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Exploratory Study

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Adoption of AI integrated partner relationship management (AI-PRM) in B2B sales channels: Exploratory study

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A R T I C L E I N F O

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A B S T R A C T

Partner relationship management (PRM) is a set of methods, tools, strategies, and web-based capabilities that a business-to-business (B2B) firm uses to manage its relationships with partners, resellers, and other third parties. Integrating artificial intelligence (AI) into PRM helps automate processes and procedures by eliminating human error and processing data faster and more accurately. Following growing attention from scholars and practitioners to AI-PRM, this study builds on the dynamic capability view (DCV) and absorptive capacity theory to develop a conceptual model to understand the requirements for a B2B firm's adoption of AI-PRM and its impact on business value. Since AI-PRM is still relatively new in scholarly research, there are no specific scales in the existing literature that could be used to capture specific factors and preconditions for its adoption, thus we explore a set of new metrics. We test the conceptual model using structural equation modeling with data from 427 B2B firms. Our results show that firms improve operational performance when an AI-PRM system is reflected in customized partner services and partner engagement, which in turn yields business value.

1. Introduction

The global partner relationship management (PRM) market is estimated to reach US$ 679 million by 2023 and is expected to grow at a compound annual growth rate (CAGR) of 17.24% to reach US$ 166.41 billion by 2027. This tremendous CAGR confirms that PRM is a necessity for channel sales. It is a computer-mediated capability (Storey & Kocabasoglu-Hillmer, 2013), a set of reliable systems, practices, procedures, and tools (Barac, Ratkovic-Živanovic, Labus, Milinovic, & Labus, 2017) that a firm uses to efficiently execute channel sales, by interacting with and managing relationships with channel partners (i.e. resellers), their customers, and other third parties. It allows suppliers (hereafter firms) to interact with their partners' customer database, to collect and analyze data at every stage of the partners' sales funnel, and to obtain information about sales (Zablah, Johnston, & Bellenger, 2005). Thus, PRM allows companies that rely on partners to sell products or services on their behalf to optimize costs, automate regular partner processes, effectively increase channel sales (Li, Peng, Xing, Zhang, & Zhang, 2021), streamline business processes, and increase revenue through sales enablement.

In practice, PRM solutions are often confused with customer relationship management (CRM) solutions. However, there is a major difference between them. In simplified terms, CRM is focused on end customers and is used by companies that are working directly with customers, while PRM solutions are used by companies with indirect sales channels to streamline the processes that occur between suppliers, their partners, and customers of the partners (Chatterjee, Tamilmani, Rana, & Dwivedi, 2020; Storey & Kocabasoglu-Hillmer, 2013). Firms that sell their products through resellers using PRM have access to their resellers' customer data, which enables them to offer their resellers customized product information, various web-based self-service tools, training, technical support, and additional resources more efficiently.

However, a PRM system brings some challenges. For example, although it allows partners (i.e. resellers) to analyze various end-customer data, including needs, buying habits, frequencies, and size of orders (Wongsansukcharoen, Trimetsoontorn, & Fongsuwan, 2015), in practice they do not have the capability to accurately analyze this huge volume of customer data (Nguyen, Chang, & Simkin, 2014). Some larger partners develop additional algorithms (e.g., artificial intelligence or machine learning) for the purpose of generating reports, but that task

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remains complex and often costly, as the application development process is usually outsourced. Hence, there is need to introduce artificial intelligence (AI) into existing PRM systems (Stone et al., 2020). Doing so lightens the partners' workload and may improve their customer relationship activities. On the other hand, an effective AI-PRM system might also help supplier firms to improve information exchange between themselves and end customers, which would lead to operational excellence. Although the benefits of AI-PRM for firms, their partners, and end customers are obvious, studies that help understand the characteristics of an AI-PRM system that might drive its adoption by partners are still in the early stages. This study aims to answer the following research questions: (1) *What are the prerequisites for effective adoption of an AI-PRM system across sales channels?* and (2): *How does the adoption of an AI-PRM system improve the business value of a firm?*

Using data from 427 firms, our study, anchored in dynamic capability view (DCV) and absorptive capacity theory, offers important theoretical and practical implications. We show that customized partner services and partner engagement are relevant antecedents of AI-PRM adoption. Namely, as the AI-PRM system becomes more incorporated in the business activities of the firm and its partners (Chaudhuri, Vrontis, Thrassou, & Ghosh, 2021; Jiang, Yang, Zhao, & Li, 2020), the services offered by firms become more tailored to the partners and their end customers (Zablah et al., 2005). In addition, in this study we provide useful insights for management and system developers on the activities that need to be carried out for successful AI-PRM system adoption across sales channels, which ultimately increases the business value of the firm.

2. Theoretical underpinning

2.1. Development of interest in AI-PRM

Adoption of AI-PRM systems within a firm is anchored in the three pillars of the literature as presented in Fig. 1.

The first anchor comes from the general literature on the use of AI in business (e.g., Tarafdar, Beath, & Ross, 2019), ranging from sales in general (Syam & Sharma, 2018), to products (e.g., Burström, Parida, Lahti, & Wincent, 2021) and services (Huang & Rust, 2018) more specifically. This literature highlights the contribution of AI to business operations but does not focus specifically on a firm's involved in indirect sales and their partner relationship activities.

