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Dual Technology Adoption

ABSTRACT

Technology adoption remains a critical managerial challenge, in general and specifically in service settings. Investments are substantial but often fail to yield the intended benefits due to low usage among frontline employees, customers, and service partners. Existing technology acceptance theories predominantly focus on an individual user's adoption, overlooking the frequent and complex scenario of dual adoption, in which the adoption of a second user is mediated by the adoption of a first user. This is especially relevant in frontline contexts, where customers' adoption of a firm's technology is mediated by frontline employees. To address this limitation, we develop the Dual Adoption Model (DAM). The DAM posits that the benefits and costs of technology use by first and second users, such as frontline employees and customers, need to be considered simultaneously to fully understand technology adoption. We test the application of the DAM in a field study on the adoption of an e-commerce platform by frontline salespeople and customers, where salespeople need to mediate customers' e-commerce adoption. The DAM provides a novel theoretical framework for diagnosing failure in technology adoption and rollout and offers service managers concrete levers to successfully manage the complex transition from incumbent to novel digital systems.

Keywords

Technology acceptance; Technology adoption; E-commerce; Online channels; Sales management

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INTRODUCTION

Despite extensive investments in technology for frontline employees (FLEs), many organizations do not reap the intended benefits (Friess et al. 2024; Gartner 2025). A key challenge undermining successful technology integration is that technologies are often not effectively adopted by these employees, customers, or service partners. For example, while the majority of leaders and managers have adopted generative AI, adoption among frontline employees has stalled at 51% (Beauchene et al. 2025). Technology adoption of FLEs remains a persistent pain point in managerial practice across a wide range of technologies, including CRM systems (Alavi et al. 2025), sales enablement systems (Hartmann et al. 2025), predictive analytics and AI (Habel, Alavi, and Heinitz 2024), and generative and agentic AI (Gonzalez, Habel, and Hunter 2026; Rangarajan et al. 2026).

Research in information systems, marketing, and service management on the organizational frontlines has provided extensive insights into how individuals evaluate and adopt technology (Davis 1989; Venkatesh, Thong, and Xu 2012; Venkatesh et al. 2003). These models, commonly referred to as technology acceptance theories, explain adoption through individual-level concepts such as performance expectancy, effort expectancy, social influence, facilitating conditions (Venkatesh, Thong, and Xu 2012; Venkatesh et al. 2003), and network externalities (Katz and Shapiro 1986, Song et al. 2009). Their predictive validity has been confirmed across numerous contexts, including service (e.g., Blut and Wang 2020) and sales (e.g., Bill, Feurer, and Klarmann 2020).

However, these theories assume that technology users are autonomous decision makers who have full access to and control over the adoption decision. This assumption often does not reflect reality, where adoption is inherently social and interdependent. In many organizational

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frontline contexts, one actor—such as a manager, salesperson, or service representative—shapes the technology use of another actor (e.g., a salesperson or a customer) by recommending, enabling, or constraining its uptake.

Prior research does acknowledge interdependencies in technology adoption, including studies on organizational adoption (Meyer and Goes 1988; Tornatzky and Fleischer 1990), diffusion and social influence (Rogers 2003), and group-based adoption (Sarker et al. 2005; Yao et al. 2021). However, these perspectives address different facets of interdependence. Organizational adoption research (Meyer and Goes 1988; Tornatzky and Fleischer 1990) focuses on processes within firms rather than on interdependent individual adopters across organizational boundaries. Diffusion and social influence perspectives (Rogers 2003) explain how adoption spreads through communication channels over time while neglecting mediated access and use. Group adoption research (Sarker et al. 2005; Yao et al. 2021) centers on shared decision-making within bounded groups, offering limited insight into contexts where adoption unfolds sequentially and across boundaries. As a result, existing technology acceptance perspectives do not fully capture multi-actor adoption processes in which one actor mediates another's use, particularly when such relationships span organizational (or other) boundaries (Table 1). Perhaps this is the reason why technology adoption remains problematic in firm practice, and in particular, at the organizational frontlines.

--- Insert Table 1 about here ---

To address this theoretical limitation, we introduce the concept of *dual technology adoption*. The term "dual" captures situations in which two actors are interdependent within a shared goal system (Fitzsimons, Finkel, and vanDellen 2015), and in which one actor (Actor 1) influences another actor's (Actor 2's) technology adoption. Dual technology adoption recognizes

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that technology use is frequently not only an individual decision but also a social process of mediation and influence that unfolds in two stages. First, Actor 1 evaluates the technology according to traditional acceptance theories and determines whether it is valuable for their own use. Second, Actor 1 evaluates whether to endorse the technology for a specific Actor 2 (e.g., a customer, salesperson, or store). Actor 2's adoption ultimately depends on both such endorsement by Actor 1 and on their own technology perceptions (see Figure 1).

--- Insert Figure 1 about here ---

Dual technology adoption should be particularly relevant in organizational frontline contexts, which are characterized by multiple actors embedded in hierarchical or interdependent structures (e.g., salespeople and customers, service organizations and frontline employees, manufacturers and after-sales service providers). We therefore empirically examine dual technology adoption in the context of e-commerce adoption by industrial customers where this phenomenon is highly prevalent and relevant. In this setting, B2B salespeople and B2B customers jointly determine adoption outcomes. Although industrial customers can use e-commerce platforms similarly to B2C consumers, industrial products and solutions typically require salesperson consultation, and business-to-business relationships depend heavily on salesperson–customer interactions. As a result, e-commerce platforms must be integrated with personal selling activities (Kassemeier, Alavi, and Habel 2025; Nahm et al. 2026), requiring sales force buy-in and adoption (Guenzi and Habel 2020; Kanuri et al. 2022). Moreover, salespeople are responsible for promoting the e-commerce channel to customers (Habel, Alavi, and Linsenmayer 2021). Thus, studying customers' and salespeople's technology adoption separately would overlook the interdependence central to this setting.

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To conceptualize how salespeople and customers evaluate the e-commerce channel, we build on the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al. 2003). Following this framework, we theorize that both actors' evaluations of e-commerce—and thereby customer e-commerce adoption—depend on the performance gains they expect, the extent to which it reduces their effort, and social influence. We explore how customers' and salespeople's e-commerce evaluations influence customer adoption by analyzing data from a European B2B company providing industrial consumables and tools for construction professionals. The company relies primarily on salespeople as frontline intermediaries, introduced an e-commerce channel during our observation period, and assigns salespeople responsibility for managing customer adoption. Our salesperson–customer–month-level panel dataset covers 36 consecutive months of transactions, including 12 months before and 24 months after the e-commerce introduction. The sample includes 521 salespeople and 36,431 customers, for a total of 260,465 observations. Our results support key predictions of the DAM by showing that e-commerce adoption arises from interdependent adoption processes across both sides of the salesperson–customer dyad.

Our research contributes to the technology adoption literature by conceptualizing the phenomenon of dual technology adoption, which is particularly prevalent in organizational frontline contexts. We propose a theoretical model of how adoption cascades across multiple actors, formalize it mathematically, and verify key predictions in an empirical application to B2B e-commerce adoption. This extends the understanding of technology adoption from a single-actor lens to a multi-actor lens and highlights that actors at organizational (or other) boundaries can mediate another actor's technology use. This extension also contributes to e-commerce research, which explores how to digitalize sales and service interactions with customers, by

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revealing how traditional technology acceptance theories can explain multi-actor adoption. Prior research has noted that e-commerce adoption in frontline contexts such as sales involves both frontline employees (e.g. salespeople) and customers, but has not yet theorized this interdependence. Dual technology adoption offers a theoretical framework for doing so, and our findings provide evidence for UTAUT-based drivers in dual e-commerce adoption. For managers, the DAM implies that managing technology adoption in interdependent contexts like the organization frontline requires identifying not just primary users, but also those whose utility depends on others' use and who can influence their adoption decisions.

DEVELOPMENT OF THE DUAL ADOPTION MODEL (DAM)

Limitations of Technology Acceptance Theories

Existing technology acceptance theories predict an individual's intention and decision to use a technology, such as computing hardware or software (Davis 1989; Habel, Alavi, and Heinitz 2023; Venkatesh, Thong, and Xu 2012; Venkatesh et al. 2003). These theories typically focus on situations in which an organization ensured the availability of the technology and thus potential users have immediate access to the technology. In such contexts, adoption primarily depends on individual motivation, which is shaped by factors such as performance expectancy, effort expectancy, facilitating conditions, social influence (Venkatesh, Thong, and Xu 2012; Venkatesh et al. 2003), and network externalities (Katz and Shapiro 1986).

Originating in the management information systems literature, technology acceptance theories have been tested in diverse contexts, including services (e.g., Wieseke et al. 2011), marketing (e.g., Blut and Wang 2020), sales (e.g., Alavi et al. 2025; Weinstein and Mullins 2012), and innovation (e.g., Zimmermann, Somasundaram, and Saha 2024). Furthermore, their focus on individual adoption has been extended by theories conceptualizing organizational

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technology adoption (Meyer and Goes 1988; Tornatzky and Fleischer 1990) and group technology adoption (Sarker et al. 2005; Yao et al. 2021). Notwithstanding their broad diffusion across academic disciplines, one limitation of these theories is that they neglect contexts in which one actor (such as an actor internal to the implementing organization) mediates the technology adoption of another actor through a sequential adoption process, and are also unable to address the possibility that actors may influence each other across boundaries.

To illustrate, consider an e-commerce channel in a B2B context that allows customers to order products from a supplier. In B2B contexts, salespeople are the main face of the organization to the customer and, therefore, will often be responsible for customers' successful e-commerce adoption. Thus, technology adoption is sequential, as salespeople's adoption influences customers' adoption, and also exists across a boundary, as salespeople and customers do not work in the same organization. Traditional technology acceptance theories do not consider this mediating role. Instead, they would predict that customers unilaterally adopt such an e-commerce channel, for example, if they perceive it as useful (performance expectancy), if it integrates with their own IT system (facilitating conditions), or if they see peer customers adopt it (social influence) (Venkatesh, Thong, and Xu 2012; Venkatesh et al. 2003). However, consider a situation in which a *salesperson* does not buy into e-commerce as a valuable channel, fails to promote it to the customer, and keeps visiting the customer in person (Habel, Alavi, and Linsenmayer 2021; Kanuri et al. 2022; Kassemeier, Alavi, and Habel 2025; Nahm et al. 2026). In such a situation, the salesperson fails to *mediate* e-commerce channel adoption in the specific salesperson–customer dyad, keeping the customer from adopting the technology even if the

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customer's motivation to adopt would otherwise be high. This interesting phenomenon is not explained by traditional technology acceptance theories.[1]

Conceptualizing Dual Technology Adoption

To address the limitations explained above, we propose a process that we label *dual technology adoption*. Dual refers to the fact that *two actors* are required, with one actor mediating the other actor's technology adoption. *Adoption* refers to the extent to which an actor uses a technology they did not use before.

