Innovation Outcomes of Digitally Enabled Collaborative Problemistic Search Capability

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ABSTRACT

A firm's use of boundary-spanning information systems (BSIS) can be beneficial for innovation by providing access to market-facing information. At the same time, BSIS use can give rise to information overload, making it difficult for firms to leverage the most pertinent information for innovation. Although there has been progress in developing our understanding of the role of IS in innovation, it is unclear what capabilities firms need to develop to facilitate innovation in the presence of information overload from BSIS use (IO-BSIS). We maintain that firms today are increasingly experiencing IO-BSIS and therefore a thorough investigation of firm-level capabilities to facilitate innovation while coping with IO-BSIS is needed. To address this key gap, we broaden the theory of problemistic search for innovation by proposing a digitally enabled collaborative problemistic search (CPS) capability. We propose that a cross-stream CPS effect — interaction of CPS with customers (CPS-C) and CPS with suppliers (CPS-S) — enables a firm to reinvigorate its internal knowledge for innovation by engaging customers and suppliers in filtering and interpreting market-facing information. Further, we theorize that the presence or absence of IO-BSIS is a contingency that affects whether the cross-stream CPS effect is likely to be beneficial or detrimental to innovation. Based on the analysis of data collected from 227 firms, we found that the cross-stream CPS effect is beneficial for innovation when firms face IO-BSIS and detrimental to innovation when firms do not experience IO-BSIS. We thus open the black box of the digitally enabled innovation activity by shedding light on specific collaborative activities that advance innovation by enabling firms to cope with information overload.

Keywords: collaborative problemistic search; boundary-spanning information systems; big data; information overload; collaborative innovation; digital innovation

INTRODUCTION

"[R]eal design problem is not to provide more information to people but to allocate the time they have available for receiving information so that they will get only the information that is most important and relevant to the decisions they will make. The task is not to design information-distributing systems, but intelligent information-filtering systems."
— Simon (1996, p. 144) discussing the importance of filtering information

"[W]hat is left unspecified are... how interpretations and meanings... were made more explicit, as a result of concrete activities."
— Weick (1995, p. 8) discussing the importance of interpreting information

Substantial research at the intersection of information systems (IS) and strategic management examines how IS contribute to firms' innovation outcomes (e.g., Gómez et al. 2017; Kohli and Melville 2019; Ravichandran et al. 2017; Saldanha et al. 2017; Trantopoulos et al. 2017). Research suggests that IS investment, especially in IS that enable firms to span boundaries and connect with their customers and suppliers, increases firms' innovation outcomes (e.g., Gómez et al. 2017; Tambe et al. 2012). When it comes to investigating the drivers of digital innovation, prior research has examined the enabling role of boundary-spanning IS (BSIS) such as customer relationship management (CRM) and supply chain management (SCM) systems. In fact, BSIS use has become instrumental in acquiring market-facing information that is considered beneficial for innovation (Joshi et al. 2010; Kleis et al. 2012). However, BSIS use can also lead to accumulation of vast amount of market-facing information and result in what we refer to as information overload from BSIS use (IO-BSIS). Firms' IS investment is expected to grow and, moving forward, in the age of big data, innovating while coping with IO-BSIS will be a major issue for firms.

Prior research has identified various sources of information overload and has proposed solutions for individuals to cope with it (see Table 1 for a summary of key recent studies examining information overload[1]). For example, an individual's use of different types

[1] To identify key recent studies, we followed a snowballing literature review process (Webster and Watson 2002). First, we searched the keyword "information overload" over the period 2000-2019 in the Association for Information Systems (AIS) senior scholars' basket of four journals: *MIS Quarterly*, *Information Systems Research*, *Journal of Management Information Systems*, and *Journal of the Association for Information Systems*.

of IS — e.g., enterprise systems, e-business websites, email systems, and brainstorming systems — has been associated with information overload (e.g., Cenfetelli and Schwarz 2011; Chandra et al. 2019; Stich et al. 2019). Information overload associated with individual use of IS has been found to lead to adverse outcomes, including stress and frustration (Ragu-Nathan et al. 2008). In design science research, technological features have been proposed to assist individuals in coping with information overload and averting these adverse outcomes. In particular, various techniques, such as personalized recommendations, visual frameworks, and effective search support, have been designed to help individuals cope with information overload when they perform various tasks (Chung et al. 2005; Sahoo et al. 2012, Dang et al. 2012).

Table 1. A Summary of Studies on Information Overload

Stream	Core Themes	Key References
Behavioral IS research	Technological sources and adverse consequences of information overload at the individual level (information overload was experimentally manipulated or surveyed)	Grisé and Gallupe (2000): Electronic brainstorming systems can cause information overload.
		Ragu-Nathan et al. (2008): IT use can be associated with information overload and technostress.
		Tarafdar et al. (2010): IT use can result in information overload and technostress.
		Cenfetelli and Schwarz (2011): Information overload inhibits technology usage.
		Stich et al. (2019): IT use can be stressful because of overload associated with information over-acquisition.
		Chandra et al. (2019): Information overload is a source of technostress which reduces creativity and innovation.
Design science research	Technological features to cope with information overload at the individual level (information overload was not measured)	Lin et al. (2000): Effective classification is critical for coping with information overload.
		Adomavicius and Tuzhilin (2005): Recommender systems are critical for coping with information overload.
		Chung et al. (2005): Effective visualization is critical for coping with information overload.
		Wei et al. (2006): Effective categorization is critical for coping with information overload.
		Dang et al. (2012): Effective search support is critical for coping with information overload.
		Sahoo et al. (2012): Collaborative filtering is critical for coping with information overload.
IS strategy research	Firm-level capabilities to cope with information overload (only conceptual work)	Hemp (2009): Conceptual ideas for coping with information overload in organizations were proposed.
		This study**:** We measure information overload at the firm level and examine precise activities that constitute firm-level capabilities to cope with information overload.

Second, we checked the references of the resulting articles from the first step to make sure we did not miss any key relevant studies from other journals.

Although prior research has identified technical features to cope with information overload at the individual level, these solutions do not necessarily scale up to firm-level capabilities to cope with information overload. Individual-level research often assumes independence of IS users — whereby individuals are free from the systematic influence of firm-level activities (Klein et al. 1994). However, a firm's innovation activity now spans its boundaries and often necessitates involvement of its customers and suppliers. Collaborative activities with customers and suppliers imply that knowledge workers in a firm are systematically influenced by inputs from its business partners when dealing with market-facing information. Therefore, facilitating interfirm collaboration for innovation while systematically coping with IO-BSIS requires the development of digitally enabled firm-level capabilities that are fundamentally different in comparison to individual level technical solutions. In summary, the solutions proposed by prior literature for coping with information overload at the individual level do not readily apply to the firm level.

The IS strategy literature is largely silent on the nature of capabilities that enable firms to cope with information overload. Technological features that help individuals cope with information overload do not fully address the information overload problem at the firm level. Coping with IO-BSIS is much more challenging — given the boundary spanning nature of the problem — especially when compared to coping with information overload associated with individual use of IS. Although some techniques help individuals filter information, effective sensemaking is necessary for firms to reinvigorate their knowledge with market-facing information for innovation (e.g., Weick et al. 2005), thereby requiring the systematic development of firm-level activities and capabilities to cope with IO-BSIS.

This is an important gap in our understanding of digital innovation, as firms today are increasingly facing severe challenges in not only generating, but also meaningfully handling vast volumes of data (e.g., Kohli and Melville 2019). In fact, many firms are so focused on gathering vast amount of information via IS use that this "big data" can often be more of a burden than an innovation opportunity (e.g., Taylor 2018). As firms grapple with vast amount of data in their innovation activity, their decision-making efficiency may be adversely affected. Additionally, knowledge workers can be so overwhelmed by information overload that they could be required to spend up to 20 hours a week managing it — cumulatively estimated to cost the U.S. economy about 900 billion USD a year (e.g., Chandra et al. 2019; Hemp 2009). In the age of big data, information overload problem has arguably exacerbated. In summary, there is an urgent need for IS strategy research to focus on specific activities that constitute firm-level capabilities to facilitate innovation while coping with IO-BSIS.

Innovation, an activity with inherently uncertain outcomes, requires a firm to search for new product and service offerings (Nelson and Winter 1982). The idea that a firm can involve its customers and suppliers to inform the interpretation of observable and predicted shifts in market demand and improve supply chain processes has received empirical support (e.g., Malhotra et al. 2005; Rai et al. 2006; Saraf et al. 2007). Extending this premise, in the presence of vast amount of market-facing information collected via BSIS use, we are motivated to uncover digitally enabled capabilities that can enable a firm to collaborate with its customers and suppliers in search for innovation. We draw on the theory of *problemistic search* (Argote and Greve 2007; Cyert and March 1963), where search is goal-directed and motivated by the need to address specific problems; in this case, search for innovation.

We broaden the concept of problemistic search from one where the search process is conducted within the boundaries of a firm (e.g., Greve 2003; Salge et al. 2015) to one where the search process spans a firm's boundaries. In particular, we propose a digitally enabled capability — *collaborative problemistic search (CPS) capability* — to facilitate innovation. By collaborating with downstream and upstream partners, a firm can develop the CPS capability with customers (CPS-C) and with suppliers (CPS-S). The interaction of CPS-C and

CPS-S for innovation is likely to be nuanced especially depending on the presence or absence of information overload. Resolving this theoretical puzzle is important for us to understand the effects of the CPS capability on innovation.

We propose that the synergistic effect of CPS-C and CPS-S enables a firm to reinvigorate its internal knowledge by collaborating with partners on both sides of its supply chain — customers on the demand side and suppliers on the supply side — for effectively filtering and interpreting market-facing information obtained via BSIS use. Thus, we theorize the interplay of CPS-C and CPS-S and posit that the *cross-stream CPS effect* (i.e., the interaction effect of CPS-C and CPS-S) creates synergies for innovation between downstream and upstream collaboration. We theorize that the cross-stream CPS effect is particularly beneficial when firms experience IO-BSIS. As a corollary, we theorize that the cross-stream CPS effect is likely to be detrimental to innovation when firms do not experience IO-BSIS. We test our theory by analyzing survey data collected from 227 U.S. firms. We found corroborating evidence suggesting that the cross-stream CPS effect is beneficial for innovation outcomes when firms face IO-BSIS and detrimental to innovation when firms do not experience IO-BSIS. Our work enables us to open the black box of the digitally enabled innovation activity by shedding light on collaborative activities between a focal firm and its customers and suppliers to advance innovation while coping with information overload.