The second major anchor is based on the more traditional literature that established the legacy of CRM in improving business operations and performance (e.g., Xu et al., 2012; Avlonitis & Panagopoulos, 2005) by supporting various business functions, improving relationships with customers, and enhancing business value (Kim & Kim, 2009; Payne & Frow, 2006). This literature has recently been enriched by studies that aim to answer various research questions related to the role of AI within CRM systems (e.g., Chatterjee, Chaudhuri, & Vrontis, 2022; Chatterjee, Rana, Tamilmani, & Sharma, 2021). Interest in AI-CRM has generated a new stream of literature showing the importance of organizational readiness prior to the adoption of AI-CRM, but also how AI-CRM technology enhance relationship management with end-customers and overall digitization process of the organization (Chatterjee et al., 2022; Ledro, Nosella, & Vinelli, 2022). Both streams of CRM literature (i.e., the more traditional and that based on an AI-enriched perspective) provide

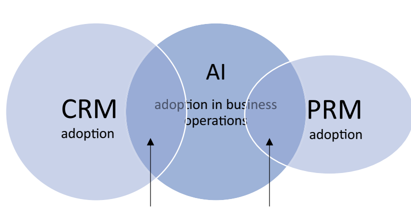

Fig. 1. Overview of theory anchors used to understand AI-PRM.

valuable insights and lessons to researchers interested in PRM tools.

Given the key differences between CRM and PRM tools discussed in our introduction (e.g., direct sales versus indirect sales; focus on relationship with customers versus focus on relationship with members of the sales channel, including resellers and their customers), which mean traditional CRM tools are ineffective for managing relationships within indirect sales channels (Mirani, Moore, & Weber, 2001), scholars recognized need for academic research that can provide answers to research questions focusing primarily on PRM (Aguirre et al., 2018; Barac et al., 2017; Storey & Kocabasoglu-Hillmer, 2013; Zablah et al., 2005). Inspired by previous studies on PRM, but also by the importance of AI in business operations and AI-based CRM, we first outline the characteristics of AI-PRM systems before developing a conceptual model of the antecedents and consequences of AI-PRM systems' adoption within sales channels.

2.2. AI-PRM characteristics

A PRM system embedded with AI can perform various tasks more effectively and more efficiently than traditional PRM due to the power of the automated capacity of AI algorithms. The automated decision-making and recommendation ability of AI effectively develops the partner-related process within PRM. This leads to more efficient learning of partners, effective partner planning capability, streamlining of different partner processes, and knowledge sharing between partners and suppliers (Baabdullah, Chatterjee, Rana, & Dwivedi, 2021). The AI-PRM solution provides customized partner services, which anticipates partners' needs and streamlines services by also fostering its adoption (Chatterjee et al., 2020) by the partner. An AI-PRM system is used for forecasting customers' needs, which emerge from a variety of data sources (Oukes & von Raesfeld, 2016). Thus, it is beneficial for different units, such as communication and marketing, inventory, IT, and sales. For example, AI-PRM streamlines the sales process by providing greater visibility of every prospect in the partner's sales funnel. When used in marketing, AI-PRM solutions allow firms' marketing executives to manage relationships with third-party influencers and communication champions (Seifzadeh, Salehi, Abedini, & Ranjbar, 2021).

Firms adopting AI-PRM solutions for their sales channels have access to multifarious data from their partners and their partners' end customers, which can also raise issues about data privacy, security, and vulnerability (Kruger, Drevin, & Steyn, 2010). Thus, an AI-PRM data protection policy is of paramount importance (Abidin, Nawawi, & Salin, 2019) for AI-PRM adoption. Partners who are trusted by firms to use an AI-PRM, and vice versa, become strategic partners. They provide broad access to their data, which in turn helps the firms to improve operations on the benefit of both, partners and the firms (Dasanayaka, Al Serhan, Glambosky, & Gleason, 2020).

The contribution of AI-PRM to a firm's business value depends on the partners' engagement with AI-PRM and their ability to use it efficiently. Segmenting the partners according to their abilities, location, and revenue generating capacity is needed to drive better partner engagement (Tsarenko & Simpson, 2017). Once a firm fully adopts an AI-PRM solution to its sales channel, its practices and processes of interacting with partners are integrated into the firm's core business operations. Thus, adoption of an AI-PRM system can help the partners to collaborate better with the supplier firm (Maxwell, Jeffrey, & Lévesque, 2011; Nguyen, Ghosh, & Chaudhuri, 2019; Rana, Tamilmani, & Sharma, 2021).

2.3. Dynamic capability view and absorptive capacity theory

This study uses DCV (Teece, Pisano, & Shuen, 1997) and absorptive capacity theory (Qian & Acs, 2013) to identify relevant factors for the adoption of an AI-PRM solution within a sales channel and its consequences. The former sees dynamic capability as a higher order capability (Teece, 2014) conceptualized through three dimensions: sensing ability, seizing ability, and transforming/reconfiguring ability. Thus, in the context of the adoption of an AI-PRM solution, firms may seize AI-PRM as an external resource or use the opportunities to address dynamic market requirements. However, seizing only external resources may not fully serve the purpose. They must also possess the capability to sense the value of new opportunities, or resources, and quickly reconfigure and orchestrate externally sourced competencies while leveraging internal resources to address dynamic business environments. After such absorption, the firm needs to properly utilize those opportunities for commercial gain. This is the central idea of absorptive capacity theory, which sees the dynamic ability of the firm as a mechanism to capture external opportunities and translate them into competitive advantage.

In the context AI-PRM adoption across sales channel, we argue that firms also need to develop several capabilities (i.e. sensing, seizing, and transforming or reconfiguring) of their partners, so they can adopt an AI-PRM system (e.g., Schreyögg & Kliesch-Eberl, 2007). Thus, AI facilitates a firm's relationship activities with partners' end-customers through PRM, and in return the firm provides customized real-time services for the partners based on data obtained through AI-PRM. This will eventually improve the partners' engagement with end customers. Such customized services for end customers can be improved by enhancing the partners' abilities to identify, develop, and co-create value with the suppliers. This is the sensing ability. The partners should also develop the ability to mobilize the required resources to fulfill customers' needs, which is known as the seizing ability. Finally, partners should adopt the ability to recombine resources to innovate and respond to changing market environments (Fainshmidt, Pezeshkan, Lance Frazier, Nair, & Markowski, 2016). This is the reconfiguring or transforming ability. Thus, DCV theory helps to explain that developing partners' customized services and partners' engagement with firms could lead to their adoption of an AI-PRM solution through the development of dynamic capability based on sensing, seizing, and reconfiguring abilities (Teece et al., 1997).

