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Performance implications of knowledge inputs in inter-organisational new product development projects: the moderating roles of technology interdependence

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ABSTRACT

Successful inter-organisational new product development (NPD) is a key source of competitive advantage, yet many NPD projects are still failing. To generate new insights on the phenomenon, we examine the performance implications of knowledge inputs among collaborating organisations, both in terms of external input ratio and input concentration. We test a set of hypotheses using multi-industry primary and secondary data on 210 inter-organisational NPD projects. Results support our hypotheses about the negative effect of input concentration on design quality, which in turn is positively associated with product market performance. Although we surprisingly find a negative linear effect of external input ratio on design quality, our post-hoc analysis confirms the relationship to be an inverse U-shaped relationship. We also find support for the roles of technology interdependence in moderating the performance implications of external input ratio and input concentration. By clarifying how knowledge inputs affect project outcomes under different levels of technology interdependence, the study provides managerial implications regarding how to select innovation partners in order to create a knowledge portfolio that best improves NPD project performance.

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New product development; knowledge input; technology interdependence; design quality; product market performance

1. Introduction

Successful new product development (NPD) projects, as a form of firm innovation, can generate and sustain competitive advantage across all industries (Ettlie and Pavlou 2006; Sivadas and Dwyer 2000). As a first and crucial step in a firm's production system, the NPD process constitutes the fuzzy front end of a manufacturer's value creation process (Schoenherr and Wagner 2016). During the NPD process, a firm needs to make important product and supply chain design decisions, which significantly affect the performance of firm operations in the marketing and production stages (Swink and Calantone 2004). A high quality product design that meets customer requirements, a main outcome resulting from a successful NPD process, could save manufacturers millions of dollars in the mass production stage, while ensuring sufficient market revenue to compensate for the high R&D investment (Frankort 2016; Choo, Chandrasekaran, and Chinaprayoon 2020). Therefore, successful NPD projects are a key driver for firm performance (Rubera, Chandrasekaran,

and Ordanini 2016; Hagedoorn, Lokshin, and Zobel 2018).

To bring new products more quickly to the market in an efficient manner, firms often need to collaborate with customers, suppliers and other types of organisations in NPD projects and tap into specific market knowledge and technological resources to lower market and development risks (Jayaram 2008). The Artemis project of the car manufacturer Audi, for example, underlines the criticality of bringing together knowledge from various partners for NPD. The Volkswagen Group, including Audi, has worked on many individual projects related to autonomous driving over more than 15 years and extended its internal R&D capabilities in this area with knowledge from external partners (Volkswagen 2017). As early as 2005, Volkswagen collaborated with specialists from Stanford University with the outcome of a rudimentary autonomously driving 'robot' vehicle. As the former head of research states: 'Cooperation and collaboration are core concepts for Volkswagen Research' (Volkswagen

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2017). Collaborative inter-organisational NPD projects could potentially improve design quality and market performance of a new product, if external knowledge inputs are effectively integrated with internal knowledge to fully realise their synergy. However, the McKinsey Global Institute estimates that between 25% and 45% of new products never make it to market or fail at market entry (De Jong, Marston, and Roth 2015), showing that collaborative inter-organisational NPD projects remain a risky endeavour. Therefore, it is still important to gain more insights on the contingencies that help predict project performance.

Since market and technological knowledge is an important resource for developing new products, the knowledge portfolio available at the beginning of a NPD project should play a critical role for NPD success (Chesbrough 2003; Lawson et al. 2009; Kahn et al. 2012). A few strategic management and innovation studies have suggested the importance of resource portfolios on a firm level (e.g. Grand et al. 2004; York and Venkataraman 2010; Bolumole et al. 2015). However, the effects of the knowledge portfolio at an inter-organisational NPD project level has received little academic attention. The knowledge portfolio is composed of the knowledge inputs from both the focal firm and all types of external project partnering organisations (Wagner 2012; von Briel, Schneider, and Lowry 2018). In the earlier example, Volkswagen Group has collaborated with different customers, suppliers and other organisations over the years. These external knowledge inputs were bundled with Volkswagen's internal knowledge at Audi's Autonomous Intelligent Driving unit, today the Artemis project, to produce multiple technology partnerships. For instance, in 2018, Audi collaborated with Luminar Technologies, a provider of laser imaging, detection, and ranging sensors and software for autonomous driving (Phelan 2018). Internal knowledge inputs came from some of the 14 associated Volkswagen brands. The NPD literature has also shown that the proportion of knowledge inputs from internal and external sources could vary significantly from projects to projects (Taylor and Poltz 2020). Together, this evidence shows the importance of studying characteristics of knowledge inputs to see how they affect inter-organisational NPD outcomes. Specifically focusing on inputs and not on the knowledge generated during the development process, we study the effects of two knowledge input characteristics on product design and ultimately on project performance: (1) *external input ratio* and (2) *input concentration*.

The NPD literature has also widely shown that the success of inter-organisational NPD projects is contingent on product and project factors (Wowak et al. 2016; Yan and Azadegan 2017). One group of contingencies

is related to the characteristics of the product and the adopted technology (Chen, Reilly, and Lynn 2005; Swink and Calantone 2004). However, research has focused on a limited set of characteristics, such as product novelty and complexity, which are on a strategic level and not directly under the discretion of the focal firm (Schoenherr and Wagner 2016; Carlo, Lyytinen, and Rose 2012). Instead, product technological architecture is an important operational level, engineering design factor that has not received enough attention from the NPD literature but at the same time could influence the types and amounts of knowledge inputs needed to facilitate successful NPD (Bstieler 2005; Yan and Dooley 2013). Thus, we introduce to our model such a factor: technology interdependence of a product, defined as the degree of interdependence among the product and process technologies to be developed (Swink and Calantone 2004). In the Artemis project, core technologies include the global positioning system, detection and ranging system, automated steering, electronic engine control, and software that used data input from all systems to make decision about the car's speed and direction (Taylor and Poltz 2020). These technologies are highly dependent on each other for the car to function well. As technology interdependence is likely to affect the absorption and integration of internal and external knowledge inputs, we examine the moderating roles of technology interdependence.

In sum, we study the effects of knowledge inputs for NPD project success under different levels of technology interdependence. Specifically, we examine how external input ratio and input concentration affect design quality and subsequent product market performance. To test our hypotheses, we use primary and secondary data on 210 NPD projects in multiple industries. Results support our hypotheses about the negative effect of input concentration on design quality, which in turn is positively associated with product market performance. Interestingly, our post-hoc analysis shows an inverse U-shaped relationship between external input ratio and design quality, although the main effect of external input ratio on design quality is negative. We also find support for the moderating role of technology interdependence in affecting performance implications of both external input ratio and input concentration.

The study contributes to the literature in three ways. First, we contribute to the inter-organisational NPD literature by showing that the characteristics of knowledge inputs are a yet overlooked but influential factor to the success of inter-organisational NPD projects. Second, we reveal the moderating roles of technology interdependence for understanding how knowledge inputs affect design quality in different architectures of technological bundles. Our findings also support the

general notion that product characteristics could affect knowledge needs, which provides insights about aligning engineering design decisions with project partner selection. Understanding both positive and negative performance implications of knowledge inputs, NPD managers could better select NPD partners by creating a knowledge portfolio that best fits the level of technology interdependence.

2. Related literature

2.1. *Inter-organisational new product development*

Inter-organisational NPD projects involve the active engagement of suppliers, customers and other non-supply chain partners, such as governmental institutions, consulting agencies, R&D institutes and universities (Petersen, Handfield, and Ragatz 2005; Najafi Tavani et al. 2013). While empirical evidence suggests that inter-organisational NPD strategies could lead to better product design quality and product market performance (Petersen, Handfield, and Ragatz 2005; Primo and Amundson 2002), these projects are not always successful (Yan and Dooley 2013). Exploring the factors and mechanisms for successful NPD yields valuable insight for scholars and practitioners.

Research has formed three distinct literature streams on inter-organisational NPD project success. The first group of studies takes on a relational view, assuming that the quality of the inherent inter-organisational relationships determines NPD project success (Cao and Zhang 2011; Mishra and Shah 2009). A second group specifically studies how, when and for how long to involve external organisations in order to improve NPD outcomes (Schoenherr and Wagner 2016; Wagner 2012). The third group investigates the effects of project organisation on the success of inter-organisational NPD projects (Kach, Azadegan, and Dooley 2012; Yan and Nair 2016). However, the existing literature has not given enough attention to knowledge management in inter-organisational NPD projects. As firms reach beyond organisational boundaries, especially to satisfy the increasing knowledge needs in NPD projects, the focal firm's knowledge management capability might be a key success factor (Cassiman and Veugelers 2006; Nonaka 1994; Pathak et al. 2019).

2.2. *Knowledge management in inter-organisational new product development*

From a knowledge management view, the inter-organisational NPD literature has shown the importance of selecting and managing different knowledge sources, i.e.

the source's position in the value chain, which affect the types of knowledge contributed and the 'stickiness' of that knowledge (Schoenherr and Wagner 2016; Wowak et al. 2016). First, prior studies have identified customers, suppliers, consultants, and universities as key knowledge sources for product innovation activities (Chesbrough and Brunswicker 2014; Laursen and Salter 2006). Researchers have compared performance implications of different knowledge sources for product novelty, design and financial performance of a new product. However, no conclusive findings have been identified (Leiponen and Helfat 2011; Wang, Modi, and Schoenherr 2020; Yu, Duan, and Fan 2020). Second, the literature has also called attention to consider different types of knowledge needs, i.e. knowledge about the technical product and process, or market knowledge (Modi and Mabert 2007). Third, NPD performance could also be affected by the characteristics of the knowledge (Kogut and Zander 1992; Madhavan and Grover 1998; Pathak et al. 2019). For example, experience-based know-how for NPD is notoriously hard to access if a focal firm does not go through the learning process to acquire the know-how itself (Ngai, Jin, and Liang 2008; Szulanski 1996). In short, this knowledge management branch of inter-organisational NPD literature highlights the importance of understanding different types and sources of knowledge for successfully managing projects.

