

ORIGINAL ARTICLE

Direct and indirect effects of degree of interdisciplinarity on firms' innovation performance: The moderating role of firms' capabilities

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Funding information

Bundesministerium für Bildung und Forschung, Grant/Award Number: 03WIR6203; German Federal Ministry of Education and Research (BMBF), Grant/Award Number: 16WIK2101A

Associate Editor: Jelena Spanjol

Abstract

Combinations of heterogeneous knowledge from different scientific domains may drive highly innovative outcomes. Our study investigates whether firms can benefit from interdisciplinary research and development (R&D) activities by also reflecting on the potential negative consequences of increasing complexity of outcome validation activities at later stages of innovation processes. We explore which resources and organizational capabilities may influence the efficacy of interdisciplinary R&D activities. We examine whether the available financial slack, collaborations with universities, and a high betweenness centrality in scientific networks may promote the flexibility, scope, and efficiency of knowledge integration, and thus moderate the direct and mediated relationships between the degree of interdisciplinarity (DoI) of a firm's R&D activities and innovation performance. To test our hypotheses, we performed an analysis of medical technology firms that are highly dependent on interdisciplinary R&D. We collected a panel dataset of R&D activities and successful market launches of new products from 79 large medical technology firms between 1997 and 2021. The measurement of a firm's DoI is based on a novel approach involving neural networks in a bibliographic data graph. Our results suggest that firms can improve their innovation performance if they conduct interdisciplinary R&D activities. However, higher levels of DoI also increase the complexity of the required outcome validation, which reduces a firm's innovation performance. We also found that high levels of financial slack help to overcome barriers of implementing interdisciplinary R&D activities. Collaborations with universities, and good access to knowledge in scientific networks, further foster interdisciplinary knowledge application in new product development.

KEYWORDS

betweenness centrality, financial slack, interdisciplinary research, medical technology industry, university–industry collaboration

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1 | INTRODUCTION

Firms can obtain valuable new knowledge for new product development by combining knowledge from different technological domains. Ideas generated in more distant knowledge fields have a high potential to induce a creative leap (Hacklin & Wallin, 2013), breakthroughs (Fleming, 2001), and foster the development of radical innovations (Xu, 2015). Thus, firms may profit from increased diversification of their knowledge base, and this interdisciplinarity has a positive impact on technology development (Kwon, 2022). This is of particular importance in high-technology industries (Hermelin et al., 2014; Keijl et al., 2016).

However, a combination of multiple knowledge domains may create risks and increase variance in product performance (either very high or particularly low performance) (Taylor & Greve, 2006), because an integration of knowledge and technologies from distant fields can be extremely challenging (Boix Mansilla et al., 2016; Buanes & Jentoft, 2009). Hence, developing and maintaining interdisciplinary innovations rely on substantial capabilities to cope with the high cognitive distance between different technological knowledge fields (Nooteboom et al., 2007) and the resulting complexity of knowledge integration and associated R&D projects (Zhang & Thomson, 2018). Understanding the mechanisms of integration and application of interdisciplinary knowledge is key to the success of interdisciplinary R&D activities (Hacklin & Wallin, 2013).

The growing relevance of interdisciplinarity in research and development is evident in the field of medical technology, for example. Manufacturers of hearing aids, for instance, are confronted with the task of adding advanced sensors to hearing aids in order to measure hearing fatigue. These data form the basis for automated fitting processes, which may make personal care by audiologists unnecessary for the majority of clients. At the same time, these sensors also enable the generation of medical data for other fields of application, for example, neurology, cardiology, or occupational medicine. For development, manufacturers therefore need extensive knowledge of diverse technological fields, such as sensor technology, acoustics, biocompatibility, data science, as well as of application domains such as audiology, neurology, and cardiology. This enables the development of a new generation of hearing devices, but simultaneously increases the complexity of outcome validation and market introduction, reflected, for instance, in extensive multi-center clinical trials (Luengen et al., 2021).

Existing literature focuses mainly on the virtues of interdisciplinary research for researchers in academia

Practitioner points

- Firms profit from a high degree of interdisciplinarity of research and development (R&D) activities but need to develop processes for managing the increased complexity in outcome validation of highly interdisciplinary R&D.
- Managers should allocate additional financial resources to buffer against the risks and unpredictabilities inherent in interdisciplinary R&D, allowing for more experimental freedom.
- Firms should forge and strengthen partnerships with universities to tap into cutting-edge interdisciplinary research and to foster knowledge integration from interdisciplinary R&D.
- Firms should aim to become central nodes within scientific networks to facilitate easier access and integration of diverse knowledge, improving their innovation potential.