A logical follow-up question is how to develop the dynamic capabilities of partners? To answer this, we rely on absorptive capacity theory (Cohen & Levinthal, 1990; Qian & Acs, 2013). This posits that the extent to which an organization can recognize the value of new external information, digest it, and use it to achieve its goal depends on its absorptive capacity. Thus, we argue that firms can develop the dynamic capabilities of their partners by absorbing appropriate external information through the partners and improving their anticipation capacity and streamlining abilities (Matikainen, Terho, Parvinen, & Juppo, 2016). To achieve this, a partner will need to engage with, and effectively utilize, their customer database to absorb data in order that the AI integrated into the PRM system can perform data analysis. Thus, the absorptive capacity of a partner plays an important role in the adoption process of an AI-PRM solution (Chatterjee et al., 2020). Improved absorptive capacity will allow customized services that will equip partners with information and the abilities needed to better meet customer needs and increase the engagement and experience of end customers with the firm's products or services. This should increase the adoption of an AI-PRM solution. In other words, firms should improve their partners' absorptive capability to better integrate themselves with the partners' ecosystem.

3. Development of conceptual model and hypotheses

Drawing on DCV and absorptive capacity theory (Cohen & Levinthal, 1990; Teece et al., 1997), we designed a conceptual model (Fig. 2) to explain the adoption of an AI-PRM system within the sales channel and how it could relate to a firm's business value through the improvement of operational excellence. The inputs of literature as well as the underpinning theories identified two salient clusters of factors that are prerequisites of adoption of an AI-PRM system: partner customized services and partner engagement.

3.1. Partner customized services

Partners need the ability to anticipate (PNA) the changing needs of customers (Hatton, Kolk, Eikelenboom, & Beaumont, 2017; Musarra, Bowen, Robson, & Spyropoulou, 2021) to structure their selling and promotional opportunities. When data about the changing needs of end customers are logged into a PRM system, the firm can redevelop and improve products and services. It can provide optimal support to partners and their selling and promotional activities through partner customized services (PCS).

A PRM system helps to streamline partners' sales processes by offering greater visibility of all the prospects in the sales funnel enabling users to manage, track, and nurture every sales lead (Vlachopoulou,

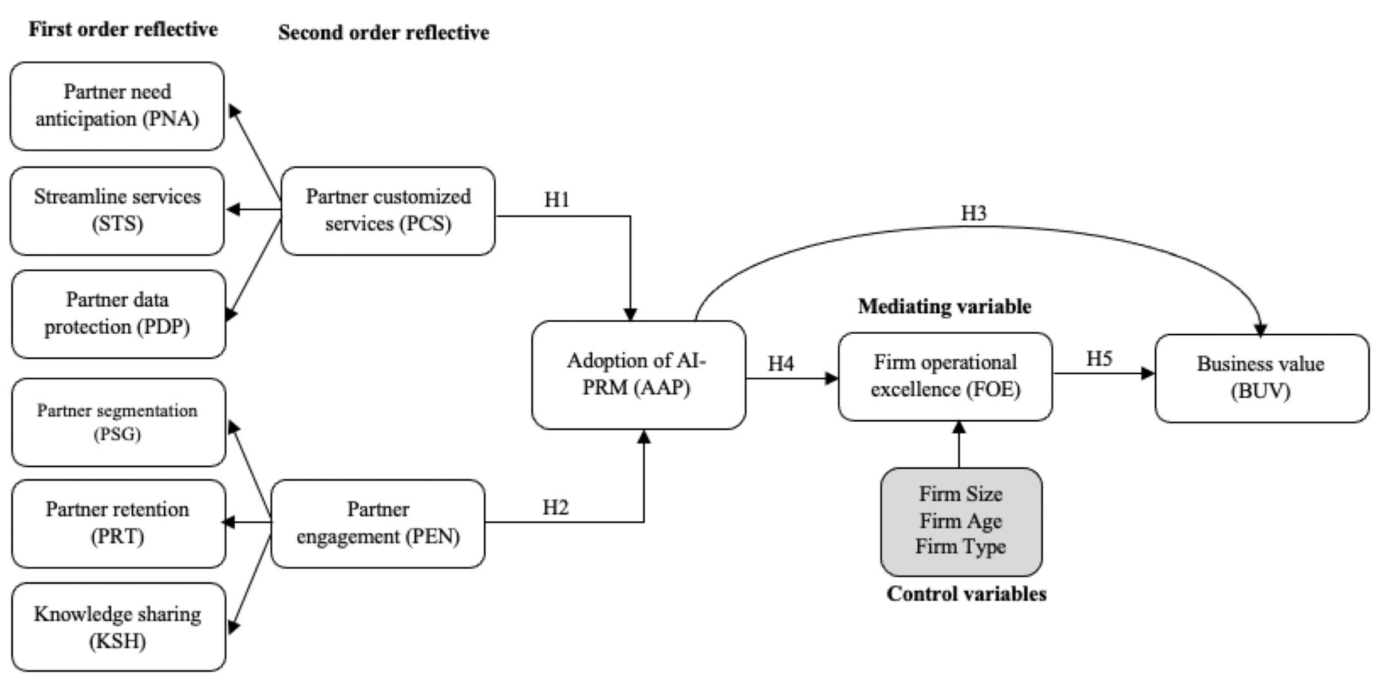

Fig. 2. Conceptual model.

