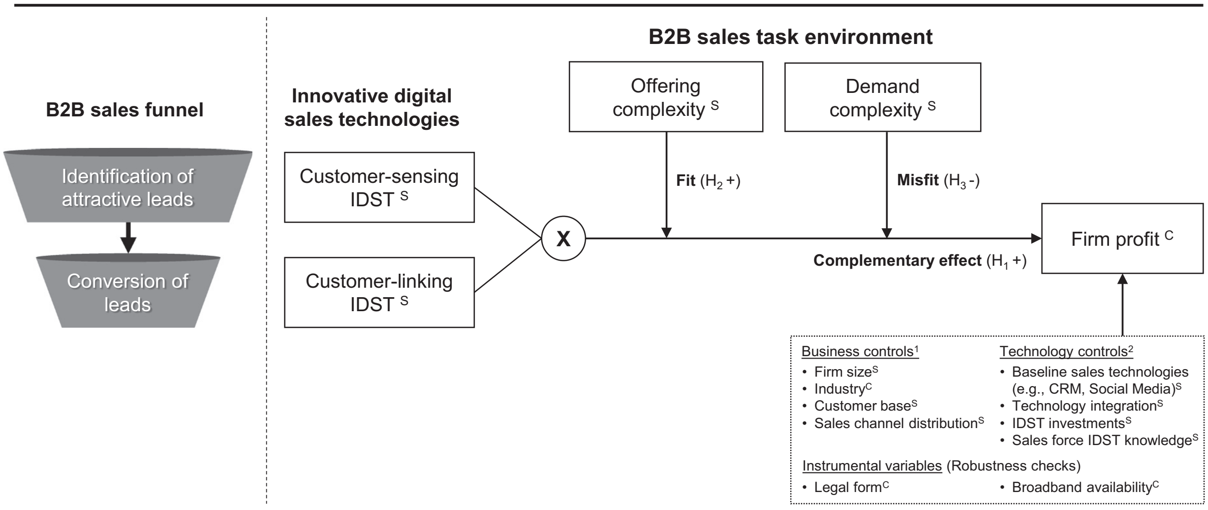
3. Conceptual model

We first present evidence of a positive firm profit effect of customer-sensing IDST, which supports the sales force in identifying attractive leads early in the B2B sales funnel. We then argue that customer-linking IDST can support the sales force in converting these attractive leads later in the B2B sales funnel, thereby enhancing the firm profit effect of customer-sensing IDST (complementary effect H1, see Fig. 1). Drawing on task–technology fit theory (Goodhue & Thompson, 1995), we then argue that this complementary effect of customer-sensing and customer-linking IDST depends on the technology's fit to a firm's central sales task environment, defined by the complexities of its offering (H2) and demand (H3).

3.1. Customer-sensing IDST and firm profit

Customer-sensing IDST can increase the quality of the firm's explicit customer knowledge. That is, innovative predictive analytics algorithms enable firms to gather data on customer preferences and prioritize customers whose needs match the firm's offerings more closely, thus creating more attractive selling opportunities (D'Haen et al., 2016; Habel et al., 2023a). For instance, 'Einstein Predictions' employs machine learning to identify potential customers (i.e., sales leads) with high conversion likelihood (Salesforce, 2023); 'Company Surge' tracks and analyzes B2B customers' digital journey, helping firms to prioritize customers that show an initial interest in their offerings (Bombora, 2024). Evidence from emerging literature on the impact of marketing analytics supports this view, indicating that deploying such applications helps identify customer leads, thereby increasing sales effectiveness and, eventually, firm performance. For example, predictive lead scoring applications (D'Haen et al., 2016) and predictive analytics to identify churning customers (Habel et al., 2023b) both improve sales performance. Employing such marketing analytics can enhance firms' sales growth, profit, and return on investment (e.g., Wamba et al., 2017) across B2B and B2C contexts (Germann et al., 2013) and various industries (Germann et al., 2014).

As shown, customer-sensing IDST can help the sales force to identify leads whose needs match to and can be adequately satisfied by the firm's offering, yielding a higher conversion likelihood. The question remains to which extent the firm's sales force can convert these attractive leads identified by customer-sensing IDST. We will elaborate on this next.



[S] Survey data (key informants). [C] Archival data, $n = 314$ B2B firms. [1] In our model, we control for industry heterogeneity by industry dummies. Alternatively, we fitted our model with objective industry data gathered from the Amadeus database on market turbulence, market volume, and sales growth per industry and found robust results. [2] We control for baseline sales technologies (CRM, social media, handhelds, and tablets).

Fig. 1. Conceptual model on task–technology fit in B2B sales organization.

3.2. The complementary effect of customer-sensing and customer-linking IDST

We propose that customer-sensing and customer-linking IDST can have a complementary effect on firm profit. The potential for the complementary effect of customer-linking and customer-sensing IDST stems from the B2B sales funnel logic of sequential lead identification and lead conversion in selling (e.g., Sabnis et al., 2013; Xu et al., 2022). Customer-sensing IDST helps to identify attractive leads with higher conversion probability (due to a closer match of customer needs to the firm's offerings), while customer-linking IDST facilitates converting these attractive leads into paying customers by tailoring the communication with customers more closely to their needs. Therefore, customer-linking IDST can enhance the positive effect of customer-sensing IDST on firm profit, which makes it more likely that the implementation of IDSTs will pay off for the firm.

Such tailored communication is achieved by IDST's improved technological functionalities to collect, process, and disseminate rich digital data. Customer-sensing IDST can handle and fuse data of large volume, velocity, and variety (Big data; e.g., Lam et al., 2017) to generate a more comprehensive knowledge of customer needs, as compared to traditional sales technologies. This knowledge can then inform customer-linking IDST to select need-matching product information to tailor sales presentations (such as ShowPad) or tailor proposals to customers (such as DealHub). Scholars repeatedly showed that technology-generated customer knowledge can improve the sales force's ability to personalize the sales encounter, which is highly appreciated by customers (Zablah et al., 2012), can increase sales performance (Ahearne et al., 2008), and firm profitability (Tuli et al., 2007). Evidence from retailing supports that analytical marketing technologies can complement the impact of further marketing technologies (e.g., to personalize communication) and thereby increase firms' revenues by 4 %–10 % (Berman & Israeli, 2022).

Thus, higher levels of customer-sensing and customer-linking IDST make it more likely that the firm can identify more attractive leads and convert them into higher sales revenues. These enhanced revenues are more likely to outweigh the costs (e.g., costs for setup, training, maintenance) associated with IDST and increase firm profits. In contrast, relying solely on either IDST may even create bottlenecks in the B2B sales funnel: Without the support of customer-linking IDST, the sales force is less able to convert the newly identified attractive leads. Without customer-sensing IDST, the effectiveness of customer-linking IDST is limited as the sales force would utilize it with less attractive leads. Concluding, we hypothesize:

H1. The positive effect of customer-sensing IDST on firm profit becomes stronger with increasing levels of customer-linking IDST (we label this effect a complementary effect).

