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THEORY/CONCEPTUAL

A theory of predictive sales analytics adoption

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Abstract

Given the pervasive ubiquity of data, sales practice is moving rapidly into an era of predictive analytics, using quantitative methods, including machine learning algorithms, to reveal unknown information, such as customers' personality, value, or churn probabilities. However, many sales organizations face difficulties when implementing predictive analytics applications. This article elucidates these difficulties by developing the PSAA model—a conceptual framework that explains how predictive sales analytics (PSA) applications support sales employees' job performance. In particular, the PSAA model conceptualizes the key contingencies governing how the availability of PSA applications translates into adoption of these applications and, ultimately, job performance. These contingencies determine the extent to which sales employees adopt these applications to revise their decision-making and the extent to which these updates improve the decision outcome. To build the PSAA model, we integrate literature on predictive analytics and machine learning, technology adoption, and marketing capabilities. In doing so, this research provides a theoretical frame for future studies on salesperson adoption and effective utilization of PSA.

Keyword Predictive analytics · Advanced analytics · Machine learning · Personal selling · Sales management · Sales force effectiveness

The sales function is a key focal area for firms' digital transformation (Alavi & Habel, 2021). Owing to the increasing adoption of customer relationship management (CRM) systems and the high quantifiability of sales performance, sales managers are particularly interested in advancing their decision-making through *analytics* and, more specifically, *predictive analytics*. When employing predictive sales analytics (PSA), managers aim to support sales employees' decision-making by providing them with information that they do not have, statistically predicted from the information they do have. As such, predictive analytics goes beyond the widely employed descriptive analysis of past developments and instead aims to estimate new observations (Shmueli & Koppius, 2011; Wedel & Kannan, 2016), such as lead conversion likelihoods, cross- and upselling potential, or customer churn (Antonio, 2018; De Bock et al., 2017; Hatami et al., 2015). By implementing PSA, organizations strive to improve sales managers' and salespeople's decision-making with regard to, for example, building customer relationships and generating revenue.

However, companies face continuous difficulties in implementing PSA applications (Ascarza et al., 2021; Harvard Business Review Analytic Services [HBRAS] 2021; Sleep et al., 2019). Many sales employees harbor concerns when asked to work with predictive analytics (Ammanath et al., 2020) and lack the necessary abilities to effectively apply the new tools (HBRAS, 2021). Consequently, all too often both firms and sales employees fail to leverage the full potential and benefits from adopting such tools. For example, Luo et al. (2021) find that sales agents show aversion to receiving feedback from artificial intelligence (AI) sales coaches, which undermines productivity improvements from the coaching, whereas Kim et al. (2022) find that service employees refuse to rely on AI assistance. AI assistants can even threaten the very identity of some users (Uysal et al., 2022).

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In this study, we aim to provide a conceptual review of PSA literature first by providing a consolidated account of PSA research and, second, by guiding managers' attention to the key levers available to optimize PSA outcomes (Hulland, 2020). Thus, we synthesize a theoretical model that explains sales employees' PSA adoption. This *PSAA model* predicts that adopting PSA increases sales employees' performance but that the effect fundamentally hinges on the value potential entrenched in the PSA application and the decision-making environment. As such, we provide an overarching frame for future work on PSA.

The key goal of the PSAA model is to provide a comprehensive account of success factors related to salespeople's PSA adoption, focusing on several categories of moderators that may govern outcomes of salespeople's PSA adoption. For this purpose, the PSAA model synthesizes seminal theories on employee technology adoption and literature at the AI–human interface. Considering that many salespeople show resistance to adopting PSA, as a first step, the model differentiates between PSA availability in a firm and salespeople's factual adoption of PSA. As a second key step, the PSAA model assumes that salespeople's adoption of PSA is generally conducive to improving work performance but that this effect is heterogeneous across PSA applications and sales employees' decision-making environments.

Our review of literature on PSA shows great improvement in advancing knowledge on drivers of PSA adoption and PSA consequences. However, this literature is largely fragmented across different specific PSA use cases, sometimes being indirectly related to the sales context or having indistinct boundaries between descriptive and predictive analytics. Moreover, while prior research has produced several important theories on general technology acceptance, these theories do not accurately conceptualize idiosycnracies of the new predictive analytics technology and thus may lack precision in this domain. The PSAA model contributes to marketing research on the potential of this new key technology by consolidating previous theory and research in a comprehensive account on effective PSA adoption in the sales force.

Conceptual background

Analytics

The literature uses various analytics terminology, such as business intelligence, big data analytics, and business analytics (Chen et al., 2015; Davenport, 2006; Holsapple et al., 2014). Although prior studies define each of these terms slightly differently, the terms encompass two recurring themes: the use of data as a source for statistical analysis and the aim to enhance decision-making (Sleep et al., 2019). For example, Grover et al., (2018: 390) define big data analytics as "the application of statistical, processing, and analytics techniques to big data for advancing business." Holsapple et al. (2014: 134) define business analytics as "evidence-based problem recognition and solving that happens within the context of business situations."

From descriptive to predictive analytics

Analytics has developed considerably over the years, driven mainly by increasing data quality (Müller et al., 2018), enhanced technological opportunities (Wedel & Kannan, 2016), and growing analytics capabilities in organizations (Kiron et al., 2011). In the past, managers' focus was mainly on *descriptive* analytics, that is, summarizing historic data to investigate what happened in the past (e.g., monthly report of sales performance per region). More recently, *predictive* models to develop forecasts and simulations of variables have grown in significance (Shmueli & Koppius, 2011; Sleep et al., 2019; Wedel & Kannan, 2016). An example of predictive analytics is the estimation of the likelihood of a successful customer win-back (Gerpott & Ahmadi, 2015) or the prediction of a customers' cross-buying likelihood several months in advance. Moreover, research often views prescriptive analytics as the next consecutive step in the development cycle of analytics applications, following predictive analytics (Huang & Rust, 2018). Prescriptive analytics augments predictive analytics by adding precise behavioral guidance and recommendations on how to act on the predictions. For example, a prescriptive analytics application such as Showpad may not only analyze and uncover customers' psychological preferences but also recommend a communication strategy to effectively address the preferences.

However, prior research is rather ambiguous on what the term "prediction" precisely means (see Table 1). Some studies define predictive analytics as the forecasting of *future* events (Gandomi & Haider, 2015), whereas others take a broader view in at least two respects. First, according to Waller and Fawcett (2013: 80) predictive analytics also answers questions on "what would have happened in the past, given different conditions." Second, Shmueli and Koppius (2011) remove the notion of time altogether: predictive analytics simply refers to the statistical estimation of values of variables for observations not incorporated in the dataset on which the prediction is based. An example would be classification tasks without a temporal perspective, such as the detection of breast cancer from biopsy results (Bazazeh & Shubair, 2016) or the identification of customer fraud (Bahnsen et al., 2016).