Manthou, & Folinas, 2005). Integrating sales processes into PRM will optimize the entire customer life cycle, starting from leads, qualified leads, opportunity management, consumption, and repeat sales (Espinosa, Ortinau, Krey, & Monahan, 2018). The above-mentioned process is part of streamlined services (STS), which aim to improve PCS.

The partners collect various customer data and use AI-PRM to analyze it for their own purposes. This data is also used by the firm to understand end-customer preferences, and enable them to act accordingly (McLean, 2017). Thus, huge volumes of customer data are stored within AI-PRM. However, customer data needs to be protected to avoid misusing or jeopardizing the customers' security and privacy. This can hamper the partner customized services.

Overall, we assume that PCS consists of partners' anticipation of needs, STS, and partner data protection (PDP). To ensure better customized services, these three abilities need to be developed. Thus, firm should provide customized services to the partners by properly anticipating their needs after analyzing their end-customer data that is stored in the AI-PRM database. When the firm observes that partners acknowledge an improvement in the customized service that they are receiving through AI-PRM, the adoption of an AI-PRM solution will also increase (Chatterjee et al., 2020). Accordingly, we hypothesize:

H1. *There is a positive association between efficient partner customized services (PCS) and adoption of an AI-PRM (AAP) solution.*

We argue that partner segmentation (PSG), partner retention (PRT), and knowledge sharing (KSH) with the partners are the salient dimensions of partner engagement (PEN). PSG helps firms to deal with different types of partners who are engaged with various customers (Dibb, Stern, & Wensley, 2002). Different partner segments are expected to look after certain customer groups with similar firmographics, buying power, purchasing patterns, or other characteristics (Nusair, Alazri, Alfarhan, & Al-Muharrami, 2021). In the context of an AI-PRM solution, segmentation of partners is needed to efficiently nurture relationships and to ensure better PEN.

In the context of indirect sales, where partners act as the resellers and the firm's business principally depends on the partners' activities (Storey & Kocabasoglu-Hillmer, 2013). Thus, it is important for the firm to retain partners, especially those who have been engaged long term (Grossberg, 2015). In this regard, the adoption of AI-PRM by engaged partners plays important role, as they ensure the firm is aware of the changing needs of customers, so the firm can act accordingly by reshaping its operational processes and practices (Jiang et al., 2020; Musarra et al., 2021).

One of the main functions of an AI-PRM system is KSH. An AI-PRM system might be seen as the partners' knowledge repository, thus sharing knowledge between firms and partners and among the partners themselves is crucial. Partners who are updated with the required information can react and respond adequately to the changing needs of customers in a dynamic market (Falasca, Zhang, Conchar, & Li, 2017). This is reflected through PEN.

As stated before, PEN is comprised of PSG, PRT, and KSH. PEN is conceptualized as partners who interact with the firm, actively participating in the firm's marketing programs and targeting partners who sell the firm's products and services (Vlachopoulou et al., 2005; Storey & Kocabasoglu-Hillmer, 2013). To improve PEN, firms should blend technology into the PRM process. This will help partners to obtain the insights needed to shape customers' perceptions and will improve their own business operations. In turn, this will increase the adoption of an AI-PRM solution. Accordingly, we hypothesize:

H2. *Partner engagement (PEN) is positively associated with the adoption of an AI-PRM (AAP) solution.*

3.2. Adoption of an AI-PRM system and its consequences

With the advanced adoption of an AI-PRM system, apart from the firm interacting with their partners, the partners are also closely involved in interactions with each other. In this way, the firm can reduce its financial overheads, as existing processes are automatized, and prospective strategic partners are identified. Consequently, through AI-PRM, firms can offer information, web-based self-service support, and useful resources to their partners to improve their own business processes and operations (Hofacker, Golgeci, Pillai, & Gligor, 2020). Today, many resellers are already using AI or related tools to store and analyze big data. However, these analyses are often complex and, thus, resellers use AI in different applications in a silo manner which results in different types of reports and unstructured input for decision-making. One of the objectives of using an AI-PRM system is to integrate the outputs of all such stand-alone applications into a single platform that supports an accurate decision-making process. By doing so, the business value of the firm increases. Thus, we hypothesize:

H3. *Adoption of AI-PRM (AAP) system is positively associated with the business value (BVU) of a firm.*

Chatterjee et al. (2020) observed that AI-PRM solutions have been mainly adopted by firms in software, hardware, manufacturing and telecommunication industries. We argue that an AI-PRM system changes the existing processes through strong partnerships, not only between firms and its resellers, but also between people who utilize it to obtain the information for needed business operations. This corresponds with the term operational excellence. This is usually achieved by highly capable people who establish good partnerships with suppliers, customers, and society in order to achieve high-quality processes to offer excellent products (Dahlgaard & Dahlgaard, 1999, p. 465). Accordingly, we develop the following hypothesis:

H4. *Adoption of an AI-PRM (AAP) system is positively associated with firms' operational excellence (FOE).*

Operational excellence is articulated through professional development plans for each partner, the involvement of partners in creating process-based practices and creating a standardized workflow to support the partners' operational activities (Barac et al., 2017). If this is ensured, we assume that the perceived business value (BVU) will increase. This includes value resulting from the adoption of AI-PRM technology, at both the sales channel level and the firm-wide level and comprises both efficiency and competitive effects (Gregor, Martin, Fernandez, Stern, & Vitale, 2006). Accordingly, we formulate the following hypothesis:

H5. *Firms' operational excellence (FOE) is positively associated with the business value (BUV) of a firm.*

4. Research methodology

4.1. Research instrument development

Since the process of PCS and PEN within an AI-PRM are new, the existing literature does not offer measurement scales that might be used to capture these constructs. Thus, for the purpose of this exploratory study, we needed to develop instruments for all the dimensions of these processes. To do so, we used approach as in Skinner, Kindermann, and Furrer (2009), where the scale development procedure was followed according to recommendations from Hinkin (1995). To develop the PCS and PEN scales, we followed three basic stages: item generation, scale development, and scale evolution.