THEORETICAL BACKGROUND

BSIS Use and Innovation

IS use has been found to be beneficial for firm innovation (e.g., Joshi et al. 2010; Trantopoulos et al. 2017). In particular, we have learned from past research that BSIS use enables firms to transact with their customers and suppliers (e.g., Rai et al. 2006) and to orchestrate the innovation activity by engaging their customers and suppliers as business partners (e.g., Gómez et al. 2017; Saldanha et al. 2017). A firm’s customers and suppliers are valuable sources of information and knowledge for its innovation activity (Leiponen and Helfat 2010).

Firms use BSIS not only to transact with their customers and suppliers, but also to access timely market-facing information that is not available via public channels. In particular, market-facing information is crucial to learn about changing customer needs for new products or services (Tambe et al. 2012). BSIS use enables the acquisition of market-facing information that serves as a key resource to guide the design and development of new products or services with desirable features that effectively meet needs of customers (Saldanha et al. 2017). Additionally, effective forecasting of demand for new product or service offerings (Yao et al. 2013) and timely introduction of new products or services (Tambe et al. 2012) can be aided by access to information obtained via BSIS use. In summary, BSIS use has strong linkages to a firm’s innovation activity. Yet, at the same time, BSIS use can also be a source of information overload on which we eleborate next.

IS Use and Information Overload

In the IS literature, information overload has been mainly studied in behavioral and design science research traditions (e.g., Chandra et al. 2019; Dang et al. 2012; Sahoo et al. 2012; Stich et al. 2019). In behavioral IS research, individual use of certain types of IS has been identified to be associated with information overload. For example, employees’ use of enterprise systems has been found to expose them to more information than they can efficiently handle (Ragu-Nathan et al. 2008; Tarafdar et al. 2010). E-business websites and email systems have also been identified as sources of information overload (Cenfetelli and Schwarz 2011). In the innovation context, individual use of electronic brainstorming systems to generate ideas has also been found to be associated with information overload (Grisé and Gallupe 2000). Adverse consequences of information overload on individual users that have been identified in the prior literature include dissatisfaction, stress, and frustration (Ragu-

Nathan et al. 2008). For example, when IT use exceeds what individuals desire, the IS use behaviors become stressful because of overload associated with over-acquisition of information (Stich et al. 2019). Information overload is a source of technostress that hinders an individual's creativity and innovation (Chandra et al. 2019).

Design science research has provided insights into the design of technological features that can enable individuals to cope with information overload. Traditionally, the progress made in neural network techniques (e.g., effective classification) can address information overload in the analysis of high-dimensional data (Lin et al. 2000). Recommendation systems have not only been found to reduce information overload, but also provide personalized recommendations in a wide variety of tasks (Adomavicius and Tuzhilin 2005, Sahoo et al. 2012). Along similar lines, visual frameworks have been developed for search engines to alleviate information overload in knowledge discovery (Chung et al. 2005). Automatic document-clustering techniques (e.g., effective categorization) are also proposed for dealing with increasing volume of online documents (Wei et al. 2006). More recently, effective search support is being designed by combining functionalities to locate, integrate, and present information to help individuals deal with overload (Dang et al. 2012).

In IS strategy research, to the best of our knowledge, there is relatively scant conceptual work on how firms can cope with information overload (e.g., Hemp 2009). As decision makers of a firm that has to contend with information overload, they are exposed to more irrelevant information that hurts efficiency of their decision making. Employees of a firm can also use various system-wide technological filters and institute various behavioral norms, such as limiting the use of "Reply-All" feature, to cope with information overload in their emails systems (Hemp 2009). Although research has identified technological features for individuals to cope with overload, there is a need for empirical research on firm-level capabilities to cope with overload from IS use.

Problemistic Search for Innovation

Innovation is an activity with inherently uncertain outcomes that cannot be predicted accurately *ex ante* (Nelson and Winter 1982) and thus necessitates search for new products or services. In the innovation activity, knowledge workers are required to engage in *problemistic search* to solve specific problems (e.g., Argote and Greve 2007; Cyert and March 1963). In particular, knowledge workers involved in the innovation activity are often confronted with vast amount of information obtained via BSIS use and thus coping with information overload is one such specific problem with which knowledge workers often grapple. Knowledge workers engaged in problemistic search are goal-directed and motivated to leverage knowledge with the express purpose of solving a specific problem (Greve 2003; Salge et al. 2015). By focusing the search for innovation on knowledge in the specific domains pertinent to solve current problems, knowledge workers are not required to attend to all the information they encounter. In doing so, knowledge workers can filter and interpret only a subset of information relevant to the goals at hand for innovation (Barber and Odean 2008).

Although past work underscores the importance of goal-directed problemistic search, it has conceived this search to primarily occur within firm boundaries (e.g., Greve 2003; Salge et al. 2015). Motivated by the need not only to collect information from customers and suppliers via BSIS use, but also to leverage their expertise in filtering and interpreting this information, we relax the constraint of goal-directed problemistic search being carried out within a firm's boundaries. We propose that problemistic search for innovation, which leverages information collected via BSIS use, may be executed effectively by digitally engaging customers and suppliers. In summary, we extend the concept of problemistic search (Argote and Greve 2007; Cyert and March 1963) by conceptualizing digitally enabled, boundary-spanning problemistic search between a firm and its customers and suppliers as a goal-directed search for solving specific problems related to innovation. The setting where firms are experiencing IO-BSIS is appropriate to examine the efficacy of boundary-spanning problemistic search capabilities in facilitating innovation while coping with IO-BSIS.

CPS Capability

We define the *CPS capability with customers (CPS-C)* as a firm's ability to digitally collaborate with its customers to filter and interpret market-facing information in its search for new products or services. Because CPS-C enables engagement with a firm's customers, CPS-C facilitates *downstream collaboration*. Similarly, we define the *CPS capability with suppliers (CPS-S)* as a firm's ability to digitally collaborate with its suppliers to filter and interpret market-facing information in its search for new products or services. Because CPS-S enables engagement with only a firm's suppliers, CPS-S differs from CPS-C in terms of the business partners involved in collaboration and thereby facilitates *upstream collaboration*.

We theorize an interactive model between downstream CPS-C and upstream CPS-S because engaging both a focal firm's customers and suppliers in filtering and interpreting information can improve the focus of a firm's innovation activity. The interaction of CPS-C and CPS-S can also enable a firm to better understand market needs for new products or services and accordingly address these needs through the incorporation of desirable features and determination of appropriate volume and timing of their offerings. We define the interaction of downstream CPS-C and upstream CPS-S as the *cross-stream CPS effect*. The interaction of downstream CPS-C and upstream CPS-S for filtering and interpreting information is synergistic as it combines insights from customers and suppliers in focusing on and making sense of the most relevant information for innovation. The theoretical justification for synergies between CPS-C and CPS-S pertains to knowledge reinvigoration.

Knowledge is a vital resource for innovation (Cohen and Levinthal 1990). From the perspective of knowledge that is used in the innovation activity, firms can vary on two dimensions by 1) exploiting internal knowledge and 2) exploring market-facing information obtained from their external environment. Proposing that reinvigoration of internal knowledge is critical for innovation, Nonaka and Takeuchi (1995, p. 6) observe that

> *"…innovation is [often due to the] linkage between the outside and the inside. Knowledge from the outside is shared widely within the organization… [and is] utilized by those engaged in developing new products… This conversion — from the outside to inside and back outside in the form of new products — is the key… internal and external activity fuels innovation..."*

Extending this theoretical logic, we propose that collaboration with business partners across the supply chain requires firms to reexamine their internal knowledge in the light of market-facing information obtained from their external environment. Reinvigoration of internal knowledge owing to collaboration with external partners (Nonaka and Takeuchi 1995), and collaboration on one side of the supply chain (e.g., customers) ultimately also enhances collaboration between the firm and its partners on the other side of the supply chain (e.g., suppliers). Thus, collaboration with both customers and suppliers facilitates reinvigoration of internal knowledge, and thus CPS-C and CPS-S can be synergistic for firm innovation.

THEORY DEVELOPMENT

Our research model is shown in Figure 1. The model suggests that the interaction of CPS-C and CPS-S has a positive effect on innovation outcomes (H1). When the IO-BSIS is taken into account, however, the interaction of CPS-C and CPS-S has a positive effect on innovation outcomes in the presence of IO-BSIS (H2) and a negative effect on innovation outcomes in the absence of IO-BSIS (H3).

We integrate research on knowledge reinvigoration (Nonaka and Takeuchi 1995) with research on synergies (Tanriverdi 2006; Nevo and Wade 2010) to theorize that the cross-stream CPS effect is on average beneficial for innovation given that firms are now increasingly experiencing information overload (Hemp 2009). In particular, we suggest that the interaction of CPS-C and CPS-S is synergistic for innovation such that each capability is likely to amplify the effect of the other capability on innovation outcomes.