Viewing knowledge as a critical innovation resource, we also need to build upon the resource allocation/distribution literature in inter-organisational innovation in order to study the influences of knowledge distribution on project performance (Garcia, Calantone, and Levine 2003; Grand et al. 2004; Meier 2011; York and Venkataraman 2010). On the firm level, Klingebiel and Rammer (2014) find that a firm's innovation performance is influenced by their choice of resource allocation strategy. They recommend a broad resource allocation strategy, understood as investing in a wide range of NPD projects, to increase revenue. Vasudeva and Anand (2011) examined how firms can access and acquire knowledge from shared alliance innovation portfolios. They derive different strategies to optimise knowledge utilisation. On a project level, resource contribution, allocation and distribution has received insufficient attention, with some notable exceptions (Choo, Chandrasekaran, and Chinaprayoon 2020; Fang 2011; Frankort 2016; Rothaermel and Deeds 2004). Mudambi and Tallman (2010), for instance, studied innovation projects and characterise knowledge management outsourcing as 'make-or-ally decision'. They provide a framework for how to govern the resulting project partnerships in the context of sensitive knowledge assets. Capaldo and Petruzzelli (2014) focused on contributions

and knowledge creations in project partnerships and performance implications. Although these studies all allude to the importance of studying knowledge distribution in inter-organisational NPD projects, this area is still lacking academic attention.

In addition, multiple studies show the effects of product characteristics on the success of the NPD project (Bstieler 2005; Tatikonda and Rosenthal 2000b). The engineering/technology-SCM interfacing literature has shown the importance to consider the alignment between product architecture and inter-organisational strategies when predicting innovation outcomes (Fine 2000; Boutellier and Wagner 2003; Ülkü and Schmidt 2011; Nepal, Monplaisir, and Famuyiwa 2012; Pashaei and Olhager 2015). However, no study has examined how technological interdependence, a critical product architecture design decision, moderate the influences of knowledge inputs from various types of organisations on NPD project outcomes. Technology interdependence refers to the degree of interdependence among the product and process technologies to be developed (Sosa, Eppinger, and Rowles 2004; Tatikonda and Rosenthal 2000b). For example, Yan and Wagner (2017) study the role of conflicts on NPD project success. They find that product novelty and technology interdependence affect project conflicts and subsequently value creation and appropriation. Similarly, we argue that the technology interdependence of a product influences how different knowledge inputs drive NPD project performance. It is conceivable that, for example, the knowledge portfolio needed to develop a product with low technology interdependence and thus higher modularity is different from the one necessary to successfully design an integral new product. Therefore, our study fills this gap in the literature by exploring technology interdependence as a contingency.

Building upon the above inter-organisational innovation studies and knowledge management, this study attempts to fill two gaps in the literature: (1) a lack of attention to the performance implications of knowledge distribution, and (2) the moderating effects of technology interdependence on performance implications of knowledge distribution. Building upon this stream of work, we will explain below how effects of external input ratio and input concentration vary with different levels of technology interdependence.

3. Theory development

In this study, we examine the effects of knowledge inputs to a NPD project on product design quality. Specifically, we look at the external ratio and concentration of these

Table 1. Description of the constructs used.

Construct Name	Description	Based on
Knowledge inputs	Knowledge inputs refers to the flow of all knowledge to a project's, as contributed by the focal company and all external partners.* The knowledge inputs from different sources make up the knowledge portfolio available for the new product development. *Note that this does not include knowledge created during the new product development process.	Letting, Roth, and Forstenlechner (2006), Salomo, Keinschmidt, and De Brentani (2010), Wagner (2012), Choo, Chandrasekaran, and Chinaprayoon (2020)
External input ratio	Input ratio indicates the ratio of knowledge inputs by external partners to those by the focal firm.	
Input concentration	Input concentration indicates the extent to which all the knowledge inputs come from a few types of organisations.	
Technology interdependence	Technology interdependence refers to the degree of interdependence among the product and process technologies to be developed.	Sosa, Eppinger, and Rowles (2004), Tatikonda and Rosenthal (2000b)
Product design quality	Product design quality is defined as the degree to which the product design meets its specifications related to the fitness for use.	Swink and Calantone (2004)
Product market performance	Product market performance reflects the product's influence on firm sales, return on investment, and profitability in comparison to competing products.	Yan and Azadegan (2017)

inputs. In addition, we explore technology interdependence as a contingency to our proposed relationships. Our constructs are formally defined in Table 1.

3.1. Knowledge inputs and knowledge integration

In this study, we see knowledge inputs to a NPD project as intangible resources (i.e. knowledge) in various forms. The knowledge inputs can come from the focal firm or any other partnering organisation, including suppliers, customers and other organisations. We specifically focus on the knowledge inputs, and not the knowledge

that is created throughout the NPD process. To examine the effects of knowledge inputs on NPD performance, we specifically look at two main characteristics of the input flows: (1) the *external input ratio* and (2) the *input concentration*. External input ratio refers to the ratio of knowledge contributed by external types of organisations to the knowledge inputs by external types of organisations plus the focal firm. Input concentration indicates the extent to which all the knowledge inputs come from a few types of organisations, including both the focal firm and external organisation types.

The knowledge portfolio that is available at the beginning of a NPD process is understood as the sum of all knowledge inputs by different partnering organisations. We propose a two-step process of how the knowledge can be used within the project: (1) *understand* and then (2) *integrate* the knowledge. First, knowledge has to be understood. The focal firm has a specific domain of internal knowledge that relates to the firm's product and service domain (Lettice, Roth, and Forstenlechner 2006). A mismatch or distance between knowledge domains of the firm and the knowledge inputs poses the challenge of adequately understanding the knowledge (Grant and Baden Fuller 2004; Yan and Azadegan 2017). Understanding depends on sufficient overlap between knowledge domains. Second, once knowledge is understood, it has to be integrated. While we acknowledge that during the NPD process, knowledge is always transferred among partnering organisations, different sources of knowledge have to be integrated before it can be utilised for meeting NPD project needs (Becker and Zirpoli 2003; Grant and Baden Fuller 2004). Characteristics of knowledge, such as contents and tangibility, could affect the challenges for the focal firm to realise synergies from integrating knowledge inputs. For instance, some tacit, hard-to-codify knowledge, such as practical skill or expertise that allows one to do something smoothly and efficient, could be very challenging to be transferred to a new context to integrate with other knowledge inputs (von Hippel 1988). The literature has shown that integrating tacit knowledge for NPD is notoriously hard to achieve, problematic and costly (Ngai, Jin, and Liang 2008; Szulanski 1996).

3.2. Knowledge inputs and product design quality

To gain insights into the effects of knowledge inputs on product design quality, we develop a set of hypotheses related to the main characteristics of the knowledge inputs: (1) external input ratio, and (2) input concentration.

External input ratio. We propose that a high external input ratio increases the chance for a focal firm to

integrate novel knowledge from external partners successfully, positively contributing to product design quality. When the knowledge inputs mainly originate from external types of organisations, the knowledge portfolio potentially contains a higher degree of new-to-the-firm technological or market knowledge (Cassiman and Veugelers 2006). In contrast, when most knowledge inputs comes from the focal firm, the knowledge portfolio will overlap largely with what the focal firm has already known, which means little is an opportunity for the focal firm to integrate new knowledge and potentially improve the NPD outcome.

When a focal firm can integrate novel knowledge from external types of organisations, product design quality potentially improves. The novel knowledge from types of external organisations could be either market-related, such as consumer demand, competitor moves, etc. or technology-related, such as new patents, and know-how (Yli-Renko, Autio, and Sapienza 2001; Yan and Azadegan 2017). This means that the focal firm has more options when searching for a best product design solution (Laursen and Salter 2006; Subramaniam and Venkatraman 2001). For instance, if the focal firm has knowledge about specific unmet customer demands, the new product could be designed to satisfy customers better. Alternatively, if a patented technology that could improve the technical performance of the product is available to the focal firm, product design could also improve.

In practice, multiple firms have dedicated specific resources to establishing knowledge exchange relationships with key suppliers, in order to foster innovation outcomes (Potter and Paulraj 2020; Wagner 2012). For example, Procter & Gamble was among the first to radically open up their R&D department to engage with suppliers and other business partners. The firm's strategic shift to actively encouraging external knowledge inputs has improved R&D productivity by 60%, contributed to 50% of the new products on the market, and generated billions of dollars in sales (Ampe-N'DA et al. 2020). In a recent interview, Tim Cook stresses the importance of working with suppliers for their knowledge (Murayama and Regalado 2019), as their supplier Seiko Advant was responsible for developing colour schemas for different Apple product lines. Therefore, we hypothesise:

Hypothesis 1a. External input ratio is positively associated with product design quality.

Input concentration. A lower level of input concentration increases diversity of the available knowledge portfolio. From the inter-organisational NPD and knowledge management literature, we know that different types of organisations tend to differ in the types of relationships with the focal firm (Argote 2012; Yan and Azadegan 2017).

Specifically, customers and suppliers, due to their strong ties with a focal firm, tend to have more common knowledge shared with the focal firm. As a result, the focal firm could more efficiently integrate knowledge, which however tends to be less novel, from customers and suppliers, as compared with knowledge inputs from other weakly connected organisations, such as consulting firms, competitors, universities, governments, and others. Again, customers and supplier, due to their different positions along a value chain, also differ in the types of knowledge they offer to a focal firm's NPD project (Chien and Chen 2010). Customers tend to provide more market-related knowledge, such as unmet consumer needs, while suppliers tend to provide more supply-related knowledge, such as a new cost-cutting production technology (Feng, Sun, and Zhang 2010).