The measurement of PCS comprised three reflective first-order dimensions: anticipating partner needs, streamlining services, and protecting partner data, and PEN comprised three reflective first-order dimensions: partner segmentation, partner retention, and knowledge sharing. First, multiple survey items were generated (Worthington & Whittaker, 2006) focusing on partner-related issues and AI-PRM systems. The process of generating items was anchored in the extant literature anchored in DCV and absorptive capacity theory and was based on interviews with 14 business managers (see appendix for details of the managers) engaged in their firms' PRM activities.

In the following scale development stage, additional 12 respondents (six experts from industry and six academics) were invited to participate in protocol and debriefing sessions (as per Malhotra, 2011), which aimed to verify the appropriateness of the preliminary list of items and to enhance their readability, as suggested by Reynolds and Diamantopoulos (1998). The industry experts were all employed at the director level and typically about 20 years of work experience in several industries. Of these six industry experts, four were from the service sector and two were from the manufacturing sector. The academic experts were all associate and full professors with PhD degrees. Their research interests were in the areas of relationship management, industrial marketing, and supply chain management. In this phase, we checked the difficulty of the questions, content, wording, sequence, and the physical characteristics of the questionnaire (Reynolds, Diamantopoulos & Schlegelmilch, 1993). In the protocol sessions, respondents tried to think out loud while answering the questions from the questionnaire. Once they had completed the questionnaire, in a debriefing session the respondents justified their answers and stated any difficulties they had encountered while answering on the survey (Malhotra, 2011).

We also undertook pre-testing of the scales through a pilot study using the same instrument that we planned to use in the main study. The pilot study was conducted to examine the complexity of the items, and to determine the expected time for the respondents to complete the survey by testing the entire process of data collection and even the first step of the analysis (Monette, Sullivan & DeJong, 2013).

Finally, 27 items (using a five-point Likert scale, "strongly disagree" - 1, to "strongly agree"- 5) were included in the main study. Details of the questionnaire and the sources used are provided in the Web Appendix. Scales for the remining constructs (operational excellence and perceived business value) were based on the literature (Gregor et al., 2006; Saeed, Tasmin, Mahmood, & Hafeez, 2021), but they also went through a similar procedure of content validation to ensure their understandability and appropriateness for the given context of data collection.

4.2. Data collection strategy

To collect data, we randomly selected 40 firms from a list of firms available from the Bombay Stock Exchange (India). After contacting the senior executives of these 40 firms, we established that only 24 firms either had experience using an AI-PRM system or were contemplating the implementation of one. Thus, these firms qualified for participation in the study.

We contacted the senior executives of the 24 firms more than once with a request to allow their managers of different ranks to participate in our study, informing them that anonymity and confidentiality of all the participants would be strictly preserved. Finally, 14 firms allowed their managers to participate in the survey. Only managers engaged in AI-PRM activities in the B2B context were selected for the sampling framework, which resulted in a list of 697, who were then sent a survey in addition to a survey guideline. After two reminders, 439 responses were received, resulting in a response rate of 62.9%. Out of 439 responses, 12 responses were incomplete, so the final analysis was performed with 427 usable responses. The demographic statistics are provided in Table 1.

Table 1
Demographic statistics ($N = 427$).

Particulars	Nature of firms	Number	Percentage (%)
Firm size	<1000 employees	107	25.0
	1000–10,000 employees	150	35.0
	>10,000 employees	170	40.0
Firm age	<10 years	64	15.0
	10–25 years	214	50.0
	>25 years	149	35.0
Firm type	Manufacturing firms	10	71.5
	Service firms	4	28.5
Working position	Senior managers	106	25.0
	Midlevel managers	192	45.0
	Junior managers	129	30.0

5. Data analysis and results

5.1. Assessment of the measurement model

A repeated indicator approach (Becker, Klein, & Wetzels, 2012) was used for the assessment of the measurement model. Thus, a measurement model estimation was first made for the first-order constructs and then for two higher order constructs: PCS and PEN. To estimate the measurement model, the partial least squares (PLS) modeling technique was selected, because it provides robust results for a complex, hierarchical model (Becker et al., 2012; Wetzels, Odekerken-Schröder, & Van Oppen, 2009). The measurement properties of all first-order constructs are presented in Table 2, based on the estimation in SmartPLS. To estimate the content validity of all the instruments, the loading factor (LF) of each item was assessed for all first-order constructs. To ensure reliability and validity of the constructs, composite reliability (CR) and average variance extracted (AVE) of the constructs were estimated. To measure the internal consistency of the constructs, Cronbach's alpha (α) of all the constructs was estimated. All the estimated values were found to be within the allowable ranges.

The PCS is conceptualized as a second-order reflective construct. It is explained by three sub-dimensions, PNA, STS, and PDP, showing appropriate CR (0.86) and AVE (0.82). Similarly, PEN is also a second-order reflective construct (CR:0.84; AVE:0.81), which is explained by three dimensions: PSG, PRT, and KSH. All the factor loadings of the second-order factors are significant ($p < 0.001$). The results are graphically presented in Figs. 3 and 4.

A discriminant validity test was performed for all first-order constructs (please see Table 3). Table 3 shows that square roots of the AVEs provided in the diagonal are greater than the corresponding bifactor correlation coefficients. This satisfies Fornell and Larcker's criteria (Fornell & Larcker, 1981), and confirms the discriminant validity of the constructs. The values of AVEs are provided in the last column of Table 3.