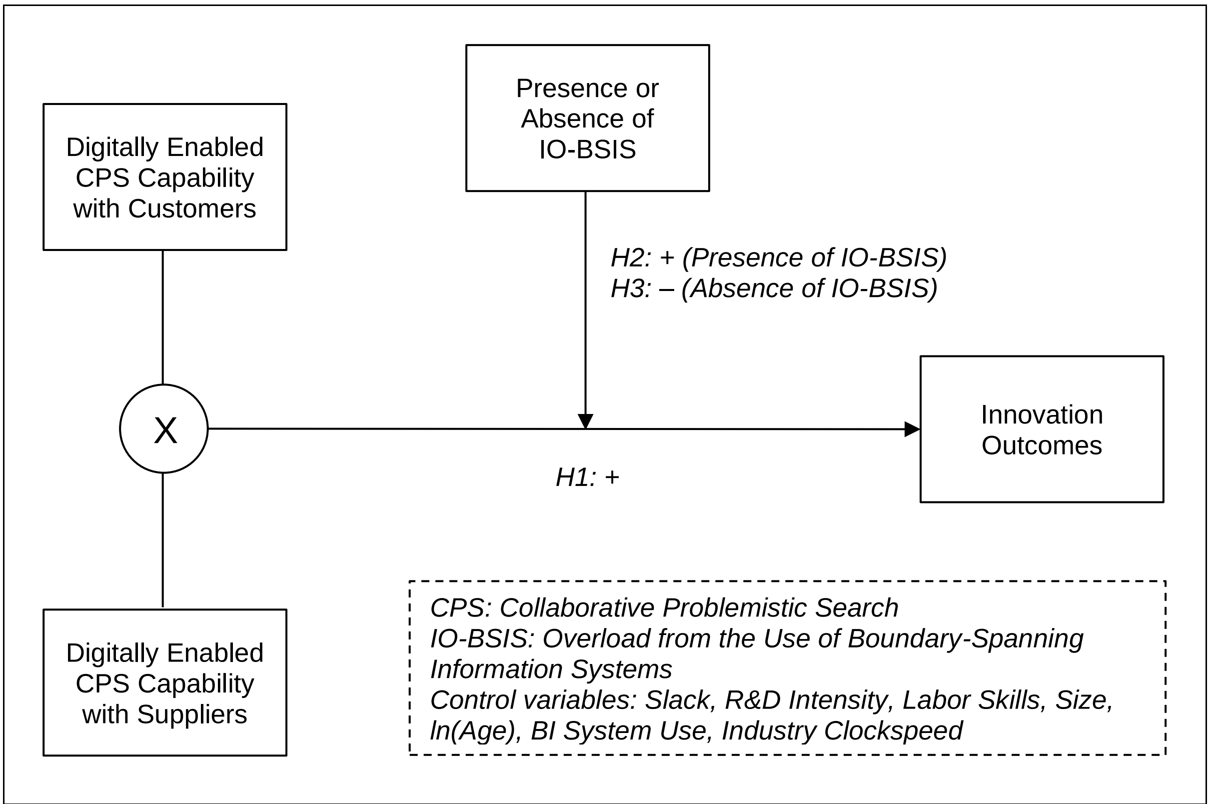

Figure 1. Research Model

We suggest two reasons for why the effect of CPS-C on innovation outcomes is likely to be amplified by CPS-S. First, although new ideas for desirable product features may be identified by a firm via CPS-C, there is a need to prioritize ideas generated in collaboration with customers by focusing on the feasibility of these ideas. This is where engaging suppliers to evaluate ideas from customers can be helpful, as suppliers with domain-specific product design expertise can weed out infeasible ideas and provide insights for prioritizing new ones (e.g., Huston and Sakkab 2006; Tambe et al. 2012). Early identification of infeasible ideas is less effective if a firm only develops CPS-C. Supplier involvement, enabled by CPS-S, is vital for a firm's search for technologically feasible new product features and can complement the effect of CPS-C on innovation outcomes.

Second, CPS-S complements CPS-C by enabling a firm to identify cost-effective ideas from customers for its new product and service offerings. Suppliers with product manufacturing experience contribute a deep understanding of cost effectiveness of individual components and overall cost implications of interrelated product design and production choices (Yao et al. 2013). Thus, incorporating suppliers' domain-specific product manufacturing knowledge (Subramani 2004) allows a firm to differentiate between ideas based on their relative cost effectiveness, thereby identifying cost-effective ideas. Such a sharpened focus on ideas for new product design that considers total costs is less likely to be achieved if a firm only develops CPS-C. Thus, CPS-S complements CPS-C because suppliers' manufacturing experience enables a firm to effectively identify cost-effective new product and service offerings.

At the same time, we suggest two reasons why the effect of CPS-S on innovation outcomes is amplified by CPS-C. First, accurately forecasting the underlying volume of demand for new products or services is critical for innovation (Aviv 2001). CPS-S enables a firm to generate precise demand estimates for new products or services based on inputs from suppliers. Supplier inputs can be augmented with customer involvement, as customers represent end users in the marketplace and thus are well positioned to infer quantities in which the new products or services will be consumed. A firm that develops both CPS-C and CPS-S can therefore improve its forecasts of market demand for new products or services (Saldanha et al. 2017; Saraf et al. 2007). Overall, CPS-C can amplify the effect of CPS-S on innovation outcomes by synergistically improving the accuracy of estimated demand for new product or service offerings.

Second, the timely introduction of products or services to the marketplace is critical for the success of innovation activity (Kessler and Chakrabarti 1996). Incorporating customers' inputs can be useful in making decisions pertaining to the timing of introduction of new products or services (Nambisan 2002; Tambe et al. 2012). CPS-S enables a firm to engage its suppliers to identify opportune times to introduce new product or service offerings, and CPS-C enables a firm to engage its customers who are knowledgeable about the market to better filter and interpret information related to the timing of product launches. CPS-C thus amplifies the overall effect of CPS-S on innovation outcomes by improving the timing of new product or service launches. Operating under the assumption that most firms experience IO-BSIS, we theorize that CPS-C and CPS-S are complementary in filtering and interpreting market-facing information, thereby jointly enhancing the focal firm's innovation outcomes.

H1: The interaction of digitally enabled CPS capability with customers and digitally enabled CPS capability with suppliers will have a positive effect on innovation outcomes.

In the presence of IO-BSIS, firms can benefit from the cross-stream CPS effect for innovation. We make this claim for two reasons. First, in congruence with research on bounded rationality (e.g., Simon 1996), we suggest that firms facing IO-BSIS experience an acute need to filter the abundant market-facing information to which they are exposed. The synergies of CPS-C and CPS-S enable firms to obtain inputs from both customers and suppliers in filtering the market-facing information obtained via BSIS use. By incorporating collaborative inputs from customers and suppliers, knowledge workers in firms facing IO-BSIS are not required to attend to all the information they encounter in the innovation activity and can thus easily leverage the most relevant information for innovation.

Second, when a firm experiences IO-BSIS, decision making for innovation is likely to suffer, as it becomes more challenging for boundedly rational knowledge workers to make sense of vast amount of market-facing information. In general, sensemaking underlies effective decision making, as has been found to be the case in a number of complex problem domains (e.g., Weick et al. 2005). For example, employees' sensemaking of features of a BSIS (e.g., using CRM system features) has been found to inform their decision making on how to leverage system features innovatively to create value (e.g., Hsieh et al. 2011). In the presence of IO-BSIS, synergies between CPS-C and CPS-S enable knowledge workers to effectively involve both their customers and suppliers for making sense of market-facing information. When firms are experiencing IO-BSIS, their knowledge workers' sensemaking of market opportunities for new products or services is aided to a greater extent by the cross-stream CPS effect. When co-present, CPS-C and CPS-S enable firms to cope with IO-BSIS by engaging both their customers and suppliers for efficiently making sense of abundant market-facing information. In summary, we theorize that the cross-stream CPS effect will be particularly beneficial for innovation in the presence of IO-BSIS.

H2: In the presence of IO-BSIS, the interaction of digitally enabled CPS capability with customers and digitally enabled CPS capability with suppliers will have a positive effect on innovation outcomes.

In contrast, in the absence of IO-BSIS, we theorize that the cross-stream CPS effect is likely to do more harm than good for innovation. We make this claim for two reasons. First, in the absence of IO-BSIS, the information environment for innovation within the firm is likely to be much simpler as firms are often dealing with less diverse information from relatively fewer sources (e.g., Leiponen and Helfat 2010; Tambe et al. 2012). If needed, knowledge workers in firms not experiencing IO-BSIS are likely to find it easier to unilaterally filter the limited information obtained via BSIS use. Such a simpler information environment with limited amount of information is not likely to be overwhelming — even for boundedly rational knowledge workers (e.g., Simon 1996). In such a simpler information environment, however, the development of collaborative capabilities could be onerous and costly (e.g., Kohli and Melville 2019). The inclusion of collaborative inputs from both customers and suppliers is likely to unnecessarily complicate knowledge workers' information processing in the innovation activity (e.g., Foss 2003); developing the cross-stream CPS effect can thus be counterproductive for innovation. Firms not facing IO-BSIS are likely to be inefficient in filtering information obtained via BSIS use if they are unnecessarily required to collaborate with their customers and suppliers.

Second, in firms that do not experience IO-BSIS, knowledge workers can singlehandedly make sense of the limited and simple information obtained via BSIS use. In the absence of IO-BSIS, unnecessary collaborative inputs from both customers and suppliers may not create “partnering synergy” (e.g., Venkatesh and Bala, 2012) and, in the worst case, can even constrain the focal firm’s decision-making discretion for innovation. Unnecessary external advice on innovation decisions can restrict managerial discretion and arguably lead to detrimental decisions (e.g., He and Wang 2009). Further, lack of discretion can stifle innovation by discouraging creativity (Majumdar and Marcus 2001; Mumford 2000). The involvement of both customers and suppliers in a simpler information environment could unnecessarily introduce conflicting viewpoints that can obfuscate a firm’s interpretation of the market-facing information obtained via BSIS use. Overall, firms not facing IO-BSIS may find it inefficient to make their innovation decisions collaboratively with their customers and suppliers. In summary, we theorize that the cross-stream CPS effect is likely to be detrimental to innovation in the absence of IO-BSIS.

H3: In the absence of IO-BSIS, the interaction of digitally enabled CPS capability with customers and digitally enabled CPS capability with suppliers will have a negative effect on innovation outcomes.

METHOD

Data

We use survey data collected from a sample of 227 U.S. firms to test our model. To facilitate data collection, we recruited a reputed market research firm[2]. Because a firm’s

[2] ResearchNow (www.researchnow.com).

innovation activity can vary across different lines of business[3], we worked with the market research firm to establish our sampling frame to be where a majority of firms (i.e., greater than 70%) were operating in a single line of business with a single line of business contributing greater than 80% of their sales. We worked closely with the market research company to ensure that our sample included a mix of small and large firms as well as firms from industries with a fast pace of innovation (i.e., high clockspeed[4]) and slower pace of innovation (i.e., low clockspeed) (see Table 2). We used Fine's (1998) classification of industry clockspeed to select high and low clockspeed industries[5].

When developing the measurements of all our constructs, we employed three strategies to achieve good reliability and validity. First, we used two-stage Q-sorting including unstructured Q-sorting in the first stage followed by structured Q-sorting in the second stage (e.g., DeVellis 1991). Two-stage Q-sorting is useful for determining if 1) all facets of a construct are measured (i.e., content validity) and 2) measurement items belong to the construct that they were intended to measure (i.e., convergent validity), and 3) measurement items are distinguishable from measures of other constructs (i.e., discriminant validity). We recruited a total of nine raters who were PhD students in IS at a research university. In two rounds of sorting, they correctly classified 87% and 95% of items into intended constructs suggesting good validity of our measurements. We excluded items that were incorrectly classified in the Q-sorting process.