Our research objective is to provide a theoretical model on the effect of predictive analytics applications on sales employees' job performance. So as not to restrict ourselves to a sub-area of the literature, we adopt a broad and

Table 1 Conceptualizations of predictive analytics

Characteristics	Forecast of future events	Forecast of future and past events	Estimation of the values of observations not incorporated in the applied dataset
Prediction	Future events	Future or past events	New observations
Temporal view	Yes	Yes	No (non-temporal)
Example	Prediction of next month's precipitation from historical weather data	Estimation of the historical and future earthquake risk from geophysical and weather data	Detection of breast cancer from biopsy results
Sample sources	Dubey et al., 2019; Gandomi & Haider, 2015; Hair, 2007; Sivarajah et al., 2017	Waller & Fawcett, 2013	Shmueli, 2010; Shmueli & Koppius, 2011

non-temporal view of predictive analytics (Shmueli & Koppius, 2011). More broadly, though, the lack of a unified view on what the term "prediction" precisely means has blurred the lines between what does and does not constitute predictive analytics. However, the inconsistent understandings of predictive analytics are rarely made transparent, indicating a potential blind spot in academia and practice.

PSA

The sales function is a key target of companies' predictive analytics endeavors—we label predictive analytics targeted at the sales function as *PSA*. That is, for variables relevant for sales employees, PSA quantitatively estimates values for observations not incorporated in the dataset on which the estimation is based. When employing PSA, managers aim to support sales employees' decision-making by providing them with information they have statistically predicted from information they do have.

To elaborate, the sales function is responsible for acquiring, as well as retaining, customers and thus is essential for a firm's success. As the firm's main decision-makers (Johnston & Marshall, 2016), sales managers recruit potential candidates, train new entrants, and lead individual salespeople (Albers & Krafft, 2013; Homburg et al., 2011). PSA can support these sales managers by, for example, forecasting sales to validate their budget plans (e.g., Pavlyshenko, 2019) or predicting employee turnover to improve their retention efforts (e.g., Bridges et al., 2007). Salespeople, in turn, are often key representatives of the firm, especially in the business-to-business (B2B) context. Their decisions pertain to the various stages of customer acquisition and customer development (Albers & Krafft, 2013; Söhnchen & Albers, 2010). Similarly, PSA can support salespeople by predicting customers' conversion likelihoods, enabling them to prioritize potential customers (e.g., Nygård & Mezei, 2020), or by predicting customers' cross-purchase likelihoods to target customers with the right offerings (e.g., Kamakura et al., 2003).

PSA applications can be integrated into CRM systems (e.g., Salesforce Einstein), provided in software independent of CRM systems (e.g., Allego, Chorus, Cogito, CrystalKnows, Showpad, bespoke tools; Burger & Habel, 2020) or as individual reports for a decision maker in sales. Furthermore, some PSA applications are marketed as AI. We refrain from using the term "AI" herein because it is vague and employed in vastly different ways (Ascarza et al., 2021; Huang & Rust, 2018; Singh et al., 2019). However, because the common core of AI and PSA is prediction (Agrawal et al., 2018), the model we advance might likewise apply to sales applications termed "AI."

Structure of prior research on PSA

The literature on PSA has rapidly evolved (e.g., Ascarza et al., 2017; Kumar & Reinartz, 2016; Mantrala et al., 2010). For example, the body of work on PSA increased almost sixfold between 2010 and 2022 (Google Scholar, 2022). These studies are highly dispersed across disciplines, such as marketing, computer science, management science, and operations research. One reason for other disciplines' interest in PSA may be that sales is a data-rich environment (Wedel & Kannan, 2016).

Literature on PSA mostly focuses on developing predictive models for specific sales-related decisions, such as to estimate a lead's conversion probability (Nygård & Mezei, 2020) or a customer's churn probability (Ascarza, 2018), oftentimes pitting different models against each other to identify that with the highest predictive validity (e.g., Au et al., 2003; Chu & Zhang, 2003). To assess the potential of these models in practice, prior research has typically *simulated* the expected outcomes should the predicted information be used effectively (Agnetis et al., 2010; Kumar et al., 2015, 2018; Rust et al., 2011). In addition, few studies have conducted field experiments that implement PSA applications in sales employees' practice (Bohanec et al., 2017; D'Haen et al., 2016; Karlinsky-Shichor & Netzer, 2019; Misra & Nair, 2011).

Moreover, prior research has not conceptualized PSA-related *constructs*, such as sales employees' PSA adoption, which would allow the examination of antecedents, outcomes, and moderators—key building blocks of sales theory. Instead, research seems to treat PSA as an umbrella term for a set of methods and often focuses on making methodological rather than theoretical contributions. That is, research seems to implicitly assume that when predictions are implemented, sales employees automatically make better decisions. However, as outlined previously, emerging insights from practice (HBRAS, 2021) and academia (Kim et al., 2022; Luo et al., 2021) suggest that implementing PSA is more complicated and does not automatically improve sales employees' decisions. Thus, to advance research on PSA and its ramifications, scholars should conceive PSA not merely as a collection of methods; they should also introduce measurable PSA-related constructs in conceptual models. Notably, fields outside the sales domain have gone further in this respect. For example, research has examined how adopting marketing analytics affects performance (see Table 2). However, this literature stream typically does not clarify analytics as predictive, descriptive, or otherwise.

Overview of the PSAA model

We synthesize from prior theoretical and empirical research a conceptual model of PSA adoption (PSAA model; see Fig. 1). This model explains how the availability of a PSA application affects sales employees' job performance. Specifically, the PSAA model posits a set of key contingencies that determine the extent to which sales employees adopt PSA and thus revise their decision-making, as well as the extent to which these revisions actually improve the outcomes of their decisions (Kim et al., 2022). The mechanisms underlying these two stages fundamentally differ. While the former is explained by technology adoption theories, the extent to which adoption improves decision-making is determined by the value potential of the PSA application and the decision-making environment, which we induce from literature on predictive analytics, machine learning, and marketing capabilities.

The two stages linking PSA availability to job performance

From PSA availability to PSA adoption

We define PSA availability as the prevalence of a predictive model that sales employees can use as a basis for decision-making in their sales organizations. PSA availability thus reflects whether a firm installed a PSA application in its processes and made it available to sales employees (e.g., a CRM application that predicts the conversion probability of new leads and opportunities, such as Salesforce Einstein). Critically, making a PSA available does not automatically imply that sales employees adopt and effectively use the PSA application (Hunter & Perreault, 2007; Kim et al., 2022); sales employees must adopt PSA applications in their daily work processes. PSA adoption means using the predicted information to make decisions. If this variable exhibits a high value, sales employees intensively use and strongly rely on PSA applications in their sales tasks. Conversely, if PSA adoption is low, they do not use PSA applications in their sales tasks.

While the distinction between availability and adoption may sound trivial, new sales technologies frequently encounter resistance for PSA applications because people tend to mistrust algorithms (e.g., Dietvorst et al., 2015). Building on prior research on sales technologies and pertinent theories on technology adoption, we propose several theories than can explain the extent to which sales employees adopt available PSA applications.