We conceptualize dual technology adoption as applicable in situations exhibiting two characteristics: First, two or more actors are *interdependent* in a shared goal system (Fitzsimons, Finkel, and vanDellen 2015), such that Actor 2's technology adoption affects Actor 1's utility. Second, Actor 1 has the power to *influence* Actor 2's technology adoption (e.g., Emerson 1962; Kim, Pinkley, and Fragale 2005). Table 2 lists several examples of technologies, actors, and their interdependence and influence, spanning contexts such as parenting, friendships, education, leadership, federal institutions, service firms, and the organizational frontline. Importantly, Table 2 shows that while the DAM is able to address situations where actors influence each other across organizational boundaries, it is not restricted to such contexts, and it also allows studying interdependence within the same organization or unit.

In these situations, Actor 2's technology adoption occurs in two stages. In Stage 1, Actor 1 accepts the technology as a tool they *generally* endorse other actors to use. Such acceptance is likely influenced by Actor 1's technology perceptions in line with traditional technology

[1] One existing driver of technology acceptance potentially related to such contexts is social influence. However, social influence is commonly conceptualized in existing models as influence through social norms internal to the implementing firm (e.g., Brown and Venkatesh 2005; Lewis, Agarwal, and Sambamurthy 2003) or herding (e.g., Feng et al. 2022; Sun 2013), which does not include an actor's mediation of technology adoption.

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acceptance theories. Subsequently, Actor 1 evaluates whether to endorse the technology for a *specific* Actor 2 and then expends effort to either foster or hinder Actor 2's adoption. We refer to such effort as *mediation effort*, defined as the investment of resources (e.g., time, attention) to influence another actor's technology adoption positively or negatively.

Extending our earlier example, consider a salesperson who perceives an e-commerce channel as a technology worth endorsing in general, for example because they appreciate that it frees up their time to focus on higher-value opportunities (Kanuri et al. 2022; Kassemeier, Alavi, and Habel 2025; Nahm et al. 2026). The salesperson may then evaluate the fit of the e-commerce channel for each of their customers. Past research has acknowledged that customer readiness for different marketing technologies may vary considerably (Friess et al. 2024). For example, the salesperson's customer A typically requires extensive consultation, leading the salesperson to infer low performance expectancy. Consequently, the salesperson dissuades the customer from using the e-commerce channel. Conversely, customer B is open to the idea of serving themselves, so the salesperson infers high performance expectancy and thus persuades the customer to use the e-commerce channel. Table 2 lists further examples of dual adoption.

--- Insert Table 2 about here ---

Formalizing the DAM

While our prior elaborations were qualitative to provide an intuition of dual technology adoption, the model can also be formalized and examined mathematically. We take this step to solidify our intuition and to derive more precise predictions about actors' decisions.

Interdependence. Interdependence entails that Actor 1's utility in Stage 2 depends on Actor 2's technology adoption in Stage 2. We conceptualize:

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$$u_1 = va_2 + \bar{u} - \frac{c}{2}m_1^2 \quad (1)$$

The indices refer to the corresponding actor (1 for Actor 1, 2 for Actor 2). That is, u_1 is the utility of Actor 1, which depends on Actor 2's level of technology adoption in Stage 2, $a_2 \in [0, 1]$. v indicates the direction of this influence: $v < 0$ entails that Actor 1's utility decreases with a_2 while $v > 0$ entails that Actor 1's utility increases with a_2. $\bar{u}$ is Actor 1's baseline utility before Actor 2 decides on their technology adoption. $m_1 \in [-1, 1]$ is Actor 1's mediation effort expended: $m_1 < 0$ entails that Actor 1 expends effort to *hinder* Actor 2's technology adoption while $m_1 > 0$ entails that Actor 1 expends effort to *foster* Actor 2's technology adoption. Expending effort causes costs for Actor 1, which decrease u_1 by $\frac{c}{2}m_1^2$.

Extending the earlier example, a customer ordering through an e-commerce channel ($a_2 > 0$) might affect the salesperson's utility positively ($v > 0$) if the salesperson gains time and can thus serve more customers and earn higher commission, or it might affect the salesperson's utility negatively ($v < 0$) if the salesperson is responsible for customers requiring consultation and customers' e-commerce orders increase product returns (Kassemeier, Alavi, and Habel 2025). In addition, nudging customers to either use or not use the e-commerce channel requires effort itself, which decreases the salesperson's utility (Kanuri et al. 2022).

Influence. Influence means that Actor 1 has the power to change Actor 2's technology adoption through mediation effort in Stage 2. This can be formalized as follows:

$$a_2 = \frac{(1 + m_1)(1 + p_2)}{4} \quad (2)$$

Like in the previous equation, a_2 is Actor 2's extent of technology adoption. It depends on Actor 1's mediation effort m_1; and on Actor 2's technology perception $p_2 \in [-1, 1]$, which is explained by traditional technology acceptance theories. We propose m_1 and p_2 to shape a_2

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interactively, considering that Actor 1's influence might be greater if Actor 1 has a positive technology perception to begin with. The equation is constructed such that a_2 is at its minimum value of 0 when either m_1 or p_2 has a value of –1 and achieves its maximum value of 1 when both m_1 and p_2 have a value of 1.[2]

Extending our earlier example, a customer might be more likely to adopt an e-commerce channel if the salesperson promotes the channel (Habel, Alavi, and Linsenmayer 2021). Such promotion may pay off particularly if the customer already has positive perceptions of the e-commerce channel that provide fertile ground for the salesperson's promotion.

Implications for technology adoption. Substituting Equation 2 into Equation 1 provides the following utility of Actor 1 in Stage 2:

$$u_1 = v\frac{(1+m_1)\,(1+p_2)}{4} + \bar{u} - \frac{c}{2}m_1^2 \tag{3}$$

Importantly, Actor 1 cannot directly observe Actor 2's private information p_2. In forming their assessment of p_2, it is plausible that Actor 1's perception is biased by the perception of the technology they formed in Stage 1, $p_1 \in [-1, 1]$. Like p_1, p_2 can be explained by traditional technology acceptance theories. That is, rather than directly observing p_2, Actor 1 will infer $\hat{p_2}$ as follows:

$$\hat{p_2} = wp_1 + (1-w)p_2 \tag{4}$$

In Equation 4, $w \in [0, 1]$ represents a projection weight indicating Actor 1's bias toward their own view, p_1, when inferring p_2. Thus, assuming u_1 is a function of $\hat{p_2}$ rather than p_2, we obtain Actor 1's utility in Stage 2 as:

[2] One limitation of Equation 2 is that it assumes a linear effect of m_1 on a_2. However, this effect may well exhibit diminishing returns. Web Appendix A shows that our model's key implications hold when explicitly modeling such diminishing returns.

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$$\widetilde{u_1}(m_1) = v\frac{(1+m_1)(1+\widetilde{p_2})}{4} + \bar{u} - \frac{c}{2}m_1^2$$
$$= \frac{v}{4}(1+m_1)(1+wp_1+(1-w)p_2) + \bar{u} - \frac{c}{2}m_1^2 \quad (5)$$

To understand Actor 1's choice of m_1 in Stage 1, we differentiate Equation 5 with respect to m_1:

$$\frac{d\widetilde{u_1}}{dm_1} = \frac{v}{4}(1+wp_1+(1-w)p_2) - cm_1 = 0 \quad (6)$$

Solving Equation 6 results in Actor 1's optimal mediation effort in Stage 1:

$$m_1^* = \frac{v}{4c}(1+wp_1+(1-w)p_2) \quad (7)$$

Thus, Actor 1 expends more mediation effort if either p_1 or p_2 increases, while w determines the extent to which such increases will translate to mediation effort. Furthermore, the costlier the mediation effort is (as indicated by c), the less p_1 and p_2 will affect mediation effort.

To derive Actor 2's realized technology adoption in Stage 2, we substitute Equation 7 into Equation 2:

$$a_2^* = \frac{(1+m_1^*)(1+p_2)}{4}$$
$$= \frac{1+p_2}{4} + \frac{v}{16c}\left(1+wp_1+(2-w)p_2+wp_1p_2+(1-w)p_2^2\right) \quad (8)$$

How does Actor 2's realized adoption in Stage 2 depend on p_1 and p_2? To investigate, we take the partial derivatives of a_2^* with respect to p_1 and p_2:

$$\frac{\partial a_2^*}{\partial p_1} = \frac{vw(1+p_2)}{16c} \quad (9)$$

$$\frac{\partial a_2^*}{\partial p_2} = \frac{1}{4} + \frac{v}{16c}(2-w+wp_1+2(1-w)p_2) \quad (10)$$

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Equation 9 is positive when $v > 0$ (i.e., Actor 2's adoption benefits Actor 1), $p_2 > -1$ (i.e., Actor 2 does not fully reject the technology), and $w > 0$ (i.e., Actor 1's technology perception carries at least some weight). Under these conditions, an increase in p_1 leads to an increase in a_2. Intuitively, when Actor 1 has a positive technology perception, the actor will expend more mediation effort, which will increase Actor 2's adoption.

Similarly, Equation 10 is positive when $v > 0$, since the minimum value of $(2 - w + wp_1 + 2(1 - w)p_2)$ is 0 (for $p_1 = -1$ and $p_2 = -1$). Thus, if Actor 1's utility increases with Actor 2's technology adoption, an increase in Actor 2's technology perception leads to an increase in Actor 2's technology adoption.

Extending our earlier example, if either the salesperson or the customer has positive perceptions of the e-commerce channel, and if the customer's e-commerce purchases increase the salesperson's utility, the salesperson will expend mediation effort and thereby increase the customer's e-commerce adoption. Table 3 summarizes the propositions of the model.

--- Insert Table 3 about here ---

APPLICATION OF THE DAM TO E-COMMERCE ADOPTION

Context

In our conceptualization of the DAM, we repeatedly resorted to e-commerce channels as a realistic and economically important example of dual adoption (e.g., Bongers, Schumann, and Schmitz 2021; Habel, Alavi, and Linsenmayer 2021; Kanuri et al. 2022; Nahm et al. 2026; Sarin, Challagalla, and Kohli 2012). In this section, we elaborate on this context to empirically test key predictions from the DAM.

We collaborated with a European B2B company that provides industrial consumables and tools for construction professionals. While the company sells its products in part through a

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network of self-owned brick-and-mortar outlets, the company relies primarily on salespeople as the frontline intermediaries with customers and thus offers customers the chance to purchase through a personal sales channel. In addition, the company relies on an inside sales force selling to customers on the phone. Salespeople for the firm typically serve their customers in personal interactions and are responsible for all product-related and company-related communication. To enable customers to serve themselves, the management of the company decided to introduce an e-commerce channel in one of its core markets.