Second, the resulting items were peer reviewed by a panel of ten academics with expertise in IS and innovation research. They assessed the content validity of measurement

[3] A single-line business firm can develop and sell a group of closely related products (Kotler and Amstrong 1989, p. 639), by relying on its innovation activity for that line of business.
[4] We used industry clockspeed to sample firms from more and less innovative industries. In line with prior literature (Fine 1998), we considered clockspeed at the industry level.
[5] To develop the taxonomy of high and low clockspeed firms, Fine (1998) recruited a panel of management and industry experts across different industries to evaluate clockspeed at the industry level. Consensus was achieved across the panel of experts in rating high vs. low clockspeed for a number of industries. Details can be found in "Appendix: Measuring Clockspeeds" of Fine (1998, p. 237-240).

items again, as well as the format, appearance and organization of the questionnaire. Based on their comments, further improvements were made to the questionnaire.

Table 2. Sample Description

Respondent Title	N	Firm Type	N	Total Sales (Thousands of USD)	N	Industry Clockspeed	N	Industry Sector	N
President/ chairman	17	Private firms	180	50-100	6	High clockspeed industries	92	Computer hardware and services	49
VP	17			101-500	15			Electronics and telecommunication	43
CEO/CFO	29	Public firms	47	501-1000	16	Low clockspeed industries	135	Food and beverages	9
CIO	35			1001-5000	31			Chemicals and pharmaceuticals	14
Senior manager	34			5001-10,000	38			Transport and logistics	16
General manager	33			10,001-50,000	42			Retail	21
Director	32			50,001-100,000	27			Business services	61
Others	30			100,000+	52			Energy and mining	14
Total	227	Total	227	Total	227	Total	227	Total	227

Finally, the questionnaire was pilot tested in 29 U.S. firms to assess the clarity in wording of measurement items and whether the items for a construct captured variance in the construct. The pilot test resulted in refinement of some items. Given that our survey questions focus on digitally enabled, firm-level capabilities to facilitate innovation, presidents, vice presidents (VPs), chief executive officers (CEOs), chief financial officers (CFOs), chief information officers (CIOs), and other senior managers were chosen as survey respondents. The pilot test confirmed that these respondents were knowledgeable about the innovation activity and thus suitable candidates to answer our questionnaire.

Following Podsakoff et al.'s (2003) recommendations to safeguard against common method bias during data collection, we randomized the order of questions and used different scales in the questionnaire. After the data collection was completed, we employed three strategies to validate our data by focusing on the responses to three questions: 1) firm employment, 2) firm age, and 3) a measurement item for innovation outcomes — the number of granted patents for which we collected additional archival data from independent sources.

First, we validated self-reported data provided by respondents on the number of employees with employment data that we independently collected from an archival database. Specifically, we merged our data with the Standard and Poor's Compustat database for 47 public firms in our sample by using firm names reported by the survey respondents. We found a significant and positive correlation between our survey data and archival data on firm employment ($r = 0.42$, $p < 0.001$) that supported the validity of our data.

Second, for both public and private firms in our sample, we collected data for the year they were established from three independent sources: 1) companies' websites, 2) companies' Wikipedia profiles, and 3) Google news and other online news. By searching company names reported by our respondents, we could identify the year of establishment for 143 firms in our sample and calculate their ages. We found a statistically significant and positive correlation between our survey data and the data collected from other sources ($r = 0.33$, $p < 0.001$), providing evidence of the validity of our survey data.

Third, we validated a key measurement item for innovation outcomes — the number of granted patents in a firm's focal line of business — by collecting patent data from the U.S. Patent and Trademark Office (USPTO) at the firm level. By searching the company names reported by the survey respondents, we obtained patent data for 213 firms in our sample from USPTO. While our survey data about patents were collected at the business line level and archival patent data were provided at the firm level, we still found a statistically significant and positive correlation between the two sources ($r = 0.30$, $p < 0.001$), suggesting that our measurement item for the dependent variable was valid.

By examining correlations between all constructs, we found that common method bias was not a concern because not all correlations were statistically significant. We formally assessed common method bias by conducting the marker variable test. We followed Lindell and Brandt's (2001, p. 118) and Malhotra et al.'s (2006, p. 1868) recommendation to assess common method variance using the second smallest positive correlation as a proxy for common method variance. Thus, the second smallest positive correlation (i.e., 0.01) was used as the proxy of common method variance to calculate partial correlations among constructs by partialling out the common method variance. Compared to the zero-order correlations between constructs, the partial correlations did not materially change in their magnitude and significance level.

Measures

We established the temporal frame of reference for each of our measures to safeguard against reverse causality. Specifically, we measured CPS capabilities and all the control variables as the average level spanning three previous years (2011-2013), while we measured the dependent variable innovation outcomes in the last year (2013). We used multiple items to measures INNO, CPS-C and CPS-S. Respective items for each of these constructs tap into the same theoretical concept and demonstrate high inter-item correlations, with measures of each of these constructs exhibiting correlations greater than 0.7. We thus used equal weighting of items to compute linear composites as measures of the constructs. An equal weighting scheme has the advantages of comparability across studies and safeguarding against weights being idiosyncratic to the sample and capitalizing on chance (Hair et al. 1995). Moreover, linear composite scores based on different weighting schemes have been found to be highly correlated when items are highly correlated (Rozeboom 1979). Next, we describe all the items that we developed to measure each construct (see Table 3).

INNO: Because the number of patents is highly correlated with the number of new products or services (Joshi et al. 2010), we considered both forms of innovation before and after commercialization by using a total of four items to measure INNO. Specifically, we measured the number of new products or services using two 7-point items (1 = none; 7 = more than 100) capturing total number of new or substantially improved products or services that a firm developed and introduced to market in the past one year (Joshi et al. 2010; Tambe et al. 2012). We measured the number of patents using two 7-point items (1 = none; 7 = more than 100) capturing total number of patents that the firm applied for and were granted in the past one year (Kleis et al. 2012; Xue et al. 2012).

Table 3. Summary of Measures

Construct	Measurement Items	Scale
CPS Capability with Customers (CPS-C)	Digitally enabled collaboration with *customers* to filter information about market needs for new products/services	5-point scale: 1 = no collaboration; 5 = very extensive collaboration
	Digitally enabled collaboration with *customers* to estimate the volume for new products/services	
	Digitally enabled collaborations with *customers* to identify the timing of market needs for new products/services	
	Digitally enabled collaboration with *customers* to reinvigorate your knowledge about desirable features for new products/services	
	Digitally enabled collaboration with *customers* to develop new products/services with enhanced features	
CPS Capability with Suppliers (CPS-S)	Digitally enabled collaboration with *suppliers* to filter information about market needs for new products/services	5-point scale: 1 = no collaboration; 5 = very extensive collaboration
	Digitally enabled collaboration with *suppliers* to estimate the volume for new products/services	
	Digitally enabled collaborations with *suppliers* to identify the timing of market needs for new products/services	
	Digitally enabled collaboration with *suppliers* to reinvigorate your knowledge about desirable features for new products/services	
	Digitally enabled collaboration with *suppliers* to develop new products/services with enhanced features	
Innovation Outcomes (INNO)	Number of patent applications	Count scale created by assigning a score at the midpoint of 7-point scale (1 = none; 2 = 1; 3 = 2-5; 4 = 6-10; 5 = 11-50; 6 = 51-100; 7 = 100+): none as 0; 1 innovation as 1; 2-5 innovations as 3; 6-10 innovations as 8; 11-50 innovations as 30; 51-100 innovations as 75; 100+ innovations as 100
	Number of granted patents	
	Number of new products/services you developed but not introduced to the market	
	Number of new products/services you introduced to the market	
Slack	Extent to which you had extra resources that could be used for purposes other than day-to-day operations	5-point scale: 1 = not at all; 3 = to some extent; 5 = to a very large extent
R&D Intensity	Your R&D expenditure as a percentage of total sales	7-point scale: 1 = 0%; 2 = 1-3%; 3 = 4-6%; 4 = 7-9%; 5 = 10-15%; 6 = 16-20%; 7 = 20%+
Labor Skills	Average percentage of employees primarily responsible for developing new products/services	7-point scale: 1 = 0%; 2 = 1-19%; 3 = 20-39%; 4 = 40-59%; 5 = 60-79%; 6 = 80-99%; 7 = 100%
	Average percentage of employees who are experts	
	Average training expenditure for human capital development as a percentage of total sales	
Size	Total sales	8-point scale: 1 = 50-100; 2 = 101-500; 3 = 501-1,000; 4 = 1,001-5,000; 5 = 5,001-10,000; 6 = 10,001-50,000; 7 = 50,001-100,000; 8 = 100,000+ (thousands of USD)
ln(Age)	Natural logarithm of number of years from registration to 2013	Continuous
Business Intelligence (BI) System Use	Your company used BI systems to filter information from customers and suppliers to manage information overload for developing new products/services	0 = no; 1 = yes
Industry Clockspeed	High or low industry clockspeed according to Fine (1998)	0 = low; 1 = high
Information Overload from Boundary-Spanning IS Use (IO-BSIS)	Amount of information you collected through CRM and SCM systems respectively for developing new products/services was 1) more than needed, 2) more than can be handled effectively, 3) a source of overload	Dichotomizing based on mean scores of 7-point Likert scale (1 = strongly disagree; 4 = neither disagree or agree; 7 = strongly agree): 0 = firms not facing IO-BSIS if mean scores < 4 from both CRM and SCM system use; 1 = firms facing IO-BSIS if mean scores > 4 from CRM and/or SCM system use

To alleviate potential measurement errors, we used a 7-point scale as it is challenging for respondents to report precise numbers but they are often able to identify a range in which the numbers fall. To more accurately represent the scale of variation in the number of innovation outcomes across firms, we computed the mean score of the four items and assigned a score at the midpoint for each closed interval (e.g., Rai and Patnayakuni 1996). By doing so, we rescaled the responses as follows: 0 for a response of no innovation; 1 for a response of 1 innovation; 3 for a response of 2-5 innovations; 8 for a response of 6-10 innovations, 30 for a response of 11-50 innovations, 75 for a response of 51-100 innovations, and 100 for a response of 100+ innovations.