A lower level of input concentration suggests that knowledge is equally distributed across all participating organisations, instead of coming from a particular type of organisations. The resulting more diverse knowledge portfolio elevates the chance for the focal firm to integrate novel market or technology knowledge, which should contribute to improved product design quality (Reagans and McEvily 2003; Salomo, Keinschmidt, and De Brentani 2010). In practice, firms actively try to diversify their supplier pool. For example, Google has launched several initiatives over the years, such as the *Google Small Business Supplier Diversity* programme, with the goal to actively engage with unique small suppliers and acquire diverse knowledge inputs in order to improve its product and service offerings (Samaniego et al. 2017). Therefore, we hypothesise:

Hypothesis 1b. Input concentration is negatively associated with product design quality.

3.3. The moderating effects of technology interdependence

Technology interdependence refers to the degree of interdependence among the product and process technologies to be developed (Sosa, Eppinger, and Rowles 2004; Tatikonda and Rosenthal 2000b). A Higher levels of technology interdependence indicates that design changes in one part of the development task, i.e. one product module, could affect activities in another part of the development task, i.e. design of another module or the manufacturing process of the same module (Tatikonda and Rosenthal 2000b). Thus, high technology interdependence reflects a more integral design, increasing the complexity of the development task. For example, personal computers originally were introduced as all-in-one packages, where components were tightly integrated with

a high level of technological interdependence (such as Intel's MCS-4, the Kenback-1, the Apple II or the commodore PET) (Schilling 2000). However, a high level of technological interdependence increases coordination challenges during the development process and limits flexibility in end configurations. Therefore, modern computers are designed in a more modular way to reduce interdependence among modules or different stages of the development process.

The associated complexity in the product technological architecture reduces the focal firm's ability to rely solely on its own knowledge base to figure out the best way to improve design quality. As a result, the need to integrate more external knowledge into the knowledge portfolio of a NPD project increases. A higher external input ratio could increase the novelty of the total knowledge portfolio because knowledge possessed by external partners are usually different from those possessed by the focal firm. This is helpful for the focal firm to challenge the status quo and facilitate 'out-of-box' thinking in order to find the optimal path in a tightly coupled, complex technology system for improving design quality. While integrating a large amount of external knowledge can be very costly, the benefits of the external knowledge are likely to outweigh the cost. Therefore, the positive effect of the external inputs ratio on design quality should be even greater when technology interdependence is high.

In contrast, when technology interdependence is low, the development task is modular and thus simpler, which reduces the overall need for novel knowledge from external types of organisations. For example, modular buildings generally consist of universal parts that are designed and manufactured in different factories and then shipped to a building site to be assembled into a variety of arrangements. In this case, technological interdependence of modular buildings is very low, which makes it less crucial for factories to integrate external knowledge to ensure design integrity. Understanding and integrating external knowledge in innovation projects with limited resources and high technological uncertainty is especially costly (Grant 1996). Given the limited benefits associated with external knowledge when technology interdependence is low, we could see fewer benefits, in terms of improving design quality, from a knowledge portfolio that is primarily composed of external knowledge. Therefore, we hypothesise that:

Hypothesis 2a. External input ratio is more positively associated with product design quality when technology interdependence is high.

In addition, we argue that technology interdependence should make more concentrated knowledge inputs less challenging for design quality. With a high level of input

concentration, the knowledge portfolio is composed of knowledge concentrated within a few types of organisations, instead of equally dispersed among a large number of diverse types of organisations. Given that the nature and content of knowledge inputs usually vary among customers, suppliers, and other non-supply chain members of a focal firm, a high input concentration indicates a lower level of knowledge diversity. A less diverse knowledge portfolio is less costly for the focal firm to integrate (Grant and Baden Fuller 2004). This lower knowledge integration cost is especially crucial for allowing the focal firm to efficiently find the optimal path towards a better design in a technologically interdependent system (Singh 2008; Santoro, Bresciani, and Papa 2020). In other words, technology interdependence increases the efficiency-boosting effect of high input concentration to counteract its novelty-reducing effect. Therefore, low input concentration should be less damaging to design quality in a technologically interdependent NPD project.

In contrast, when technology interdependence is low, the path to the optimal design will usually be easier to find due to a lower level of design complexity (Danese and Filippini 2010). Consequently, the focal firm will have more slack resources left to integrate a diverse set of knowledge for improving design quality. Therefore, knowledge inputs that are more concentrated will hurt design quality more when technology interdependence is low (Wang, Chen, and Fang 2018; Fredrich, Bouncken, and Kraus 2019). Therefore, we hypothesise that:

Hypothesis 2b. Input concentration is less negatively associated with product design quality when technology interdependence is high.

3.4. Product design quality and product market performance

High product design quality is one driver of the market performance of the new product (Biedenbach and Müller 2012; Lawson, Krause, and Potter 2015). Effectively understanding and integrating external and internal knowledge, improves product design quality, characterised by good dimensional integrity, durability, functionality, manufacturability, and fits with customer needs, should be expected (Yan and Dooley 2013). Good product design has been shown to help the product gain market share, produce profits, and generate high return-over-investment, for the focal firm (Yan and Azadegan 2017). Therefore, we hypothesise:

Hypothesis 3. Product design quality is positively associated with product market performance.

In sum, we examine the effects of knowledge inputs on NPD project performance. In this section, we have developed arguments as to why and how knowledge inputs affect product design quality, which ultimately drives product market performance. Specifically, we look at the external input ratio and input concentration of these knowledge inputs. In addition, we explore technology interdependence as a contingency to our proposed relationships. The resulting research model is depicted in Figure 1.

4. Method

The objective of our study was to examine the effects of knowledge inputs on product design quality, which in turn affects product market performance. We also

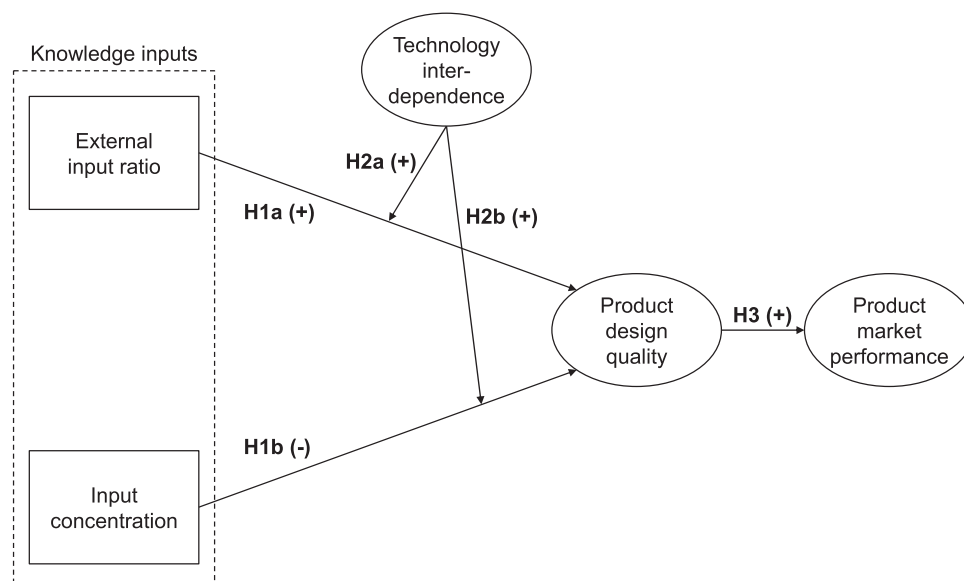


Figure 1. Conceptual model.

investigate potential moderation effects of technology interdependence on the relationships between external input ratio and input concentration, and product design quality. To test our hypotheses, we estimated a set of linear regressions using survey data of 210 NPD projects in Italy.

4.1. Data collection and sample description

In our sample selection, we specifically focused on the manufacturing industry while also sampling closely related industries, such as services, transportation, and trade. However, we excluded the general services and software industries, due to their distinctly different innovation processes and outcomes (von Hippel and von Krogh 2003). Accordingly, an initial list of potential respondents was retrieved from the AIDA – Bureau Van Dijk database, which holds records on public and private firms in Italy. Italy presents an interesting case to study European inter-organisational NPD activities (De Martino and Magnotti 2018; Hofstede 1984; Nakata and Sivakumar 1996). Highly customised products and knowledge-intensive innovation processes, characterise the Italian economy. Specifically, highly innovative clusters, such as the fashion industry in Northern Italy, drive NPD efforts by maintaining close relationships with suppliers and customers (Maltz 2012; Nassimbeni 2003).

The initial set included 994 potential respondents. The survey was hosted on the Qualtrics platform and participants were contacted via email. The online questionnaire introduced the context and objective of our research project. Participants later received the anonymised study results for benchmarking purposes. The questionnaire was carefully pre-tested (Ambulkar, Blackhurst, and Grawe 2015). The main objective of our pretest was to assure substantive validity of our measures and the overall survey design (Anderson and Gerbing 1991). We further made sure that the questions could be correctly understood and easily answered by the survey respondents. The questionnaire was translated into Italian and then back-translated into English (Brislin 1986). A group of supply chain managers from three large Italian firms was involved to increase clarity and avoid misinterpretations. Afterwards, a panel of three academics scholars from the operations management area reviewed the final draft once more and were asked to consider each item's and measure's relevance to the study objective.

Out of the 994 managers who were willing to participate, and after three follow-ups made via emails and phone calls, 251 respondents completed the survey by the end of 2014 (25.3% response rate). To ensure knowledgeable respondents, we selected managers with job titles

and positions related to the NPD project, such as engineering, manufacturing, product development, project management, or purchasing. Participants also had to demonstrate adequate and up-to-date NPD experience by indicating that they have been actively involved in an inter-organisational NPD project during the last three years. Our sample covers a wide range of projects, ranging from foundational R&D initiatives to more specific product development and improvement. Foundational research is conducted to explore materials and systems to reduce waste and improve efficiency, such as creating new material compositions to improve vehicle safety. Other projects are concerned with developing antennas to improve mobile network coverage, testing filtration systems to reduce the pollution levels of cruise ships, and improving industrial air heat exchangers to limit energy consumption.