The introduction of the e-commerce channel in this company is particularly suited to test the DAM for two reasons. First, the company counts customer purchases through the e-commerce platform toward salespeople's quotas, ensuring that salespeople receive the same compensation regardless of whether their customers order from the e-commerce platform or directly from the salesperson. This likely entails $v > 0$ in Equations 9 and 10, such that an increase in p_1 or p_2 should increase a customer's e-commerce adoption (under the plausible assumption that $w > 0$). In our hypotheses, we thus focus on factors increasing p_1 and p_2. Second, in this context, customers' adoption of the e-commerce channel is largely mediated by salespeople. That is, the company did not employ centralized means (e.g., marketing communications) to nudge customers to migrate to the e-commerce channel. Instead, the company, as is common in B2B contexts for industrial firms, relied on salespeople's influence over customers to promote the e-commerce channel (Habel, Alavi, and Linsenmayer 2021; Kanuri et al. 2022).

In line with prior technology adoption literature (e.g., Venkatesh et al. 2003; Venkatesh, Thong, and Xu 2012), we operationalize customers' e-commerce adoption as their behavioral intensity of e-commerce use, measured as customer revenue generated in the e-commerce

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channel. This operationalization offers the advantage that it captures the extent to which the e-commerce channel is actively utilized in customer buying practices. For a robustness check, we also operationalize adoption as a customer's first-time use of the e-commerce channel.

Hypotheses

As outlined earlier, the technology perceptions of Actor 1 (p_1) and Actor 2 (p_2) might be explained by traditional technology acceptance theories. Building on this notion, we deduce potential drivers of p_1 and p_2 from the UTAUT (Venkatesh et al. 2003). Specifically, we propose that salespeople's and customers' evaluations of e-commerce depend on (1) the performance gains they expect from it, (2) how much effort it could save them, and (3) how they are influenced by their social environment. We omit the UTAUT-based driver of facilitating conditions because in our context facilitating conditions are invariant.

Table 4 maps these theoretical constructs to pertinent variables in our institutional context. In line with predictions by the DAM, we propose that each of these variables will shape a customer's e-commerce revenue as an indicator of the customer's e-commerce adoption. We elaborate and posit formal hypotheses in the following sections.

--- Insert Table 4 about here ---

Performance expectancy and salesperson product breadth. Performance expectancy in UTAUT reflects the belief that using a technology will enhance task performance (Venkatesh et al. 2003). In our context, we propose that a salesperson's product breadth shapes their expectations of performance gains from adopting the e-commerce channel. Salespeople with a high product breadth usually provide extensive consultation to customers to identify unmet needs that they can satisfy by selling additional products (e.g., Schmitz 2013; Wiseman et al. 2025).

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To advise customers effectively, salespeople must possess broad product knowledge and the ability to apply this knowledge effectively in customer interactions (Schmitz and Ganesan 2014). This allows salespeople to uncover additional needs and offer complementary products, thereby increasing customer share and overall sales performance (Palmatier, Miao, and Fang 2007; Schmitz et al. 2020). However, this sales approach aligns poorly with serving customers through an e-commerce channel, which typically limits interpersonal consultation and individualized solution selling (Kassemeier, Alavi, and Habel 2025). Consequently, salespeople with higher product breadth are likely to expect fewer performance gains from adopting e-commerce, since they likely anticipate their consultation ability to be compromised in e-commerce channels. According to the DAM, they should therefore expend lower mediation effort, which should ultimately reduce customers' e-commerce revenue. Thus:

H_1: Salesperson product breadth has a negative effect on customers' e-commerce revenue.

Effort expectancy and salesperson transaction frequency. Effort expectancy refers to the perceived ease of using a technology and the extent to which it reduces effort for its user (Venkatesh, Thong, and Xu 2012; Venkatesh et al. 2003). Salespeople who handle more transactions should perceive a higher potential to save effort through the new e-commerce channel. This is because a high transaction frequency usually entails many time-consuming customer visits (Krämer et al. 2022), which the e-commerce channel could effectively reduce. Thus, for high salesperson transaction frequency, the DAM predicts higher mediation effort and an increase in customers' e-commerce revenue. In contrast, salespeople with a lower transaction frequency face a lower resource strain and might thus perceive lower effort reductions through the e-commerce channel, reducing mediation effort and customers' e-commerce revenue. Thus:

H_2: Salesperson transaction frequency has a positive effect on customers' e-commerce revenue.

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Social influence and peer salesperson e-commerce revenue share. Social influence reflects the degree to which individuals perceive that important others believe they should use a new technology (Venkatesh et al. 2003). For salespeople, such important others include peer salespeople who work in the same team or under the same managers (Wieseke et al. 2011). Indeed, in our context and in many others, salespeople typically have regular group meetings in which sales performance indicators and best practices are shared and discussed. Thus, when peers adopt the e-commerce channel more and thus have a higher e-commerce revenue share, a focal salesperson's perception of the e-commerce channel should improve. As a result, the DAM predicts that the focal salesperson is more likely to expend mediation effort and thereby increase customers' e-commerce revenue. We propose:

H_3: Peer salesperson e-commerce revenue share has a positive effect on customers' e-commerce revenue.

While the previous hypotheses referred to *salespeople's* perceptions of the e-commerce channel, the remaining hypotheses propose drivers of *customers'* perceptions of the e-commerce channel as derived from UTAUT. The variables and underlying arguments mirror the ones developed for salespeople.

Performance expectancy and customers' product breadth. Much like salespeople, customers should form performance expectancy regarding an e-commerce channel based on the channel's ability to satisfy their needs (Neslin et al. 2006). B2B customers differ in their needs based on how diverse the portfolio of products is that they are buying (Friess et al. 2024). Whereas customers who buy a narrow product portfolio should already know more about the products or use them in more straightforward ways, customers buying more diverse products should use these for more diverse use cases and thus likely need more consultation (Wiseman et al. 2025). However, compared to the personal selling channel, the e-commerce channel lacks

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such consultation. Consequently, customers with high product breadth should expect the e-commerce channel to offer lower performance. As a result, these customers are less likely to adopt the e-commerce channel and exhibit a reduced e-commerce revenue. We posit:

H_4: Customer product breadth has a negative effect on customers' e-commerce revenue.

Effort expectancy and customer transaction frequency. In line with UTAUT, customers are more likely to adopt a technology if they expect adopting it to be low effort, and if adopting it will save them effort. In B2B buying, customers frequently balance effort across multiple procurement channels and select those that minimize transaction costs and coordination effort (Li, Lobschat, and Verhoef 2018; Neslin et al. 2006). Research on multichannel buying emphasizes that customers tend to allocate transactions to channels that offer greater convenience and process efficiency, particularly for routine or standardized purchases (Gensler, Leeflang, and Skiera 2012; Verhoef, Neslin, and Vroomen 2007).

Customers with a high transaction frequency face considerable administrative burdens related to order processing, documentation, and coordination with sales representatives. E-commerce channels can substantially reduce these burdens by automating routine tasks, enabling reordering, and offering continuous availability (Kanuri et al. 2022; Kassemeier, Alavi, and Habel 2025). Thus, customers with higher transaction frequency should perceive e-commerce as a more efficient and less effort-intensive alternative to traditional channels. In contrast, customers with infrequent transactions will experience comparatively limited efficiency gains and may not find learning to use e-commerce systems worth the effort. Drawing on the DAM, they should thus be less likely to adopt the e-commerce channel, which would be reflected in a reduced e-commerce revenue. Thus:

H_5: Customer transaction frequency has a positive effect on customers' e-commerce revenue.

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Social influence and peer customer e-commerce share. In B2B markets, social influence is often exerted by peers within the same industry, including competitors, partners, and trade associations (Crecelius et al. 2024). Industry norms or practices should shape technology perceptions by creating perceived legitimacy, setting norms, and reducing uncertainty. In the e-commerce context, industries differ widely in their digital maturity and multichannel integration levels. When e-commerce adoption becomes widespread within an industry—for example through the influence of trade fairs, community platforms, or industry publications—customers are exposed to positive references and normative expectations regarding e-commerce use. Such social influence should improve customers' perceptions of the e-commerce channel. Accordingly, dual adoption should be more likely to occur, which would increase customers' e-commerce revenue. Therefore, we posit:

H_6: Peer customer e-commerce share has a positive effect on customers' e-commerce revenue.

Data and Measures

We acquired a salesperson–customer–month-level panel dataset covering 36 consecutive months of sales transactions, consisting of 12 months before and 24 months after the introduction of the e-commerce channel. Studying 24 months after the introduction allows us to effectively capture the gradual build-up of e-commerce adoption: salespeople and customers require time to adjust routines, and peer-influence mechanisms at both the salesperson and customer levels might diffuse slowly through teams and industries. Our sample contains continuous monthly observations from 521 salespeople and 36,431 customers, for a total of 260,465 observations.

Table 5 presents the operationalization of variables and Table 6 presents the correlations and descriptive statistics. In line with our hypotheses, our dependent variable is customer e-

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commerce revenue, operationalized as the total monthly revenue generated through the e-commerce channel for each customer *i* in month *t*.

--- Insert Table 5 and Table 6 about here ---

The independent variables of product breadth and transaction frequency at the customer level and salesperson level are time-invariant and constructed from transactions during the twelve months before the e-commerce introduction. Because this period predates the e-commerce introduction, these variables are exogenous indicators of pre-existing selling and purchasing features, unaffected by any subsequent experience with the e-commerce channel. Salesperson and customer product breadth are count variables counting the number of unique products a salesperson has sold or a customer has bought. They only increase when a salesperson sells a product to a customer or a customer buys a product from a salesperson that they have not sold or bought before. Salesperson transaction frequency indicates how many invoices a salesperson raises with customers and customer transaction frequency reflects how often a customer has bought from the company.

Salespeople's and customers' peer e-commerce revenue share are time-varying variables and assessed for each month after the channel's introduction to capture evolving peer effects. Peer salesperson e-commerce revenue share indicates the average proportion of revenue that is generated in the e-commerce channel by team members when compared to their total revenues. Peer customer e-commerce revenue share assesses the same proportion of e-commerce revenue compared to total revenue, but for peer customers within the same industry as the respective customer. We log-transform our dependent variable and independent variables due to skewness.

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Analytical Approach

We estimate a linear mixed-effects model that accounts for the dyadic structure of the data. This modeling approach allows us to simultaneously capture customer-level variation in e-commerce adoption and salesperson-level effects, while controlling for unobserved heterogeneity at both levels. Specifically, we model customers' e-commerce revenue, *E*, as a function of salesperson- and customer-level predictors, with random intercepts for both salespeople and customers. The model is expressed as follows:

$$E_{ijt} = \beta_0 + \beta_1 X^S_{i(t)} + \beta_2 X^C_{ij(t)} + T_{ijt} + \gamma_t + \mu^S_i + u^C_j + \varepsilon_{ijt} \quad (11)$$

Where $X^S_{i(t)}$ and $X^C_{ij(t)}$ denote vectors of salesperson- and customer-level predictors, T_{ijt} denotes the customer's total revenue across all channels excluding the e-commerce channel, γ_t denotes the monthly fixed effects to control for aggregate time variation, such as seasonality, product campaigns, or economic fluctuations. μ^S_i and u^C_j are random intercepts for salesperson *i* and customer *j*, capturing unobserved, time-invariant heterogeneity at the salesperson and customer levels, and ε_{ijt} is the idiosyncratic error term.