3.3. Role of sales task–sales technology fit

Firms implement IDSTs in the hope of increasing firm performance. However, such implementation is often prone to potential pitfalls, such as low acceptance (e.g., Speier & Venkatesh, 2002), data quality and reliability issues (e.g., inconsistent data; Lam et al., 2017), or mere misalignment with strategic objectives and operative tasks. Critically, implementing IDSTs may be effective for some tasks but ineffective for others, such that firms do not realize the desired gains (Bohling et al., 2006) but still incur higher costs for operating IDSTs than for operating traditional sales technologies.

Task–technology fit theory (Goodhue & Thompson, 1995) suggests that technologies can realize their full potential only when the fit to the task environment is high; that is, the functionalities and capabilities of the technology correspond to the

Table 4
Description of offering and demand complexity.

Concept	Offering complexity	Demand complexity
Definition	The extent to which a firm's products and services are difficult to understand by the customer	The extent to which customers' needs are difficult to understand by the firm
Potential reason for greater complexity[1]	The products and services of the firm are highly diverse	Customer needs are highly diverse, as well as more difficult to articulate and document in written form
Company examples for greater complexity	• A tool manufacturer produces and distributes numerous professional tools, highly specialized for various construction applications, maintenance services, and outsourcing of fleet management processes. • A multinational industrial construction firm offers a large variety of services and individualized solutions, such as scaffolding systems, building construction, infrastructure development, and facility management. • A global manufacturer of mobility solutions providing a wide variety of customized high-speed trains that have to match customers' existing infrastructure, as well as specialized monitoring software and a wide variety of maintenance services.	• B2B customers of an IT provider have intricate business processes and possess idiosyncratic needs related to adaptability, cybersecurity, user-friendliness, or network integration. These diverse needs tend to evolve organically over time, and they are difficult to specify, document, and articulate by buying center members. • B2B customers of a specialized logistics firm have diverse distribution needs, such as tracking, inventory analytics, or reverse logistics. However, unpredictable downstream demand and limited expertise in global logistics make it difficult for them to formulate these needs accurately. • B2B customers of a leading business consulting agency come from various industries and often have a broad array of vaguely defined and unclear business issues and needs, such as business model development, digital transformation, and supply chain risk management.

[1] Insights are based on a survey with 150 sales and marketing managers on the nature of offering and demand complexity (Web Appendix C).

tasks of respective users. Then, technologies may more likely be adopted by individual users and exert stronger performance impacts (Goodhue & Thompson, 1995). Applying this idea to our conceptual model, the complementary effect of customer-sensing IDST and customer-linking IDST may likely depend on the technology's fit to the firm's task environment. Complexity is a core dimension of a firm's task environment (Holm et al., 2012) and is associated with greater task difficulty (Godes, 2003; Johnson & Sohi, 2014). Complex tasks are characterized by a high diversity of task components (e.g., Achrol & Stern, 1988; Campbell, 1988) and uncertainty, such that task outcomes are not explicit and may be difficult to measure (Zigurs & Buckland, 1998). To investigate this important notion, we differentiate firms' sales task environment by the complexity of (1) their offering and (2) customers' demand (Table 4).

First, we define *offering complexity* as the extent to which suppliers' products and services are difficult for the customer to understand. Second, we define *demand complexity* as the extent to which customer needs are difficult to comprehensvively understand by the firm (for a related concept, see Schmitz & Ganesan, 2014). Evidence from a supplemental survey with 150 sales and marketing managers (Web Appendix C) provides precise insights into the moderators: offering complexity and the difficulty for customers to understand the firm's offerings primarily stem from the high diversity of firms' products and services. By contrast, demand complexity and the firm's difficulty to understand customers' needs arise because customer needs are diverse and hard to document in written form and communicate across organizations (e.g., Cui & Wu, 2016).

3.4. Moderating role of firms' offering complexity

We propose that the complementary effect of IDSTs strengthens as offering complexity increases. That is, we expect customer-linking IDST to increase the positive effect of customer-sensing IDST on firm profit by a greater amount as offering complexity increases.

With increasing offering complexity, the firm's products and services become more diverse, resulting in a wider range of potential value contributions to customers' businesses. This has two implications: First, with a lack of relevant information, prospective customers experience uncertainty in such a buying situation on whether the proposed solution will truly deliver the desired outcome (Ulaga & Kohli, 2018). Customers may require considerable guidance and explanation from the firm to understand which of the various offerings satisfies their individual needs best (e.g., Agnihotri et al., 2009). Second, due to the potential numerous variations, a diverse offering portfolio poses higher challenges for managing it (Fernhaber & Patel, 2012). The sales force faces the difficult task of matching these product variations to the right customers (Johnson & Sohi, 2014). For instance, it becomes more difficult to select suitable product information and formulate the value proposition of an offering to match individual customers (Ulaga & Reinartz, 2011).

Based on these notions, we propose that complementing customer-sensing IDST with customer-linking IDST should improve firm performance to a greater extent as offering complexity increases. This is because the technological functionalities provided by customer-linking IDST ease and alleviate the key challenges for the sales force and customers in such environments, and therefore, help the firm to convert the attractive leads identified by customer-sensing IDST. Customer-linking IDST can (often automatically) preselect product information that is more relevant to the identified lead, closely match the communication message to the customer, and convey this message effectively (e.g., Boyd & Koles, 2019). The resulting highly individualized and informative communication with customers improves customers' understanding of how the proposed offering configuration meets their needs, resolves their uncertainty, and facilitates their decision-making in this context (e.g., Agnihotri et al., 2009).[6] Consider, for example, a smart offer configurator such as the software DealHub. The software assists the sales force in creating compelling offering proposals, pre-selecting product portfolios for the customer's individual situation and requirements. It matches product variations to suitable customers. Such a customer-linking IDST should be particularly effective to improve the conversion of attractive leads identified by customer-sensing IDST, if the supplier offers a diverse product portfolio.

Such technology-assisted tailored communication of offerings supports the sales force in finding an optimal offering configuration to match customers' needs and likewise reduces customers' uncertainty when choosing from diverse offerings. As a result, the sales force can more likely convert the attractive leads identified by customer-sensing IDST into higher sales performance (Ulaga & Kohli, 2018) and higher firm profit. On the other hand, as offerings become less complex, the positive complementary effect of IDSTs on firm profit should weaken. This is because simpler offerings cause less uncertainty among customers and require less matching of product variations with customers. Hence, the relative advantage of customer-linking IDST diminishes, rendering traditional sales technology potentially more cost-effective for supporting the sales force in lead conversion. Thus:

H2. The complementary effect of customer-sensing and customer-linking IDST on firm profit becomes stronger with increasing levels of offering complexity. That is, the higher the offering complexity, the more do higher levels of customer-linking IDST strengthen the firm profit impact of customer-sensing IDST (positive three-way interaction).

3.5. Moderating role of firms' demand complexity

Next, we propose that the complementary effect of IDSTs weakens as demand complexity increases. Specifically, we expect customer-linking IDST to increase the positive effect of customer-sensing IDST by a smaller amount as demand complexity increases.