(Leahey et al., 2017) and public research centers (Jung et al., 2021). The relevance and performance impact of interdisciplinary research and development activities in industry is reflected only to a lesser extent in the literature. The conditions necessary for firms to profit from interdisciplinarity remain largely unexplored in the existing literature, since findings from the analysis of interdisciplinary research results in academia cannot easily be transferred to businesses. The obstacles include difficulties to measure the degree of interdisciplinary R&D activities at the firm level and limited insights into the necessary complementary assets, such as the firm's resources and capabilities needed for interdisciplinary R&D.

A firm's knowledge base is a decisive input for its competitive advantage (Grant, 1996a, 1996b). Integration of specialized knowledge is a core *organizational capability* that Grant (1996a) defines as "a firm's ability to perform repeatedly a productive task which relates [...] to a firm's capacity for creating value through effecting the transformation of inputs into outputs" (Grant, 1996a, p. 377). Interdisciplinary R&D activities require a recombination of multiple disciplines and the integration of distant ideas, and thus it depends on an organizational capability to support knowledge integration (Grant, 1996a, 1996b). Therefore, we investigate the set of resources and capabilities that firms need to achieve the necessary flexibility, scope, and efficiency of knowledge integration (Grant, 1996a). We argue that this set of resources and capabilities enable

successful interdisciplinary knowledge integration and its application in a firm's innovative activities.

Complex learning processes governing interdisciplinary research demand novel organizational capabilities to facilitate the *flexibility of knowledge integration*; and these depend on the firm's current financial resources (Herold et al., 2006). A firm's current financial health affects its willingness to invest in highly risky but promising explorations of new technologies or undeveloped markets. To increase their *scope of knowledge integration*, organizations also need impulses from their environment to overcome a path dependency on their own knowledge base (Kogut & Zander, 1992; Nooteboom et al., 2007). Therefore, they depend on their external learning capabilities to widen the knowledge breadth needed for interdisciplinary research. Through collaborations with universities doing research at the boundaries of distant scientific disciplines, firms can extend their knowledge base for recombination and get a pioneering advantage in emerging knowledge and technology fields. Through engaging in social and scientific networks, firms can also improve the *efficiency of knowledge integration* at a lower cost by obtaining valuable ideas from weak ties to scientific academic communities (Baba & Walsh, 2010; Liebeskind et al., 1996), but only if they have a high level of ability to bridge different actor and knowledge clusters due to a high betweenness centrality position in these scientific networks (Gilsing et al., 2008; Guan et al., 2016; Hermelin et al., 2014). Although financial resources, collaborations with universities, and a central position in social scientific networks can foster interdisciplinary knowledge integration, these same elements may increase the diversity and amount of knowledge to be integrated and, thus, may raise issues of knowledge application complexity. The high level of complexity of applied knowledge might reduce firms' innovative output (Yayavaram & Chen, 2015).

Thus, the purpose of our study is to clarify whether firms benefit from the degree of interdisciplinarity (DoI) of their R&D activities. We explore how DoI affects a firm's innovation performance, and we account for the role of the increasing complexity of the validation of intended outcomes and its potential negative consequences for a firm's innovative performance. Complexity of validation processes may mediate the relationship between DoI and a firm's innovative performance. We also elucidate the ways in which the organizational capabilities moderate the relationships between the DoI and the firm's innovation performance, and between the DoI and the complexity of outcome validation. To test our hypotheses, we analyzed firms in the field of medical

technology, since the medical technology industry builds upon multiple medical and engineering domains of scientific knowledge and is highly dependent on interdisciplinary R&D (Chandra, 2013). We collected a panel dataset containing scientific publications, successful product approvals by the regulatory bodies, patent activities, clinical trials, and financial data of 79 large medical technology firms between the years 1997 and 2021. Our measurement of a firm's DoI is based on a novel approach involving convolutional neural networks in a bibliographic data graph.