CPS-C: Drawing on past research on how a firm digitally collaborates with its customers (e.g., Malhotra et al. 2005; Nambisan 2002; Saldanha et al. 2017; Saraf et al. 2007), we developed a five-item measure to capture a firm's digitally enabled collaboration with its customers for problemistic search. These items tapped into underlying motivations guiding digitally enabled collaboration between a focal firm and its customers: 1) filtering information about market needs with customers, 2) estimating the volume of new product and service offerings with customers, 3) identifying the timing of market needs with customers, 4) reinvigorating knowledge about desirable features with customers, and 5) developing new products or services with enhanced features with customers. Each of these items was measured as the extent of collaboration using a 5-point scale (1 = no collaboration; 5 = very extensive collaboration) between the firm and its customers in the past three years. We computed the mean score of these five items to measure CPS-C.

CPS-S: Drawing on past research on how a firm digitally collaborates with its suppliers (e.g., Patnayakuni et al. 2006; Rai et al. 2006; Subramani 2004; Yao et al. 2013), we developed a five-item measure to capture a firm's digitally enabled collaboration with its suppliers for problemistic search. These items tapped into underlying motivations guiding digitally enabled collaboration between a focal firm and its suppliers: 1) filtering information about market needs with suppliers, 2) estimating the volume of new product and service offerings with suppliers, 3) identifying the timing of market needs with suppliers, 4) reinvigorating knowledge about desirable features with suppliers, and 5) developing new products or services with enhanced features with suppliers. Each of these items was measured as the extent of collaboration using a 5-point scale (1 = no collaboration; 5 = very extensive collaboration) between the firm and its suppliers in the past three years. We computed the mean score of these five items to measure CPS-S.

IO-BSIS: We used a binary variable to indicate firms facing IO-BSIS (value = 1) and firms not facing it (value = 0). Using a 7-point Likert scale (1 = strongly disagree; 4 = neither disagree or agree; 7 = strongly agree), we asked respondents to indicate the degree to which information collected via use of CRM or SCM systems was 1) more than needed, 2) more than what could be efficiently used, and 3) a source of information overload in the past three years (e.g., O'Reilly III 1980; Malhotra 1982; Cenfetelli and Schwarz 2011). Due to the necessity of conducing a split sample analysis to test H2 and H3 (to be explained later), we created two groups of firms facing IO-BSIS and firms not facing IO-BSIS. We used the three items discussed above to assess the presence or absence of IO-BSIS in our sample. Firms with a mean score of these three items greater than 4 for *either* CRM *or* SCM system use were facing IO-BSIS (N = 164), and those with a mean score smaller than 4 for *both* CRM *and* SCM systems use were not facing IO-BSIS (N = 63). For firms with a mean score equal to 4 for *both* CRM *and* SCM systems use (N = 22), it was unclear about the presence of IO-BSIS so they were removed from the final sample. In our sample, 73% firms reported the presence of IO-BSIS (N = 164), of which 9% experienced information overload from CRM system use only (N = 20), 8% experienced information overload from SCM system use only

(N = 18), and 56% experienced information overload from both CRM and SCM systems use (N = 126).

Control Variables

Because search for innovation may also be triggered by slack resources (Cyert and March 1963; Greve 2003), we controlled for a firm's *slack* by relying on a 5-point scale (1 = not at all; 5 = to a very large extent) to measure the extent to which a firm had extra resources that could be used for purposes other than day-to-day operations (Nohria and Gulati 1996; Wang et al. 2016). We controlled for a firm's *R&D intensity* by relying on a 7-point item (1 = 0%; 7 = greater than 20%) to capture the firm's R&D expenditure as a percentage of its total sales (Cohen and Levinthal 1990). We further controlled for a firm's *labor skills* by relying on the mean score of the following three items with a 7-point scale (1 = 0%; to 7 = 100%): 1) the percentage of employees who were primarily responsible for developing new products or services, 2) the percentage of employees who were experts, and 3) the average training expenditure for human capital development as a percentage of total sales (Bapna et al. 2013). Again, an equal weighting scheme was used to compute a linear composite score for labor skills. We also controlled for *firm size* by using an 8-point scale with a specified range of sales at each interval (1 = 50-100; 8 = more than 100,000 thousand USD)[6] (Cohen and Klepper 1996). We controlled for *firm age* by computing the natural logarithm of the number of years since the firm was established till 2013 (Huergo and Jaumandreu 2004). To rule out alternative explanations, we also controlled for a firm's *business intelligence (BI) system use* by relying on a binary scale (0 = no; 1 = yes) to measure if BI systems were used to manage information overload for developing new products or services (Chen et al. 2012). Finally, we controlled *industry clockspeed* by using a binary variable (0 = low clockspeed; 1 = high

[6] Recalling precise sales of a firm in the past three years can be difficult for respondents. Thus, to assist our respondents, we measured the average sales of a firm in the past three years by using a scale with 8 intervals.

clockspeed) (Fine 1998). This classification was developed by a panel of management and industry experts who were familiar with the pace of innovation across industries, provided in "Appendix: Measuring Clockspeeds" by Fine (1998, p. 237-240).

RESULTS

Table 4 presents descriptive statistics and correlations of our variables. H1 proposes the cross-stream CPS effect, namely the interaction of CPS-C and CPS-S, exerts a positive effect on INNO. We calculated the interaction term of CPS-C and CPS-S by multiplying CPS-C and CPS-S at the construct level. CPS-C and CPS-S are conceptually distinct and so are their measurement items — those for CPS-C capture activities jointly conducted between a firm and its customers only, and the items for CPS-S capture activities jointly conducted between a firm and its suppliers only. Yet, we observed a high correlation between CPS-C and CPS-S ($r = 0.81$) suggesting that many firms develop both CPS capabilities[7].

Table 4. Descriptive Statistics and Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) INNO											
(2) CPS-C	0.12										
(3) CPS-S	**0.28**	0.00									
(4) Slack	**0.26**	0.07	**0.55**								
(5) R&D Intensity	**0.23**	0.12	**0.49**	**0.49**							
(6) Labor Skills	**0.24**	0.07	**0.37**	**0.28**	**0.34**						
(7) Size	**0.16**	-0.01	**0.18**	0.04	**0.18**	0.05					
(8) ln(Age)	0.02	-0.06	-0.06	**-0.13**	-0.03	-0.11	**0.26**				
(9) BI System Use	**0.17**	**0.16**	**0.40**	**0.43**	**0.43**	**0.28**	0.01	-0.11			
(10) Industry Clockspeed	**0.19**	0.11	0.09	0.02	0.07	**0.17**	0.12	-0.05	**0.13**		
(11) IO-BSIS	**0.18**	0.04	**0.39**	**0.37**	**0.32**	**0.25**	0.03	-0.03	**0.28**	0.07	
Mean	17.29	0.03	0.03	3.15	4.12	4.00	5.53	3.45	0.69	0.41	0.72
SD	24.69	0.97	1.00	0.90	1.51	1.16	1.97	0.83	0.46	0.49	0.45
Min	0	-4.17	-2.75	1	1	1.50	1	1.10	0	0	0
Max	100	3.52	1.85	5	7	7	8	6.86	1	1	1

Notes: Correlations in bold are significant at $p < 0.05$. CPS-C and CPS-S are orthogonalized.

[7] Economies of scale can explain this phenomenon. For instance, firms that develop a digital infrastructure to collaborate with customers are likely to economize on these costs and also collaborate with suppliers.

If variables in a regression model are highly collinear (e.g., $r > 0.8$), a modified Gram-Schmidt process[8] can be used to orthogonalize variables (Saville and Wood 1991; Sine et al. 2006). This technique can partial out the common variance between highly correlated variables by subtracting the vector from its projection thereby resulting in transformed variables that are uncorrelated with one another. Because orthogonalized variables and original variables have the same linear span after the transformation, this technique does not bias hypothesis testing and, at the same time avoiding multicollinearity (e.g., Golub and Van Loan 1989). Thus, we orthogonalized CPS-C, CPS-S, and the interaction term of CPS-C and CPS-S to test our hypotheses. In doing so, we found that multicollinearity is not an issue after orthogonalization by examining the variance inflation factor (VIF) and condition index (mean VIF = 1.41, maximum VIF = 1.83; mean condition index = 8.51, maximum mean condition index= 27.05).

Our dependent variable[9] (i.e., INNO) has a count scale, making ordinary least squares (OLS) model not suitable for data analysis (Greene 2003). Additionally, given that our data demonstrate overdispersion (mean = 16.55, standard deviation = 24.34), a quasi-Poisson or negative binomial model is more appropriate to analyze the data, relative to a Poisson model that assumes the equality of mean and standard variance (Greene 2003). Following the guidance from prior literature, we chose quasi-Poisson model over negative binomial model for two reasons. First, the quasi-Poisson model is a better choice for hypothesis testing and estimation of regression coefficients, whereas the negative binomial model is better suited for prediction of individual observations (Breslow 1983; Gardner et al. 1995)[10]. Second and more

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[8] A Gram-Schmidt process is a mathematical method for orthogonalizing a set of vectors in an inner product space R_n (Cheney and Kincaid 2009). Specifically, it takes a linearly independent set $S = \{v_1, v_2, ..., v_k\}$ for $k \leq n$ and generates an orthogonal set $S' = \{u_1, u_2, ..., u_k\}$ that spans the same k-dimensional subspace of R_n as S.

[9] We found consistent evidence for correlation between firm size and each of the four items used for measuring innovation outcomes.

[10] There is no formal test for choosing between quasi-Poisson and negative binomial models, as common criteria, such as Akaike information criterion (AIC) and Bayesian information criterion (BIC), cannot be used to compare quasi-models. Quasi-AIC (QAIC) can only be used to compare models within the class of quasi-models. Thus far, only a rudimentary approach is being debated — one that plots the variance-to-mean

importantly, the negative binomial model assumes that the data are generated by memoryless Poisson processes (Gardner et al. 1995) — a stringent assumption that survey data may not perfectly meet. However, quasi-Poisson model, estimated by generalized linear model (GLM), does not specify the probability distribution of the data and is thereby a generalizable model. As such, given our research objectives and the generalizable nature of quasi-Poisson model, we use a quasi-Poisson model to test our model. Quasi-Poisson model can generate unbiased, asymptotically normal estimates of regression coefficients and standard errors in the presence of overdispersion (Cox 1983, Ver Hoef and Boveng 2007).