With increasing demand complexity, B2B customers exhibit a larger number of different needs, which sometimes can be difficult to comprehend and articulate by customers (Tuli, Kohli, & Bharadwaj, 2007; Cui & Wu, 2016). Such increasing customer need diversity creates uncertainty on the selling firm side in "obtaining and assimilating information and formulating [...] marketing responses" (Achrol & Stern 1988, p. 38). For instance, customers may have very different (potentially conflicting) expectations on "product specifications, delivery time, coordination across sites" (Schmitz & Ganesan, 2014, p. 63), information that is particularly difficult to acquire comprehensively (Cui & Wu, 2016). Unlike higher offering complexity, which may be effectively managed and controlled by processing and communicating the firm-internal, well-documented product information via customer-linking IDST (see H2), managing higher demand complexity requires the acquisition of external information from customers, often with restricted access and control of the selling firm (Worm et al., 2017; Krämer et al., 2022). Consequently, with increasing demand complexity, the firm likely has less comprehensive customer knowledge, which restricts the sales force's control over the outcomes of their selling efforts, especially in tailoring offerings to meet the needs of promising leads.

Therefore, we expect demand complexity to hamper the complementary effect of IDSTs. The high diversity of expressed (and potentially unexpressed) customer needs limits a firm's ability to control this type of complexity. Specifically, it limits the comprehensiveness of firms' customer knowledge,[7] and thereby also the precision of customer linking IDST's personalization efforts ("Personalization hinges on the availability of customer information"; Huang & Rust 2017, p. 916); it hampers providing customers with need-matching product information and tailoring communication messages to fit their diverse, and most pressing needs. Importantly, the higher levels of personalization in customer communication, achievable by customer-linking IDST, can even backfire if the customer receives need-mismatching information that does not address their needs or even contradicts them (e.g., Arora et al., 2008). Such mismatching lowers lead conversion rates and harms customers' satisfaction and loyalty (Homburg et al., 2009). For instance, PERI (PERI, 2023), an industrial scaffolding provider, employs AR to showcase tailored solutions for customers' unique industrial facilities. However, with higher demand complexity, PERI often lacks precise and comprehensive knowledge of the range and priorities of individual customers' needs. In such cases, using a personalized AR application increases the risk that virtually presented product features are irrelevant to the customer. Consequently, customers may struggle to perceive the value of the solution and are more likely to disengage from the sales encounter, which prevents additional profit for the firm.

In summary, with increasing demand complexity, customer-linking IDST does less increase the conversion of attractive leads (identified by customer-sensing IDST) into higher sales revenues and firm profits. Given the higher risk of ineffective

[6] Research argues that in B2C contexts, providing *relevant* information based on comprehensive digital data reduces consumers' information overload, helps them identify preferences, and facilitates decision-making, particularly when offerings are diverse, are interdependent, and require high involvement (Reinartz et al., 2019).

[7] One may raise the point that customer-sensing IDST may serve to complement firms' understanding of customer needs by analyzing contextual information, such as industry trends or information on customers' business models (Cui & Wu, 2016). However, particularly in heterogeneous customer contexts, such knowledge tends to be less precise and reliable than knowledge derived from explicitly expressed customer needs (Ahearne et al., 2012). Even in B2C settings, inferring diverse customer preferences from text-mining customer reviews and big data analytics can provide inconsistent results (Roelen-Blasberg et al., 2023). Thus, despite customer-sensing IDST, higher demand complexity creates gaps in firms' customer knowledge, which hampers the efficacy of technology-enabled personalization by customer-linking IDST.

personalization in such complex B2B settings, the relative advantage of customer-linking IDST over traditional sales technologies in supporting lead conversion diminishes. Conversely, when demand is less complex (customers have fewer, clearly articulated needs), IDSTs may have a stronger complementary effect on firm profit. This is because simpler demands allow for a comprehensive understanding of customers, leading to more precise personalization by customer-linking IDST and improving the conversion of attractive leads identified by customer-sensing IDST. Thus:

H3. The complementary effect of customer-sensing and customer-linking IDST on firm profit becomes weaker with increasing levels of demand complexity. That is, the higher the demand complexity, the less do higher levels of customer-linking IDST strengthen the firm profit impact of customer-sensing IDST (negative three-way interaction).

4. Empirical study

4.1. Data collection and sample

We adopted a key-informant approach (e.g., Reinartz et al., 2004) and conducted a large-scale mail survey on firms' implementation of innovative digital technologies in sales across several national and multinational B2B companies and industries to generate a diverse sample of sales organizations. To gain insights into the strategic perspective of IDSTs' financial chances and risks for the firm, we focused on executives and high-level managers, such as CEOs, heads of sales, or heads of business units. This approach ensures that informants have sufficient experience to provide high-quality responses (Wilden & Gudergan, 2015).

We received responses from 597 key informants from different companies across various industries—an overall response rate of approximately 6 %, which is comparable to cross-industry firm studies with high-ranking key informants in the field of marketing capabilities (e.g., Krush et al., 2015; Wilden & Gudergan, 2015). Respondents have an average professional experience of 20 years in sales. Their firms represent a variety of B2B industries, such as industrial goods (32 %), industrial services (25 %), retail and trade (8 %), and health care and pharmaceuticals (3 %) (see Web Appendix D for our sample composition). For 314 of the 597 firms, we were able to match available objective firm profit data from the Dafne and North Data databases as well as public company reports. Thus, our final sample for the analysis of financial firm profit effects of IDSTs comprises 314 different B2B firms. The firm profit data covers the next entire year, starting five months after the survey, to avoid potential causality issues.

To rule out the possibility of a selection bias, we examined how firms in our sample are distributed across industries compared with a representative sample of 10,000 B2B firms (no significant differences; $\chi^2(6) = 5.8827$, $p > 0.10$) and applied a Heckman selection correction to our model as a robustness check. The risk for common method variance (CMV) is low, as the independent and dependent variables come from different data sources and prior research indicates that CMV can only deflate, not create, interaction effects (Siemsen et al., 2010).

4.2. Measures

4.2.1. Customer-sensing and customer-linking IDST

All measures appear in Appendix B. To measure the extent to which firms have implemented customer-sensing and customer-linking IDST, we developed new scales. For the measurement development, we followed established procedures comprising an initial conceptualization, item generation, discussions with five academic experts and five practitioners, and measurement validation with 76 salespeople (see Web Appendix E for details). In essence, drawing on marketing capabilities theory (Day, 2011), sales technology research (Hunter & Perreault, 2007), and insights from the in-depth interviews with 22 sales executives, we developed and refined a six-item measure for customer-sensing IDST (to identify sales opportunities, or all activities related to the identification of new business potentials, lead generation, and customer prioritization). We also developed a five-item measure for customer-linking IDST (to close sales opportunities, or activities related to the communication with customers, product presentation, and individualization of proposals).

In the key-informant survey, our scales show high face validity, as indicated by the technologies that firms with lower or higher customer-sensing or customer-linking IDST have implemented (Web Appendix C). For example, predictive analytics are three times more prevalent in firms with higher than lower customer-sensing IDST ($\Delta\% = +300\ \%$, $p < 0.05$).

4.2.2. Offering complexity and demand complexity

We based the offering and demand complexity measures on Cannon and Perreault (1999) and Zott and Amit (2007). Offering complexity (sample item: "Our customer solutions have a high need for explanation") reflects the difficulty for customers to understand the firm's offerings, while demand complexity (sample item: "The needs of our customers are not easy to understand") reflects the difficulty to understand customer needs. We also find robust results with alternative measures for offering (firm's service ratio; e.g., Fang et al., 2008) and demand complexity (firms' share of large customers; e.g., Schmitz & Ganesan, 2014) (Web Appendix F).