5.2. Results of the structural model

Using the bootstrapping approach with 5000 replications, we applied the PLS-SEM technique (Hair Jr., Hult, Ringle, & Sarstedt, 2016) in SmartPLS 3.2.3 software (Ringle, Wende, & Becker, 2015) for testing our hypotheses. This process helped to estimate the path coefficients along with the other parameters and to test the hypotheses (please see Table 4). Fit indices (chi square/degree of freedom = 2.011, CFI = 0.949, NFI = 0.968, TLI = 0.979, RMSEA = 0.02) cautiously implied "(Hair et al., 2017; Henseler & Sarstedt, 2013) that PLS path model can explain given set of data.

PCS and PEN are significantly related with AAP (H1 and H2), as the path coefficients are 0.31 and 0.34, respectively, with levels of significance at $p < 0.01$(**) and $p < 0.001$(***). The results also demonstrate that AAP is related with BUV and FOE (H3 and H4) significantly and positively, since the path coefficients are 0.33 and 0.27 with respective levels of significance of $p < 0.001$(***) and $p < 0.01$(**). The results also show that FOE is associated with BUV significantly and positively, with a path coefficient of 0.26 and level of significance of $p < 0.01$(**). So far as coefficients of determination are concerned, it appears that PES and PEN could explain AAP to the extent of 44% ($R^2 = 0.44$), whereas AAP could explain FOE by as much as 47% ($R^2 = 0.47$). The AAP and FOE could explain BUV to the extent of 72% ($R^2 = 0.72$), which is the explanative power of the model.

Table 2
Measurement properties.

Constructs / Items	Mean	SD	LF	t-values
Partner Need Anticipation (PNA) (AVE: 0.81; CR: 0.85; α:0.89)				
AI-PRM helps to anticipate various kinds of needs of partners.	3.8	1.2	0.90	22.41
AI-PRM can predict the partners' requirements in advance.	2.7	1.4	0.85	29.07
It is important to anticipate the needs of the partners much earlier so that customized services can be provided when required.	2.9	1.1	0.95	26.11
Streamline Services (STS) (AVE: 0.80; CR: 0.84; α: 0.88)				
Streamlining of different services to the partners makes them more efficient.	3.7	1.3	0.94	28.11
The AI-PRM tool provides efficient streamlining services to the partners	2.9	1.4	0.90	26.17
Streamlining of different services to the partners helps to provide better customized services.	4.1	1.2	0.85	24.04
Partner Data Protection (PDP) (AVE:0.85; CR:0.91; α:0.94)				
It is important to protect the partners' data from unauthorized access.	3.4	1.7	0.94	27.09
Protecting partner data is essential to grow trust between the firm and its partners.	2.6	1.6	0.89	24.11
The AI-PRM tool can protect partner data from unauthorized access.	2.7	1.4	0.93	25.51
Partner Segmentation (PSG) (AVE:0.82; CR:0.86; α:0.92)				
The partner segmentation process is important for improving business outcomes.	3.7	1.3	0.90	26.18
The segmentation process is vital for selection of partners for a particular project.	2.7	1.9	0.96	24.17
Segmentation helps to closely engage with the partners.	3.9	1.1	0.85	31.19
Partner Retention (PRT) (AVE:0.80; CR:0.84; α:0.89)				
Retaining partners is important for our growth.	2.8	1.7	0.93	26.12
Our firm has a good strategy towards retaining partners.	2.0	1.1	0.85	25.11
Retaining partners for longer periods helps to develop close partner engagement.	3.7	1.6	0.89	24.07
Knowledge Sharing (KSH) (AVE:0.82; CR: 0.87; α:091)				
Knowledge sharing with the partners is an important task.	3.4	1.4	0.93	28.12
AI-PRM plays a vital role in knowledge sharing with the partners.	3.5	1.2	0.95	24.17
Knowledge sharing with partners on a regular basis is crucial to remain up to date.	3.1	1.7	0.89	29.06
Adoption of AI-PRM (AAP) (AVE:0.89; CR:0.93; α:0.97)				
We use an AI-PRM tool on a regular basis.	3.7	1.9	0.96	28.11
Integration of AI technology with the existing PRM tool helps the overall partner relationship process.	2.9	1.8	0.85	26.16
We have adequate support staff to help the end users using AI-PRM.	3.1	1.6	0.90	25.13
Firm Operational Excellence (FOE) (AVE:0.79; CR:0.83; α:0.87)				
Execution of our internal processes is efficient.	2.9	1.4	0.95	24.17
We achieve excellence in processes.	3.8	1.6	0.85	25.09
Our leadership team encourages people to grow.	3.6	1.1	0.89	26.15
Perceived Business Value (AVE:0.85; CR:0.89; α:0.92)				
We created a competitive advantage.	2.9	1.7	0.88	24.11
We have superior communication between the firm and its partners.	2.8	1.5	0.92	25.11
Our partners have been served in a better way.	3.1	1.8	0.96	29.17

Effect size (f^2 values) were also estimated to assess the contributions of the latent exogenous variables on the corresponding endogenous variables. According to Cohen's (1988) recommendations, the f^2 values are weak when between 0.020 and 0.150, medium if between 0.150 and 0.350, and large when greater than 0.350. The results show that the values are either medium or large.

Finally, operational excellence (FOE) was controlled for firm size, firm age, and firm type. From the reported results of the β-values reported in Table 4, it appears that firm size, firm age, and firm type are insignificantly associated with FOE, each having a level of non-significance of $p > 0.05$(ns). Thus, since the R^2 values were not affected by the control variables (Hossain, Akter, Kattiyapornpong, & Dwivedi, 2020), we assume the model is stable.