This specification implements a two-way random intercept model, analogous to a dyadic panel structure in multilevel modeling (Raudenbush and Bryk 2010; Wooldridge 2010). By including random effects for both salespeople and customers, the model captures persistent differences in their baseline adoption tendencies, such as a salesperson's inherent openness to technology or a customer's long-term digital orientation. The inclusion of month fixed effects further purges the estimates of temporal confounders common to all dyads, allowing identification to rely on cross-sectional and within-dyad variation in adoption behavior.

The model is estimated using the restricted maximum likelihood procedure, which provides consistent and efficient estimates of variance components under conditions of

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unbalanced panel data. We cluster standard errors at both the salesperson and customer levels to account for residual correlation within each dimension of the dyad.

Results

Salesperson-level drivers of customers' e-commerce revenue. Table 7 presents the results of our analysis. In Model 1, we initially focus on the salesperson-level drivers and evaluate H_1 through H_3 and then turn to customer-level drivers to evaluate H_4 through H_6.

First, the results show a negative and significant effect of salesperson product breadth on customer e-commerce revenue (–.200, $p < .001$), providing support for H_1. This supports the argument that salespeople with a higher product breadth endorse the e-commerce channel less to their customers, probably because they perceive lower performance expectancy.

Second, the effect of salesperson transaction frequency on customer e-commerce revenue is positive and significant (.068, $p < .001$), providing support for H_2. Consequently, salespeople with more frequent transactions influence their customers to adopt the e-commerce channel more, probably because they expect to save effort from it.

Finally, in relation to social influence, the effect of salesperson peer e-commerce revenue share on customer e-commerce revenue is positive and significant (.248, $p < .01$), providing support for H_3. Thus, salespeople whose peers adopt e-commerce more also promote it more to their customers, indicating that adoption diffuses through social learning within sales teams.

--- Insert Table 7 about here ---

Customer-level drivers of customers' e-commerce revenue. Consistent with H_4, customer product breadth decreases customer e-commerce revenue (–.050, $p < .001$). Thus, customers who have more diverse buying needs adopt e-commerce less because they should require more consultation from salespeople, which salespeople provide during personal visits.

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In line with H_5, customer transaction frequency has a positive effect on customer e-commerce revenue (.107, $p < .001$). This supports our prediction that customers who purchase more frequently can gain more efficiency from the e-commerce channel, which should be supported by salespeople managing these accounts.

Finally, we find support for H_6, as peer customer e-commerce revenue share is significantly and positively related to a customer's e-commerce revenue (.821, $p < .001$). Thus, customers whose industry peers adopt e-commerce more also have higher e-commerce revenue, highlighting the role of social and normative influences.

Overall, these findings confirm that e-commerce adoption arises from interdependent adoption processes across both sides of the salesperson–customer dyad, supporting key predictions from the DAM.

Robustness check. A potential concern is that the estimated salesperson peer effects may reflect shared shocks at the team level, such as coordinated managerial initiatives, or other common influences that affect all members of a sales team simultaneously. To address this concern, we include salesperson team fixed effects, absorbing all time-invariant differences across teams. Model 2 in Table 7 presents the results of this analysis. The coefficients for salesperson- and customer-level predictors remain stable in both magnitude and statistical significance. It is worth noting that the coefficient for peer salesperson e-commerce revenue share becomes smaller (.058) and statistically nonsignificant once team fixed effects are included. This pattern is consistent with the notion that part of the variation in peer adoption reflects shared team-level influences rather than purely idiosyncratic peer-to-peer effects. At the same time, peer adoption is inherently based on the behavior of coworkers within the same team. Consequently, including team fixed effects absorbs a substantial portion of the variation through

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which peer influence operates, leaving only within-team deviations to identify the effect. While peer effects are partly intertwined with shared team environments, the stability of all other coefficients provides strong support for our proposed dual-adoption framework, particularly the roles of performance expectancy, effort expectancy, and customer-side social influence.

Supplemental analysis

Machine learning prediction for customer e-commerce adoption. To further strengthen our findings from the prior regression analysis, we conduct a supplemental analysis to disentangle customer-level factors from salesperson-mediated adoption. This analysis leverages the unique structure of our data: we observe customers' purchasing behavior for 12 months prior to the e-commerce introduction when customers had no exposure to the e-commerce channel. We exploit this feature to construct a measure of each customer's *expected* e-commerce revenue based solely on their own attributes and thus exogenous to any salesperson mediation effort. We use these pre-period characteristics as inputs to machine learning models, trained to predict each customer's monthly e-commerce revenue in the post-introduction period. Specifically, the prediction for customer e-commerce revenue is estimated using a two-stage boosted-tree hurdle model. At the first stage, a calibrated gradient-boosting classifier predicts whether a customer generates any e-commerce revenue in month *t;* at the second stage, an XGBoost model is used to predict the amount of e-commerce revenue. The resulting predicted e-commerce revenue for each customer captures the extent to which customers would be likely to adopt the e-commerce channel, based solely on their own profiles. We provide technical details of implementing this machine learning approach in Web Appendix B.

The XGBoost model achieves a root mean square error (RMSE) of 38.11 and a mean absolute error (MAE) of 8.87 ($R^2 = 384$), indicating that customers' characteristics provide

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informative signals about their subsequent e-commerce adoption. Using these predictions, we then compute, for every customer, the difference between actual and predicted monthly e-commerce revenue, as Δ *customer e-commerce revenue*, which represents the extent to which customers adopt the e-commerce channel *above or below the level* implied by their inherent, pre-existing characteristics alone. Conceptually, this variable isolates the portion of adoption plausibly shaped by salesperson mediation.

In the final step, we regress Δ *customer e-commerce revenue* on the salesperson-level predictors used in our main analysis. We retain the random-intercept structure and include monthly fixed effects to account for time-specific shocks. Table 8 reports the results and verifies salesperson product breadth, transaction frequency, and peer salesperson e-commerce revenue share as drivers of customers' e-commerce revenue.

--- Insert Table 8 about here ---

First adoption analysis. We conducted an additional supplemental analysis by re-estimating the model using a binary first-adoption indicator instead of customers' e-commerce revenue. The dependent variable equals 1 in the first month in which a customer records positive e-commerce revenue and zero in all prior months. This specification focuses on the timing of initial adoption rather than the subsequent intensity of e-commerce use. The results are consistent with the main findings. The details of the model specification and results are provided in Web Appendix C. Taken together, our analysis suggests that dual adoption mechanisms shape both the occurrence and the intensity of customer e-commerce adoption.

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GENERAL DISCUSSION

Theoretical Implications

This research has substantive implications for (1) technology acceptance research in general and (2) e-commerce adoption research in particular, both of which deepen our understanding of technology adoption within organizational frontline contexts. We elaborate on both implications here.

The dual adoption model as a lens for future technology acceptance research. This research adds a novel lens to technology acceptance theories, such as TAM (Davis 1989), UTAUT (Venkatesh et al. 2003), UTAUT2 (Venkatesh, Thong, and Xu 2012), or PSAA (Habel, Alavi, and Heinitz 2023). These theories traditionally predict an individual actor's use of a technology based on the individual's perceptions and dispositions. That is, they focus on the extent to which actors perceive a technology as useful and easy to use (Davis 1989), the extent to which they perceive social influence (Venkatesh, Thong, and Xu 2012; Venkatesh et al. 2003), or the extent to which they have the capabilities to succeed without the technology as well as the capabilities to draw value from the technology (Habel, Alavi, and Heinitz 2023, 2024).

However, these theories have neglected that technology adoption frequently includes one actor mediating another actor's technology use, and that this mediation often takes place across organizational or other boundaries. Our research conceptualizes this phenomenon as *dual technology adoption* and proposes a theoretical model of how technology adoption cascades between these two actors. We describe this process, formalize it mathematically, and verify key predictions in a sample application to B2B customers' e-commerce channel adoption.

The DAM provides a novel lens that researchers can (1) utilize to explain novel phenomena of technology utilization and transfer and (2) extend to improve our understanding of

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dual technology adoption. First, in today's digital age and with the emergence of new technologies (e.g., Alavi et al. 2025; Gonzalez, Habel, and Hunter 2026; Hung, Lee, and Hu 2025), studies on technology adoption are proliferating (FakhrHosseini et al. 2024; Musa et al. 2024). However, it is plausible that in many contexts, individual actors' adoption of such technologies is mediated, for example by their direct managers (Wieseke et al. 2011) or their suppliers' salespeople or customer success managers (Gehring et al. 2025; Hochstein et al. 2021). This can root their technology adoption firmly in the domain of dual technology adoption. In these cases, future research can build more accurate empirical models of individuals' technology use by deriving predictions from the DAM. For example, future research should focus on the mediating actor's technology perceptions and utility. As mediation may not only enable but also constrain adoption, mediating actors can act as bottlenecks, helping to explain why technologies are often not adopted (e.g., Alavi et al. 2025; Habel, Alavi, and Heinitz 2024). Future research should examine the underlying mechanisms through which mediation shapes adoption, such as what types of mediation effort are used (e.g., e-commerce promotion) and what social processes occur between actors during mediation. Building on these insights, scholars could explore managerial strategies to prevent actors from becoming adoption bottlenecks or, conversely, from excessively promoting technologies when adoption may be inappropriate.

Second, the DAM should be seen as the core of an emergent theory, open to further developments. Specifically, every equation in our formalization of the theory provides interesting avenues for future research, whether using analytical, conceptual, or empirical methods. Web Appendix D provides intriguing questions that we encourage future research to address.

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In addition, although we conceptualized the DAM with respect to two actors, the model might extend to contexts involving more than two actors. For example, when a manager exerts effort to motivate a salesperson, who in turn exerts effort to encourage a customer to adopt an e-commerce channel. Future research could explore whether the DAM's theoretical predictions generalize to such "adoption cascades," such that upstream actors' technology perceptions and mediation effort ultimately shape the furthest-downstream actor's technology adoption. This would allow research to help understand and solve a central managerial challenge: how top managers can ensure that novel technologies are used effectively at the organizational frontlines (Beauchene et al. 2025; Gartner 2025; Habel, Alavi, and Heinitz 2023; Rangarajan et al. 2026)?