4.2.3. Firm profit

We obtained objective firm records and calculated the natural logarithm of firms' earnings before interest, taxes, depreciation, and amortization (Luffarelli et al., 2019). This measure disregards a depreciation of non-material goods (e.g., licenses) and allows us to investigate the operative impact of IDSTs, independent of initial investment costs.

Table 5
Descriptive statistics and correlations.

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1. Customer-sensing IDST												
2. Customer-linking IDST	0.000[a]											
3. Demand complexity	0.020	0.074										
4. Offering complexity	0.179**	0.114*	0.375**									
5. Firm profit (log)	0.092	0.092	−0.071	−0.046								
6. Firm size	0.143*	0.078	0.082	0.028	0.232**							
7. Customer base	−0.072	0.021	0.098	−0.023	0.029	0.167**						
8. Sales channel distribution	0.113	0.097	−0.124	−0.122	0.062	0.162*	−0.082					
9. Prior IDST investments	0.201**	0.051	−0.042	−0.081	0.253**	0.380**	−0.016	0.240**				
10. Sales force IDST knowledge	0.405**	0.171**	0.108	0.156**	0.088	0.088	0.022	0.071	0.103			
11. Technology integration	0.455**	0.145*	−0.032	0.103	0.089	0.130*	0.055	0.206**	0.140*	0.458**		
12. Baseline technologies	0.111	0.102	−0.083	0.082	0.027	0.085	−0.025	0.107	0.129*	0.103	0.098	
M	4.589	4.955	4.958	6.118	1.852	3.485	56.445	6.746	4.947	4.351	3.957	0.831
SD	1.520	1.378	1.364	1.090	3.863	2.407	23.510	11.277	4.201	1.407	1.737	0.375
Composite reliability	0.916	0.897	0.798	0.818						0.935	0.896	
Average variance extracted	0.648	0.636	0.578	0.612						0.828	0.743	

* $p < 0.05$, ** $p < 0.01$ (two-tailed).
[a] Variables are orthogonalized. Correlation between customer-sensing and customer-linking IDST before orthogonalization: r = 0.569.

4.2.4. Controls

Firms' profitability (and their ability to generate higher profits) may vary by industry and business model (Homburg & Wielgos, 2022). Hence, we control for firms' industry affiliation (industry dummies; Homburg et al., 2017), firm size (number of employees; Homburg et al., 2012a), sales channel distribution (share of revenue generated with online shops), and firms' customer base (customer concentration; Patatoukas, 2012) (revenue share with large customers).

Firms' ability to effectively use IT is important to generate competitive advantages (e.g., Pavlou & El Sawy, 2006), which potentially increase firm profits. We control for sales forces' technology knowledge, or their proper understanding of technology and how to apply and make effective use of it to improve performance. We adapted three items from the IT Use Capability scale of Wang et al., (2012). To account for heterogeneity in firms' technological infrastructure, we control for firms' implementation of baseline sales technologies, such as CRM applications, social media, or tablets and handhelds, which are not captured by our IDST measures (Web Appendix C). These technologies may help firms develop digital marketing capabilities and generate higher profits (Homburg & Wielgos, 2022). Relatedly, we control for the degree to which sales technologies are integrated and able to exchange data (sample item: "Our technologies are able to share data and information"; based on an interfirm IT integration scale of Rai & Tang, 2010). We also control for firms' recent investments in digital technologies. Recent technology investments may indicate an ongoing change process, which may (temporarily) tie up human capital in sales, hamper sales efficiencies, and limit firm profit.

4.2.5. Psychometric properties, descriptive statistics, and correlations

Psychometric properties, descriptive statistics, and correlations appear in Table 5. We checked for reliability and conducted a confirmatory factor analysis to test the validity of our measures. The analysis yielded widely acceptable measurement model fit: $\chi^2(300.800\,(208), p < 0.05)$, CFI = 0.981, TLI = 0.977, RMSEA = 0.038, SRMSR = 0.053. All measures meet the recommended thresholds for internal consistency and composite reliability, average variance extracted (Bagozzi & Yi, 1988), and discriminant validity (Fornell & Larcker, 1981). Customer-sensing and customer-linking IDST are empirically discriminant but correlate at a moderately high level (r = 0.569), suggesting that firms often make holistic rather than selective decisions on sales digitalization. For example, 37 % of firms in our sample show higher values for customer-sensing *and* customer-linking IDST. We account for this relationship in our model specification.

4.3. Model specification and results

To estimate the effects of customer-sensing and customer-linking IDST with greater accuracy and reduce endogeneity issues (see section 4.4), we orthogonalized the variables (e.g., Hall et al., 2015; Homburg et al., 2005). Therefore, we obtained the residuals from regressing customer-linking IDST on customer-sensing IDST before our model estimation and then used these residuals as indicators for customer-linking IDST in our model.[8] We then specified regression models with a maximum likelihood estimator robust to non-normality (using Mplus 8.6) and tested our hypotheses in the fully specified model 4 (Table 6). Our model shows a moderate explanatory power for objective firm performance ($R^2 = 0.15$, comparable to other studies in the field, e.g., Homburg & Wielgos, 2022), and shows significant model fit increases when adding the IDST interaction effects of interest.

[8] The residuals reflect the part of customer-linking IDST that is not explained by customer-sensing IDST. This procedure does not unduly influence our results, as results remain stable when not orthogonalizing customer-linking and customer-sensing IDST (see Web Appendix G).

Table 6
Estimation results.