Technology acceptance theories Technology acceptance theories propose drivers of users' acceptance and, thus, adoption of technology. For example, the technology acceptance model posits that user adoption depends on perceived usefulness and perceived ease of use (Davis et al., 1989). Perceived usefulness is "the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organizational context," and perceived ease of use is "the degree to which the prospective user expects the target system to be free of effort" (Davis et al., 1989: 985). Later works added other drivers. For example, the unified theory of acceptance and use of technology (UTAUT) stresses the importance of social influence (whether important others believe a prospective user should use the system) and facilitating conditions (whether use is supported by infrastructure) (Venkatesh et al., 2003). An extension to this theory (UTAUT2) adds prospective users' hedonic motivation, price–value, and habit as drivers of adoption (Venkatesh et al., 2012).

Accordingly, PSA adoption may be more likely if sales employees perceive a PSA application as useful (i.e., conducive to their job performance) and easy to use (i.e., free of effort). The former likely depends on sales employees' confidence that the application will allow them to improve their decisions, while the latter may depend on whether predictions are easy to access (e.g., through the CRM system), easy to interpret (e.g., free from data science jargon), and easy to base decisions on (e.g., low ambiguousness).

Table 2 Selected literature on the effect of marketing analytics

Author	Independent variables	Dependent variables	Applied data	Key findings
Ariker et al. (2015)	Use of marketing analytics	Firm profit, marketing return on investment (ROI)	2015 CMO survey data	Marketing analytics usage has a positive effect on firm profit and marketing ROI
Cao et al. (2019)	Data availability, managerial perception, managerial support, competitive pressure	Use of marketing analytics, marketing decision-making, product development management, sustained competitive advantage	Survey data from 221 marketing managers	Marketing analytics usage has an indirect positive effect on sustained competitive advantage through product development management
Cao et al. (2022)	Use of big data	Use of marketing analytics, marketing capabilities, product development management	Survey data from 316 firms	Big data increases the use of marketing analytics, which in turn increases firm marketing planning, marketing implementation, brand management, customer relationship management, and product development management
Germann et al. (2013)	Top management advocacy	Analytics culture, analytics skills, data and IT, deployment of analytics, firm performance (sales growth, profit ROI)	Survey data from 212 senior executives	Marketing analytics usage has a positive effect on firm performance
Germann et al. (2014)	Deployment of customer analytics	Firm performance (sales growth, profit, ROI)	Survey data from 418 senior executives	Customer analytics deployment has a positive effect on firm performance, especially for firms in the retail industry
Hallikainen et al. (2020)	Use of customer big data analytics	Customer relationship performance, sales growth	Survey data from 551 senior executives	Customer big data analytics usage has a positive effect on customer relationship performance and sales growth
Johnson et al. (2017)	Exploration orientation, exploitation orientation	Big data volume, big data usage, big data velocity, new product revenue	Survey data from 261 managers	Big data volume and variety have a positive direct effect on new product revenue, but customer turbulence as a moderator interacts differentially with the big data usage dimensions

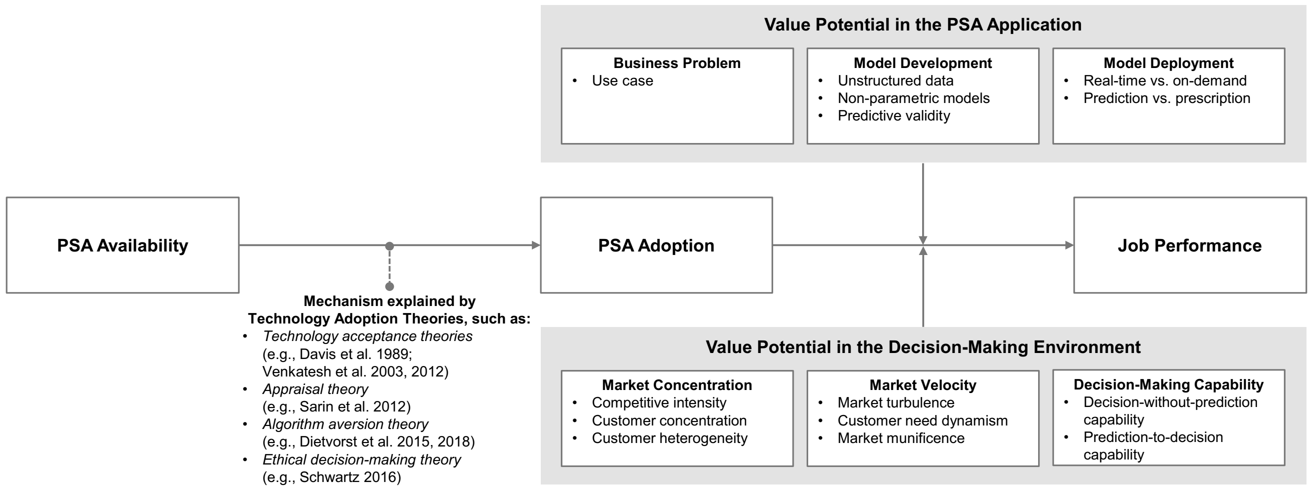

Fig. 1 The PSAA model

Appraisal theory Appraisal theory (Lazarus & Folkman, 1984) explains how individuals evaluate whether and in what ways a particular event is relevant to them and how to cope with it (Folkman et al., 1986). This evaluation process comprises two kinds of appraisals. During *primary* appraisal, individuals evaluate the consequences for themselves, such as whether they consider the event a benefit or harm (Bala & Venkatesh, 2015; Major et al., 1998). During *secondary* appraisal, individuals evaluate whether they have the ability or resources to cope with the event and its consequences (Latack et al., 1995; Sarin et al., 2012). Coping refers to individuals' ability to actively derive actions to turn a situation to their favor (Carver et al., 1989; Folkman et al., 1986). Primary and secondary appraisals determine individuals' response to an event, such as trying to change it, accepting it, or opposing it (Lazarus & Folkman, 1984).

Accordingly, we can conceive of the implementation of a PSA application as the new event that sales employees encounter. Depending on the result of their appraisal process, sales employees should be more or less likely to base their decisions on the PSA application. Previous research has employed cognitive appraisal theory to investigate similar phenomena, such as implementations of information technology (Bala & Venkatesh, 2015), marketing strategies (Sarin et al., 2012), and innovation campaigns (Choi et al., 2011).

Algorithm aversion theory Individuals often prefer to rely on human rather than algorithmic predictions, even when algorithms deliver superior results (Castelo et al., 2019; Jussupow et al., 2020; Kim et al., 2022). Especially when a prediction is wrong, individuals tend to lose trust in an algorithm faster than they do in a human forecaster (Dietvorst et al., 2015, 2018). The literature also suggests various countermeasures to algorithm aversion (Burton et al., 2020), such as allowing individuals to modify the results of an algorithm (Dietvorst et al., 2018).

Accordingly, sales employees may lack trust in PSA applications and therefore refrain from adopting them. Importantly, the theory also allows for a dynamic perspective on PSA adoption: when sales employees see a PSA application err, they are particularly likely to lose trust and thus decrease PSA adoption. At the same time, the theory provides practical advice on how to mitigate algorithm aversion and thus increase PSA adoption, such as by allowing sales employees to use their own judgments to adjust predictions.