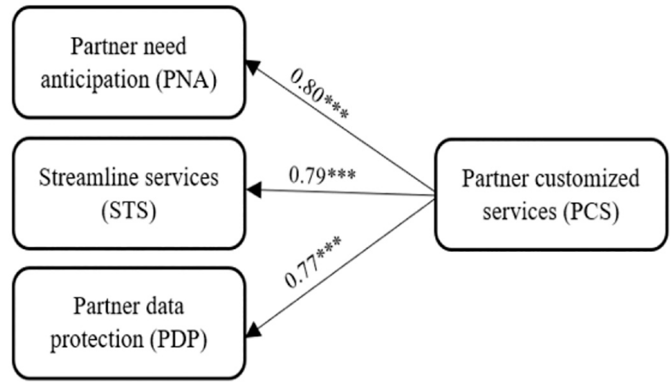

Fig. 3. PES and its three subdimensions.

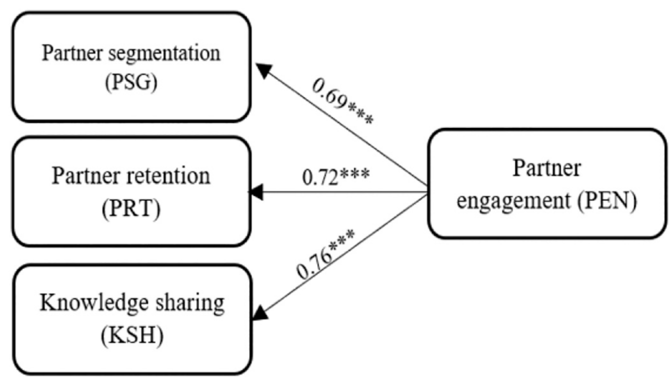

Fig. 4. PEN and its three subdimensions.

Mediation analysis was conducted post hoc, to examine the effects of FOE within the AAP → FOE→BUV linkage, using the bootstrapping procedure (Model 4) as per Preacher and Hayes (2008). The effects of AAP → FOE and FOE→BUV were significant at $p < 0.001$(***). Importantly, the indirect mediating path from AAP to BUV through FOE was 0.070, and significant at $p < 0.001$(***). Hence, the results provide strong support for FOE as a mediator.

5.3. Common method variance

Since the data emerged from a survey, common method variance (CMV) was tested. As a procedural technique for mitigating CMV, the respondents were assured that their anonymity and confidentiality would be strictly preserved. In terms of statistical remedies, Harman's single factor test was performed. The results show that the first factor emerged as 21.62% of the variance, which is less than 50% (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

Since Ketokivi and Schroeder (2004) argued that Harman's single factor test is not a robust test for CMV, the marker variable test, following the guidelines recommended by Lindell and Whitney (2001), was conducted. We compared the proposed model with the revised model, which introduced the marker variable organizational commitment (Richardson, Simmering, & Sturman, 2009). This marker variable has no relation with the other constructs of the proposed model. The results of the marker variable test indicate that the differences between the original and CMV-adjusted correlations are very small (≤0.06), relating to all the constructs (Mishra, Maheswarappa, Maity, & Samu, 2018). Based on the above, we assumed that CMV does not distort the results of the study.

Table 3
Discriminant validity test.

Constructs	1	2	3	4	5	6	7	8	9
1 PNA - Partner Need Anticipation	**0.90**								
2 STS - Streamline Services	0.17	**0.89**							
3 PDP - Partner Data Protection	0.22	0.29	**0.92**						
4 PSG - Partner Segmentation	0.26	0.24	0.32	**0.91**					
5 PRT - Partner Retention	0.32	0.17	0.26	0.39	**0.89**				
6 KSH - Knowledge Sharing	0.19	0.18	0.29	0.31	0.34	**0.91**			
7 AAP - Adoption of AI-PRM	0.27	0.32	0.17	0.19	0.21	0.16	**0.94**		
8 FOE - Firm Operational Excellence	0.25	0.28	0.36	0.34	0.32	0.25	0.29	**0.89**	
9 BUV - Business Value	0.31	0.18	0.22	0.23	0.27	0.39	0.35	0.37	**0.92**

Table 4
Structural model results.

Relationships	Path coefficients	R^2	*p*-values	Effect size f^2*	Remarks
PCS → AAP	0.31	$R^2 = 0.44$	$p < 0.01$ (**)	0.289 (M)	H1 Supported
PEN → AAP	0.34		$p < 0.001$ (***)	0.411 (L)	H2 Supported
AAP → BUV	0.33	$R^2 = 0.72$	$p < 0.001$ (***)	0.405 (L)	H3 Supported
FOE→ BUV	0.26		$p < 0.01$ (**)	0.365 (L)	H5 Supported
AAP → FOE	0.27	$R^2 = 0.47$	$p < 0.01$ (**)	0.391 (L)	H4 Supported
Control variables					
Firm size →FOE	0.02		$p > 0.05$ (ns)		Not supported
Firm age →FOE	0.01		$p > 0.05$ (ns)		Not supported
Firm type →FOE	0.03		$p > 0.05$ (ns)		Not supported

* L: Large; M: Medium.

6. Discussion

Our study explores different exogenous factors relevant for successful adoption of AI-PRM across sales channel. We explore how the three factors: partner need anticipation, streamlined services, and partner data protection, interpret partner customized services. We also explore that partner segmentation, partner retention, and knowledge sharing reflect partner engagement.

The present research informs how adoption of an AI-PRM solution improves the business value of a firm directly. In addition, using the procedure recommended by Preacher and Hayes (2008) our study found that firms' operational excellence acts as a critical mediator between the two constructs – adoption of AI-PRM and business value. These findings are consistent with Coltman, Devinney, and Midgley (2011), who demonstrated that customer relationship management improves firm performance. Hence, the ideas involved in H3, H4, and H5 validate Coltman et al. (2011) in a context of indirect sales channel.