		Model 1 Main effects		Model 2 2-way interaction effects		Model 3 3-way interaction effects		Full Model 4 Model 3 with controls		Model R1 + Selection correction I		Model R2 + selection correction II[1]		Model R3 + Gaussian copulas[2]	
	Hyp.	Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)
Main Effects															
Customer-sensing IDST (CS)		0.259*	(0.141)	0.267*	(0.145)	0.277*	(0.144)	0.063	(0.156)	0.103	(0.164)	−0.116	(0.163)	−0.330	(0.525)
Customer-linking IDST (CL)		0.352*	(0.195)	0.435**	(0.205)	0.327	(0.201)	0.222	(0.186)	0.248	(0.186)	0.229	(0.173)	−0.002	(0.431)
Offering complexity		−0.207	(0.237)	−0.274	(0.240)	−0.306	(0.241)	−0.266	(0.216)	−0.301	(0.225)	−0.155	(0.197)	0.817**	(0.385)
Demand complexity		−0.168	(0.182)	−0.123	(0.184)	−0.074	(0.182)	−0.095	(0.175)	0.004	(0.196)	−0.111	(0.191)	−0.396	(0.410)
Interactive Effects															
CS x CL	H1			0.129	(0.116)	0.153	(0.124)	**0.190***	(0.115)	**0.182**	(0.114)	**0.201***	(0.107)	**0.204**	(0.129)
CS x offering complexity				−0.210	(0.198)	−0.054	(0.174)	0.002	(0.162)	0.024	(0.166)	0.125	(0.143)	0.126	(0.166)
CL x offering complexity				0.032	(0.253)	0.311	(0.278)	0.242	(0.230)	0.262	(0.228)	0.313	(0.203)	0.328	(0.226)
CS x CL x offering complexity	H2					0.307*	(0.162)	**0.324****	(0.144)	**0.327****	(0.146)	**0.372*****	(0.125)	**0.367****	(0.168)
CS x demand complexity				0.091	(0.108)	0.032	(0.106)	−0.015	(0.103)	−0.011	(0.102)	−0.049	(0.102)	−0.033	(0.106)
CL x cemand complexity				−0.079	(0.167)	−0.232	(0.182)	−0.282*	(0.163)	−0.290*	(0.159)	−0.300**	(0.153)	−0.289*	(0.166)
CS x CL x demand complexity	H3					−0.252**	(0.104)	−**0.321*****	(0.096)	−**0.314*****	(0.093)	−**0.296*****	(0.092)	−**0.291*****	(0.101)
Control Effects															
Firm size								0.637***	(0.244)	0.722*	(0.279)	−0.004	(0.298)	−0.035	(0.318)
Customer base								0.079	(0.231)	0.007	(0.254)	−0.002	(0.239)	0.067	(0.245)
Sales channel distribution								−0.312	(0.220)	−0.277	(0.221)	−0.370*	(0.191)	−0.314	(0.237)
Prior IDST investments								0.611**	(0.240)	0.634***	(0.236)	0.606***	(0.216)	0.602**	(0.238)
Sales force IDST knowledge								−0.009	(0.247)	0.039	(0.263)	0.202	(0.271)	0.226	(0.282)
Technology integration								0.159	(0.292)	0.139	(0.287)	0.149	(0.277)	0.175	(0.296)
Baseline technologies								0.044	(0.622)	0.180	(0.628)	0.488	(0.574)	0.132	(0.667)
Industry dummies								Yes		Yes		Yes		Yes	
Robustness Checks															
Inv. Mills ratio no. (selection effect 1)										2.031	(1.912)	0.951	(1.697)	0.612	(1.804)
Inv. Mills ratio no. (selection effect 2)												−2.96***	(0.495)	−2.92***	(0.530)
Gaussian copula: customer-sensing IDST														0.343	(0.768)
Gaussian copula: customer-linking IDST														0.229	(0.510)
Gaussian copula: offering complexity														0.413	(0.554)
Gaussian copula: demand complexity														−1.276***	(0.455)
R^2		0.026		0.035		0.059		0.149		0.156		0.272		0.353	
Log-likelihood difference test[3] (p-value)				< 0.01		< 0.01		< 0.01		< 0.05		< 0.01		< 0.01	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed). Notes: n = 314. We report unstandardized coefficients. Robust standard errors are in parentheses.

[1] Results remain stable when we include the second inverse Mills ratios only.

[2] We use bootstrapped standard errors (10,000 draws) in the copula model, as suggested by prior research (Park & Gupta, 2012). [3] To receive chi-square distributed test statistic, we rely on log-likelihood and scaling correction for robust maximum likelihood estimator in Mplus. We computed the scaling correction using the formula cd = p0 × c0 – p1 × c1)/(p0 – p1), with p0 (p1) being a parameter count in the baseline (comparison) model and c0 (c1) being a scaling correction factor of the baseline (comparison) model. Then, we computed the log-likelihood difference with scaling correction using the formula: –2 (L0-L1)/cd suggested by Asparouhov and Muthén (2010), with L0 (L1) being the log-likelihood value of the baseline (comparison) model.

Regarding H1, we find a marginally significant two-way interaction effect of customer-sensing and customer-linking IDST ($b_{CS\times CL}$ = 0.190, p < 0.10). However, the effect does not prove robust (models R1–R3), so we reject H1. This result was not unexpected, as we assumed that the complementary effect of IDSTs is highly contingent on firms' sales task environment.

In support of H2, we find a significant, positive three-way interaction effect of offering complexity, customer-sensing, and customer-linking IDST ($b_{CS\times CL\times OC}$ = 0.324, p < 0.05). With increasing offering complexity, the positive interaction effect of customer-sensing and customer-linking IDST grows more pronounced. As panel A of Fig. 2 depicts, the proposed complementary effect of IDSTs on firm profit becomes significant (p < 0.05) at $\geq$ 0.077 SD above the mean of offering complexity ($b_{CS\times CL}$ = 0.218, p = 0.05). For instance, at greater offering complexity (+1.5 SD), customer-sensing IDST increases firm profit only if customer-linking IDST is higher (b_{+1SD} = 0.879, p < 0.05; $b_{+1.5SD}$ = 1.286, p < 0.05; $b_{+\,2SD}$ = 1.694, p < 0.01) and even decreases firm profit if customer-linking IDST is lower (b_{-1SD} = –.754, p < 0.05; $b_{-1.5SD}$ = –1.161, p < 0.01; b_{-2SD} = –1.569, p < 0.01). In such contexts, implementing higher levels of both IDSTs fits the sales task and increases profits.

In support of H3, we find a significant, negative three-way interaction effect of demand complexity, customer-sensing IDST, and customer-linking IDST ($b_{CS\times CL\times DC}$ = –.321, p < 0.01). The greater the demand complexity, the less positive is the interaction effect of customer-sensing and customer-linking IDST. Panel B of Fig. 2 shows a positive interaction effect on firm