Our results suggest that firms can improve their innovation performance if they conduct interdisciplinary research. However, interdisciplinary research increases the complexity of the necessary medical validation, which reduces the innovative performance of the analyzed medical technology firms. Our findings also show that firms can effectively integrate interdisciplinary R&D results in innovation if they improve the flexibility of knowledge integration by providing sufficient financial resources to invest in interdisciplinary research projects. Through collaborations with universities, they can enhance their scope of knowledge integration capability, which fosters interdisciplinary knowledge translation and application in innovative outcomes. However, collaborations with academia also drive the complexity of the required outcome validation by diversifying firms' knowledge base and, thus, reduce the potential of interdisciplinary research to contribute to a firms' innovation performance. We find a similar interplay between facilitating and hampering roles of organization capabilities for a high betweenness centrality position in scientific networks. Such a favorable network position strengthens the direct relationship between DoI and a firm's innovation performance, but also elevates the complexity of the firm's validation activities, diminishing the effect of interdisciplinary research outcomes on a firm's innovative performance.

We contribute to existing research on the impact of interdisciplinary R&D activities on a firm's innovation performance and the relevance of organizational capabilities for knowledge integration in high-technology industries. Our study expands the knowledge-based view by suggesting that a firm's DoI is a strategic knowledge resource that can have positive and negative consequences. Our study clarifies the conditions for a firm to profit from interdisciplinary R&D activities, and it suggests that managers of high-technology firms should improve its organizational capability with regards to flexibility, scope, and efficiency of knowledge integration. However, managers should be aware that interdisciplinary research increases the complexity of the relevant

processes of validating the intended outcomes and thereby alleviates the firm's innovation performance.

2 | THEORETICAL BACKGROUND AND HYPOTHESES

2.1 | Degree of interdisciplinarity and a firm's innovation performance

According to the knowledge-based view, a firm's knowledge is a crucial strategic resource, the combination, integration and application of which secures its sustainable competitive advantage (Barney, 1991; Grant, 1996a, 1996b). A firm's innovativeness directly depends on its ability to recombine knowledge and technologies (Carnabuci & Operti, 2013) beyond its core technological base and its own borders (Guan & Liu, 2016; Tether, 2002). Thus, a high degree of interdisciplinarity of R&D activities may enhance its innovation performance and, therefore, secure its competitive advantage.

Interdisciplinarity is "a mode of research that integrates concepts or theories, tools or techniques, information or data from different bodies of knowledge" (Rafols & Meyer, 2010, p. 265). In a scientific environment, Yegros-Yegros et al. (2015) find that the larger the diversity of scientific knowledge domains used for knowledge combinations, the higher the impact that a scientific publication can have. We argue that a firm's innovation performance is also dependent on the degree of interdisciplinarity (DoI) of its R&D activities. We define DoI as the extent to which a firm integrates knowledge from different distant knowledge domains, scientific and technical concepts, and methodologies within its research projects. Atypical knowledge linkages may result in breakthrough ideas (Schilling & Green, 2011), and a high level of knowledge diversity can lead to creative ideas and improve product performance (Hacklin & Wallin, 2013; Taylor & Greve, 2006). Hence, interdisciplinary projects can facilitate the production of new innovation ideas, generate increased technological impact (Keijl et al., 2016), and enhance a firm's technological performance (Lo & Kennedy, 2015). Firms drawing on a sizeable breadth of knowledge, such as that inherent in knowledge and technology base diversity, can successfully integrate and apply that knowledge to develop radical innovations (Xu, 2015). We therefore argue that a firm's DoI is positively related to the firm's innovation performance:

H1. A higher DoI of R&D activities is positively associated with a firm's innovation performance.

2.2 | Degree of interdisciplinarity and the complexity of necessary validation of outcomes

Integration and recombination of knowledge from diverse scientific and technological domains may increase the complexity of validation steps, especially if knowledge needs to be integrated across a firm's entire value chain (Maleki & Rosiello, 2019). Based on the definition by Maleki and Rosiello (2019), we define *complexity* according to two system characteristics: (1) the number of different units configuring a firm's applied knowledge system and (2) the strength of interdependencies between the underlying applied knowledge units within an innovation project. A higher level of knowledge interdisciplinarity demands more coordination of specialists from different knowledge areas (Zhang & Thomson, 2018). Interdependencies within the application of interdisciplinary knowledge occur if one element in the system has a considerable impact on the functionality of other elements, and a modification of such a unit would result in the adaptation or substitution of one or more other units.