Ethical decision-making theory Models of ethical decision-making (EDM) "typically present the EDM process as a series of temporal and sequential process stages, typically beginning with initial awareness or recognition of an ethical issue leading to a moral judgment, intention to act, and finally to behavior" (Schwartz, 2016: 756). While not a technology acceptance theory, EDM might explain sales employees' adoption of PSA applications because PSA will undoubtedly increase ethical issues. That is, the data-driven and automatic nature of PSA applications might give rise to unintended discrimination, stereotyping, and exclusion of specific customer segments. For example, a PSA tool for customer prioritization might predict specific customer types as less worthy of personal visits and intense servicing.

No study that we are aware of, however, has examined PSA through an ethical lens. Scholars have addressed ethical questions in various other analytics fields, such as education, health care, retail, and traffic management (Kitto & Knight, 2019; Patil & Seshadri, 2014; Tene & Polonetsky, 2013). For example, Haddadi et al. (2012) explore privacy challenges associated with using personal data for advertising analytics. Adapting such research to the field of PSA is important for multiple reasons. First, certain PSA applications intend to support sales managers and salespeople when influencing customers. For example, prospect profiling uses personal data to help salespeople increase their persuasiveness, which might be deemed ethically questionable. As studying ethical behavior of salespeople is an important field of sales research (Cadogan et al., 2009; Cicala et al., 2014), future studies could benefit from examining PSA from an ethical perspective.

Second, inaccurate predictions from sales analytics applications can bias the perceptions of sales managers and salespeople and thereby lead to ethically questionable decisions. For example, a sales manager might refrain from promoting a salesperson because of a high predicted likelihood of leaving the firm, even if the salesperson is highly committed.

Third, PSA requires the extensive collection and use of granular data. For example, many PSA applications build on data lakes merging individual salesperson data such as age, gender, and period of employment with individual customer data such as purchase history, channel preference, and geographic location. Such granular data might cause privacy concerns.

Fourth, PSA allows sales managers to intensify monitoring of individual salespeople, which might also raise staff's or works councils' ethical concerns. For example, PSA applications that audiorecord and analyze calls give employers unprecedented insight into the behavior and performance of individual sales employees. This could result in issues such as sales employees' anxiety, stress, turnover, and gaming of systems (e.g., the tension between structuring a sales call to receive high PSA scores and satisfied customers).

Fifth, salespeople might also fear endangering their reputation if they use PSA applications that their customers find intrusive. An example is PSA applications that generate personality profiles of customers and/or recommending a certain line of persuasive argumentation to a salesperson. If salespeople are instructed to use such tools, they might feel a need to hide usage of such tools from customers, leading to anxiety and stress.

From PSA adoption to job performance

To explain the link between sales employees' adoption of a PSA application and their job performance, we draw on the marketing capabilities model (Morgan, 2019). A firm's marketing capabilities comprise complex, coordinated patterns of skills, knowledge, and technology that become embedded as routines over time (Day, 1994; Jaworski & Lurie, 2019; Morgan et al., 2009). The concept originated from the resource-based view, which argues that firms acquiring inimitable resources and capabilities can gain a sustainable competitive advantage (Kozlenkova et al., 2014). This theoretical lens suggests that different resources, such as the adoption of new technologies, can help companies develop certain capabilities that, in turn, enhance performance (Day, 1994). In the marketing domain, Day (1994) particularly emphasizes the importance of market-sensing capability (see also Sett, 2018). That is, firms may sense or identify business opportunities in the market through information gathering and analysis (Day, 1994). Sensing capabilities are rooted in a firm's internal analytical activities, and typical tasks include the identification of new potential customers, lead generation, and customer prioritization (Morgan et al., 2009). Applying this logic to our conceptual model, we argue that adopting PSA applications augments sales employees' market-sensing capability and equips them with important information to manage sales organizations and sell to customers more effectively and efficiently (see Day, 2011; Feng et al., 2017; Guenzi & Habel, 2020). For example, PSA applications may increase effectiveness by allowing sales employees to generate higher-quality leads, identify cross-/upselling potential, and prioritize customers by their predicted future value (Guo et al., 2020). PSA applications may increase efficiency by allowing sales employees to optimize effort allocation toward the most valuable customers and minimize time resources by automating analyses.

Not all sales employees are expected to equally benefit from adopting PSA applications. Again, the marketing capabilities framework is instructive in identifying relevant contingency factors, as it suggests that effects of marketing capabilities on employee performance will inherently depend on employees' work environment (Day, 2011). We propose two sets of contingencies in this respect.

First, we argue that effects of PSA adoption should be contingent on factors directly associated with how the PSA application is designed and deployed. As the underlying conceptual mechanism, we propose that these variables will determine the value potential inherent in the particular application for employees (Wedel & Kannan, 2016). This value potential, in turn, will moderate effects of adopting the PSA application on job performance. We define "value potential" as the degree to which a PSA application can help sales employees achieve desired outcomes.

Second, we propose that variables related to the decision-making environment, such as competitive intensity or market turbulence, will moderate the effect of PSA adoption on job performance. This is because these variables will determine sales employees' demand for accurate information. The higher sales employees' information demand, the greater the value potential of adopting PSA in a certain environment will be (Wedel & Kannan, 2016).

Contingencies related to PSA adoption

Business problem

PSA applications aim to help solve particular sales-related business problems (Schoenherr & Speier-Pero, 2015). In the sales context, the onus on solving these business problems is mainly on sales managers and salespeople (Johnston & Marshall, 2016). Essentially, sales managers' business problems and decisions pertain to the management of their sales business unit, which comprises sales strategy development and business planning with sub-activities, such as prioritizing customer acquisition and retention, optimizing the sales force size (Albers & Krafft, 2013), and effectively leading salespeople. Salespeople, in turn, are often the key representatives of the firm, especially in the B2B context. Their business problems and decisions pertain to the stages of the sales funnel, from customer acquisition to customer development (Albers & Krafft, 2013; Söhnchen & Albers, 2010).

Research has developed PSA applications for a wide variety of sales managers' and salespeople's business problems (see Fig. 2). For example, PSA applications support sales managers in decisions about allocating the efforts of salespeople, sales forecasting, sales force size and structure, incentive plans for salespeople, and salespeople retention (Panel A). They support salespeople in lead qualification, price quotation, time allocation on existing customers and prospects, customer feedback handling, cross-selling, customer churn prevention, customer lifetime valuation, and customer win-back (Panel B).

Different use cases help sales employees in different work tasks and thus likely exhibit different value potential, rendering the effect of a sales employee's PSA adoption on job performance more or less pronounced. To understand which use cases exhibit lower or higher value potential, consider that a predictive model aims to help sales employees improve their *decisions* (e.g., which product to offer to a customer). Accordingly, we propose that the value potential of a PSA use case should be determined by the expected value of the *decision* a use case aims to improve, which amounts to the multiplication of (1) the possible outcome (e.g., sales revenue generated in case the customer accepts the offer) with (2) the probability that the decision results in that outcome (e.g., the customer accepts the offer) (Magee, 1964).

First, the possible outcome of decisions supported by PSA strongly depends on the specific use case. For example, for decisions that aim to retain salespeople, a firm's maximum possible outcome is given by its current costs due to salesperson turnover. For decisions that aim to improve cross-selling, a firm's maximum possible outcome is given by the sales potential in its customer base, given the firm's product portfolio. These examples show that the outcomes of a PSA application are likely to be highly context dependent.