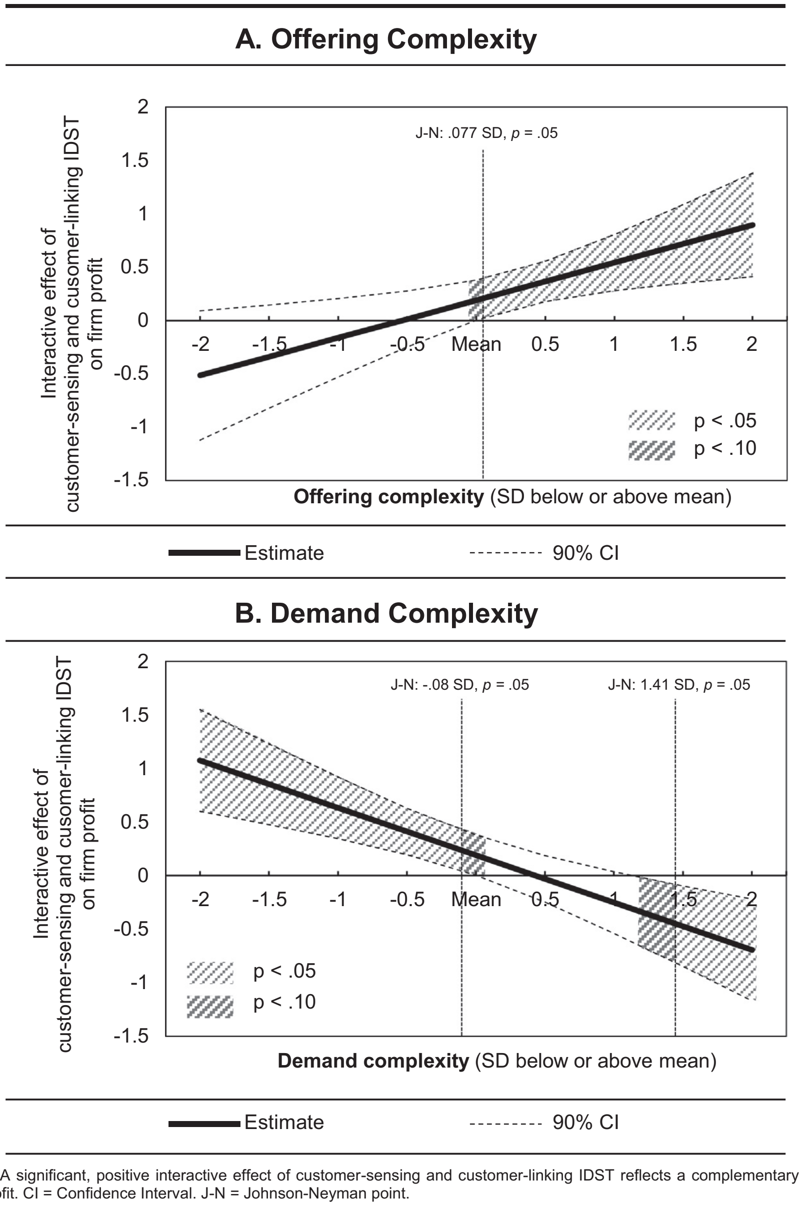


Fig. 2. Interactive effects of customer-sensing and customer-linking IDST at levels of offering and demand complexity.

profit at $\leq$ -0.080 SD below the mean of demand complexity ($b_{CS \times CL}$ = 0.226, p = 0.05) and a negative interaction effect at $\geq$ 1.41 SD above the mean ($b_{CS \times CL}$ = –.424, p = 0.05). Specifically, at greater demand complexity (+1.5SD), customer-sensing IDST tends to increase firm profit if customer-linking IDST is lower (b_{-1SD} = 0.569, p > 0.10; $b_{-1.5SD}$ = 0.837, p < 0.10; b_{-2SD} = 1.105, p < 0.10), but tends even to harm profit if customer-linking IDST is higher (b_{+1SD} = –.503, p > 0.10; $b_{+1.5SD}$ = –.770, p < 0.10; b_{+2SD} = –1.039, p < 0.10). Implementing both IDSTs to a higher extent yields a weak fit and may even harm firm profit in this context.

4.4. Robustness checks

4.4.1. Sample selection

We employ a Heckman (1979) selection correction to account for two potential sources of endogeneity related to sample selection. First, given the limited availability of archival firm data, we could include only 314 of 597 survey respondents in our analysis. Equivalent to prior research (Homburg et al., 2012b; Homburg & Wielgos, 2022), we examine firms' legal forms as a relevant predictor of the availability of archival financial data. Thus, we coded the legal form by firms' obligation to publish financial records. Although exceptions are possible, the legal form likely predicts the public availability of financial records (Wielgos et al., 2021) but not firm profit, as it does not imply differences in resources, capabilities, or markets.[9] In the first stage, we predict our sample selection of 314 B2B firms by legal form and all independent variables from our main analysis. Results show that firms with a legal obligation to report financial records are more likely to be in our sample (b = 0.814, p < 0.01; Web Appendix G). In the second stage, we integrated the inverse Mills ratio in our main analysis and found robust results (model R1).

Second, we account for potential differences between our research sample and a representative, random population of B2B firms. For example, firms with strong digital infrastructure (broadband availability) may be more likely to participate in a digitalization survey. However, broadband internet availability should not directly influence the profit of B2B firms[10] whose business models rely more on physical production facilities and engineering capabilities and which often cover distinct sales territories by independent distributors (Ulaga & Reinartz, 2011), rather than own digital distribution channels. To predict our sample selection, we gathered additional data on a random sample of 10,000 B2B firms in terms of their firm size (number of employees) and industry from the Dafne database. We also gathered and matched nationwide data on firms' technological infrastructure (measured as a percentage of broadband availability by zip codes) for more than 10,900 regions from the National Ministry of Digital Infrastructure. Results of the first stage show that technological infrastructure (b = 0.393, p < 0.01) and firm size (log of number of employees, b = 0.113, p < 0.01) significantly predict our sample selection (Web appendix G). Incorporating the inverse Mills ratio and repeating our main analysis in the second stage yielded robust results (Model R2).

4.4.2. Omitted variable bias

We further address potential endogeneity from omitted variables and relationships among our predictors by fitting our model using Gaussian copulas (Park & Gupta, 2012; for recent applications, see Carson & Ghosh, 2019; Homburg et al., 2020), which we calculated for customer-sensing and customer-linking IDST and offering and demand complexity. Copulas account for the potential correlation of endogenous variables with the error term (Park & Gupta, 2012). The results of the Shapiro–Wilk test ($W_{MS\text{-}DT}$ = 0.98, p < 0.01, $V_{MS\text{-}DT}$ = 2.71; $W_{CL\text{-}DT}$ = 0.97, p < 0.01, $V_{CL\text{-}DT}$ = 6.61) support non-normality in the distribution of potentially endogenous variables, which allows us to proceed with the Gaussian copula approach. Including the copulas for all four predictors in our model and repeating our analysis yielded robust results (Model R3).

5. Discussion

5.1. Research implications

Although marketing research has demonstrated that sales technologies such as CRM can improve firm performance, many B2B firms fail to realize hoped-for financial results from implementing innovative digital sales technologies. We argue that this discrepancy occurs because the impact of IDSTs on firm profit depends on their interaction and the firm's sales task environment. Our investigation is one of the first studies to empirically show when the implementation of IDSTs for two essential sales functions of B2B firms increases or decreases firm profit. We offer three key contributions to marketing research.

First, drawing on the marketing capabilities framework, we introduce a differentiated conceptualization of the implementation of IDSTs in sales organizations (customer-sensing and customer-linking). Our conceptualization contributes to the literature on technology implementation because prior marketing research has either examined performance implications of single sales technologies, such as CRM systems (e.g., Rapp et al., 2010; Reinartz et al., 2004), social media (Trainor et al., 2014), e-commerce systems (Saini & Johnson, 2005), or chatbots (Luo et al., 2019), or taken a holistic perspective on digital (marketing) capabilities (e.g., Homburg & Wielgos, 2022), without differentiating key sales functions of B2B firms. However, with one notable exception (i.e., Hunter & Perreault, 2007), prior research has not differentiated the performance impact of

[9] Within some legal forms, the legislator differentiates disclosure requirements by firm size but not firm profit.

[10] Findings on the potential value of broadband internet for economic growth remain ambivalent (e.g., Ford, 2018).

sales technologies with primary analytical and primary communicative functions. Our results show that such differentiation is essential to understanding the impact of implementing IDST on firm performance.