The quasi-Poisson regression results are presented in Table 5. To begin with, we estimated a baseline model with control variables only. Slack, R&D intensity, labor skills, firm size, firm age and industry clockspeed had statistically significant and positive effects on INNO. However, BI system use does not have a statistically significant effect on INNO. Next, we estimated a downstream model that adds CPS-C to the baseline model and an upstream model that adds CPS-S to the baseline model. We found that both CPS-C (β = 0.138, $p < 0.001$) and CPS-S (β = 0.188, $p < 0.001$) had statistically significant and positive effects on INNO in the downstream and upstream models. Finally, to test H1, we estimated a cross-stream model, by including CPS-C, CPS-S and CPS-C × CPS-S. In this full model, we found that CPS-C × CPS-S had a statistically significant and positive effect on INNO (β = 0.067, $p < 0.001$). These results corroborate our theory that the cross-stream CPS effect is beneficial for INNO. Thus, H1 was supported.

relationship for model selection, which only relies on eyeballing of the plot (Ver Hoef and Boveng 2007).

Table 5. Quasi-Poisson Regression Results for Testing H1				
	DV: INNO			
	Control Model	**Downstream Model**	**Upstream Model**	**Cross-Stream Model**
CPS-C × CPS-S				0.067*** (0.019)
CPS-C		0.138*** (0.018)		0.148*** (0.019)
CPS-S			0.188*** (0.024)	0.181*** (0.025)
Slack	0.289*** (0.021)	0.290*** (0.021)	0.215*** (0.023)	0.185*** (0.023)
R&D Intensity	0.067*** (0.012)	0.063*** (0.012)	0.047*** (0.013)	0.038** (0.013)
Labor Skills	0.162*** (0.015)	0.161*** (0.015)	0.132*** (0.016)	0.131*** (0.016)
Size	0.087*** (0.009)	0.082*** (0.009)	0.076*** (0.009)	0.067*** (0.009)
ln(Age)	0.091*** (0.021)	0.092*** (0.021)	0.092*** (0.021)	0.097*** (0.021)
BI System Use	0.071 (0.046)	0.049 (0.046)	0.018 (0.046)	0.004 (0.047)
Industry Clockspeed	0.444*** (0.033)	0.428*** (0.033)	0.442*** (0.033)	0.435*** (0.033)
Constant	-0.161 (0.122)	-0.108 (0.120)	0.350** (0.137)	0.528*** (0.137)
Log Likelihood	-3046.844	-3018.761	-3015.041	-2973.513
AIC	26.915	26.676	26.644	26.295
BIC	4129.921	4079.180	4071.739	3999.533
N	227	227	227	227

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in the parentheses. CPS-C, CPS-S and CPS-C × CPS-S are orthogonalized.

In Figure 2, we plot the marginal cross-stream CPS effect by reversing the log link function of quasi-Poisson model in a continuous manner. We define mean minus one standard deviation as the low level and mean plus one standard deviation as the high level. CPS-C was more beneficial for INNO if CPS-S was high, as INNO increased to a larger extent with increasing CPS-C when CPS-S was higher than lower.

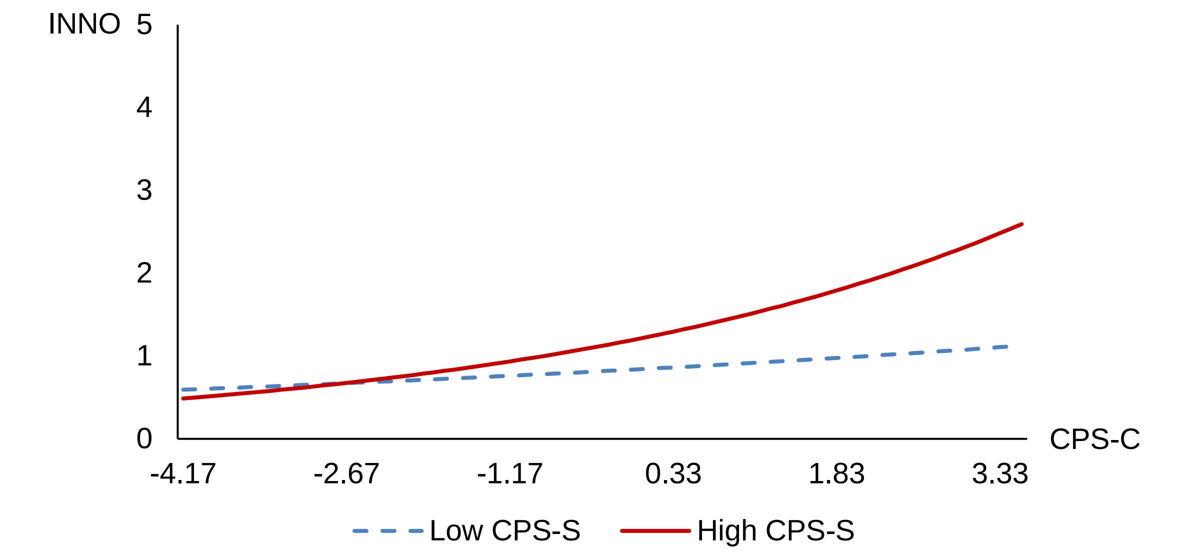

Figure 2. The Marginal Cross-Stream Effect of CPS-C and CPS-S

H2 suggested that the cross-stream CPS effect on INNO will be positive in firms facing IO-BSIS, and H3 suggested that the cross-stream CPS effect on INNO will be negative in firms not facing IO-BSIS. Because H2 and H3 predicted the cross-stream CPS effect can change direction in the presence or absence of IO-BSIS, a three-way interaction approach cannot be used to detect such flip of the sign. We therefore conducted a split-sample analysis for firms facing IO-BSIS and firms not facing IO-BSIS, respectively. A split sample analysis allows us to not only test H2 and H3, but also investigate the systematic differences between two groups of firms (Iacobucci et al. 2015). In other words, not only would the effect of CPS-C × CPS-S be different, but also the effects of other variables may be distinct across groups.

As shown in Table 6, the effects of control variables on INNO were different in a few ways. First, several control variables affect INNO in a similar manner across the two groups of firms that face and do not face IO-BSIS. Specifically, the effects of labor skills ($\beta = 0.075$, $p < 0.001$; $\beta = 0.524$, $p < 0.001$), firm size ($\beta = 0.028$, $p < 0.01$; $\beta = 0.359$, $p < 0.001$), and industry clockspeed ($\beta = 0.545$, $p < 0.001$; $\beta = 0.474$, $p < 0.001$) were statically significant and positive across both groups.

Table 6. Quasi-Poisson Regression Results for Testing H2 and H3		
	DV: INNO	
	Firms facing IO-BSIS	**Firms not facing IO-BSIS**
CPS-C × CPS-S	0.179*** (0.023)	-0.252*** (0.058)
CPS-C	0.204*** (0.021)	0.005 (0.046)
CPS-S	0.071* (0.029)	0.157* (0.061)
Slack	0.155*** (0.027)	0.129 (0.075)
R&D Intensity	0.076*** (0.014)	-0.314*** (0.041)
Labor Skills	0.075*** (0.017)	0.524*** (0.042)
Size	0.028** (0.010)	0.359*** (0.033)
ln(Age)	0.088*** (0.024)	-0.012 (0.065)
BI System Use	-0.173** (0.056)	0.528*** (0.098)
Industry Clockspeed	0.545*** (0.037)	0.474*** (0.093)
Constant	1.092*** (0.159)	-1.495*** (0.342)
Log Likelihood	-2221.138	-557.362
AIC	27.221	18.043
BIC	3054.184	731.390
N	164	63
Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in the parentheses. CPS-C, CPS-S and CPS-C × CPS-S are orthogonalized.		

Second, some control variables had statistically significant effects on INNO in only one group of firms. In particular, slack had a statistically significant and positive effect on INNO in the group of firms facing IO-BSIS ($\beta = 0.155$, $p < 0.001$) but did not affect INNO in the group of firms not facing IO-BSIS. Along similar lines, firm age had a statistically significant, positive effect on INNO in the group of firms facing IO-BSIS ($\beta = 0.088$, $p < 0.001$) but did not affect INNO in the group of firms not facing IO-BSIS.

Third, the effects of two control variables were markedly different across the two groups of firms such that the sign of the coefficients were different. In particular, R&D intensity had a statistically significant and positive effect on INNO in the group of firms that face IO-BSIS ($\beta = 0.076$, $p < 0.001$), whereas the effect of R&D intensity on INNO was statistically significant and negative in the group of firms that do not face IO-BSIS (β = -

0.314, $p < 0.001$). BI system use had a statistically significant and positive effect on INNO in the group of firms that do not face IO-BSIS ($\beta = 0.528$, $p < 0.001$), whereas the effect of BI system use on INNO was statistically significant and negative in the group of firms that face IO-BSIS ($\beta = -0.173$, $p < 0.01$). This finding suggests that technological solutions alone do not address information overload in the innovation activity and may even do more harm than good by oversimplifying the interpretation of abundant market-facing information, suggesting that collaborative capabilities might indeed be needed.

For the effects of CPS-C, CPS-S, and CPS-C × CPS-S on INNO across groups of firms in the presence or absence of IO-BSIS, the main effects of CPS-C and CPS-S were different across the two groups of firms that face and do not face IO-BSIS. CPS-C had a statistically significant and positive effect on INNO in the group of firms that face IO-BSIS ($\beta = 0.204$, $p < 0.001$) but did not affect INNO in the group of firms that do not face IO-BSIS. In contrast, the effect of CPS-S on INNO was statically significant and positive in both groups of firms that face IO-BSIS ($\beta = 0.071$, $p < 0.05$) and firms that do not face IO-BSIS ($\beta = 0.157$, $p < 0.05$). Overall, CPS-C was more important for firms facing IO-BSIS and CPS-S was more important for firms not facing IO-BSIS. More importantly, we found that the effect of CPS-C × CPS-S on INNO was statistically significant and positive in the group of firms that face IO-BSIS ($\beta = 0.179$, $p < 0.001$)[11]. Thus, H2 was supported. Additionally, the effect of CPS-C × CPS-S on INNO was statistically significant and negative in the group of firms that do not face IO-BSIS ($\beta = -0.252$, $p < 0.001$). Thus, H3 was also supported.