Additionally, we asked respondents to '... consider a recent NPD project, finished within three years, where external organizations were involved in the development process' when answering all the NPD-project related questions, to reduce the potential bias towards reporting on successful NPD projects only. We dropped 30 responses due to inadequate experience with the research topic; and another 11 due to extensive missing data. The final sample contained responses regarding 210 NPD projects. To reduce common method bias, we complemented the survey responses with secondary data (Craighead et al. 2011). Specifically, we utilise firm data on sales revenue, R&D intensity, and industry SIC codes, using both the AIDA – Bureau Van Dijk database and Thomson Reuters DataStream. We also calculate our main independent variables, rather than using latent constructs, which significantly reduces common method concerns (Wooldridge 2010).

In our final sample, the most common industries were Manufacturing (50.0%), such as machinery or appliances, closely related Services (16.67%) and Retail & Trade (10.5%). Our sample consists of both SMEs and larger firms. Our sample is comprised of 54% SMEs with less than 250 employees and 46% with more than 250. Annual sales revenue, for example, ranged from \$0.6 million to \$33.7 billion in 2016, with an average of \$66.5 million. Taking Italian accounting practices into account, which tend to limit the percentage of firms reporting numerical R&D information in financial reports, we now also include other firm documents and notes to the firm balance sheet to provide a more representative measure of R&D intensity (Koh and Reeb 2015). The average R&D intensity in our sample is 2.4%. See Table 2 for more detailed sample demographics. This wide range of industries, firm and project sizes ensures high levels of generalisability and reliability.

Table 2. Sample demographics.

Respondents Role	Responses	%	Industry	Responses	%
Project Manager	93	44.29	Construction	3	1.43
Product Manager	41	19.52	Finance and Real Estate	25	11.90
Design Engineer	29	13.81	Manufacturing	105	50.00
Manufacturing Engineer	18	8.57	Mining	5	2.38
R&D Manager	5	2.38	Retail Trade	5	2.38
Purchasing Manager	3	1.43	Services	35	16.67
Other	21	10.00	Transportation, Utility, etc.	10	4.76
Total	210	100.00	Wholesale Trade	22	10.48
			Total	210	100.00

Project size	Responses	%	R&D intensity	Responses	%
≤ 5	40	19.05	≤ 0.5%	52	24.76
5–15	87	41.43	0.5%–1.0%	34	16.19
16–25	27	12.86	1.0%–2.0%	26	12.38
26–35	21	10.00	2.0%–3.0%	23	10.95
36–45	8	3.81	3.0%–5.0%	35	16.67
46–55	4	1.90	5.0%–7.0%	17	8.10
> 56	23	10.95	> 7.0%	15	7.14
Total	210	100.00	NA	8	3.81
			Total	210	100.00

Employees	Responses	%	Sales revenue (th. USD)	Responses	%
≤ 10	22	10.48	≤ 1000	18	8.57
10–50	27	12.86	1000–10,000	35	16.67
50–100	23	10.95	10,000–100,000	68	32.38
100–250	31	14.76	100,000–1,000,000	59	28.10
250–500	34	16.19	> 1,000,000	26	12.38
500–1,000	31	14.76	NA	4	1.90
> 1000	36	18.10	Total	210	100.00
NA	6	1.90			
Total	210	100.00			

4.2. Variables and measures

To test the relationships proposed in our conceptual model, we employ several measures using calculated measures from survey response scores, latent variables and archival firm data. Table 3 shows our measures, including factor loadings, average variance extracted (AVE), construct reliability, and Cronbach's Alphas for all latent variables.

4.2.1. Independent variables

We calculate knowledge inputs based on four questions. Each question assesses the level of knowledge inputs from different types of potentially involved organisations: the focal firm, customers, suppliers, and other types of organisations. The item prompts the respondent to evaluate the inputs of several types of resources on a 7-point Likert scales, with '1' indicating 'low inputs' and '7' indicating 'high inputs'. We specifically calculate our measures of knowledge inputs on one item. Calculating different measures from similar items is commonly done in the context of value creation (Scheer, Kumar, and Steenkamp 2003; Wagner, Eggert, and Lindemann 2010).

Specifically, we calculated external input ratio and input concentration according to their definitions in Table 3. External input ratio was operationalised as the fraction of knowledge inputs from all external types

of organisations to the sum of external and internal (i.e. by the focal firm) knowledge inputs to the project. We calculated input concentration among all involved organisations to a NPD project as the standard deviation of knowledge input over the mean. If a type of organisation was not involved in a NPD project, knowledge inputs from that type of organisations were set to zero, to account for potentially different number of participants. As we are dealing with calculated measures, we also control for the overall level of knowledge inputs (see Section 4.2.2). See Table 3 for the exact calculations.

4.2.2. Moderator and dependent variables

For our constructs technology interdependence, product design quality, and product market performance, we use established multi-item constructs utilising 7-point Likert scales, with '1' indicating *strong disagreement* and '7' indicating *strong agreement*. Technology interdependence, our moderator, refers to 'the degree of interdependence between and among the product and process technologies to be developed' (Tatikonda and Rosenthal 2000b). Technology interdependence is measured by a three-item scale used in Tatikonda and Rosenthal (2000a). The three items measure interdependence among modules, stages and technologies by asking the extent to which

Table 3. Variables and measures.

Construct	Item	Source
	Regarding this project, please evaluate the inputs your own organisation/customers/ suppliers/other organisations contributed to and this project: Intangible (know-how and patents) contributions to the project were very high.	Scheer, Kumar, and Steenkamp (2003), Wagner, Eggert, and Lindemann (2010)
External input ratio	External input ratio = $\frac{\text{Knowledge}_{\text{Cust}} + \text{Knowledge}_{\text{Suppl}} + \text{Knowledge}_{\text{Other}}}{\text{Knowledge}_{\text{Firm}} + \text{Knowledge}_{\text{Cust}} + \text{Knowledge}_{\text{Suppl}} + \text{Knowledge}_{\text{Other}}}$	
Input concentration	Input concentration = $\frac{\sigma(\text{Knowledge}_{\text{Cust}}, \text{Knowledge}_{\text{Suppl}}, \text{Knowledge}_{\text{Other}}, \text{Knowledge}_{\text{Firm}})}{\mu(\text{Knowledge}_{\text{Cust}}, \text{Knowledge}_{\text{Suppl}}, \text{Knowledge}_{\text{Other}}, \text{Knowledge}_{\text{Firm}})}$	
Product design quality	The design of the product developed in this project: 1. Fully complies with the specifications regarding dimensional integrity (components fit together well) ($\lambda = 0.80$) 2. Fully complies with the specifications regarding durability ($\lambda = 0.83$) 3. Fully complies with the specifications regarding functionality ($\lambda = 0.82$) (AVE: 0.66, Construct reliability: 0.83, Cronbach's Alpha: 0.83)	Swink and Calantone (2004)
Product market performance	Relative to similar new products developed by your competitors, please rate the performance of the product as follows: 1. Sales of this new product were better than competitors' ($\lambda = 0.71$) 2. Return on investment of this new product was higher than competitors' ($\lambda = 0.91$) 3. Profitability derived from this new product was higher than competitors' ($\lambda = 0.92$) (AVE: 0.71, Construct reliability: 0.88, Cronbach's Alpha: 0.86)	Yan and Azadegan (2017)
Technology interdependence	With respect to what was perceived at the beginning of the project, please evaluate how various technologies interact with each other: 1. On average, a design change in one product module was expected to impact the design effort for other product modules to a great extent ($\lambda = 0.70$) 2. On average, a design change in one manufacturing stage was expected to impact the design effort for other manufacturing stages to a great extent ($\lambda = 0.91$) 3. A design change in the product technologies was expected to impact the design effort for the manufacturing technologies to a great extent ($\lambda = 0.72$) (AVE: 0.69, Construct reliability: 0.78, Cronbach's Alpha: 0.76)	Tatikonda and Rosenthal (2000a)
Input level	$\text{Input level} = \mu(\text{Knowledge}_{\text{Cust}}, \text{Knowledge}_{\text{Suppl}}, \text{Knowledge}_{\text{Other}}, \text{Knowledge}_{\text{Firm}})$	
Product novelty	This NPD project represents developments that: 1. Make your prevailing product/service lines obsolete ($\lambda = 0.80$) 2. Fundamentally change your prevailing products/services ($\lambda = 0.84$) 3. Make your existing expertise in prevailing products/services obsolete ($\lambda = 0.66$) (AVE: 0.64, Construct reliability: 0.80, Cronbach's Alpha: 0.79)	Biedenbach and Müller (2012)
Innovation breadth	Please choose the types of organisations actively participated and/or significantly contributed to this NPD project (more than one type could be chosen): <ul style="list-style-type: none"> • (0/1) Customers (organisations who potentially could purchase the product developed in this project) • (0/1) Suppliers (organisations who potentially could supply components to the product developed in this project) • (0/1) Competitors • (0/1) Consulting firms • (0/1) Universities • (0/1) Government • (0/1) Independent R&D institutions • (0/1) Other (please specify) sum of the eight binary variables above is used to measure innovation breadth.	Laursen and Salter (2006)
Firm sales revenue	Logarithm of firm sales revenue in the most recent fiscal year prior to the survey, as provided by Thomson Reuters DataStream.	Yan and Wagner (2017)
Firm R&D intensity	Ratio of R&D expenses to firm sales revenue in the most recent fiscal year prior to the survey, as provided by Thomson Reuters DataStream.	Singh (2008)
Industry	Industry classifications were based on 2-digit firm SIC codes provided by the AIDA – Bureau Van Dijk database.	Yan and Wagner (2017)

a design change in one could influence that in another area.

In addition, we operationalised product design quality adopting a 3-item scale from Swink and Calantone (2004). Following Yan and Azadegan (2017), we measured product market performance as a latent construct using three items, which assesses the product's influence on firm sales, return on investment, and profitability in comparison to competing products.