Second, the probability that a decision made using PSA achieves the desired outcome also depends on the specific use case. We expect a use case's probability to realize a specific value potential (1) to decrease with the the *scope of action* (i.e., the number of different, potential measures a sales employee can take based on a prediction) and (2) to increase with the *influenceability* of outcomes (i.e., the extent to which outcomes depend on sales employees' decisions rather than other factors). For example, when trying to retain a salesperson with a high probability of departing, a sales manager might face a high scope of action and moderate influenceability. A sales manager might offer a salesperson with a high turnover probability a different compensation plan, a reduction of workload, job enrichment, reassignment to a different team, or a new job title, to name just a few of the available options. Even when the sales manager identifies the right decision to take, retention will depend on other factors, such as a salesperson's disengagement from the current employer and alternative job offers. Conversely, when a predictive model suggests that a customer might cross-purchase a certain product, the scope of action requires offering this specific product. Similarly, influenceability might be moderate to high, increasing the probability of achieving a cross-sale.

Model development

PSA applications are developed from predictive models on the basis of appropriate data (Shmueli & Koppius, 2011). We propose three model development choices that determine the value potential of a PSA application: (1) the use of unstructured (vs. structured) data, (2) the use of nonparametric models, and (3) the model's predictive validity.

Unstructured data Most prior studies developed PSA models from *structured* data, that is, data in a tabular format in which observations are stored in rows and clearly defined variables in columns. Typical data sources in this respect include (1) transaction data, comprising information on the time, quantity, specific products, and terms at which a customer made a purchase (e.g., Glady et al., 2009); (2) CRM data, comprising master data of customers, information on company–customer interactions, and sales funnel–related variables such as leads, opportunities, and quotations (e.g., Eitle & Buxmann, 2019); (3) web analytics

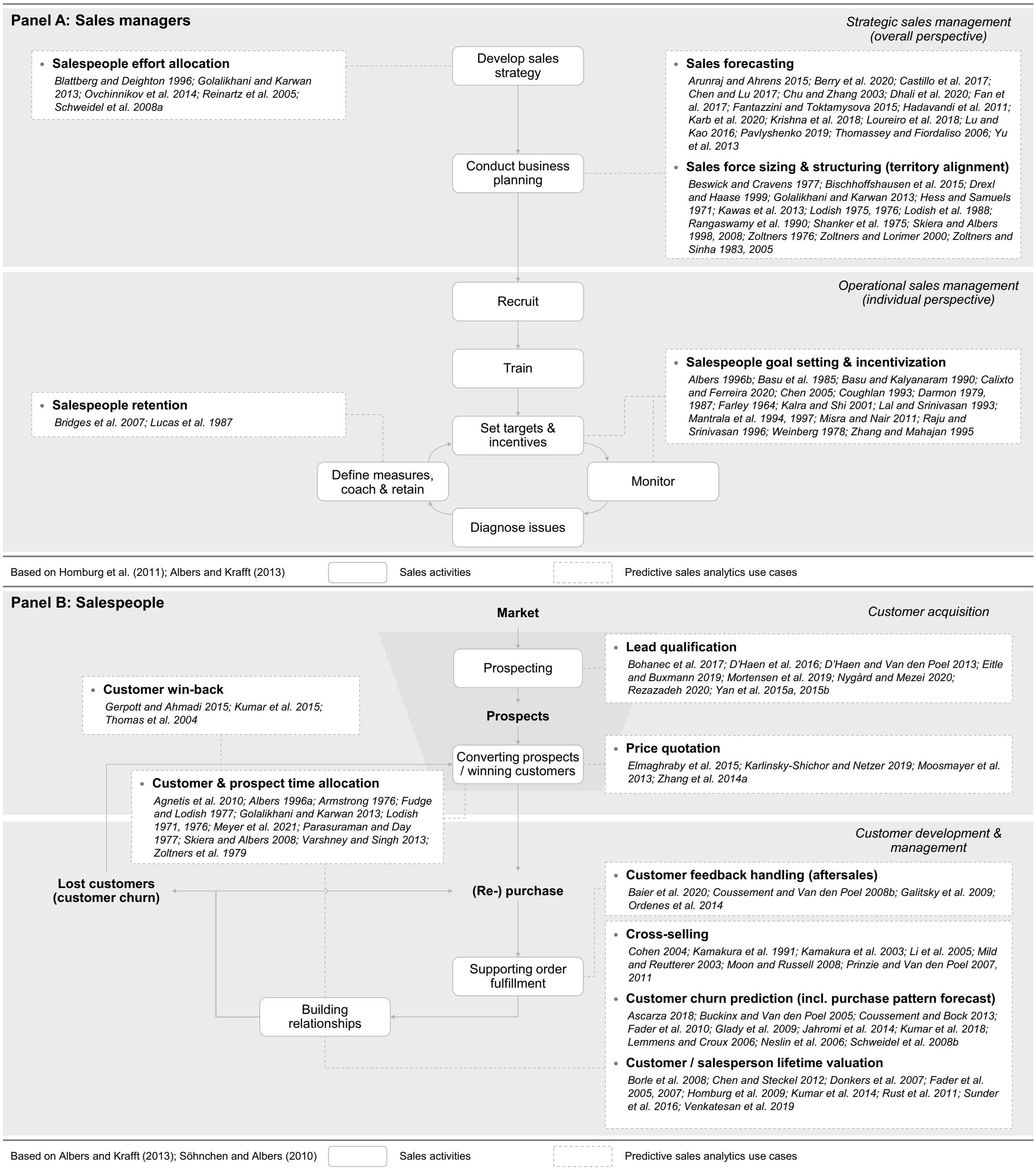

Fig. 2 Use cases of PSA

data, such as website impressions and click-throughs (e.g., Nygård & Mezei, 2020); (4) human resources data, such as a salesperson's tenure, age, or compensation (e.g., Misra & Nair, 2011); and (5) company-external data, such as macroeconomic information (e.g., Hadavandi et al., 2011). For example, studies that developed models to forecast sales primarily used historical transaction data complemented by macroeconomic data, such as consumer price index, unemployment rate, and gross domestic product (e.g., Fantazzini & Toktamysova, 2015; Hadavandi et al., 2011).

Some studies have also made predictions from *unstructured* data, which are not stored in a structured, tabular format; instead, the data comprise continuous text, image, audio, and video data (Ma & Sun, 2020). The sales context is rife with such data, including salespeople's written communication (e.g., visit reports, email exchanges in the CRM system) and recordings of audio and video calls between them and customers. Scholars have used such data to classify written customer feedback (e.g., Coussement & Van den Poel, 2008b; Ordenes et al., 2014) or predict customer churn (Coussement & Van den Poel, 2008c). In addition, sales research outside predictive analytics has increasingly used unstructured data to test theory (Bharadwaj et al., 2022; Lawrence et al., 2021; Singh et al., 2018, 2020; Zhang et al., 2014b).