Interdisciplinary research intensifies the interdependencies between specialists' knowledge and various medical technology application areas, and hence increases complexity (Sorenson et al., 2006; Yayavaram & Chen, 2015). In the medical technology industry, the complexity of validation results from the interdependencies of different clinical trials and different clinical investigators for newly developed medical device products. Companies with interdisciplinary R&D activities face increasing difficulties in demonstrating that their products are safe and effective and need to validate outcomes in ethnically diverse patient cohorts. As such, firms may struggle to recruit enough patients in one country and conduct clinical trials in multiple countries. The resulting diversity of local principal investigators involved allows firms to gain rich knowledge beyond regulatory requirements, for example, by learning about local processes and requirements and developing complementary services (Kaplan et al., 2004). Accordingly, when firms conduct their clinical trials in different countries, they have to deal with major cultural differences (Sahin et al., 2020), need to provide additional management resources in terms of personnel and knowledge, and may face a higher probability of failure. Therefore, we suggest that interdisciplinary research enhances both knowledge diversity and interdependencies, and will increase the complexity of outcome validation.

H2. A higher DoI of R&D activities is positively associated with a higher complexity of a firm's activities of outcome validation.

2.3 | Complexity of a firm's validation activities as a mediator

The underlying complexity may hamper knowledge integration and application in a firm's innovation projects and may also increase project costs. We argue that the level of complexity of validation reflects the trade-off between the value of interdisciplinary research outcomes and the increased coordination costs of interdependent interdisciplinary knowledge elements. Recent empirical findings from the knowledge and technology-intensive pharmaceutical industry suggest that knowledge complexity also has attendant negative consequences for a firm's innovation performance (Hou et al., 2023). The increasing complexity of the integration of multiple knowledge domains, and the strong interdependence between them, may decrease a firm's innovation performance (Yayavaram & Chen, 2015). Grant (1996a) warns that a flexible integration of diverse knowledge may be achieved at the cost of diminishing the total knowledge integration. A high interdependence of knowledge components may thus result in higher costs of coordination. We therefore argue that complexity of outcome validation will increase with DoI, on the one hand, but will decrease a firm's innovative performance on the other hand, suggesting that DoI is a double-edged sword with direct positive and indirect negative effects.

H3. A higher complexity of a firm's activities of outcome validation is negatively associated with a firm's innovation performance.

2.4 | Moderating effects of organizational capabilities on knowledge integration

A firm may need to utilize its organizational capabilities to integrate specialized knowledge from different domains. We argue that these capabilities are related to the three characteristics of knowledge integration: *flexibility of integration*, *scope of integration*, and *efficiency of integration* (Grant, 1996a). These three characteristics result in the relevance of financial slack, the intensity of university collaborations, and a firm's position within the scientific networks being relevant moderators of the DoI performance relationship.

Flexibility of knowledge integration refers to the constant renewal of competitive advantages through development of novel capabilities (Grant, 1996a). Grant (1996a) argues that such capabilities can be achieved either by extending existing capabilities for the incorporation of new types of knowledge, or by reshaping existing knowledge for the creation of new types of capabilities. In both

cases, firms need additional financial resources to extend or reconfigure their knowledge integration and to invest in the organizational capability extension.

The *scope of integration* implies the breadth of knowledge that is needed to be integrated. Through collaborations with universities, firms can obtain deep, valuable, and complementary knowledge from different scientific fields. Hence, collaborations with academia can improve the scope of knowledge integration. However, different types of knowledge may also require different modes of integration, unavoidably increasing the complexity of knowledge integration and a firm's coordination costs (Kogut & Zander, 1992).

The *efficiency of knowledge integration* determines the firm's ability to gain easy access to specialized knowledge (Grant, 1996a). Social networks of specialists, such as researchers, are highly efficient for knowledge integration, since scientific ties enable reliable information exchange and facilitate the quality of communication between actors within the network (Liebeskind et al., 1996). Thus, the level of interaction and exchange in such scientific social networks defines the level of efficiency of knowledge integration. The efficiency of knowledge integration improves, especially if a firm has a central betweenness position within the network and can access knowledge and information from different internally homogeneous subnetworks beyond its own boundaries.

2.5 | Moderating effect of financial slack

Organizations with substantial financial slack can afford more experimentation (Hornsby et al., 2002). They can thus improve the flexibility of their knowledge integration by extending their capabilities to incorporate new knowledge types. Firms with sufficient financial resources can also invest in the interdisciplinary competencies of their personnel to increase their motivation to engage in interdisciplinary research projects. This may also allow for more formal and informal meetings to facilitate exchange of ideas and motivate staff to nurture an interest in interdisciplinary work (Claus & Wiese, 2019). Moreover, through investments in employees' interdisciplinary competencies, firms can achieve a higher level of employee experience of interdisciplinary projects, which, in turn, increases an employee's initiative to engage in new interdisciplinary projects (Claus & Wiese, 2019). To be innovative and competitive, it is important that firms allow sufficient time and access to resources for employees who have different functional backgrounds. Diverse teams support multiple transformations in joint knowledge integration that, together, fosters creative and innovative problem solutions (Majchrzak et al., 2012). The integration of knowledge from different technological fields is