4.2.3. Control variables

To ensure validity and reliability of our results, we included a diverse set of control variables at the industry, firm and project level. We used archival firm data from Thomson Reuters to measure these variables. The industry context influences a firm's ability to create and appropriate value from inter-organisational NPD practices (Lawson and Potter 2012; Yan and Wagner 2017). Different industries show varying degrees of innovation

intensity, which could influence the NPD process (Subramaniam and Youndt 2005). We controlled for industry effects using two-digit SIC codes. We select *Manufacturing* as the base category, since it is the largest industry group (Wooldridge 2010).

At the firm level, we controlled for firm size and R&D intensity. The size of a firm could indicate its capabilities and resources available to manage knowledge in general (Leonard-Barton 1992). Larger firms are also more likely to possess superior project management and inter-organisational collaboration capabilities and experience. Suppliers might show more commitment, when working with a large firm, due to greater perceived power of bigger firms (Maloni and Benton 2000; Tang and Tomlin 2008). Large firms have additional means to market a product and facilitate its commercial success (Ketchen and Hult 2007). We operationalised firm size as the natural logarithm of the firm's revenues from sales and services in US Dollar. We use US Dollar to ensure comparability with related studies. Other currencies were converted to US Dollar using the exchange rate of the reporting date. In addition, a firm's innovation resources, indicated by R&D intensity, could affect the overall NPD process. Therefore, we also included the firm R&D intensity, defined as the ratio of expenditures on research and development to firm sales, as an additional control variable (Singh 2008).

At the project-level, as we evaluate calculated measures of knowledge, we also controlled for the average level of knowledge inputs to the NPD project, operationalised as the mean contribution by the focal firm, customers, suppliers, and other types of organisations. In addition, we controlled for inter-organisational innovation breadth, measured as the number of unique types of participants. A more diverse team, indicated by a large number of different types of organisations, such as suppliers, customers, universities, and consultants, might affect the knowledge management in an NPD context (Laursen and Salter 2006). The novelty of a product could also affect the types of inter-organisational interactions in the process (Ragatz, Handfield, and Scannell 1997). Product novelty is the degree to which a product fundamentally differs from a firm's existing product offerings (Olson, Walker Jr, and Ruckert 1995). We operationalised product novelty as a three-item latent construct adapted from Biedenbach and Müller (2012) and Subramaniam and Youndt (2005), who measure the 'newness' of a product from the focal firm's point of view.

4.3. Measurement assessment and data analysis

To ensure methodological rigour of our study, we tested for discriminant validity, content validity and construct

reliability of our multi-item latent constructs. To test for overall construct validity, we first conducted a chi-square discriminant validity test (Bagozzi, Yi, and Phillips 1991; Garver and Mentzer 1999). We run a series of pairwise chi-square difference tests for all latent constructs, comparing an unconstrained CFA model with all latent constructs and one model with a fixed correlation between the two tested constructs. All construct pairs showed significant chi-squares, indicating discriminant validity. Since we conducted repeated comparisons, we used the Bonferroni-corrected p -values (Kroes and Ghosh 2010). Second, the square root of the AVE for each factor was also greater than the correlation of the factor with any other constructs (see Tables 3 and 4), which further supports the assumption of discriminant validity (Anderson and Gerbing 1988; Fornell and Larcker 1981). The AVE values of our constructs are greater than 0.6, indicating adequate convergent validity. To assert content validity, we relied on scales that are widely established in the operations and supply chain management literature.

We utilised AVE, construct reliability score, and Cronbach's Alpha as our measures of construct reliability (Garver and Mentzer 1999). All latent constructs demonstrated Cronbach's Alpha above 0.60, as recommended by Nunnally and Bernstein (1994). AVE and construct reliability scores were higher than 0.70 and 0.50 respectively, indicating adequate construct reliability (Garver and Mentzer 1999). Table 3 shows Cronbach's Alpha, AVE, and construct reliability score as well as factor loadings for all our latent constructs.

To test for non-response and selection bias in our study, we used two different test procedures (Armstrong and Overton 1977; Wagner and Kemmerling 2010). First, we compared the first and last 30 survey responses. Results show no significant mean differences for our model items and variables (at $p > 0.05$). Second, 100 randomly selected sample firms were compared to 100 randomly selected non-responding firms. We conducted t -tests on sales revenue and R&D intensity and did not find significant differences (at $p > 0.05$). We concluded that non-response and selection bias was not a concern in our study.

To reduce potential common method bias, we use archival firm data, whenever possible, to complement survey responses. For instance, firm size, R&D intensity and industry are measured using archival firm data. Following Lindell and Whitney (2001), we examined the correlation matrix. All variable correlations were low, except our two calculated measures external input ratio and input concentration, which is reasonable. Correlations suggest that common methods bias was not a major concern in our study (Bagozzi, Yi, and Phillips 1991; Hair et al. 2010). Table 4 provides variable means, standard

Table 4. Descriptive statistics and correlations.

	Mean	SD	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
1. Product novelty	3.25	1.44																	
2. Innovation breadth	2.08	0.70	0.03																
3. Firm sales revenue	10.71	2.86	-0.07	-0.02															
4. Firm R&D intensity	2.44	2.46	0.11	-0.07	0.07														
5. Manufacturing	0.50	0.51	0.01	0.00	-0.02	-0.11													
6. Construction	0.01	0.12	0.02	-0.12	-0.04	0.01	-0.12												
7. Finance and Real Estate	0.12	0.34	-0.11	-0.02	0.01	0.12	-0.37*	-0.04											
8. Mining	0.02	0.15	0.21*	-0.07	0.12	0.35*	-0.16*	-0.02	-0.06										
9. Retail Trade	0.02	0.17	0.08	0.03	0.03	-0.01	-0.16*	-0.02	-0.06	-0.02									
10. Services	0.17	0.37	0.00	0.10	0.03	0.03	-0.45*	-0.05	-0.16*	-0.07	-0.07								
11. Transportation, Utility, etc.	0.05	0.21	0.06	-0.03	-0.06	-0.13	-0.22*	-0.03	-0.08	-0.03	-0.03	-0.10							
12. Wholesale Trade	0.10	0.31	-0.10	-0.01	-0.02	-0.07	-0.34*	-0.04	-0.13	-0.05	-0.05	-0.15*	-0.08						
13. Input level	4.77	1.13	0.24*	-0.17*	-0.02	-0.07	0.00	-0.14*	-0.03	0.06	0.10	0.05	0.01	-0.07					
14. Technology interdependence	4.82	1.26	0.12	0.10	-0.01	-0.09	0.06	0.03	-0.15*	0.07	-0.16*	0.05	0.00	0.03	0.16*				
15. External input ratio	0.57	0.13	0.11	0.42*	0.06	-0.05	0.09	-0.09	-0.10	0.06	0.03	0.03	-0.09	-0.03	0.23*	0.09			
16. Input concentration	0.79	0.34	-0.12	-0.66*	-0.04	0.09	-0.09	0.09	0.06	0.05	-0.09	-0.02	0.08	0.04	-0.15*	-0.11	-0.69*		
17. Product design quality	5.79	0.93	-0.07	0.14*	-0.07	-0.07	-0.09	-0.05	-0.02	-0.08	0.01	0.08	0.13	0.04	0.14*	0.20*	-0.07	-0.15*	
18. Product performance	4.21	0.99	0.10	-0.02	0.09	-0.01	-0.11	0.03	0.07	0.08	0.08	0.02	0.00	0.00	0.00	0.04	0.04	-0.06	0.19*

* $p < .05$.

deviations, and correlations. Mean and standard deviation were calculated prior to scaling, correlations are on scaled variables as used in our regression models.

We tested our hypotheses utilising linear regression analysis due to its statistical power in testing complex statistical models, with a relatively small sample (Cohen et al. 2013; De Beuckelaer and Wagner 2012). We apply confirmatory factor analysis to our measurement model of latent variables and use the resulting factor scores as the variables in our regression model (Rönkkö et al. 2016; Shah and Ward 2003). We assessed the Variance Inflation Factors (VIF) and found that all VIFs were well below three, as suggested by Hair et al. (2010), which alleviates potential concerns about multi-collinearity biasing our results. The low VIFs also ease concerns regarding the correlation between our calculated IVs. Further, we did scale our variables to reduce potential collinearity and minimise the bias from different data sources and measurement scales. We estimated ordinary least squares (OLS) regression models.

5. Results

5.1. Regression results

The results for the structural relationships and hypotheses tests regarding the influence of knowledge inputs on product design quality and product market performance are summarised in Table 5 and illustrated in Figure 2.

First, we examine the effects of external input ratio and input concentration within the NPD project on product design quality. Model 1 in Table 5 is the control model on product design quality. We find that product novelty negatively affects product design quality ($\beta = -0.12$; $p < 0.10$). It is conceivable that highly novel products are characterised by more uncertainties, which present more complex challenges, and are thus inherently more difficult to design. Innovation breadth seems to foster product design quality, as more external project partners indicate a more diverse knowledge portfolio ($\beta = 0.12$; $p < 0.05$). The overall level of knowledge contribution to the NPD project fosters design quality, as expected ($\beta = 0.13$; $p < 0.05$). We also find that technology interdependence positively influences product design quality ($\beta = 0.15$; $p < 0.01$).

Hypotheses H1a suggest a direct positive effects of external input ratio on product design quality. However, Model 2 in Table 5 indicates a significant negative relationship ($\beta = -0.33$; $p < 0.001$). While we find the opposite effect to be significant, we have to reject our original Hypothesis H1a. We will explore this finding in our post-hoc analysis. In H1b, we propose a negative relationship, as high input concentration within a

Table 5. Linear regression results.