Dual technology adoption of B2B e-commerce. By applying the DAM to the phenomenon of e-commerce adoption in B2B supplier–customer relationships, we contribute to the literature on e-commerce. We show that e-commerce adoption can be understood in terms of dual adoption, such that a customer's e-commerce adoption is driven both by their own *and* by salespeople's performance expectancy, effort expectancy, and social influence. This contribution is noteworthy because prior research offers insights into *either* customers' e-commerce adoption (Avery et al. 2012; Trenz, Veit, and Tan 2020) *or* salespeople's e-commerce adoption (Kassemeier, Alavi, and Habel 2025), while often neglecting their interdependence. Only a few recent studies have recognized that salespeople play a role in customers' e-commerce channel adoption (Bongers, Schumann, and Schmitz 2021; Habel, Alavi, and Linsenmayer 2021; Josephson, Lee, and Sridhar 2021; Kanuri et al. 2022; Kassemeier, Alavi, and Habel 2025; Nahm et al. 2026; Sarin, Challagalla, and Kohli 2012). However, these studies have not recognized the role of traditional technology acceptance theories in explaining how both salespeople and customers perceive and ultimately adopt e-commerce channels. That is, past research did not

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conceive e-commerce from a technology perspective but more from a strategic channel perspective. By integrating e-commerce literature with technology acceptance literature, our research provides novel pathways to integrating prior findings and opening new research avenues on e-commerce as a technology.

To illustrate, consider a firm's online sales push involving special incentives for generated e-commerce revenue (Kanuri et al. 2022). Such an online sales push can be conceptualized as a firm's manipulation of parameter *v* in Equation 1, increasing salespeople's marginal utility for customers' e-commerce channel adoption. To understand the effect of an online sales push on mediation effort and customers' e-commerce channel adoption, consider the partial derivatives of m_1^* and a_2^* with respect to *v*:

$$\frac{\partial m_1^*}{\partial v} = \frac{1}{4c}(1 + wp_1 + (1-w)p_2) \tag{12}$$

$$\frac{\partial a_2^*}{\partial v} = \frac{1}{16c}\left(1 + wp_1 + (2-w)p_2 + wp_1p_2 + (1-w)p_2^2\right) \tag{13}$$

Equations 12 and 13 are never negative and usually positive (except for edge cases involving *w*, p_1, and p_2). Thus, the dual adoption model predicts that an online sales push usually increases salespeople's mediation effort m_1^* and customers' e-commerce channel adoption a_2^*, which fully aligns with the findings by Kanuri et al. (2022). Extending beyond their work, future research could empirically examine how salespeople's and customers' technology perceptions shape the effectiveness of an online sales push, or how firms can shape p_1 and *w* through pre-push training and p_2 through customer-directed communication to maximize the effectiveness of an online sales push.

In addition, future research can build on our confirmed drivers of a customer's e-commerce channel adoption: Salespeople's and a customer's product breadth, transaction

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frequency, and peer e-commerce revenue share. Studies on e-commerce adoption may employ these variables to improve the predictive validity and reduce omitted variable bias. In addition, we encourage future research to conceptualize and test further variables that drive salespeople's and customers' perceptions and usage of e-commerce channels.

Managerial Implications

Similar to the theoretical implications, the managerial implications of this research pertain to (1) technology adoption in general and (2) e-commerce adoption in particular. We elaborate on both implications in the following sections.

Technology adoption. Technology adoption is a notorious pain point in managerial practice. Whether it be CRM systems (Alavi et al. 2025), sales enablement systems (Hartmann et al. 2025), predictive analytics/AI (Habel, Alavi, and Heinitz 2024), or generative and agentic AI (Gonzalez, Habel, and Hunter 2026; Rangarajan et al. 2026), managers consistently face challenges with ensuring employees and customers use novel technologies in frontline and service contexts. The DAM provides important guidance to managers.

First, rather than focusing exclusively on those individuals requested to use the technology (e.g., employees, customers), managers should identify individuals whose utility depends on others' technology use and who can influence their technology use (e.g., supervisors, salespeople, customer success managers). Managers should then make a concerted effort to deploy these individuals as mediators of technology adoption.

Second, managers should ensure these individuals are aware that they stand to benefit when others adopt the technology (i.e., ensure a high parameter v). For example, managers may incentivize them on others' technology use monetarily (Kanuri et al. 2022) or give accolades to

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those who excel at driving technology adoption. One way to accomplish this may be through rankings in publicly available dashboards (Ahearne et al. 2025).

Third, managers should ensure that these individuals have positive technology perceptions (p_1) and understand how their own effort can influence others to adopt the technology (m_1). For example, managers may train them to understand the benefits the technology provides (to develop high performance expectancy) and to master the technology's interface and functionalities (to counter effort expectancy). Managers may also surface others' perceptions and use of the technology to foster social influence (Sun 2013; Wieseke et al. 2011). Training on how to expend mediation effort may include, for example, role plays on how to promote the technology (Habel, Alavi, and Linsenmayer 2021; Kanuri et al. 2022). Importantly, such effort should incur low costs since individuals may otherwise shy away from it. Extending beyond our findings, we believe that managers might reduce such costs by equipping individuals with semiautonomous AI agents that periodically nudge the target group to use a technology in the name of the mediating individual—a novel application of AI agents not previously described in the literature (Gonzalez, Habel, and Hunter 2026).

Fourth, managers should continue to manage traditional success factors of technology acceptance. Most importantly, managers need to ensure that those who ultimately use the technology view it positively (p_2). Again, training and communication seem quintessential.

E-commerce channel adoption. Like technology adoption in general, e-commerce adoption is a significant challenge for sales organizations (Bongers, Schumann, and Schmitz 2021) and there is little guidance for sales managers and salespeople on how to engage in successful multichannel selling (Habel, Alavi, and Linsenmayer 2021; Kanuri et al. 2022; Kassemeier, Alavi, and Habel 2025; Nahm et al. 2026). Accordingly, we encourage managers to

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follow our recommendations outlined in the previous section specifically for e-commerce channels. To reiterate, managers should (1) focus on salespeople as mediators of customers' e-commerce channel adoption, (2) ensure they benefit from customer adoption (e.g., by counting e-commerce revenue toward salespeople's quotas), (3) train salespeople to foster their understanding of the benefits of online selling and enable them to expend low-cost mediation effort, and (4) ensure customers have positive perceptions of the e-commerce channel.

While all these recommendations seem important, we would like to especially highlight the third recommendation. Our results show that even when customers have very favorable perceptions of the e-commerce channel, their adoption is reduced when salespeople have the opposite perceptions. In other words, even when a customer expects high performance from adopting an e-commerce channel (e.g., due to high customer transaction frequency), the salesperson seems to counteract this customer's adoption if her own perception is less positive (e.g., due to low salesperson transaction frequency). This is in line with the dual technology adoption's proposition that salespeople are biased by their own technology perceptions when assessing customers' perceptions (i.e., $w > 0$).

This interesting insight calls for dedicated salesperson training in perspective taking (Homburg, Wieseke, and Bornemann 2009): managers should enable salespeople to accurately assess whether customers would or would not benefit from adopting an e-commerce channel. One potential training method in this respect involves role plays. While role plays traditionally focus on discovering customers' *product*-related needs (e.g., Geiger, Bischoff, and Vogler 2022; Kassemeier et al. 2022), we believe such role plays should also train salespeople in understanding manifest and latent *channel*-related needs. If such needs explicitly or implicitly

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favor e-commerce channels, the role plays may allow salespeople to try out different mediation techniques to foster adoption (Habel, Alavi, and Linsenmayer 2021).

Limitations and Avenues for Future Research

Our empirical application of the DAM has two limitations that can serve as avenues for future research. First, we rely on objective data to approximate differences in salespeople's and customers' technology perceptions. Whereas this data offers high validity in terms of determining real-world effects, and thus helps managers directly implement our implications, it limits us in exploring actual perceptions and attitudes. Future research could delve deeper into salespeople's and customers' perceptions of the unique characteristics of e-commerce, for example from a task–technology fit perspective (Goodhue and Thompson 1995). Such an approach could unveil deeper insights into the psychological drivers of e-commerce adoption.

Second, our empirical setting is a single B2B firm in industrial consumables. Key characteristics of this context are short purchase cycles, which may facilitate customers' e-commerce adoption. At the same time, however, this context is fairly traditional, and actors are not necessarily as digitally savvy as actors in other industries. Therefore, it is not immediately clear whether it was particularly easy or particularly difficult to identify the proposed effects in this context. To ensure generalizability and test boundary conditions, future research should replicate our findings in other sectors, such as pharmaceuticals and software-as-a-service.

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Table 1
Overview of Technology Acceptance Theories

Theory	Core Assumptions About Adoption	Level of Adoption	Individual Cognitive Evaluation	Social Influence Included	Assumes Autonomous Adopter	Multi-Actor Adoption	Actor Interdependence	Sequential Adoption	Across Organizational Boundaries
Network Externalities (Katz and Shapiro 1986)	Adoption increases with number of adopters.	Individual	✓	✓	✓	–	✓	–	–
Innovation Assimilation (Meyer and Goes 1988)	Contextual attributes, innovation attributes, and interaction of innovation attributes drive adoption.	Organization	✓	–	✓	–	–	✓	–
Technology Acceptance Model (Davis 1989)	Adoption is an individual cognitive decision based on beliefs about a technology.	Individual	✓	–	✓	–	–	–	–
Technology-Organization-Environment (Tornatzky and Fleischer 1990)	Organizational adoption is shaped by technological, organizational, and environmental factors.	Organization	✓	–	✓	–	–	–	–
Diffusion of Innovations (Rogers 2003)	Technology spreads through communication channels over time.	Individual	✓	✓	✓	–	–	–	–
UTAUT (Venkatesh et al. 2003)	Adoption depends on individual expectations and facilitating conditions.	Individual	✓	✓	✓	–	–	–	–
UTAUT2 (Venkatesh, Thong, and Xu 2012)		Individual	✓	✓	✓	–	–	–	–
PSAA (Habel, Alavi, and Heinitz 2023)	Integrates different adoption theories; adds that adoption pay-off depends on the value potential in the technology and in the environment	Individual	✓	✓	✓	–	–	–	–
Technology Adoption by Groups (Sarker et al. 2005)	Group valence drives group adoption and forms through individual attitudes, technology characteristics, and psycho-social factors	Group	✓	✓	–	✓	✓	–	–
GTA based on GCS (Yao et al. 2021)	Group green technology adoption emerges from group decision-making processes.	Group	✓	✓	–	✓	✓	–	–
Dual Technology Adoption (this study)	In some contexts, adoption occurs in interdependent relationships where one actor mediates another's technology use.	Individual	✓	✓	–	✓	✓	✓	✓

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Table 2
Examples of Dual Technology Adoption

Technology	Actor 1	Actor 2	Examples		
			Interdependence	**Influence**	**Dual Adoption**
E-commerce	Salesperson	Customer	The salesperson's sales outcomes depend on whether customers adopt the online channel.	The salesperson can persuade or guide customers to use the platform.	A salesperson accepts e-commerce as a viable channel (Stage 1). She encourages a Gen Z customer to transact online but not a Gen X customer who values personal contact (Stage 2).
Prospecting tool	Sales manager	Salesperson	The manager's performance depends on whether salespeople adopt the prospecting tool.	The manager allocates access and communicates expectations that guide adoption.	A sales manager accepts ZoomInfo as a prospecting tool (Stage 1) and encourages "hunters" but not "farmers" to use it (Stage 2).
LLMs	Educator	Student	The educator's teaching effectiveness depends on whether students adopt LLMs appropriately.	The educator sets rules that allow or restrict students' LLM use.	An educator accepts LLMs as a learning tool (Stage 1) and allows it in a coding class but not in a critical thinking course, believing it would not support that learning objective (Stage 2).
Location sharing	Friend	Friend	Each friend's safety utility depends on whether the other enables location sharing.	Each friend can request or decline sharing, affecting mutual adoption.	A person accepts location sharing as a valuable smartphone feature (Stage 1). They persuade one friend to share locations to ensure safety but not another one who values privacy (Stage 2).
Social media	Child	Parent	The child's sense of privacy depends on whether the parent adopts the same platform.	The child can shape the parent's adoption by sending or withholding invitations.	The child accepts a new social media platform in general to remain connected with others (Stage 1). She invites friends but not parents (Stage 2).
Smartphone	Parent	Child	The parent's ability to ensure the child's safety depends on the child's smartphone use.	The parent controls access and decides whether the child receives a smartphone.	A parent accepts smartphones in general as a technology for their children (Stage 1). The parent then allows the older child to have a smartphone but not the younger one (Stage 2).