Second, we provide first insights into the interplay of customer-sensing and customer-linking IDST in their impact on firm profit. Implementing higher levels of both IDST types can exert complementary effects (we adopted this approach from Voss et al., 2010; Homburg & Wielgos, 2022) on firm profit. Although researchers prominently argue for interactive effects of different marketing capabilities (e.g., Morgan et al., 2009), research has not considered the interactive effects of IDSTs serving the essential capabilities of customer-sensing and customer-linking but rather has tended to examine technologies in isolation (e.g., Luo et al., 2019). To the best of our knowledge, our study is the first to apply this aspect of marketing capabilities to B2B sales and conceptually propose and empirically examine the interactive effect of different technology types. Future research should consider interactive effects, as we found that they substantially alter both the magnitude and the direction of IDSTs' impact on firm profit.

Third, prior research has significantly advanced the understanding of the beneficial effects of implementing digital technologies in sales and has underscored the potential of innovative sales technologies (Table 1). However, the notion of potential risks and detrimental effects of such new sales technologies is less explored, though recent research highlights persistent difficulties for sales organizations in this area (Alavi & Habel, 2021). Thus, we contribute to sales research by identifying conditions under which implementing IDSTs in sales harms firm profit. The essential idea for identifying harmful and beneficial effects derives from the task–technology fit theory (Goodhue & Thompson, 1995). Based on this theory, we show that the complementary firm profit effect from implementing customer-sensing and customer-linking IDST intensifies with increasing offering complexity. However, we also show that the complementary effect weakens with increasing demand complexity. In such contexts, generated customer knowledge may be less comprehensive, and incorporating such knowledge into customer-linking IDST can lead to recommendations that mismatch customers' needs. Here, implementing higher levels of customer-linking IDST may not yield the potential to produce higher revenue; rather, it creates additional costs, such as operating and complexity costs (e.g., Lam et al., 2017). More critically, with increasing demand complexities, human involvement and capabilities, such as empathy and intuition (Hall et al., 2015), become more important in effectively matching offerings to customers' true needs and closing sales opportunities (Ahearne et al., 2012). Our findings align with recent works on AI technologies in service settings (Huang & Rust, 2018, 2021). It shows that such new technologies have highly specific application areas, and firms may face harmful consequences if they mistakenly implement them in an unsuitable internal or external environment (Habel et al., 2023a).

5.2. Limitations and further research

This study has several limitations that provide fruitful avenues for future research. First, our measurements (1) focus on the innovative technology of the early 2020 s, (2) may not cover the full spectrum of technology in sales organizations today, and (3) could be subject to variance in respondents' perception of innovativeness. Some years from now, IDSTs may be different, provide new, value-adding functionalities, and incur additional costs. Our findings, however, should remain valid, as we base our model on the notion that IDSTs promote key sales capabilities and fundamental task–technology fit logic. Widely established SFA technologies may also contribute to firms' customer-sensing and customer-linking capabilities, even if only freeing up resources for the sales force. While we account for the implementation of traditional sales technologies, our IDST measure does not capture whether B2B firms employed IDST as complements or replacements. Initial insights from our interviews indicate that B2B firms typically implement IDSTs as complements for traditional sales technologies (e.g., "We now build up intelligence with big data analytics, but based on our current databases"; #17). Likely, the nature of IDSTs as complements to or replacements for traditional sales technology may affect not only sales effectiveness but also the costs of implementation. Consequences could include lower setup or operational costs, but also redundancies or unused potential due to missing interfaces. We ask future research to explore the complementary or replacing nature of IDSTs and how it may affect their firm profit impact. Future research could assess IDST at the technology level, enhancing measurement objectivity and enabling further differentiation of the effects and interactions of individual technologies. Further, our study does not consider technologies used solely for maintaining relationships (e.g., customer service), not sales. We ask future research to explore how these technologies interact with customer-sensing and customer-linking IDST in their impact on firm profit.

Second, we focused on two essential marketing capabilities, customer-sensing and customer-linking, that strongly relate to key activities in the B2B sales funnel. However, research has discussed a broad variety of strategic and functional marketing capabilities, many of which may similarly benefit from implementing IDSTs, such as channel management or pricing (Vorhies & Morgan, 2005). Future research might investigate conditions under which digitalizing additional marketing capabilities yields a task–technology fit and benefits firm profit. Furthermore, as studies have repeatedly shown the importance of human capital in complementing technologies (e.g., Lam et al., 2017; Habel et al., 2023a), we call on scholars to investigate the interactive effects of IDSTs with distinctive human resources (competencies), particularly in contexts in which extensive digitalization can harm firm profit.

Third, regarding our moderators, we focus on two specific facets of firms' sales task environments: offering and demand complexity. Yet prior research has developed different conceptualizations of complexity in firms' environments, such as organizational complexity (e.g., Schmitz & Ganesan, 2014) or market complexity (e.g., Hartmann et al., 2018). Further, the impact of such complexities may vary with firms' sales structures. For example, a sales force may be structured around specialists selling a limited product range. Here, implementing IDSTs may show a weaker impact on firm profit as the diversity of firms' offerings may constitute a less decisive factor. We consider it to be an important endeavor for future research to examine the moderating effects of further firm complexities and organizational factors, as our results show strong heterogeneity in the effects of IDST in different contexts.

Last, prior research has emphasized the key role of salespeople's technology adoption (e.g., Speier & Venkatesh, 2002). Our focus on sales executives may provide diagnostic information on technology implementation, but executives are less reliable respondents for salespeople's technology use. Although task-technology fit should foster technology's adoption (Goodhue & Thompson, 1995), salespeople's actual technology usage remains an unobserved mediator in our model. From our firm-level perspective, important follow-up questions arise for individuals' application of IDSTs, such as: How does implementing both IDST types affect salespersons' effectiveness in utilizing these technologies? Does customer knowledge gained from customer-sensing IDST affect a salesperson's choice of customer-linking IDST for an upcoming encounter? Which skills and behaviors are required for an effective use of IDST? (see recent discussions in the literature, e.g., Davenport et al., 2020). A supplemental analysis indicated that positive and negative firm profit effects of IDST may manifest only after a certain period after initial implementation, presumably due to delayed adoption by the sales force or increasing training effects of such technologies. We ask future research to combine manager and salesperson data to more closely examine the interplay of organizational and individual factors and the longitudinal dynamics when implementing IDST in B2B firms.

5.3. Managerial implications

B2B sales managers can benefit from a more profound understanding of why implementing costly IDSTs might fail to produce the expected returns. Our analyses identify conditions when customer-sensing and customer-linking IDST yield a stronger or weaker complementary effect on firm profit. Thus, the results of our study provide straightforward guidance to managers on whether to implement customer-sensing and/or customer-linking IDST in different situations of offering and demand complexity. Managers might consider implementing customer-sensing IDST, customer-linking IDST, or both to a higher extent.

We suggest a convenient, directly actionable two-step process for managers: (1) evaluate the extent of offering and demand complexity of their firm environment and, (2) based on our study results, determine to what extent to implement customer-sensing and customer-linking IDST. Such an assessment should be feasible if managers draw on the measurement items in our study to inform their evaluation.