Dependent variable:	Product design quality			Product market perf.
	(1)	(2)	(3)	(4)
<i>Control variables</i>				
Product novelty	-0.12+ (0.06)	-0.13* (0.06)	-0.12* (0.06)	0.11+ (0.06)
Innovation breadth	0.12* (0.06)	0.06 (0.08)	0.08 (0.07)	-0.12 (0.08)
Firm sales revenue	-0.05 (0.05)	-0.04 (0.05)	-0.02 (0.05)	0.07 (0.05)
Firm R&D intensity	0.02 (0.06)	0.02 (0.06)	0.01 (0.06)	-0.06 (0.06)
Manufacturing Construction	base -0.04 (0.46)	base -0.11 (0.44)	base -0.12 (0.43)	base 0.22 (0.45)
Finance and Real Estate	0.07 (0.18)	0.02 (0.17)	0.02 (0.17)	0.30+ (0.17)
Mining	-0.28 (0.39)	-0.08 (0.38)	-0.11 (0.37)	0.47 (0.38)
Retail Trade	0.27 (0.36)	0.16 (0.35)	0.03 (0.35)	0.41 (0.35)
Services	0.17 (0.15)	0.18 (0.15)	0.15 (0.14)	0.12 (0.15)
Transportation, Utility, etc.	0.56* (0.26)	0.53* (0.25)	0.51* (0.24)	-0.03 (0.25)
Wholesale Trade	0.15 (0.18)	0.16 (0.17)	0.17 (0.17)	0.07 (0.18)
Input level	0.13* (0.06)	0.15* (0.06)	0.11+ (0.06)	-0.10 (0.06)
Technology interdependence	0.15** (0.06)	0.14** (0.05)	0.14** (0.05)	-0.02 (0.06)
<i>Hypothesised variables</i>				
External input ratio		-0.33*** (0.08)	-0.27** (0.08)	0.06 (0.08)
Input concentration		-0.31** (0.10)	-0.25* (0.10)	-0.06 (0.10)
External input ratio x Technology interdependence		0.23* (0.09)		
Input concentration x Technology interdependence		0.28** (0.08)		
Product design quality				0.19** (0.06)
R^2	0.13	0.20	0.25	0.11
Model F	2.20	3.26	3.67	1.43
Model Comparison ^a		8.99***	5.55**	
N	210	210	210	210

Notes: *** $p < .001$, ** $p < .01$, * $p < .05$, + $p < .10$; standard errors in parentheses.

^aAnalysis of variance test against previous model (F -statistic).

NPD project might affect knowledge processes and limit product design quality. Model 2 in Table 5 confirms our Hypothesis H1b ($\beta = -0.31$; $p < 0.01$).

Second, we investigate the moderation effects of technology interdependence. In Hypotheses H2a and H2b, we argue that technology interdependence attenuates the relationships between both external input ratio and input concentration, and product design quality. Model 3 in Table 5 shows the interaction effects. We find that the effects of input ratio are positively moderated by technology interdependence, supporting H2a ($\beta = 0.23$; $p < 0.05$). Figure 3 illustrates the interaction. To gain more nuanced insights on the moderation effect, we conduct

a simple slopes analysis (Preacher, Curran, and Bauer 2003). Results suggest that for products characterised by low technology interdependence, higher external input ratio hurts the product design quality. Having access to widely dispersed and diverse knowledge does not significantly affect product design quality in cases of high technology interdependence.

In addition, we also find support for H2b. Model 3 in Table 5 suggests a positive moderation effect on input concentration ($\beta = 0.28$; $p < 0.01$). Figure 4 illustrates the slopes for the interaction. High interdependence products are characterised by high complexity, which might impose additional challenges for firms to integrate knowledge from distinct sources. Thus, accessing concentrated knowledge might create less costly overhead for applying the knowledge to improve product design quality. However, the effect for high interdependent products is not significant. Design quality for products characterised by low technology interdependence is hurt significantly by higher input concentration, as lower complexity suggest a more seamless integration from a variety of knowledge sources.

Third, in Hypothesis H3, we argue for a direct positive association of product design quality with product market performance. Model 4 in Table 5 provides support for H3 ($\beta = 0.19$; $p < 0.01$). This indicates that a firm's capability to acquire valuable technical and market knowledge enables the firm to not only design higher quality products but also perform better in the market.

5.2. Post-hoc analysis

In Hypothesis H1a we argue for a positive effect of external input ratio on product design quality. However, results suggest a significant negative relationship. We conduct additional post hoc tests to bring further nuance to this finding and derive more detailed insights.

While we assume linear relationships, the literature suggests that knowledge integration processes are inherently complex and thus, these relationships might not necessarily be linear (Argote 2012; Yan and Azadegan 2017). Consequently, we further explore how our independent variables, external input ratio and input concentration, affect product design quality by testing for curvilinear relationships (Figure 5).

We run regression models adding quadratic terms for our independent variables and consider unstandardised coefficients to facilitate interpretation. We find indication of an inverse U-shaped relationship between external input ratio and design quality (quadratic term : $\gamma = -3.66$, $p < 0.05$; linear term : $\beta = 2.59$, ns). The resulting inverse U-shape is illustrated in Figure 3. Intuitively,

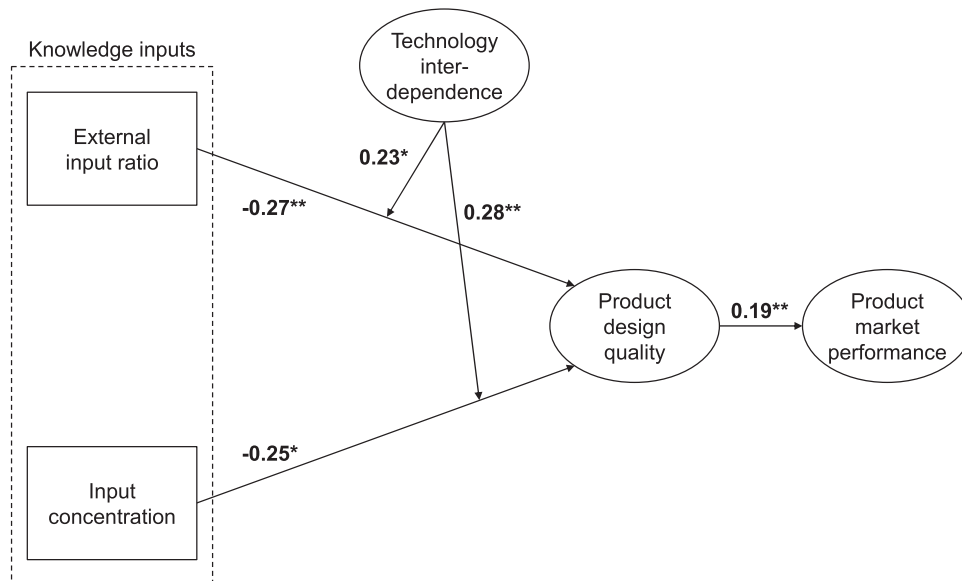


Figure 2. Results of our analysis.

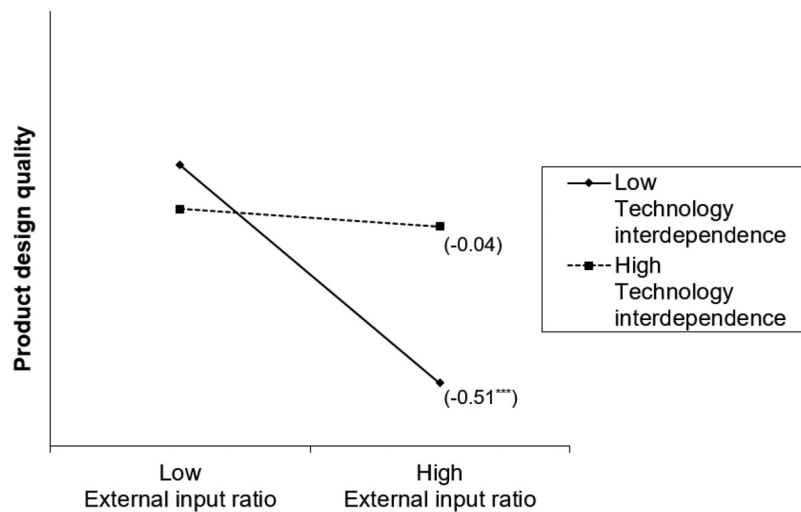


Figure 3. The moderation effect of technology interdependence on external input ratio (Coefficients for slopes at ± 1 SD in parentheses).

results suggest a ‘sweet spot’ around a 40% to 50% external input ratio, where accessing external knowledge can lead to significant improvements in product design quality. In contrast, we observe no significant curvilinear effect of input concentration on product design quality. Results are available upon request.

As a critical test procedure for the existence of an inverse U-shaped relationship between external input ratio and product design quality, we follow Lind and Mehlum (2010). They argue that statistical significance of the quadratic term is not a sufficient test for curvilinear relationships and propose a more rigorous approach. The procedure is based on three criteria conditions: (1) significant quadratic terms, (2) the 90% confidence interval

for the extreme point has to be within the range of the sample data, and (3) significant positive and negative slopes at the minimum and maximum of the sample data. Table 6 presents the curvilinear analysis results following Lind and Mehlum (2010). Again, we observe a significant quadratic term. The extremum point is estimated at 0.48 and we derive a Fieller 90% confidence interval (Fieller 1954), which is [0.313, 0.563] and sits well within our data range [0.125, 1.000], thus meeting the second criterion. The third criterion requires that the slope of the relationship at the lower bound of the sample data interval is significantly positive and the slope at the higher bound is significantly negative, creating the inverse U-shaped case. As seen in Table 6, both conditions are satisfied.