Unstructured data hold the potential to increase a model's predictive validity (Ma & Sun, 2020; Nygård & Mezei, 2020) and provide deep insights into markets (Humphreys, 2021). In doing so, sales employees receive more accurate information, which helps improve their market-sensing capabilities and thus enables them to make better decisions. Thus, we expect PSA applications built from unstructured data to strengthen the effect of sales employees' PSA adoption on job performance.

Non-parametric models When building PSA applications, data scientists often compare the predictive validity of different analytical methods (e.g., Au et al., 2003; Chu & Zhang, 2003). These methods often include non-parametric machine learning algorithms, such as neural networks (e.g., Nygård & Mezei, 2020), decision tree classifiers (e.g., Eitle & Buxmann, 2019), and random forest classifiers (e.g., Ascarza, 2018). Non-parametric models do not rely on data scientists making assumptions about the shape of effects (e.g., linear effects, quadratic effects, specific interaction terms) but derive these effects from the data while allowing for complex non-linearities and interactions. Therefore, non-parametric models hold the potential to increase the predictive validity (Ma & Sun, 2020; Nygård & Mezei, 2020). For example, in their prediction of customer churn, Glady et al. (2009) found that neural networks and decision trees outperformed a logistic regression by at least 16% based on the area under the profit curve. Similarly, the predictive validity evaluation in the work of Coussement and Van den Poel (2008a) revealed an improved top-decile lift of 6% for a random forest model compared with a logistic regression. When predicting the purchase probability of potential customers, Nygård and Mezei (2020) achieved a 9% higher area under the curve value with a random forest model than a logistic regression. Loureiro et al. (2018) found that multiple machine learning algorithms outperformed a logistic regression model in forecasting sales by up to 24% in terms of the mean absolute percentage error.

Again, higher predictive validity entails more accurate information for sales employees, improving their market-sensing capabilities and helping them make better decisions. Thus, we expect PSA applications built from non-parametric models to strengthen the effect of sales employees' PSA adoption on job performance.

Predictive validity Our previous propostions regarding the use of unstructured data and non-parametric models rely on their ability to improve a model's predictive validity. We next argue that regardless of the data and specific model used, the higher the predictive validity of a model, the more PSA adoption should increase job performance.

Predictive validity indicators capture how likely a prediction will be correct (e.g., Eitle & Buxmann, 2019). As the predictive validity increases, sales employees receive more accurate information, which improves their market-sensing capabilities and thus should enable them to make better decisions. Consider, for example, a salesperson who decides whether to submit a proposal to a prospect based on a prediction of conversion likelihoods. If the predictive validity of the model is poor, the model will produce false positives (i.e., predict that leads of low quality will convert) or false negatives (i.e., predict that leads of high quality will not convert). As a result, the salesperson may take the wrong decision to submit or refrain from submitting a proposal if he or she relies on the model too strongly.

We can also envision non-linear moderation effects of the predictive validity because minor changes in the predicted information might not necessarily pass sales employees' perceptual threshold. For example, suppose that an increase in predictive validity changes the predicted conversion likelihood of a lead by two percentage points. Arguably, such a change might *not* lead salespeople to change their decision of whether to submit a proposal. Only if an increase in predictive validity causes larger changes might salespeople reconsider the decisions they take. We encourage future research to explore such non-linear moderation effects.

Furthermore, examining the moderating effect of the predictive validity on the PSA adoption–job performance linkage would help identify adequate value ranges for these indicators. Specifically, what predictive validity is necessary in the sales context to make the adoption of a PSA application worthwhile? The answer to this question might also depend on the use case. For example, a higher predictive validity might be required for a sensitive task, such as defining retention measures from predicted salesperson turnover, than for a less sensitive task, such as making cross-selling offers based on predicted purchase probabilities.

Model deployment

Following the development and successful validation of a PSA model, organizations design processes for how employees should use these predictions (Burger & Habel, 2020). We propose two deployment-related contingencies that might determine the value potential in a PSA application: (1) the use of real-time versus on-demand predictions and (2) the use of predictions versus prescriptions. We elaborate on these contingencies in the following.

Real-time versus on-demand Some PSA applications deliver predictions in real time, supporting sales employees in making decisions as soon as a decision point arises. For example, "AI coaches" (Luo et al., 2021; Tong et al., 2021) analyze salesperson–customer conversations while they are occurring and predict what salespeople should say next (e.g., right answer to a question) and how they should say it (e.g., adjust communication speed, mimicry), some sales enablement applications (Lauzi et al., 2023; Peterson et al., 2021; Rangarajan et al., 2020) provide real-time advice on which documents to show to customers at which point in time to enhance purchase probability (Hyken, 2020), and some CRM systems show conversion probabilities of leads and opportunities as soon as they are logged. By contrast, PSA can also deliver predictions on-demand. For example, consider an analyst or data scientist predicting the next-best offer for a segment of customers (Moon & Russell, 2008; Prinzie & Van den Poel, 2007), a sales employee using a PSA application such as CrystalKnows to predict a prospect's personality (Fatemi, 2019), or a PSA application allowing sales representatives to score individual leads based on those leads' characteristics (Burger & Habel, 2020).

We expect that real-time deployments increase the value potential of PSA applications and thus strengthen the effect of PSA adoption on job performance for two reasons. First, real-time applications enable fast decision-making. By contrast, on-demand PSA requires sales employees to take more time-intensive manual action (e.g., coordinate with analysts or data scientists), thereby creating opportunity costs. Second, real-time applications allow faster retraining of predictive models, thereby improving their predictive validity. By contrast, on-demand applications often do not include automatic model updates (Burger & Habel, 2020).

Prediction versus prescription While a predictive application provides only the predicted information (e.g., the probability of a lead converting) and leaves it to sales employees to infer the right decisions, a prescriptive application translates predictions into specific courses of action (e.g., whether to submit a proposal) (Wedel & Kannan, 2016). Prior studies rarely discuss this implementation aspect of PSA, but those that do seem to regard PSA as a supporting information tool rather than a substitute for sales employees' decisions. More specifically, PSA is supposed to provide information that employees autonomously use as one input in their decision-making. For example, Karlinsky-Shichor and Netzer (2019) developed and implemented a price recommendation model. For incoming requests for quotations, the model provided a recommended price that salespeople could use in their pricing decision. Moreover, Bohanec et al. (2017) predicted the conversion likelihood of potential sales opportunities. After the sales team completed its manual monthly forecast, it received the model prediction to re-evaluate and potentially adapt the initial forecast.

Despite the focus of prior research on predictive applications, prescriptions might increase the value potential of PSA applications because they potentially mitigate sales employees' decision-making errors (HBRAS, 2021). That is, prescriptions may narrow down the scope of action to a few selected, effective alternatives. As a result, the effect of a sales employee's PSA adoption on job performance might increase. However, because sales employees might perceive prescriptions as infringing on their freedom of decision (Dietvorst et al., 2018), they might also implement prescriptions less rigorously, which might decrease their job performance. Thus, implementing PSA applications as predictions versus prescriptions may provide interesting tensions for future research to empirically investigate.