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Table 3
Propositions of the Analytical Model

Change in	Effect on m_1^*	Effect on a_2^*
p_1	+	+
p_2	+	+
v	+	+
c	−	−
w	+	+

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Table 4
Contextualized Drivers of Technology Perceptions

Actor	UTAUT Dimension	Proposed Variable	Definition	Hypothesis
Salesperson (i.e., Stage 1)	Performance expectancy	Salesperson product breadth	Extent to which a salesperson sells varied products	H_1
	Effort expectancy	Salesperson transaction frequency	Number of deals a salesperson generates	H_2
	Social Influence	Peer salesperson e-commerce revenue share	Extent to which a salesperson's coworkers adopted the e-commerce channel	H_3
Customer (i.e., Stage 2)	Performance expectancy	Customer product breadth	Extent to which a customer buys varied products	H_4
	Effort expectancy	Customer transaction frequency	Number of purchases a customer makes	H_5
	Social Influence	Peer customer e-commerce revenue share	Extent to which a customer's industry adopted the e-commerce channel	H_6

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Table 5
Operationalization of Variables

Variable	Operationalization	Relevant Studies
Customer e-commerce revenue	Total monthly revenue generated through the e-commerce channel for each customer i in month t.	Habel, Alavi, and Linsenmayer (2021), Kanuri et al. (2022)
Salesperson product breadth	Number of unique products sold by a salesperson to customers in the year prior to e-commerce introduction.	Reinartz and Kumar (2003); Schmitz (2013)
Salesperson transaction frequency	Total number of sales transactions completed by a salesperson in the year prior to e-commerce introduction.	Schmitz and Ganesan (2014)
Peer salesperson e-commerce revenue share	Average e-commerce revenue share of team members in month t–1.	Naylor, Lamberton, and West (2012); Wieseke et al. (2011)
Customer product breadth	Number of unique products purchased by a customer in the year prior to e-commerce introduction.	Wiseman et al. (2025)
Customer transaction frequency	Total number of purchases made by a customer in the year prior to e-commerce introduction.	Schmitz and Ganesan (2014)
Peer customer e-commerce revenue share	Average e-commerce revenue share generated by other customers in the same industry in month t–1.	Dwivedi et al. (2021); Crecelius et al. (2024)

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Table 6
Correlations and Descriptive Statistics

Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1 Customer e-commerce revenue								
2 Salesperson product breadth	-.013***							
3 Salesperson transaction frequency	-.009***	.903***						
4 Peer salesperson e-commerce revenue share	.018***	-.080***	-.075***					
5 Customer product breadth	.011***	.242***	.242***	-.019***				
6 Customer transaction frequency	.016***	.204***	.203***	-.019***	.924***			
7 Peer customer e-commerce revenue share	.040***	-.035***	-.035***	.200***	-.024**	-.017***		
8 Customer total revenue excluding revenue generated in e-commerce channel	-.294***	-.005***	-.045***	.031**	.310***	.366***	.021***	
Mean	.11	-.01	-.01	.01	-.01	-.01	-.01	-.01
Standard deviation	.76	.29	.63	.02	.92	1.18	.01	1.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are shown in their log-transformed form, in line with how they enter the empirical model.

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Table 7
Results

Predictors		**DV: Customer E-commerce Revenue**	
		Model 1	Model 2
Constant		.066 ***	.177 ***
		(.009)	(.046)
Salesperson product breadth	H_1 (–)	-.200 ***	-.158 ***
		(.030)	(.037)
Salesperson transaction frequency	H_2 (+)	.068 ***	.052 ***
		(.015)	(.018)
Peer salesperson e-commerce revenue share	H_3 (+)	.248 **	.058
		(.079)	(.082)
Customer product breadth	H_4 (–)	-.050 ***	-.052 ***
		(.008)	(.008)
Customer transaction frequency	H_5 (+)	.107 ***	.108 ***
		(.006)	(.006)
Peer customer e-commerce revenue share	H_6 (+)	.821 ***	.292 *
		(.126)	(.134)
Customer total revenue excluding revenue generated in e-commerce channel		-.253 ***	-.253 ***
		(.002)	(.002)
Observations		260,465	260,465
Random intercept		Salesperson and customer	Salesperson and customer
Monthly fixed effects		Yes	Yes
Salesperson team fixed effects		No	Yes
R^2		.361	.356

Notes. Model 1 is estimated using linear mixed-effects regressions with monthly time fixed effects. The dependent variable is the customer's log-transformed e-commerce revenue. Predictors are mean centered. The model includes both salesperson- and customer-level predictors, with random intercepts for both salesperson and customer to capture unobserved heterogeneity across these levels. We control for monthly time effects to account for aggregate temporal variation. Standard errors are clustered at the appropriate random-effect level. R^2 values represent the proportion of variance explained by both fixed and random effects. In model 2, we added salesperson team fixed effects as a robustness check.
* $p < .05$, ** $p < .01$, *** $p < .001$.

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Table 8
Supplemental Analysis: Δ Customer E-commerce Revenue

Predictors	**DV: Δ Customer E-commerce Revenue**
Constant	-1.291 ***
	(.009)
Salesperson product breadth	-.221 ***
	(.027)
Salesperson transaction frequency	.177 ***
	(.014)
Peer salesperson e-commerce revenue share	.587 ***
	(.112)
Customer total revenue excluding revenue generated in e-commerce channel	-.328 ***
	(.002)
Observations[a]	288,246
Random intercept	Salesperson and customer
Monthly fixed effects	Yes
R^2	.17

Notes. The model is estimated using linear mixed-effects regressions with monthly time fixed effects. The dependent variable Δ customer e-commerce revenue is the difference between the actual customer e-commerce revenue and the predicted customer e-commerce revenue, and we log-transformed this variable. Predictors are mean centered. The model includes salesperson-level predictors, with random intercepts for both salesperson and customer to capture unobserved heterogeneity across these levels. We control for monthly time effects to account for aggregate temporal variation. Standard errors are clustered at the appropriate random-effect level. R^2 values represent the proportion of variance explained by both fixed and random effects.

[a] The number of observations differs from Table 7 because the models rely on different sets of covariates. Table 7 uses the full set of salesperson and customer level predictors. Table 8 uses the Δ customer e-commerce revenue, and regresses it on salesperson-level predictors.

* $p < .05$, ** $p < .01$, *** $p < .001$.

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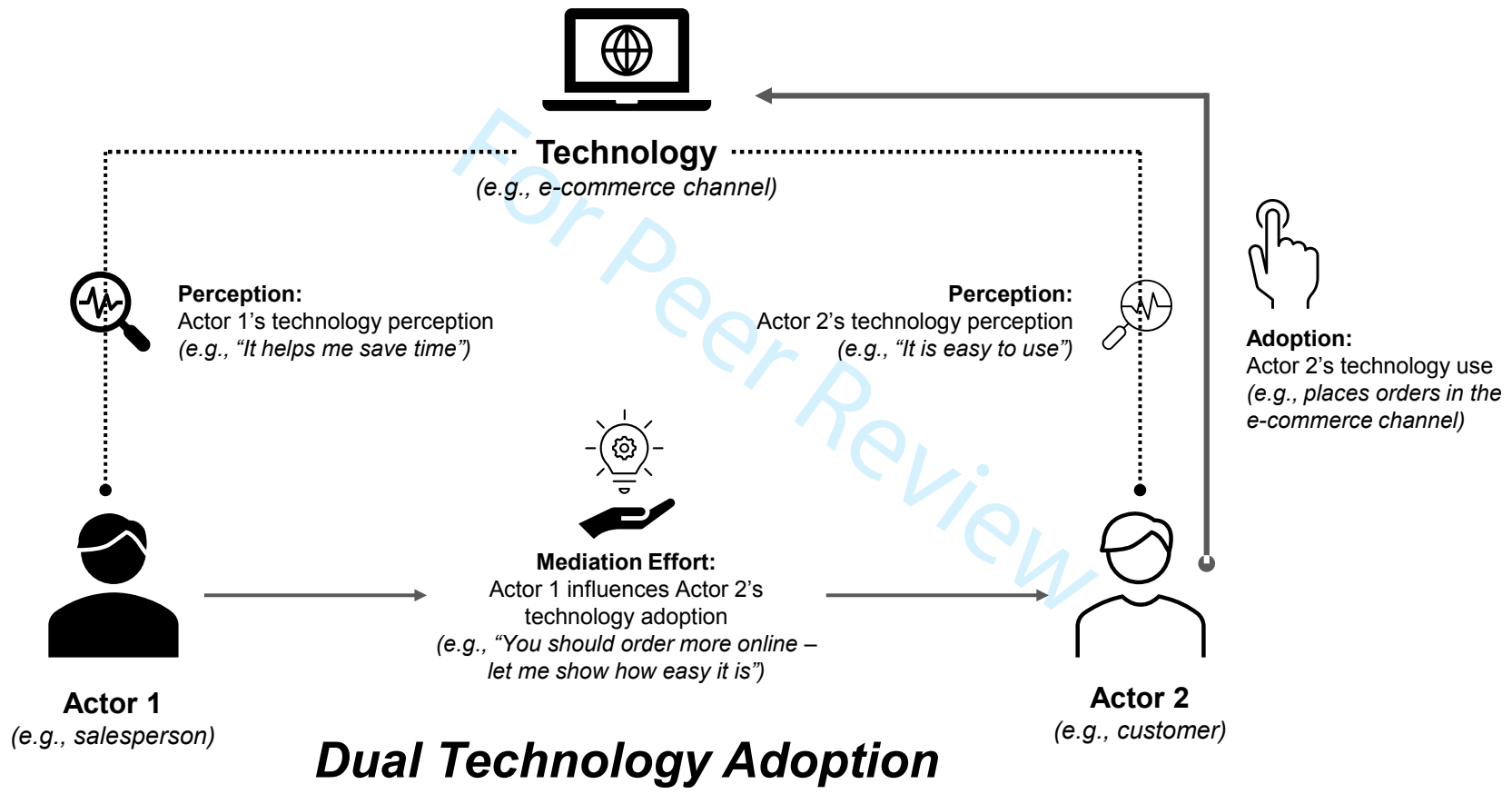
Figure 1
The Dual Technology Adoption Model