7. Conclusion

7.1. Theoretical contributions

The present study, although exploratory, provides several theoretical contributions to the relationship management literature. First, building on the important contributions of studies on the role of AI in business operations (Kulkov, 2021; Chen et al., 2022), studies that established the legacy of CRM systems (Rababah et al., 2011; Xu et al., 2012), and the benefits of AI integration in CRM systems (Chatterjee et al., 2022), we introduce idea of observing the adoption of AI-PRM within the sales channel. Hence, to the best of our knowledge, we introduce AI-PRM to academic research, which is a timely idea given the growing interest of practitioners in the subject.

Building on DCV theory (Teece et al., 1997), our study explore two dynamic capabilities: partner customized service ability and partners' ability to be more engaged with customers. By extending the applicability of DCV theory to describe PCS and PEN as two dynamic abilities, our study successfully interprets the relevance of these two capabilities for reacting to and responding to ever-changing customer needs in dynamic environments. To do so, firms must not only select the right partners, but also help them to improve the capabilities necessary to adopt AI-PRM tools that ultimately will improve the overall value of the firm.

By extending the applicability of absorptive capacity theory (Qian & Acs, 2013), we interpret how the PCS and PEN abilities of partners further develop and enrich AI-PRM adoption. This could be accomplished by recognizing external information, accurately assimilating it, and then applying that knowledge to ensure successful and effective usage of an AI-PRM system to improve the overall business value.

Finally, given that AI-PRM systems are just being introduced in B2B sales channels, our study, although exploratory, brings the idea of this new technology to the B2B marketing literature. For example, it builds on Coltman et al. (2011), who studied the use of CRM in firms and extends it to the realm of AI-PRM systems and the business value of a firm.

7.2. Implications for practice

The present study provides a specification for managers who intend to adopt an AI-PRM system into their sales channels. Based on our findings, managers can assess their resellers and their abilities to understand, seize, and sense opportunities and develop the capabilities needed to perform their part in AI-PRM adoption. For the development of these partners' abilities, support from supplier firms will be necessary. Thus, supplier firms should sponsor the development of specific partners' ability (e.g., partner need anticipation, streamlined services, and partner data protection) that will allow effective integration of partners into the AI-PRM system. To this end, coaching, as well as external internships, may be recommended to partner employees, allowing them to spend time with the supplier firm to develop specific skills beyond the product and sales training that suppliers typically provide to their resellers. The benefits of these investments will ultimately be reflected in the broader adoption of AI-PRM systems across sales channels and will help firms to customize support services and improve partner engagement. This helps to develop better collaborative environments among partners, among partners and suppliers, as well as between customers and partners in a real-time environment.

Firms should also be ready to arrange either in-person training or virtual training for their partners, so that they learn how to effectively use the AI-PRM system. Training sessions might be based on the best practices in regard to reporting, customer acquisition, and customer retention using AI-PRM. This could help to motivate the partners to effectively utilize AI-PRM on a day-to-day basis. Effective utilization of an AI-PRM system by the partners will ensure the operational excellence of the parent firm, which will increase its perceived business value.

Thus, it is also essential that the firms completely support their partners so that they do not have any hindrances while using the AI-PRM system.

The present study also shows that effective implementation of an AI-PRM system helps the firm to exchange knowledge with the partner community. Thus, the adoption of an AI-PRM system will ensure that appropriate knowledge is exchanged among the partners as well as between partners and firm executives.

7.3. Limitations and future scope

The findings of this exploratory study should be taken with great care, due to inherent limitations of the exploratory research design. First, our study is based on cross-sectional data, which implies that it cannot prove causality between the constructs, and creates endogeneity defects. Thus, future studies might be based on longitudinal data to remove the defects. In addition, individual respondents acted as key informants about the firms' use of AI-PRM. This inevitably leads to respondent bias. Further research could include dyadic data collection, which would pool respondents from both the firms and the partners.

Furthermore, although DCV is widely used, as Ling-Yee (2007) noted, it also suffers from the lack of context insensitivity, as it is unable to identify the specific conditions under which firms' capabilities are most valuable (Schilke, 2014). Therefore, future studies might investigate the optimal conditions under which the adoption of an AI-PRM system can provide the greatest benefit to the firm.

Finally, PRM is believed to have contributed to B2B relationships within the sales channel. However, with the introduction of AI in PRM systems, AI might take over some of the tasks that previously required human intelligence. It is not expected that AI-PRM will completely replace human interactions. Similar to developments in other areas in which AI has been introduced, we can expect that humans with knowledge of AI tools will replace those who do not possess these skills. However, the focus of our study is not on B2B relationships and the scope of human involvement in the operation of AI-PRM. Based on the data collected and within the scope of our study, we are unfortunately unable to draw valid and reliable conclusions regarding AI-PRM effects on quality/satisfaction with B2B relationships. This is an opportunity for scholars to conduct further research on this relevant aspect of AI-PRM.

Appendix A. Details of the managers

Participant #	Firm Type	Hierarchy	Professional Experience	Education	Skillset
1	Service	Mid-Level Manager	12	Post Graduate	Tech
2	Service	Mid-Level Manager	8	Under Graduate	Tech
3	Manufacturing	Senior Manager	17	Post Graduate	ADM
4	Service	Senior Manager	18	Post Graduate	ADM
5	Manufacturing	Senior Manager	4	Under Graduate	Tech
6	Manufacturing	Mid-Level Manager	12	Under Graduate	BOM
7	Service	Mid-Level Manager	10	Post Graduate	BOM
8	Service	Junior Manager	4	Post Graduate	Tech
9	Service	Junior Manager	3	Under Graduate	Tech
10	Manufacturing	Mid-Level Manager	11	Post Graduate	BOM
11	Manufacturing	Mid-Level Manager	13	Under Graduate	Tech
12	Service	Senior Manager	18	Post Graduate	ADM
13	Service	Junior Manager	5	Under Graduate	Tech
14	Service	Mid-Level Manager	12	Post Graduate	ADM

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.indmarman.2022.12.014.

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