[11] We divided firms facing IO-BSIS into two groups with high and medium IO-BSIS. We coded firms facing overload from *both* CRM *and* SCM systems use to be in the high IO-BSIS ($N = 126$). Firms facing IO-BSIS from *either* CRM *or* SCM system use were coded to be in the medium IO-BSIS group ($N = 38$). In both these groups, we found that the interaction effect of CPS-C and CPS-S on INNO was statistically significant and positive (high IO-BSIS: $\beta = 0.307$, $p < 0.001$; medium IO-BSIS: $\beta = 0.306$, $p < 0.05$). Thus, we find consistent results to corroborate our theory that the cross-stream CPS effect is detrimental only when firms do not face IO-BSIS.

In Figure 3, we plot the marginal cross-stream CPS effect for the group of firms facing IO-BSIS by reversing the log link function of quasi-Poisson model. As seen in Figure 3, CPS-C and CPS-S were complementary for INNO. Similar to the pattern in Figure 2, the interaction effect of CPS-C and CPS-S was more beneficial for INNO when both CPS-C and CPS-S are high.

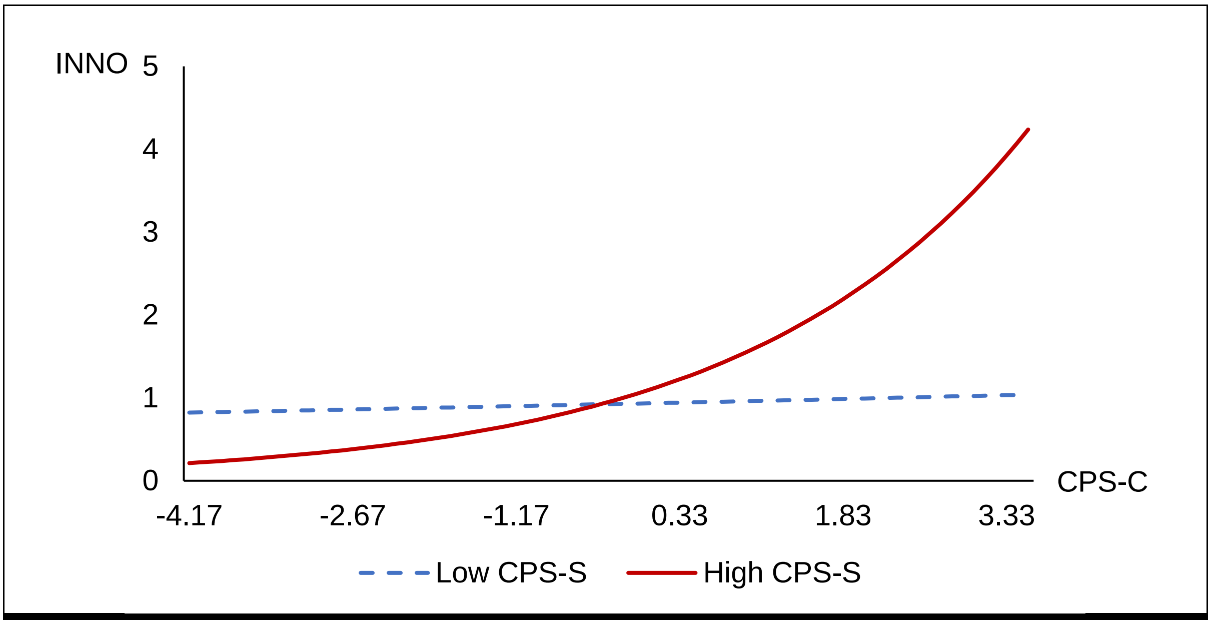

Figure 3. The Marginal Cross-Stream Effect of CPS-C and CPS-S in Firms Facing IO-BSIS

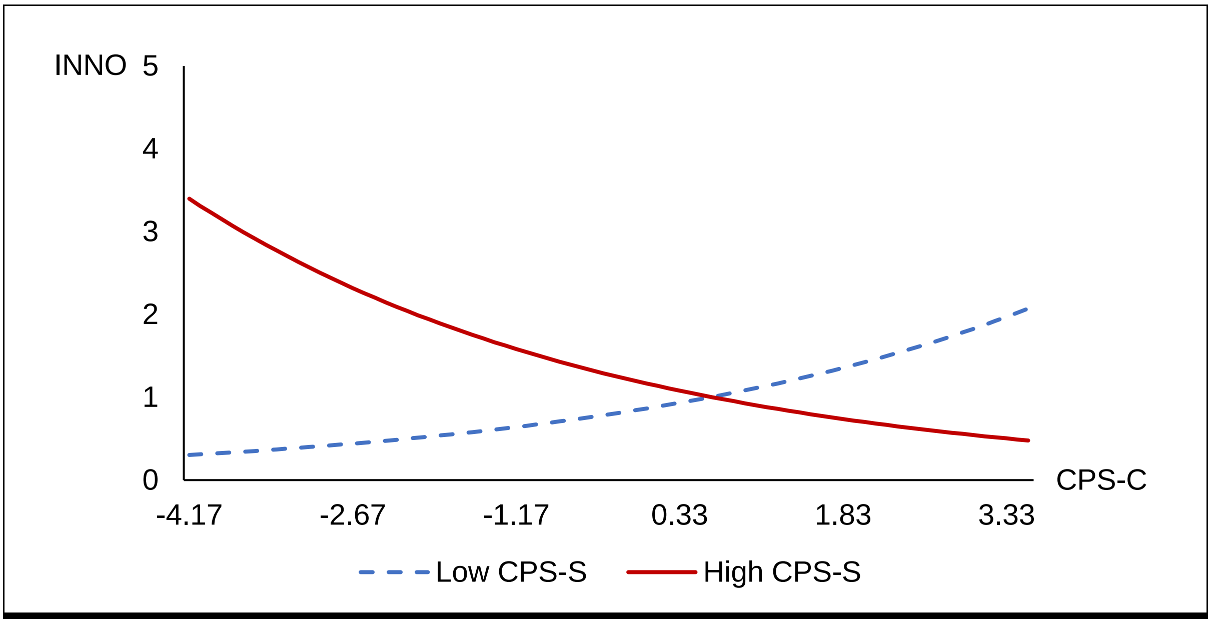

Figure 4. The Marginal Cross-Stream Effect of CPS-C and CPS-S in Firms Not Facing IO-BSIS

In Figure 4, we plot the marginal cross-stream CPS effect for the group of firms that do not face IO-BSIS by reversing the log link function of quasi-Poisson model. In contrast to Figure 3, in Figure 4, the cross-stream CPS effect was detrimental to INNO when both CPS-C and CPS-S were high, and an increase in CPS-C (CPS-S) was beneficial for INNO only if CPS-S (CPS-C) was low.

Table 7. Endogeneity Test

	DV: INNO		
	Full Sample	**Firms Facing IO-BSIS**	**Firm Not Facing IO-BSIS**
CPS-C × CPS-S	0.047* (0.019)	0.129*** (0.024)	-0.253*** (0.060)
CPS-C	0.093*** (0.019)	0.129*** (0.021)	0.006 (0.046)
CPS-S	0.101*** (0.026)	-0.031 (0.031)	0.157* (0.062)
Inverse Mills Ratio	-0.861*** (0.067)	-1.121*** (0.084)	0.015 (0.126)
Slack	0.147*** (0.023)	0.134*** (0.026)	0.129 (0.075)
R&D Intensity	0.017 (0.013)	0.049*** (0.014)	-0.314*** (0.041)
Labor Skills	0.103*** (0.016)	0.040* (0.018)	0.525*** (0.043)
Size	0.042*** (0.009)	0.002 (0.010)	0.360*** (0.035)
ln(Age)	0.099*** (0.021)	0.098*** (0.024)	-0.011 (0.065)
BI System Use	-0.130** (0.048)	-0.358*** (0.058)	0.529*** (0.098)
Industry Clockspeed	0.469*** (0.033)	0.582*** (0.037)	0.474*** (0.093)
Constant	1.708*** (0.160)	2.469*** (0.182)	-1.524*** (0.421)
Log Likelihood	-2887.890	-2125.764	-557.355
AIC	25.550	26.070	18.075
BIC	3833.712	2868.536	735.520
N	227	164	63

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in the parentheses. CPS-C, CPS-S and CPS-C × CPS-S are orthogonalized.

Finally, we tested for potential endogeneity of the CPS capability. We used the Heckman two-stage model (Heckman 1979; Shaver 1998) to examine the endogeneity of CPS-C and CPS-S. We followed and procedures of Bharadwaj et al. (2007) and created a new binary variable indicating the sum of CPS-C and CPS-S as high or low based on the mean of our sample (0 = below or equal to the mean; 1 = above the mean). In the first stage, we used a Probit model to regress this new binary variable on four items about a firm's number of customers/suppliers (9-point scale) and the maturity of digital collaborations with customers/suppliers (5-point scale), all of which were expected to influence the firm's degree of collaborative activities related to CPS-C and CPS-S. Endogeneity was accounted for by computing the inverse Mills ratio (IMR) using estimates obtained from the first stage. In the second stage, we tested our hypotheses again with the IMR as an additional control for the endogeneity of CPS-C and CPS-S. We found qualitatively similar results supporting our hypotheses, suggesting endogeneity did not bias our findings (see Table 7).

DISCUSSION AND CONCLUSION

Theoretical Implications

Our results suggest that the cross-stream CPS effect was beneficial for innovation when firms face IO-BSIS. Further, we found that the cross-stream CPS effect was detrimental to innovation when firms do not face IO-BSIS. These findings collectively provide several important theoretical implications. First, our conceptualization of the CPS capability and the cross-stream CPS effect contributes to the IS literature that formulates problemistic search to primarily operate within a firm's boundaries (e.g., Salge et al. 2015). A recent literature review on problemistic search has revealed the challenges to the original conceptualization of problemistic search and the refinements of this concept from adjacent fields are needed (Posen et al. 2018). We broaden the current thinking on problemistic search by examining the synergistic role of digitally enabled capabilities that allow a firm to engage both its customers and suppliers in problemistic search for innovation. We introduced CPS as a firm-level capability to engage external business partners in the search for innovation. The conceptualization of a new important construct has been suggested as a theoretical contribution at the highest level for empirical study (Colquitt and Zapata-Phelan 2007). In particular, we identified two CPS capabilities, CPS-C and CPS-S, that can enable firms to synergistically incorporate inputs from customers and suppliers in filtering and interpreting market-facing information generated via BSIS use. These firm-level capabilities are designed to intentionally challenge the myopic, inward focus by compelling firms to reinvigorate their internal knowledge by efficiently integrating the insights of customers and suppliers in the light of external, market-facing information generated through digital collaborations with their business partners. A key insight is that, in the presence of IO-BSIS, the synergistic effect of CPS-C and CPS-S is beneficial for innovation. Firms need to engage both customers and suppliers for reinvigorating their internal knowledge and, more importantly, for infusing their innovation activity with a goal-directed focus — relevant in the presence of IO-BSIS — for successfully developing new products or services.