With increasing offering complexity, managers may anticipate stronger profit gains from implementing customer-sensing *and* −linking IDST to a greater extent. Customer-sensing IDST increases firm profits by up to 8 % when combined with customer-linking IDST in the case of average complex offerings (6). Compared to a situation of average offering complexity, implementing customer-linking IDST additionally increases firm profit by 10 % in the case of more extensively complex offerings (6.5). However, they should be aware that in these environments, implementing higher customer-sensing IDST and neglecting customer-linking IDST can harm firm profit. By contrast, with increasing demand complexity, managers should refrain from implementing both IDSTs to a higher extent. In this case, implementing customer-sensing and customer-linking IDST to a higher extent may result in a task–technology misfit and lead to profit losses. While customer-sensing IDST increases firm profits by up to 12 % when combined with customer-linking IDST in the case of average complex demand (5), we observe only 4 % higher firm profits when customer-linking IDST is added in the case of higher complex demands (5.5). In situations of demand complexity, managers should avoid implementing customer-linking IDST, which underlines our paper's key argument that the implementation of IDST is not unconditionally beneficial and, in fact, can harm firm performance if employed in the wrong circumstances.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT 3.5 by OpenAI, and Grammarly by Grammarly.com in order to improve language and readability only. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Maximilian Friess: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Till Haumann:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Sascha Alavi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Investigation, Conceptualization. **Alexandru Ionut Oproiescu:** Writing – original draft, Validation, Conceptualization. **Christian Schmitz:** Supervision. **Jan Wieseke:** Supervision, Conceptualization.

Data availability

The authors do not have permission to share data.

Appendix A. Overview on qualitative study

A. Sample Overview of Qualitative Interviews

No.	Position	Sales revenue (Mio. €)	Firm size(No. employees)	Industry
1	Head of digital sales	301	1,100	Event Service Provider
2	Managing partner	1	9	Aerospace
3	Head of global online marketing	194	2,700	Industrial Manufacturing
4	Director strategic planning	34	300	Consulting
5	Key account manager	2370	6,711	Industrial Manufacturing
6	Program management manager	71,860	481,000	Logistics
7	Sales director	102,900	8,922	Industrial Manufacturing
8	Managing director	n/a	29	Consulting
9	Head of digital transformation and corporate development	778	1,564	Industrial Manufacturing Solutions
10	Chief executive officer	n/a	8	Technology Solutions
11	Group vice president sales excellence	1463	7,830	Industrial Manufacturing
12	Head of sales excellence	778	1,564	Industrial Manufacturing Solutions
13	Chief transformation officer	44	228	Retail
14	Senior consultant	43	183	Consulting
15	Senior manager	804	4,193	IT Consulting
16	Business development manager	77,700	9,500	Industrial Manufacturing Solutions
17	Senior manager	109,000	125,934	Insurance
18	Sales manager	2,686	1,769	Energy
19	Director sales development	500	3,000	Healthcare
20	Account manager	86	272	Industrial Manufacturing
21	Business manager	12,821	17,492	Chemicals
22	Group director sales	66	378	IT Solutions Consulting

B. Interview Guide

Introductory information: "This interview is part of a study on the implementation of digital technologies in B2B sales. Specifically, we want to discuss digital technologies that are particularly innovative from your point of view and for your sales organization."

Part 1: Background information and Introductory questions

- Please describe your current position and the tasks for which you are responsible in your company.
- How much experience do you have in this company (in years) and in sales (in years)?
- Please briefly describe your company's business model and sales organization.

Part 2: Application of innovative digital sales technologies

- Which digital (and non-digital) sales technologies are relevant in today's sales organizations? (and your organization)
- Please describe how innovative digital sales technologies may provide value along a typical sales process (e.g., from pre-sales to sales).
- Please describe the potential contribution (if any) of digital sales technologies to key sales functions and tasks. (e.g., identification of business potentials, lead generation, customer prioritization, communication with customers, product presentations, customization of offerings)

Part 3: Digital technology contingencies

- Please describe how distinct digital technologies interact with each other in your sales organization.
- Which potential synergies or interactive effects can you imagine when different core sales functions are highly digitalized in your sales organization?
- Please describe the potential impact of digital technologies on particularly complex business models? (vs. simple, standardized business models).
- Please describe the potential role of digital technologies when customer needs and demands are particularly complex (vs. rather simple customer demands).

Part 4: Ending

- How often do you use digital sales technologies?
- Are digitalized sales functions a new or common phenomenon in your organization?
- Please rate the following technologies with regard to your understanding of innovativeness in sales. (Tablets and handheld devices, VR/AR applications)

Appendix B. Measures

Key constructs

Firm Profit (Natural logarithm of) Firms' earnings before interest, taxes, depreciation and amortization (e.g., Luffarelli et al., 2019)

(Introductory information for survey respondents regarding IDST scales: "In the following, we are interested in how far your firm implemented innovative, digital technologies")

Customer-sensing IDST (own development) (1 = "strongly disagree," 7 = "strongly agree")

We have implemented digital technologies…

- …to generate information regarding new potential customers.
- …to qualify potential customers.
- …to identify new potential customers.
- …to generate leads.
- …to measure and analyze the potential of customers.
- …to prioritize customers.

Customer-linking IDST (own development) (1 = "strongly disagree," 7 = "strongly agree")

We have implemented digital technologies…

- …to present customers our products and services.
- …to show customers certain product-related characteristics or utilities.
- …to convince customers within the interaction of our products and services.
- …which allow us to tailor our proposals to the customer needs.
- …which allow us to customize our proposals.

Offering complexity (based on Cannon & Perreault, 1999; Zott & Amit, 2007) (1 = "strongly disagree," 7 = "strongly agree")

- Our business model combines products, services and information.
- Our business model requires to consult customers intensively.
- Our customer solutions have a high need for explanation.

Demand complexity (developed based on Cannon & Perreault, 1999) (1 = "strongly disagree," 7 = "strongly agree")

- The needs of our customers are complex.
- The needs of our customers are not easy to identify.
- The needs of our customers are not easy to understand.

Controls

Firm size (number of employees) (based on Homburg et al., 2012a)

How many employees work for your company?

- (1) < 50; (2) 50–250; (3) 251–500; (4) 501–750; (5) 751–1,000; (6) 1,001–2,500; (7) 2,501–5,000; (8) > 5,000

Industry (based on Homburg et al., 2017)

Which industry does your firm belong to?

- Industrial Goods; Service Providers; Retail/Trade; Consumer Goods; Healthcare and Pharmaceuticals; Financial Institutions; Telecommunications; Others

Customer base (based on Patatoukas, 2012)

- Which sales revenue share is generated with the 20 % largest customers:__%

Sales channel distribution (own operationalization)

- Which sales revenue share is generated with online shops:__%

Investments in IDST implementation (past three years) (based on Ravichandran et al., 2009)

- What is the investment volume into digital technology implementation in the last three years?__€

Baseline sales technologies

- Dummy = 1 if company has implemented CRM applications, tablets or handheld devices, or social media applications in sales, 0 otherwise

Sales force IDST knowledge (based on Wang et al., 2012) (1 = "strongly disagree," 7 = "strongly agree")

Our sales force…

- …has extensive knowledge on the digital technologies that we implemented in sales.
- …know how to apply digital technologies in the sales process.
- …can make effective use of digital technologies in the sales process.

Appendix B. Measures (*continued*)

Key constructs
Technology integration (own development) (1 = "strongly disagree," 7 = "strongly agree") Our sales technologies… • …are synchronized. • …are integrated into a system. • …are able to share data and information.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2024.05.004.

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