Contingencies related to the decision-making environment

The value potential of adopting PSA applications can strongly vary depending on the decision-making environment of the sales employees (Wedel & Kannan, 2016). That is, in some environments, adopting PSA applications should strongly increase sales employees' performance, while in other environments, relying on the PSA applications may not increase performance. To gain a more profound understanding of PSA consequences, disentangling these moderating influences of charateristics of the decision-making environment is essential. Moreover, practitioners can benefit from such a detailed concept because it helps them evaluate whether adopting PSA would be appropriate in their specific environment.

In general, the value potential in the decision-making environment should be particularly high in three circumstances (Achrol & Stern, 1988): (1) low market concentration (i.e., if the market features a high number of heterogeneous actors such as customers and competitors), (2) high market velocity (i.e., if the market features frequent and rapid changes), and (3) certain configurations of sales employees' decision-making capability. The first two circumstances suggest an exceptionally high need and demand for accurate information by sales employees (Galbraith, 1974; Tushman & Nadler, 1978). The marketing capabilities model suggests that such complexity in the market environment shapes the effectiveness of marketing capabililities (Feng et al., 2017). In this sense, adopting a PSA application will increase performance if the application helps sales employees satisfy their information demands and better cope with the complexity (e.g., many different actors, frequent and rapid changes) in the environment. For the third circumstance, if sales employees have low capabilities to make decisions *without* PSA and/or high capabilities to make decisions *based on* PSA, adopting PSA should be more conducive to their job performance.

Market concentration

Competitive intensity Competitive intensity constitutes a key marker of market environments and has been intensively treated in prior research as a contingency factor for technology effectiveness (Feng et al., 2017). Competitive intensity reflects the number of competitors in the market environment as well as the fierceness of competitive actions. As such, it is highly indicative of market concentration (Achrol & Stern, 1988), where high competitive intensity suggests many competitors and low market concentration. In such environments, sales employees' information demands should be exceptionally high, and thus PSA applications should exhibit high value potential. Prior research agrees that implementing new technologies may be particularly important in environments with fierce competition (Germann et al., 2013). In general, the argumentation rests on the logic of the resource-based view, such that in difficult and complex environments (e.g., heavy competition), being endowed with the appropriate resources is especially important to sustain or grow performance. Applying this logic to our conceptual model, we argue that the value potential for adopting PSA applications will be particularly high in market environments with high competitive intensity.

Customer concentration Customer concentration means the number of customers in a market, that is, whether the market encompasses a large number of mostly smaller customers or a few key account customers. Sales employees' demands for accurate and timely information should be especially high if customer concentration is low (i.e., a large number of different customers). Adopting PSA applications allows sales employees to be adaptive and responsive to such a larger number of customers. Conversely, markets with only a few key accounts should hold less value potential for adopting PSA applications. Usually, sales organizations and key account managers already hold in-depth, detailed knowledge about the key accounts and are higly responsive. The incremental value potential of adopting PSA applications under such circumstances is thus limited.

Customer heterogeneity A market with high customer heterogeneity comprises a highly diverse customer base, with customers' characteristics and needs strongly differing. In such a market, a plethora of different micro customer segments may exist. Conversely, with low customer heterogeneity, customers in a specific market are relatively similar with only a few major customer segments. High customer heterogeneity is indicative of a highly complex market environment, as previously discussed, creating strong information demands for sales employees to cope with the complexity. We thus argue that such market environments hold especially high value potential, which can be realized through the adoption of PSA applications.

Market velocity

Market turbulence and customer need dynamism Market turbulence reflects the frequency and scope of changes in a market. For example, price levels, the number of competitors, and customer needs change rapidly in turbulent markets. According to the market environment concept of Achrol and Stern (1988), market turbulence is related to the velocity facet of a market. Along with competitive intensity, market turbulence represents a key characteristic of market environments (Wang et al., 2015). Prior research suggests that analytics technologies in general are especially important in turbulent environments (Davis-Sramek et al., 2010), because such technologies help process large amounts of data originating from these markets. That is, analytical technologies may hold strong value potential in turbulent markets because they account for market complexity and help fulfill sales employees' information demands. This reasoning can be directly applied to the effects of sales employees' PSA adoption. If market environments are turbulent and marked by rapid changes, predictions should prove especially useful to sales employees. That is, the prediction about customers in these environments should help sales employees be adaptive, responsive, and customer-oriented, even in such difficult, complex environments.

This is most clearly illustrated by the concept of customer need dynamism, which is an oft-studied marker of the market environment (Germann et al., 2013). If customer needs change frequently and rapidly, possessing up-to-date knowledge of customer needs may be challenging. In such a situation, sales employees' information demands escalate, which inflates the value potential that can be realized through PSA applications. Again, adopting PSA applications to effectively develop customer knowledge should be particularly conducive to job performance if customer needs are frequently and rapidly changing.

Market munificence Market munificence, intensely examined in research on marketing capabilities (e.g., Morgan, 2012), reflects the amount of resources and opportunities available in a market (Feng et al., 2017). If market munificence is high, a market holds an abundance of different selling opportunities, and the number of opportunities may even dynamically increase. In such an environment, sales employees' information demands may be particularly high, to ensure they can quickly learn about the plethora of opportunities and efficiently adapt and react. Especially sales employees' information demands for priorizing the vast number of opportunities should be paramount. In markets with high munificence, given sales employees' substantial information demands, adopting PSA applications should have particularly high value potential to sales employees.

Decision-making capability

The degree to which PSA adoption affects job performance should also depend on sales employees' effectiveness in using the information from the applications. We expect that two concepts related to such effectiveness are particularly likely to moderate the PSA adoption–job performance relationship: (1) sales employees' decision-making skills in the absence of PSA (hereinafter, *decision-without-prediction capability*) and (2) sales employees' decision-making skills based on the information predicted by PSA (hereinafter, *prediction-to-decision capability*).

Decision-without-prediction capability We define decision-without-prediction capability as a sales employee's decision-making skills in the absence of predictive models provided by PSA. The higher a sales employee's decision-without-prediction capability, the less likely adopting a PSA application will alter his or her decision compared with the status quo, rendering the value potential of such an application lower. For example, after adopting a PSA application that predicts customers' churn probabilities, a salesperson who had already effectively intuited customers' churn probabilities and taken the right decisions to retain them would likely reap fewer additional benefits from the PSA application.

Prediction-to-decision capability Prediction-to-decision capability refers to a sales employee's decision-making skills based on the information predicted by PSA. The higher a sales employee's prediction-to-decision capability, the more effectively he or she will be able to adopt predicted information. Extending the previous example, to effectively adopt PSA predicting customer churn, the salesperson needs to possess proficient knowledge to decide which actions are most instrumental in retaining specific customers.

Decision-without-prediction capability and prediction-to-decision capability are relatively broad concepts. Future research might examine which more specific constructs shape these capabilities. Examples include sales employees' experience (Habel et al., 2021), sensing (Alavi et al., 2016; Day, 1994), intuition (Cron et al., 2021, 2022), and adaptiveness (Alavi et al., 2019). Furthermore, future research could examine how sales organizations can foster these capabilities. For example, which mathematic skills should be trained to ensure sales employees' ability to use predictions effectively (Burton et al., 2020)? To what extent should employees learn which data are used in predictive models, which algorithms predictions are developed with, and how to interpret their predictive validity?