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Web Appendix

Dual Technology Adoption

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WEB APPENDIX A: ANALYTICAL MODEL

In the main manuscript, we specify Actor 1's influence on Actor 2's technology adoption through mediation effort in Stage 2 as follows:

$$a_2 = \frac{(1 + m_1)\,(1 + p_2)}{4} \tag{2}$$

One limitation of this equation is its assumption of a linear effect of m_1 on a_2. However, this effect may well exhibit diminishing returns. Therefore, in the following we relax the assumption of such a linear effect and allow for diminishing returns. Specifically, we revise equation 2 as follows:

$$a_2 = \frac{1 + p_2}{2}\left(\frac{1 + m_1}{2}\right)^{\gamma} \tag{2'}$$

a_2 is Actor 2's extent of technology adoption. It depends on Actor 1's mediation effort m_1; and on Actor 2's technology perception $p_2 \in [-1, 1]$, which is explained by traditional technology acceptance theories. Like before, we propose m_1 and p_2 to shape a_2 interactively, considering that Actor 1's influence might be greater if Actor 2 has more positive technology perceptions. However, we define $0 < \gamma < 1$, such that m_1 exhibits a diminishing effect on a_2. Like before the equation is constructed such that a_2 is at its minimum value of 0 when either m_1 or p_2 have a value of –1.

Substituting Equation 2' into Equation 1 from the manuscript provides the following utility of Actor 1 in Stage 2:

$$u_1 = v\frac{1 + p_2}{2}\left(\frac{1 + m_1}{2}\right)^{\gamma} + \bar{u} - \frac{c}{2}m_1^2 \tag{3'}$$

As explained in the manuscript, rather than directly observing p_2, Actor 1 will infer $\hat{p_2}$ as follows:

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$$\widehat{p_2} = wp_1 + (1-w)p_2 \quad (4)$$

where $w \in [0, 1]$ represents a projection weight indicating Actor 1's bias toward their own view, p_1, when inferring p_2. Thus, assuming u_1 is a function of $\widehat{p_2}$ rather than p_2, we obtain Actor 1's utility in Stage 2 as:

$$\widetilde{u_1}(m_1) = v\frac{1+\widehat{p_2}}{2}\left(\frac{1+m_1}{2}\right)^{\gamma} + \bar{u} - \frac{c}{2}m_1^2 = v\frac{1+\widehat{p_2}}{2^{\gamma+1}}(1+m_1)^{\gamma} + \bar{u} - \frac{c}{2}m_1^2 \quad (5')$$

To understand Actor 1's choice of m_1 in Stage 1, we differentiate Equation 5' with respect to m_1:

$$\frac{d\widetilde{u_1}}{dm_1} = v\gamma\frac{1+\widehat{p_2}}{2^{\gamma+1}}(1+m_1)^{\gamma-1} - cm_1 = 0 \quad (6')$$

Solving Equation 6 results in Actor 1's optimal mediation effort in Stage 1:

$$m_1^*(1+m_1^*)^{1-\gamma} = v\gamma\frac{1+\widehat{p_2}}{c2^{\gamma+1}} \quad (7a')$$

Or:

$$m_1^*(1+m_1^*)^{1-\gamma} = v\gamma\frac{1+wp_1+(1-w)p_2}{c2^{\gamma+1}} \quad (7b')$$

Thus, Actor 1's optimal mediation effort increases in p_1 and p_2. Furthermore, the costlier mediation effort is (as indicated by c), the less p_1 and p_2 will affect mediation effort.

Furthermore, Actor 2's realized technology adoption in Stage 2 is:

$$a_2^* = \frac{1+p_2}{2}\left(\frac{1+m_1^*}{2}\right)^{\gamma} \quad (8')$$

Unlike the baseline specification, this first-order condition does not yield a closed-form solution for m_1^*. However, because m_1^* increases with both p_1 and p_2, and a_2^* increases with both m_1^* and p_2, a_2^* increases with both p_1 (indirectly via mediation effort) and p_2 (both directly and indirectly). Thus, the implications of the analytical model in our manuscript hold.

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WEB APPENDIX B: DETAILS OF MACHINE LEARNING APPROACH

We conduct a supplemental analysis to separate customer-specific propensity to adopt the e-commerce channel from salesperson-mediated adoption. Specifically, we generate a prediction for each customer's expected monthly e-commerce revenue based on customer-side observables alone. We then use deviations of actual from predicted e-commerce revenue to isolate the portion of adoption plausibly attributable to salesperson mediation.

We generate this prediction using a two-stage boosted-tree hurdle model at the customer–month level. In the first stage, we estimate $\hat{P}_j$, the probability that customer *j* generates any positive e-commerce revenue (i.e., adopts e-commerce channel) in month *t*, using a gradient boosting classifier. To improve probabilistic accuracy, the classifier is calibrated using Platt scaling (sigmoid calibration). In the second stage, we estimate the magnitude of e-commerce revenue conditional on adoption using an XGBoost regressor applied to the log-transformed e-commerce revenue. The final expected e-commerce revenue is computed as the product of the predicted adoption probability and the predicted conditional revenue:

$$\widehat{E\left[Y_j^{(Rev)}\right]} = \hat{P}_j \times \widehat{Y_j^{(Rev)}},\ \hat{P}_j = \Pr\left(Y_j^{(Rev)} > 0 \,\middle|\, X_j\right)$$

The model uses only customer-side predictors. First, we construct baseline customer characteristics using the 12-month before the e-commerce channel introduction, during which customers had no exposure to the e-commerce channel. These features capture stable differences in purchasing behavior and include purchase frequency, average monthly revenue, average order value, median order value, average discount percentage, price sensitivity, product breadth, and product concentration. Second, for each post-introduction customer-month, we construct a set of dynamic predictors using only information available up to month *t-1*, which avoids look-ahead

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bias at the feature level. These include lagged e-commerce revenue, lagged total revenue, second-order lags, month-to-month changes, cumulative average e-commerce revenue to date, and the number of months since first e-commerce use. We also include calendar-month indicators to capture seasonal patterns. Importantly, no salesperson-level predictors enter the machine-learning stage.

The dynamic feature construction ensures that predictions for month *t* rely only on past information, thereby preserving temporal ordering and avoiding look-ahead bias. After fixing the feature set, we estimate the model on the full post-introduction panel and generate predicted e-commerce revenue for each customer-month. This approach reflects the role of the model as a flexible first-stage approximation of customer-side adoption rather than a standalone forecasting exercise.

In implementation, the adoption stage is estimated using gradient boosting with 200 trees, a learning rate of 0.05, maximum tree depth of 4, and subsampling of 0.8. The intensity stage uses an XGBoost regressor with 800 trees, a learning rate of 0.04, maximum depth of 7, and subsampling of 0.8. To assess whether the predicted outcome is sensitive to modelling choices, we conducted additional stability checks. We re-estimated the model using alternative reasonable machine-learning specifications, including a more regularized boosted-tree specification (e.g., random forest regressor) and a simpler hurdle model combining a calibrated logistic adoption model with a tree-based intensity model. With these tests, the results remain stable.

The resulting model achieves an RMSE of 38.11, an MAE of 8.87, indicating that customer-side observables contain substantial information about subsequent e-commerce adoption. We then define Δ *customer e-commerce revenue* as the difference between actual and predicted monthly e-commerce revenue. Conceptually, this variable captures the extent to which

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customers adopt the e-commerce channel above or below the level implied by their own observable characteristics and prior purchasing dynamics.

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WEB APPENDIX C: CUSTOMER E-COMMERCE FIRST ADOPTION

We performed an adoption-onset modelling using a binary first-adoption indicator instead of customers' e-commerce revenue. Specifically, we define a binary variable, *customer e-commerce first adoption* that equals one in the first month in which customer records positive e-commerce revenue and zero in all prior customer-month observations. Observations after first adoption are excluded.

To preserve comparability with the main analysis, we retain the same dyadic linear mixed-effects framework with random intercepts for both salespeople and customers. This choice is consistent with the manuscript's core analytical strategy, which models adoption outcomes while accounting for the nested and repeated-observation structure of the salesperson–customer–month panel. We replace monthly fixed effects with a duration term that captures how the likelihood of first adoption evolves over the post-introduction period. This is appropriate in our setting because the e-commerce adoption builds gradually over the 24 months following channel introduction, as salespeople and customers adjust routines and peer effects diffuse over time.

Table W1 presents the results of our analysis. The results are consistent with the main findings. Time duration has a positive and significant effect (.001, $p < .001$), indicating that first adoption becomes more likely as time passes after the rollout.

At the salesperson level, product breadth remains negative and significant (–.030, $p < .001$), transaction frequency remains positive and significant (.010, $p < .001$), and peer salesperson e-commerce revenue share remains positive and significant (.043, $p < .001$). Thus, the same salesperson characteristics that indicate higher customer e-commerce revenue in the main model also suggest earlier customer adoption of the e-commerce channel.

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On the customer side, transaction frequency (.010, $p < .001$) and peer customer e-commerce revenue share (.181, $p < .001$) remain positive and significant, whereas customer product breadth becomes statistically insignificant in this first-adoption specification. This pattern is theoretically plausible, as customer product breadth may matter more for the depth of channel usage after adoption than for the initial decision to try the channel at least once. By contrast, customer transaction frequency and peer customer adoption appear to be more directly linked to crossing the threshold into first use. In summary, the first-adoption model supports the conceptualization of the DAM that customer adoption is shaped by interdependent drivers on both sides of the salesperson–customer dyad.

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Table W1
Results

Predictors	**DV: Customer E-commerce First Adoption**
Constant	0.023 ***
	(0.001)
Time duration (month)	0.001 ***
	(0.001)
Salesperson product breadth	-0.030 ***
	(0.006)
Salesperson transaction frequency	0.010 ***
	(0.003)
Peer salesperson e-commerce revenue share	0.043 ***
	(0.011)
Customer product breadth	0.005
	(0.002)
Customer transaction frequency	0.010 ***
	(0.001)
Peer customer e-commerce revenue share	0.181 ***
	(0.019)
Customer total revenue	-0.028 ***
	(0.001)
Observations	243,576
Random intercept	Salesperson and customer
R2	0.600

Notes. The dependent variable is a binary indicator equal to one in the first month in which a customer records positive e-commerce revenue and zero in all prior months. The variable *Time duration (month)* captures the number of months since the introduction of the e-commerce channel. The model is estimated using linear mixed-effects regressions with random intercepts for both salesperson and customer to account for unobserved heterogeneity at each level. The model includes both salesperson- and customer-level predictors. All continuous predictors are mean-centered.