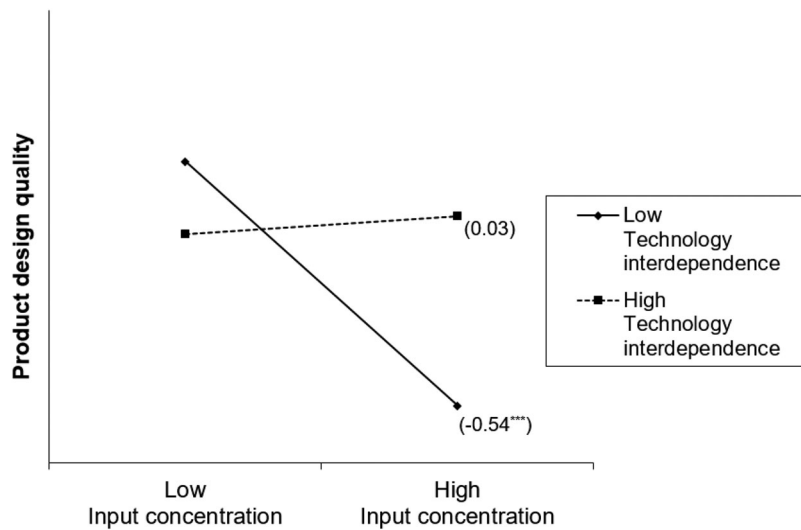


Figure 4. The moderation effect of technology interdependence on input concentration (Coefficients for slopes at ± 1 SD in parentheses).

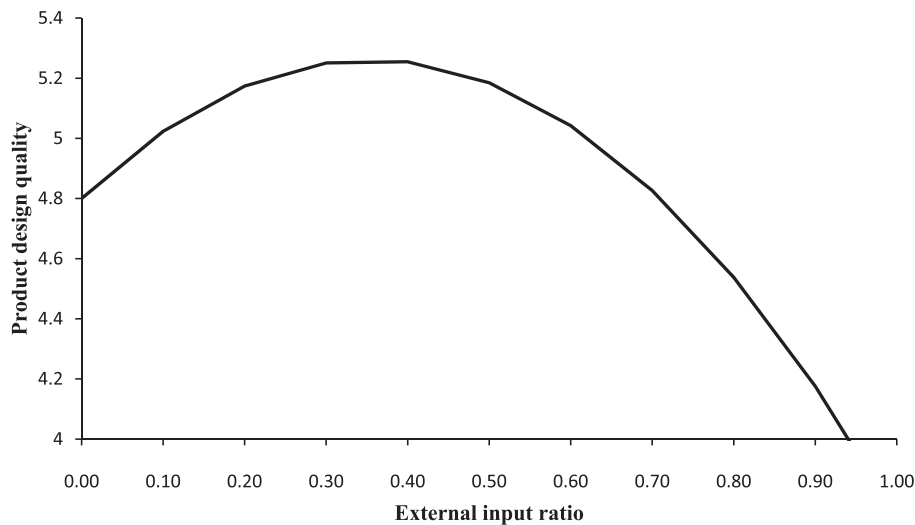


Figure 5. Curvilinear effects of external input ratio on product design quality (unstandardised dependent and independent variables for visualisation purposes; we use average values for control variables).

Table 6. Test for an inverse U-shaped relationship between external input ratio and product quality management.

Dependent variable:	
Product quality management	
External input ratio <i>squared</i>	-3.66**
Extremum point	0.48
90% confidence interval, Fieller method	[0.313, 0.563]
Slope at lower bound = 0.125	4.78***
Slope at higher bound = 1.000	-5.39**

*** $p < .001$, ** $p < .01$, * $p < .05$, + $p < .10$.

Hence, there is a significant inverse U-shaped (hump-shaped) relationship over the full range of our sample data ($atp < 0.05$).

5.3. Robustness checks

We include two robustness checks: (1) alternative variable measurements and (2) a multi-group structural equation modelling approach to retest the moderation effects of technology interdependence. Our robustness checks substantiate reliability and validity of our findings.

First, we check for robustness regarding our latent variables. Initially, we use the factor scores of our latent variables derived by maximum likelihood factor analysis in our regression models. However, there are other construct scoring approaches potentially leading to substantially better results in terms of reliability (Hair et al. 2010; Rönkkö et al. 2016). As alternatives, we consider

average and sum item scores. Both sets of regression models confirm our previous results and indicate robustness of our study. Detailed estimates are available upon request.

Depending on its operationalisation, the measure for input concentration might not adequately account for the number of project partners. In our main analysis, we set the contribution of non-involved parties to zero. Alternatively, we calculate the standard deviation only using the involved partners and adding the inverse number of project partners. After including this measure of input concentration in the regression model, we are able to confirm all the hypothesis-testing findings. In addition, we also test alternative operationalisation of the non-latent variables. For example, we use the number of firm employees as a proxy for firm size and control for sales growth, as younger and expanding firms might have different innovation processes than bigger incumbent players. All our results are confirmed.

Second, we run structural equation models (SEM) with maximum likelihood estimation. We estimate our SEM using Stata 15. SEM is a second generation multivariate method allowing for the specification of a measurement model including multiple indicators for latent unobserved variables as well as a structural model defining relationships between multiple observed and latent variables (Bagozzi and Yi 1988; Fornell and Larcker 1981). As SEM can create issues when examining multiple interaction terms (Sardeshmukh and Vandenberg 2017), we use regression models in our main analysis. However, as a robustness check, we split our sample at the median level of technology interdependence, to test the moderation effects (Hair et al. 2010). Our results are robust to the multi-group SEM. Detailed results are available in Table A1 in the Appendix.

6. Discussion and conclusion

In this study, we examine how the knowledge input characteristics among collaborating types of external organisations affects inter-organisational NPD project outcomes. Interestingly, we find that a high external input ratio has a negative effect on product design quality, an effect that is attenuated by technology interdependence of the new product. An interesting inverse U-shaped relationship between external input ratio on design quality is also found in our post-hoc analysis. We also find that high knowledge concentration could hurt product design quality, especially in a product setting with low technology interdependence. Overall, our results are indicative of the key role of knowledge inputs in explaining the product design outcomes in inter-organisational NPD projects. We discuss the theoretical and managerial

implications of these findings and our post-hoc analysis below.

6.1. Theoretical implications

Theoretically, we contribute to the inter-organisational NPD literature by studying the performance implications of a rarely examined influencer of project performance: the characteristics of knowledge inputs. The strategic alliance and NPD literature have widely recognised the importance of understanding knowledge flows among partnering organisation types in a joint NPD project (Grant and Baden Fuller 2004; Lawson and Potter 2012; Sarin and McDermott 2003). Most often, the literature generally focuses on inter-organisational governing structures and team processes that encourage knowledge acquisition, integration and utilisation (Bstieler 2006; Yan et al. 2020). However, very rarely has the literature examined the knowledge inputs by different NPD project partners. To contribute to this stream of work, this study discovered significant influences of two knowledge input characteristics: external input ratio and input concentration.

Specifically, we show that when the knowledge portfolio is largely composed of external knowledge, product design quality also could be negatively affected. We see one main explanation for our findings. Although a higher external input ratio might help by creating greater access to external knowledge, the focal firm could also face challenges of integrating a higher percentage of external knowledge for improving the final product design (Grant 1996; von Briel, Schneider, and Lowry 2018). Knowledge integration will be more challenging when the knowledge portfolio is mainly made up of externally originated knowledge. Compared to internally created knowledge, externally accessed knowledge usually overlaps less with a focal firm's business domain and product design needs. As a result, it is more challenging to integrate external knowledge with internal knowledge to facilitate NPD project success (Easterby Smith, Lyles, and Tsang 2008; Modi and Mabert 2007). In contrast, when the knowledge portfolio is primarily composed of a focal firm's own knowledge, it is easier to integrate the knowledge, and improve the product design due to a shorter distance between the knowledge portfolio and the product development needs.

To better understand this counterintuitive negative influence of external input ratio on design quality, we conducted post hoc analysis and identified an inverted U-shape relationship between external input ratio and design quality. Our findings provide evidence for a 'too much of a good thing' effect (Busse, Mahlendorf, and Bode 2016). In other words, an intermediary level of

external input ratio seems to work best for the focal firm to improve design quality. When the knowledge portfolio is composed of a balanced set of internal and external knowledge, the focal firm could benefit from accessing novel external knowledge without being burdened too much in integrating them with internal knowledge. A significant level of internal knowledge gives the focal firm better control on how the total knowledge portfolio contributes to the improvement of design quality. Therefore, although the overall effect of the external input ratio on design quality is negative, we are able to show that a low to medium level of external input ratio could still help. Overall, these interesting findings encourage future research to examine the interaction between internal and external knowledge in affecting NPD outcomes.

We also add to the literature by examining the effects of another overlooked predictor of NPD project outcomes, input concentration. As expected, we found that input concentration affects product design quality negatively. While a highly dispersed knowledge portfolio creates significant knowledge integration challenges, it provides the focal firm with a more diverse set of knowledge. Knowledge concentrated within few types of organisations also results in a higher level of focal firm dependency on that partner, creating additional challenges for knowledge integration due to the asymmetric power between the main knowledge contributor and the focal firm. These interesting findings should encourage future studies to investigate whether a higher level of concentration of other types of NPD project resources (i.e. financial, human, physical) also negatively affect team processes and project outcomes.

Further, this study provides important theoretical insights to the inter-organisational innovation literature by identifying the moderating role of technology interdependence in a knowledge intensive task environment. Technology interdependence is a product characteristic that introduces uncertainty and complexity to a NPD project. In NPD projects where technology interdependence is low, we found that both external input ratio and input concentration hurt design quality significantly more. Products with high technology interdependence often require more complex design solutions as well as more design-manufacturing interactions. A high external input ratio indicates a higher chance for the focal firm to access distant, external knowledge possessed by partnering organisation types. These distant knowledge, though challenging to be integrated, should be crucial for the focal firm to overcome the design challenges created by a complex, interdependent product structure (Argote 2012; Grant and Baden Fuller 2004; Lawson and Potter 2012). This finding sets up a stage for future studies about product architectures, modular vs integral, to take

a knowledge acquisition and integration view and examine the knowledge management implications posed by product architecture.