Discussion

Theoretical implications

Academia and practice are increasingly focusing on PSA (Alavi & Habel, 2021; Luo et al., 2021). However, despite its growing relevance, many firms confront lingering difficulties when attempting to implement new PSA applications in their sales force. At best, such implementation hurdles limit the productivity increases potentially enabled by PSA; at worst, they undermine established sales processes, even reducing sales productivity. Against this backdrop, our study integrates existing literature with pertinent theory into the *PSAA model*, which predicts how PSA affects sales employees' job performance. To that end, we integrated key findings from our literature review on predictive analytics and machine learning with technology adoption theories (Davis et al., 1989; Venkatesh & Bala, 2008; Venkatesh et al., 2003, 2012) and the marketing capabilities model (Day, 1994, 2011; Morgan, 2019). This procedure allowed us to conceptualize and propose important moderators that reside in the PSA application and decision-making environment.

Future research on PSA effectiveness could readily employ this model to explain how sales employees adopt and use PSA applications.

The theoretical novelty and conceptual value of the PSAA model derive from the comprehensive but nuanced depiction of the contextual factors governing the impact of PSA adoption on job performance. Previous accounts have tended to prioritze specific categories of contingency factors at the expense of others, focusing mostly on the external environment and less on the value potential of the application itself (e.g., Germann et al., 2013). However, providing a comprehensive model of the boundary conditions is essential to be able to accurately understand the ramifications of using these new PSA applications. In this respect, the PSAA models posit that the value potential in both the application itself and the decision-making environment must be considered—given the critical determining influences of these concepts, omitting one or the other might prevent researchers and practitioners from fully understanding the ramifications of PSA. We encourage future research to create an even more nuanced and granular account of the potentially complex interplay of the value potential in the PSA application and the decision-making environment. For example, prescriptive analytics might be particularly effective and viable in dynamic decision environments with high pressure and urgency for salespeople, while it might backfire when salespeople are less pressed and want autonomy in decision-making.

Furthermore, the PSAA model offers novel concepts that can provide building blocks for future theory building on predictive analytics (Zeithaml et al., 2020). For example, we propose that salespeople (and employees at large) differ in both their *decision-without-prediction capability* (i.e., decision-making skills in the absence of predictive models) and their *prediction-to-decision capability* (i.e., decision-making skills based on the information predicted by PSA). To the best of our knowledge, these concepts have not been established in the literature, but they offer an intriguing explanation for why some salespeople benefit more or less from PSA (Alavi & Habel, 2021; HBRAS, 2021). Put simply, some salespeople may *not need* PSA to make good decisions, while others may *not be able* to improve their decisions even when using PSA. We encourage future research to empirically validate these capabilities.

A key prediction of the PSAA model is that adopting PSA applications can constitute a valuable resource to sales employees, as they provide them with a competitive advantage, increasing their job performance (Hunt, 2015; Morgan, 2015). However, a limitation of this conceptualization is that it presumes a rather traditional, static perspective on market development and individual decision-making. That is, our model does not account for how new PSA applications may leverage diverse data sources to create innovations that may transform markets and, as such, does not take a dynamic, iterative, and longitudinal perspective on market development. Thus, future research should incorporate the idea of *market shaping* in the PSAA model as an essential outcome of sales employees' PSA adoption (Flaig et al., 2021; Nenonen & Storbacka, 2021; Nenonen et al., 2019). This idea is inexorably intertwined with how sales employees' PSA adoption relates to innovation in general and value creation for customers in particular (Ozkok et al., 2019). Extending the PSAA model to this domain should be feasible because prior research has shown that effective knowledge management, particularly backed by advanced analytics, paves the way for innovation in different areas (Fligstein, 2021; Seggie et al., 2017; Velu, 2015). For example, PSA applications may leverage the abundance of customer data to create business model innovations that can permanently disrupt and shape markets (Kim et al., 2019). Moreover, because salespeople are the "voice" of the customer within the firm, employing internal data from salespeople in innovation processes through PSA applications might significantly improve the innovation process (Homburg et al., 2017). Given that firms increasingly rely on the sales force as an engine of business model innovation, integrating a market-shaping perspective with the PSAA model would be meaningful for future research and firm practice. As a starting point in this respect, we envision a dynamic, two-step feedback loop on (1) how PSA adoption creates market-shaping innovations in different areas and (2) how these innovations, in turn, create data that feed into PSA and thus help ensure continuous market development.

To further advance our conceptual model, future research could examine other challenges of implementing PSA than sales employees' adoption (Ascarza et al., 2021). In addition, future research could extend our model by building on a range of existing theories. For example, as outlined previously, technology acceptance theories view perceived usefulness, perceived ease of use, and social influences as the key determinants for using a technology (Davis et al., 1989; Venkatesh & Bala, 2008; Venkatesh et al., 2003, 2012). Furthermore, previous research on algorithm aversion shows that individuals prefer humans to algorithmic forecasters (e.g., Dietvorst et al., 2015). To overcome the lack of trust in algorithms, studies propose giving individuals control over forecast results (Dietvorst et al., 2018), fostering algorithmic literacy (Burton et al., 2020), or making the superiority of algorithms more transparent (Castelo et al., 2019). Last, future research might draw on theories that explain the emergence of stress, such as cognitive appraisal theory (Bala & Venkatesh, 2015; Lazarus & Folkman, 1984) or the job demands–resources model (Bakker & Demerouti, 2007). For example, research could examine the conditions under which sales employees perceive PSA as beneficial (i.e., as a job resource) or harmful (i.e., as a job demand) and which resources help them reap benefits and avoid harm.

Managerial implications

The PSAA model should raise managers' awareness that offering a PSA application to sales employees does not automatically pay off but requires employees to effectively use it. To ensure such effective utilization, the PSAA model provides two sets of recommendations. First, managers need to ensure that sales employees adopt the PSA application, meaning that they process the predicted information and try to adjust their decisions based on it. This is by no means a given, considering that adoption of novel sales technologies (e.g., CRM systems, sales enablement tools) often lags behind expectations. To foster adoption, managers should carefully analyze and remove obstacles to PSA adoption, such as a lack of perceived usefulness and ease of use (Davis et al., 1989), algorithm aversion (Burton et al., 2020), or ethical concerns (Schwartz, 2016). Achieving this is certainly not easy and requires managers to carefully direct change and reduce uncertainty (Alavi et al., 2022; Sarin et al., 2012).

Second, even when sales employees adopt a PSA application, success only ensues if sales employees improve their decisions based on the predicted information. Managers thus need to ensure that PSA applications as well as the decision-making environment offer high value potential. For example, managers should implement PSA applications for use cases when decisions need improvement and strive for high predictive validity (which might increase through unstructured data and non-parametric models). They should also carefully decide whether offering predictions suffices or whether to translate these predictions into prescriptions. For example, consider a prediction of customers' churn probability. It may be difficult for sales employees to know the best decision when a customer's churn probability is predicted to be, say, 10%, 30%, 50%, 70%, or 90%. In this case, managers may need to prescribe specific actions, such as retention measures proven to be effective given a certain churn probability.

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