One of the challenges in the search processes for solutions in complex problem domains is the risk of premature closure without engaging in adequate search to understand the problem and explore plausible solutions. Indeed, in complex innovation tasks, such as diagnosing complex medical conditions, premature closure is among the top reasons for diagnostic errors (Norman and Eva 2010). Our findings suggest that a collaborative model of innovation that leverages expertise of customers and suppliers for coping with IO-BSIS by both filtering and interpreting information generated via BSIS use is likely to be helpful in generating superior innovation outcomes.

BSIS use and digital collaboration with customers and suppliers have been found to be beneficial for innovation (e.g., Gómez et al. 2017; Kohli and Melville 2019; Ravichandran et al. 2017; Saldanha et al. 2017; Tambe et al. 2012). However, prior literature has been largely silent on the specific collaborative activities that comprise the overall innovation activity of a focal firm. Given the evidence that CPS-C and CPS-S can synergistically facilitate innovation in the presence of IO-BSIS, our findings have implications for coping with information overload by both filtering and interpreting market-facing information in collaboration with a firm’s customers and suppliers.

Second, our findings imply that, in the presence of IO-BSIS, the interaction of CPS-C and CPS-S was associated with superior innovation outcomes. Digitally enabled extroversion — that is, a firm's tendency to digitally engage with its external partners and thereby gather vast amount of market-facing information by BSIS use — has been found to be beneficial for enhancing a firm's innovation outcomes (e.g., Gómez et al. 2017; Saldanha et al. 2017; Tambe et al. 2012). Our findings enable us to discover the limits to digitally enabled extroversion and deepen our understanding of collaborative capabilities essential for managing information overload while supporting firms in achieving superior innovation outcomes. We found that, in the absence of IO-BSIS, the cross-stream CPS effect was detrimental to innovation that allows us to broaden conventional wisdom pertaining to digitally enabled extroversion given the measurement of IO-BSIS as it is pertinent to the innovation activity. This finding challenges the current thinking on the benefits of digitally enabled extroversion and suggests that, in the absence of IO-BSIS, developing collaborative capabilities with customers and suppliers can arguably be detrimental because costs of developing these boundary-spanning collaborative capabilities can exceed the potential benefits that can accrue from the cross-stream CPS effect. This finding implies, that in the absence of IO-BSIS, engaging business partners might be arguably costly, as incorporating their diverse viewpoints for innovation can hurt the ability to achieve consensus and efficiency of the overall decision making for innovation. Simpler domains that are not information-intensive do not overwhelm managers and do not necessitate collaborative inputs from customers and suppliers. A simpler system- or tool-based approach involving BI systems seems to be a better enabler of innovation in such relatively sparse information contexts. Differential effects of customer and supplier engagement are also evident from our results, as CPS-C was more important for firms facing IO-BSIS, whereas CPS-S was more important for firms not facing IO-BSIS, explained by the fact that downstream partners contribute more information as they are closer to the market (e.g., Saldanha et al. 2017; Saraf et al. 2007).

In summary, although prior research proposed how design of specific technological features can enable individuals to cope with information overload (e.g., Adomavicius and Tuzhilin 2005; Chung et al. 2005; Dang et al. 2012; Sahoo et al. 2012; Wei et al. 2006), our work explained the role of firm-level capabilities to contend with overload while engaging in innovation that require processing substantial amount of information. Our findings suggest that a collaborative model that leverages the expertise of customers and suppliers is an effective way for coping with IO-BSIS while achieving gains in innovation outcomes.

Managerial Implications

Our findings have important implications for how firms can effectively filter and interpret "big data" (McAfee and Brynjolfsson 2012) emerging from their interactions with customers and suppliers in their search for innovation. Firms can develop collaborative capabilities with their customers and suppliers to facilitate innovation in contexts where they are facing IO-BSIS. As customers and suppliers can contribute complementary perspectives (Leiponen and Helfat 2010), firms can develop capabilities to leverage complementarities to infuse their innovation activity with a goal-directed focus specifically for coping with information overload. In particular, they can collaborate with customers and suppliers for both filtering and interpreting information obtained via BSIS use and leverage the resulting insights for innovation. These capabilities can be beneficial when knowledge workers involved in the innovation activity are overwhelmed by vast amount of market-facing information, thereby challenging their attention and focus. In this scenario, a firm should plan to develop capabilities to engage both customers and suppliers in reinvigorating its internal knowledge with information filtered and interpreted through the diverse inputs from its customers and suppliers.

Before we delve into the specifics of activities for enabling boundary-spanning collaboration, we would like to point out that engaging customers and suppliers can also be costly. In particular, our findings shed light on the possible detrimental effects of (unnecessary) boundary-spanning collaboration and encourage managers to involve their business partners only when they find themselves overwhelmed in the presence of abundant market-facing information obtained via BSIS use. There are a few specific activities constituting the CPS capabilities that managers of a firm need to focus on when developing these capabilities. First, firms need to identify opportunities to develop new products or services by filtering and interpreting market-facing information collaboratively with their customers and suppliers. Second, as knowledge about the demand for new products or services plays a critical role in a firm's innovation decisions (Yao et al. 2013), firms need to ensure that they develop the ability to engage customers and suppliers in filtering and interpreting market-facing information not only to understand what kinds of products or services are in demand in the marketplace, but also to estimate the volume in which to produce these products or services. Third, as timing the introduction of new product or service offerings to the marketplace is a strategic decision for innovation (Tambe et al. 2012), firms need collaborative inputs from customers and suppliers to make this decision effectively. In summary, these specific activities constituting the CPS capability serve as a roadmap by guiding managers in managing collaboration with their customers and suppliers for effectively facilitating innovation in the presence of IO-BSIS.

Our findings also suggest that managing innovation activity in the presence of IO-BSIS requires firms to develop capabilities that are different from capabilities to enable innovation in the absence of IO-BSIS. The presence or absence of IO-BSIS represents a key contingency factor that guides the development of distinct innovation strategies. As BSIS use is a source of IO-BSIS and given this technological source of information overload, it is plausible that firms are likely to adopt a technological solution for coping with IO-BSIS. For example, BI system use is a technological solution for coping with IO-BSIS, as BI systems can deliver actionable insights by analyzing vast amount of market-facing information. However, we found that BI system use is beneficial for innovation only when firms do not face IO-BSIS and the same "solution" is detrimental to innovation when firms do face IO-BSIS. This is aligned with the literature suggesting that IS use does not help mitigate negative outcomes of technostress at the individual level (see Tarafdar et al. 2019 for a literature review). These findings collectively reaffirm the need for coping with IO-BSIS by relying on digitally enabled collaborative capabilities that engage business partners for filtering and interpreting market-facing information from BSIS use, rather than simply using another IS without developing the required capabilities.

Limitations and Future Research

Our study has some limitations that should be noted. These limitations provide fruitful avenues for future research. First, as our survey research design is cross-sectional in nature, our results provide evidence of association rather than causation. Although our research design incorporated a time lag between the measurement of independent and dependent variables, and a Heckman approach was used to address potential endogeneity, our findings cannot fully support a causal linkage between the cross-stream CPS effect and innovation outcomes. Moving forward, building on our study that provided evidence for the cross-stream CPS effect, future research can collect longitudinal data to further investigate the causal linkages underlying our theory.

Second, given our research design, we were unable to ascertain how CPS capabilities evolve over time. We modeled CPS capabilities as exogenous factors and did not consider the antecedents and evolutionary dynamics associated with these CPS capabilities. However, firm capabilities depend on vital resource bases and gradually develop and enhance these resource bases over the lifetime of these capabilities (e.g., Helfat and Peteraf 2003). Using a process-oriented lens, future research can enhance our understanding of the temporal progression of resource investments driving the evolution of CPS capabilities.

Third, we investigated the outcomes of the innovation activity exclusively from a focal firm's point of view. In other words, a limitation of our research design was that we did not examine the innovation activity from the point of view of the business partners collaborating with a focal firm. In particular, innovation outcomes from CPS capabilities could be appropriated by not only the focal firm, but also its customers and suppliers that entails numerous value appropriation issues (e.g., Jacobides et al. 2006). Building on our findings, future research can examine the innovation activity by adopting the "firm-customer" or "firm-supplier" dyad as the unit of analysis, and collecting dyad-level data to better understand the benefits a firm's customers and suppliers can appropriate by collaborating with an innovative firm. Moving forward, how the value derived from CPS capabilities is partitioned between a firm and its business partners is a fruitful question to examine.

Last but not least, our findings are based on the analyses of data collected only from firms based in the U.S. We need to be cautious when generalizing our findings to firms in other countries. In particular, firms in developing countries or emerging markets may be systematically different from firms in the U.S. with regard to the extent of their IS investment and use, digitally enabled capabilities and their overall innovativeness. Moving forward, scholars can gather data from other countries to examine the generalizability of our findings. Additionally, research that conducts comparative analysis to uncover contingencies that enhance or limit the value of CPS capabilities across national contexts can also be a fruitful avenue to pursue in the future.

Conclusion

Our work revealed that a firm can promote innovation in the presence of IO-BSIS by engaging in digitally enabled collaborative problemistic search with its customers and suppliers. By involving customers and suppliers in filtering and interpreting market-facing information, a firm can be effective in enhancing innovation while contending with information overload. We hope the ideas of collaborative problemistic search and the cross-stream CPS effect will promote future work on how a firm can leverage insights of its business partners on downstream and upstream supply chain to contend with rapidly increasing volume of data for innovation.

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