We further show that the negative effect of input concentration on design quality is accentuated when technology interdependence is low. The significant design challenges associated with technology interdependence seem to pose enough coordination challenges within a NPD project to the extent that any further coordination need is hard to be met, which could make a less concentrated knowledge portfolio challenging to manage. As the literature suggests, close relationships are easier to maintain with fewer contributing partners, allowing for flexibility and agility when applying knowledge to develop the best design solution (Choo, Chandrasekaran, and Chinaprayoon 2020; Slot, Wuyts, and Geyskens 2020). Therefore, low knowledge concentration increases the challenge to keep close relationships with external partners, thus increasing knowledge integration challenges, especially when there are a lot of moving parts in the product design due to a high level of technology interdependence. The moderation effect of technology interdependence on the negative effect of input concentration on design quality provides an indication for a potential dark side of a highly dispersed knowledge portfolio in inter-organisational NPD projects. In general, we add to the literature by showing the importance of understanding product technological architectures for managing knowledge flows in inter-organisational NPD projects by establishing technology interdependence as a contingency factor that moderates effects of knowledge input characteristics on design quality. Future studies should explore other contingencies on performance implications the knowledge flows in inter-organisational NPD project.

Overall, our findings advance the inter-organisational collaboration literature that examines performance implications of resource distributions among partners by providing project-level evidence about the crucial roles of knowledge inputs. A few strategic management studies have provided evidence about the influences of resource diversification and concentration on firm-level or business-unit level innovation performance (Chen and Chu 2012; Cui and O'Connor 2012; Bos, Faems, and Noseleit 2017). Since knowledge is a critical type of innovation resources, the innovation literature has also shown the importance of considering diversity in knowledge, indicated by partner type diversity, innovation objective diversity, etc. could affect firm innovation performance (Leiponen and Helfat 2011; Wuyts and Dutta 2014; Hagedoorn, Lokshin, and Zobel 2018; Zhang, Yuan, and Wang 2019). The supply chain management literature has also shown that the concentration of sourcing resources among a few suppliers could benefit

the absorption of external knowledge in certain situations (Moeen, Somaya, and Mahoney 2013). The literature suggests the nature of the total knowledge available to a focal firm in its inter-organisational network, i.e. diversity, distance, etc. could affect the extent to which the focal firm could effectively absorb and integrate the knowledge (Vasudeva and Anand 2011). Adding to these firm-level insights, our inter-organisational project-level empirical analyses show that characteristics of knowledge inputs could also affect product design quality, an effect that is contingent on the level of technological interdependence. By showing the contrasting effects of external inputs ratio and total inputs concentration on design quality, our study opens up a new field for future studies to examine project-level performance implications of other types of resources inputs, i.e. tangible assets, financial investments, and others.

6.2. Managerial implications

Successful NPD projects are a key means for firm innovation. However, NPD managers are facing a plethora of complex decisions, especially when external organisation types are involved. Managers are responsible for managing knowledge flows among the collaborating types of organisation in order to facilitate successful NPD projects (Im, Rai, and Lambert 2019; Lawson and Potter 2012). Managers often struggle with creating, acquiring and internalising technical and market knowledge from outside partners, such as suppliers, R&D institutes or universities, in a most efficient and effective way. The findings in our study mainly concern the underlying knowledge input tradeoffs. While our study is set on the project level, our results still provide insights to guide higher-level managerial decision-making, e.g. partner selection, in the NPD context.

Specifically, our results provide insights to managers concerned with NPD partner selection decisions and managing knowledge inputs among collaborating organisations. When following an open innovation strategy and opening the NPD process to external types of organisations, the focal firm needs to select those partners with complementary and valuable innovation resources, among which intangible knowledge is an important one. Instead of sticking to a 'more is better' mindset when soliciting knowledge inputs from each partner type, NPD managers of the focal firm should consider the different performance implications of external input ratio and input concentration.

Based on our findings, we make three practical recommendations. First, even though a knowledge portfolio that is largely composed of external knowledge creates many learning opportunities, the challenge of accessing

and integrating the external knowledge might limit or even cancel out the learning benefits. Based on our post-hoc analysis, we recommend an intermediate level of external input ratio, which seems to most improve the focal firm's NPD outcomes. Achieving the appropriate level of external knowledge involves prospective supplier selection. Remembering the introductory example, Volkswagen Group's Artemis project successfully balanced knowledge inputs by internal and external project partners based on current knowledge needs. We advise managers to examine carefully what potential suppliers can add to a project. Building long-term supplier relationships can also help with ensuring consistent knowledge inputs. We further suggest managing and maintaining a solid internal knowledge base, enabling a firm to balance out internal and external knowledge in a NPD project.

Second, given the complex tradeoffs in the context of external knowledge inputs, we emphasise the importance of building and maintaining a solid internal knowledge base. For example, without a solid internal knowledge base, the focal firm might be overwhelmed by the amount of external knowledge, i.e. the dark side of a high external input ratio, which could cause knowledge integration to be costly or even unfeasible. We advise an open innovating firm to develop its own core knowledge base before opening up the innovation process to outside partners.

Third, when selecting external partners, the focal firm should also manage the concentration of knowledge inputs among few types of organisations. For example, a less concentrated (more dispersed) knowledge portfolio creates significant knowledge integration challenges, as the added diversity may complicate the knowledge management processes. Only when technology interdependence is low, which suggests a lower information processing need, managers could consider sourcing knowledge more broadly from external partners. In contrast, for products with high technology interdependence, stronger ties with a few types of external organisations (i.e. high knowledge concentration) could be crucial for the focal firm to discover the best design.

Finally, we also advise NPD managers to consider product architecture when making project partner selection decisions. In many firms, engineering is concerned with designing product architectures. Our results suggest that these architecture decisions affect the types of knowledge needed and determine the optimal configuration for knowledge inputs of a NPD project. During the Artemis project, Audi always had to select technology partners to complement the knowledge within the complex technology architecture. However, partner selection is often a (strategic) management decision. Communication and collaboration between management and the project engineering team might be insufficient or non-existent, a

problem widely discussed in project management practice (Laufer et al. 2015; Pedersen and Ritter 2017). We advise managers to engage with the engineering team and understand specific project needs and characteristics to make more informed decisions on inter-organisational NPD project partner selection.

6.3. Limitations and conclusion

This study has some limitations that need to be taken into account when interpreting its findings and conducting future research. First, we only focus on product design quality as our primary project outcome. Despite the fact that product design quality is a highly important and relevant outcome from a knowledge acquisition and integration view in an inter-organisational NPD project, there exist other important outcomes, such as time-to-market performance. We encourage future studies to extend our framework to other project outcome indicators. Second, the study is based on data from Italian firms. Italy presents an interesting case to study inter-organisational NPD activities, given its highly innovative clusters characterised by close relationships with suppliers and customers. While this premise is likely to have provided valuable insights, it also limits the generalisability of the study. Therefore, future research should also study the effects of knowledge inputs in different cultural contexts, including emerging markets. Third, knowledge is inherently difficult to measure. We chose to employ perceptual scales for the knowledge inputs. Specifically, we derive calculated variables based on these perceptual scales. While we assume that our calculated variables are still valid even based on perceptual measures, future research is encouraged to employ alternative measures of knowledge inputs. Fourth, we focus on design quality as the primary project performance measure for several reasons. Product design quality is directly related to the absorption and integration of various streams of knowledge inputs in the NPD process and is also tightly connected with technology interdependence. Given our focus on understanding how knowledge inputs affect NPD project performance, we believe that our variable is appropriate. However, we encourage future studies to explore the effects of knowledge inputs on alternative project performance measures, such as development process efficiency, product market performance, and others. Finally, when investigating the effects of knowledge contributions, we did not consider the implications of different types of organisations, i.e. those with more distant knowledge vs those with closer knowledge to the knowledge base of the focal firm. While Yan and Azadegan (2017) show that there is no difference between the supply chain members and non-supply-chain sources'

influences on product novelty, it is still quite possible that knowledge distance between the focal firm and innovation partners might affect NPD outcomes. Therefore, we encourage future studies to take the type of organisation into account or even directly measure knowledge distance when studying inter-organisational NPD projects. Finally, we decided to examine project-level factors, as fewer studies explore inter-organisational knowledge flows on the project level. However, this focus could limit our attention to other important firm-level outcomes that are potentially affected by the focal NPD project. These outcomes and effects include inter-project knowledge flows, knowledge partner relationships and selection processes. We encourage future research to take on different perspectives on the role of knowledge inputs in NPD projects.

In conclusion, this study investigates a rarely examined influencer of inter-organisational NPD project performance: the characteristics of knowledge inputs. We focus on the ratio between external and internal knowledge inputs and the concentration of knowledge inputs between all types of collaborating organisations. Our results show how the characteristics of knowledge inflows affect NPD project success. Understanding and realising the performance benefits associated with different knowledge input characteristics, NPD managers could make more informed decisions when select innovation partners to create a knowledge portfolio that matches the specific project goals.

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Appendix

Table A1. Multi-group SEM results.

Group	Low technology interdependence		High technology interdependence	
	Product design quality	Product market perf.	Product design quality	Product market perf.
Dependent variable:				
<i>Control variables</i>				
Product novelty	−0.04 (0.05)	0.07 (0.06)	−0.05 (0.06)	0.09 (0.06)
Innovation breadth	0.27** (0.12)	−0.12 (0.11)	0.31*** (0.07)	0.07 (0.10)
Firm sales revenue	−0.24*** (0.10)	0.18 (0.11)	0.10 (0.11)	−0.04 (0.08)
Firm R&D intensity	0.10 (0.10)	−0.13 (0.12)	−0.11 (0.10)	0.14 (0.10)
Industries	Yes	Yes	Yes	Yes
<i>Hypothesised variables</i>				
External input ratio	−0.21* (0.17)		−0.32** (0.07)	
Input concentration	−0.39*** (0.13)		−0.06 (0.13)	
Product design quality		0.02* (0.11)		0.46*** (0.10)
SRMR (group-level)	0.085		0.061	
CD (group-level)	0.266		0.147	
χ^2 (model-level)	216.2***			
RMSEA (model-level)	0.103			
CFI (model-level)	0.862			
N	102		108	

Note: *** $p < .001$, ** $p < .01$, * $p < .05$, + $p < 0.10$; standard errors in parentheses.