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

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WEB APPENDIX D: FUTURE RESEARCH AVENUES

Table W2
Avenues for Extending the DAM

Equation	Element	Sample Question for Further Theoretical Development
1	Actor 1's utility	• How should firms manage a focal actor's utility from other actors' technology use (through parameter v)? • What externalities resulting from other actors' technology use shape v and how do actors infer and interpret such externalities? • What costs (c) does mediation effort incur in what situations?
2	Actor 2's adoption rationale	• When making adoption decisions (a_2), how do actors weigh their own technology perceptions (p_2) compared to the mediation effort expended on them (m_1)? • What if own technology perceptions (p_2) fundamentally conflict with the mediation effort experienced (m_1)? • What if Actor 2 experiences competing mediation effort from multiple other actors? • How does the radicalness of new technology shift adoption dynamics?
4	Actor 1's inference of Actor 2's technology perceptions	• When inferring another actor's technology perceptions ($\hat{p_2}$), how are actors biased by their own technology perceptions (p_1)? • Under what conditions is this bias (w) stronger or weaker? • How do Actor 2's dispositions (e.g., digital orientation) shape inferences?
7	Actor 1's mediation effort	• What types of mediation effort are used, such as e-commerce promotion or application of power? • What social processes occur between actors during such mediation?
9–10	Marginal effects on Actor 2's adoption	• How do both actors' technology perceptions (p_1, p_2) interact in shaping Actor 2's adoption decision (a_2^*)? • How does Actor 2's adoption (a_2^*) evolve over time? • Does Actor 2's adoption (a_2^*) feed back into Actor 1's technology perception (p_1)?

For Peer Review

Dual Technology Adoption

Author Biographies

Skyler Xie recently completed his PhD at the University of Warwick and is currently based at the Alan Turing Institute in London.

Roland Kassemeier is an Associate Professor at Warwick Business School. His research focuses on the impact of digital and AI on the sales function, multichannel selling, and sales incentives. He is founding co-director of the Warwick Business School Sales Excellence Hub, a knowledge transfer hub for sales leaders in the UK.

Johannes Habel is an Associate Professor of Marketing at C.T. Bauer College of Business, University of Houston. His research focuses on the digital transformation of sales and sales psychology. Johannes has published in journals such as the *Journal of Marketing* and the *Journal of Marketing Research*.

Nick Lee is Professor of Marketing and founding co-director of the Sales Excellence Hub, Warwick Business School. His work blends behavioral science, data science, social-cognitive psychology, and philosophy, and has appeared in journals including *Journal of Marketing Research, Journal of the Academy of Marketing Science*, *Organization Science*, *Organizational Research Methods*, and *Journal of Management*.

Sascha Alavi is a Full Professor of Marketing at the University of Dortmund, Germany. His research focuses on sustainable, digital transformation in marketing. Sascha has published in journals such as the *Journal of Marketing* and the *Journal of Marketing Research*.

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Dual Technology Adoption

Executive Summary

Organizations invest billions of dollars in new technologies such as CRM systems, e-commerce platforms, predictive analytics, and artificial intelligence. Yet many technology implementations fail because employees, customers, or service partners do not fully adopt the new systems. Existing technology acceptance theories explain adoption primarily as an individual decision driven by factors such as perceived usefulness, ease of use, and social influence. However, these theories largely overlook situations in which one person's adoption depends on another person actively encouraging or discouraging the technology's use.

This study introduces the concept of dual technology adoption, which occurs when one actor's technology adoption is mediated by another actor. The authors argue that many frontline business situations involve this type of interdependence. For example, customers' adoption of a supplier's e-commerce platform may depend heavily on whether salespeople support and promote the platform. Similarly, managers may influence employees' use of AI systems, or customer success managers may influence clients' adoption of digital tools. Existing technology acceptance theories do not adequately explain these multi-actor adoption processes.

To address this limitation, the authors develop the Dual Adoption Model (DAM). The model proposes that technology adoption depends not only on the perceptions of the ultimate user, but also on the perceptions and incentives of an intermediary actor whose behavior influences adoption. The intermediary actor can expend "mediation effort" to either encourage or discourage adoption, depending on whether the intermediary believes the technology benefits them and the target user.

The authors test the model in a business-to-business e-commerce setting. They analyze a salesperson–customer–month panel dataset from a European industrial supplier that introduced a new e-commerce platform. The dataset covers 36 months, including 521 salespeople, 36,431 customers, and more than 260,000 observations. Because the company relied on salespeople to promote the platform to customers, the setting provides a natural environment for examining dual adoption.

The results strongly support the Dual Adoption Model. Customer e-commerce adoption was influenced not only by customer characteristics but also by salesperson characteristics. Customers were less likely to adopt the platform when their salesperson sold a broad range of products, likely because these salespeople relied heavily on consultation and therefore saw less value in e-commerce. In contrast, customers were more likely to adopt when their salesperson handled many transactions and therefore expected greater efficiency gains from the platform. Customers also adopted more when their salesperson's peers were successfully using the e-commerce channel, highlighting the importance of social influence within sales teams. On the customer side, adoption increased when customers had frequent purchasing transactions and when other firms in their industry were actively using the platform, but decreased when customers had complex product needs that benefited from salesperson consultation.

The findings suggest that technology adoption often fails because organizations focus exclusively on the intended users while neglecting the individuals who mediate adoption. Even customers who would personally benefit from a technology may not adopt it if salespeople have unfavorable perceptions and therefore fail to encourage its use. In other words, technology adoption is not merely an individual decision but frequently a social process involving multiple actors whose incentives and perceptions interact.

For managers, the study offers several important lessons. First, organizations should identify individuals who can influence others' technology adoption, such as supervisors, salespeople, customer success

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managers, or service representatives. Second, these individuals should be given incentives that align their interests with successful adoption outcomes. Third, organizations should invest in training and communication efforts that help these mediators understand the technology's benefits and learn how to effectively promote it. Finally, managers must continue to improve the perceptions of the ultimate users, but should recognize that user-focused initiatives alone may be insufficient if influential intermediaries remain unconvinced.

For sales organizations specifically, the findings suggest that successful e-commerce adoption requires treating salespeople as active change agents rather than passive participants. Salespeople should be rewarded for customers' online purchases, trained to recognize when customers would benefit from digital channels, and taught how to guide customers toward adoption. Managers should also help salespeople avoid projecting their own preferences onto customers. Even when customers are likely to benefit from e-commerce, adoption may be suppressed if salespeople mistakenly assume customers share their own reservations. By managing both sides of the adoption process simultaneously, organizations can significantly improve the success of digital transformation initiatives.

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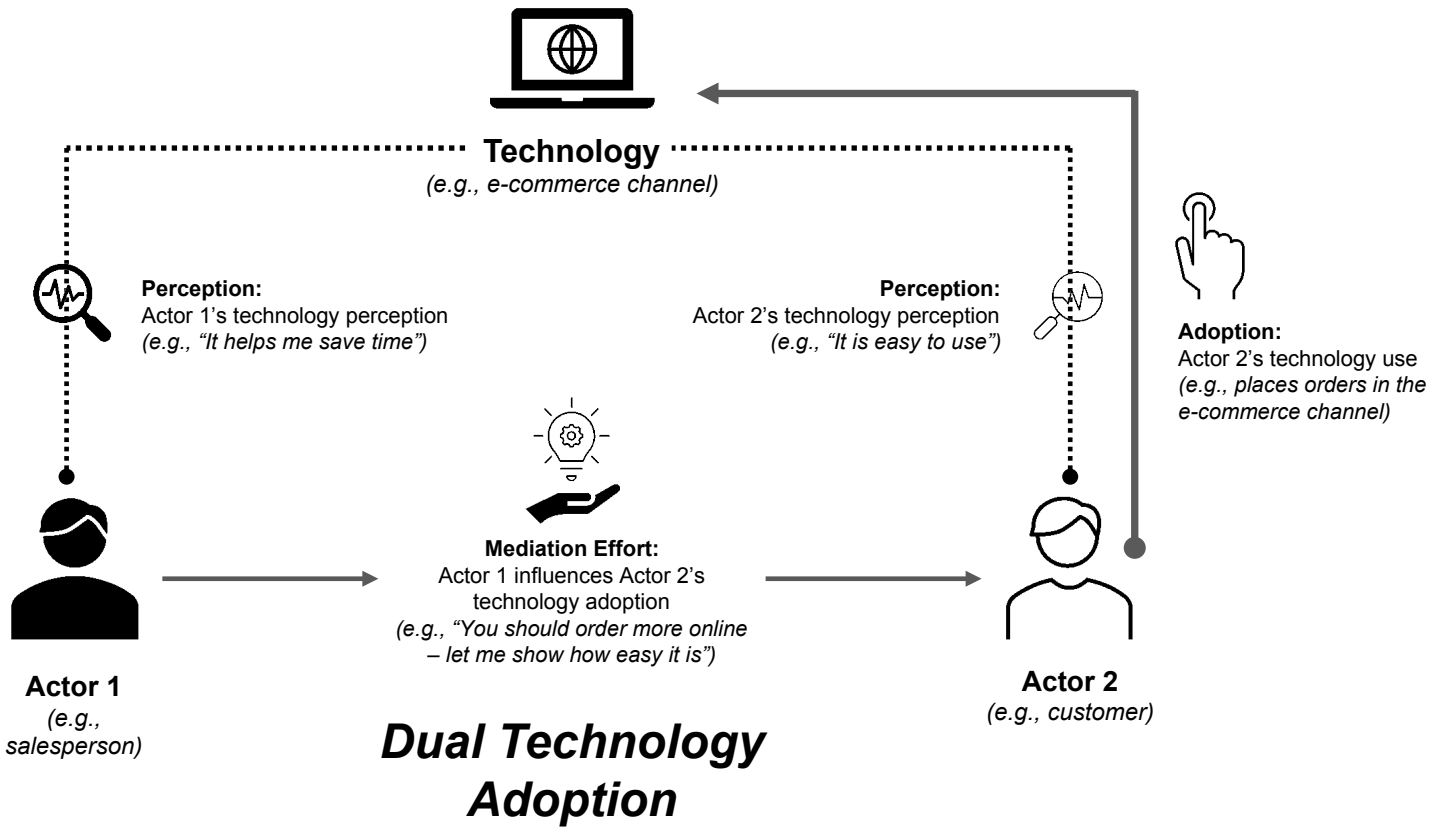
Technology
(e.g., e-commerce channel)
Perception:
Actor 1's technology perception
(e.g., "It helps me save time")
Perception:
Actor 2's technology perception
(e.g., "It is easy to use")
Adoption:
Actor 2's technology use
(e.g., places orders in the e-commerce channel)
Mediation Effort:
Actor 1 influences Actor 2's technology adoption
(e.g., "You should order more online – let me show how easy it is")
Actor 1
(e.g., salesperson)
Actor 2
(e.g., customer)
Dual Technology Adoption