challenging and requires specific infrastructure (Carlile, 2002). Therefore, firms need to provide the necessary resources to transfer the results of interdisciplinary R&D activities to complex products that require the integration of multiple technologies. Firms that have sufficient financial resources can thus be more prepared to take innovation risks (Lungeanu et al., 2016), and management will allocate resources to risky and explorative projects with unknown outcomes but potentially higher payoffs (Herold et al., 2006). This goes hand in hand with a higher acceptance level of the investment of financial resources in interdisciplinary research projects by internal stakeholders, and thus with lower internal innovation barriers. The financial investments in scientific research capabilities help to bridge different scientific domains and disciplines, decrease the cognitive distance between various research fields, and increase atypical knowledge linkages between different knowledge domains. We therefore argue that financial slack is necessary for the flexibility of successful knowledge integration in a firm's interdisciplinary projects. This financial slack exists in the case of financial performance growth—a condition that will improve the efficacy of R&D with a high DoI.

H4a. In case of financial slack, the positive effect of DoI activities on a firm's innovation performance will be strengthened.

H4b. In case of financial slack, the positive effect of DoI activities on the complexity of a firm's activities of outcome validation will be strengthened.

2.6 | Moderating effect of university–industry collaborations

Universities have a large knowledge base in very specific scientific and technological fields (Un et al., 2010). Science-intensive industry sectors therefore apply research results from universities and public research organizations to their R&D activities (Cohen et al., 2002). Universities can help firms to absorb, assimilate and internalize external scientific knowledge, decrease their general R&D costs (George et al., 2002), and reduce the risks of uncertain research outcomes, particularly high in interdisciplinary R&D activities. Science-intensive firms specifically, such as companies that manufacture medical devices, that operate within innovation clusters comprising universities and public research organizations, can increase their technological performance (Melnichuk et al., 2021; Rothaermel & Ku, 2008). Industrial and academic researchers can build mutual trust and exchange and disseminate their tacit knowledge without the risk of

imitation (Veer et al., 2016). The genuine curiosity of university researchers to discover new phenomena and to use methods, instruments and techniques from other disciplines can increase the efficiency of a firm's interdisciplinary R&D (Meyer-Krahmer, 1997). Universities and research institutions can assist firms to close the complementary knowledge gaps effectively, because they have a very broad knowledge base, specific research infrastructure, and specialized equipment that firms might not possess. Such specialized knowledge and purpose-built equipment are particularly important for complex interdisciplinary research projects comprising knowledge from multiple domains. In this regard, Du et al. (2014) found that R&D collaborations with universities and research institutions can speed up the progress of very complex technological research projects to the development stage. Hence, we claim that collaborations with universities can enhance a firm's knowledge integration and recombination in interdisciplinary projects, leading to the firm's increased levels of innovation performance.

Simultaneously, such collaborations will also increase the *complexity of activities of outcome validation*, due to enhanced diversity of knowledge and a higher demand for coordination in the downstream activities to apply and translate the interdisciplinary knowledge to prototypes or innovative products. Furthermore, knowledge produced in collaboration with academia may be very tacit in nature, which hampers the successful internalization of such knowledge and demands high levels of absorptive capacity to successfully apply collaborative knowledge (Melnichuk et al., 2021). This will therefore increase the complexity of activities of outcome validation. We thus argue that collaborations with universities will increase the complexity of activities of outcome validation.

H5a. The positive effect of DoI on a firm's innovation performance will be strengthened by a higher intensity of collaborations with universities.

H5b. The positive effect of DoI on the complexity of a firm's activities of outcome validation will be strengthened by a higher intensity of collaborations with universities.

2.7 | Moderating effect of betweenness centrality in scientific networks

Knowledge is unequally distributed across scientific and technological networks (Guan & Liu, 2016), and firms operating in highly technological spheres usually need this very diverse external knowledge residing in

subnetworks of scientific communities. Nevertheless, due to a shortage of resources (required financial slack and human capital) and high coordination costs, firms can only engage in a limited number of direct collaborations with different actors within these scientific networks. To obtain non-redundant diverse knowledge, firms can strive to obtain an advantageous structural betweenness centrality position in those subnetworks (Gilsing et al., 2008). Betweenness centrality in the scientific network can be defined as the proportion of the shortest linkage paths between all pairs of actors that pass through a given scholar or their organization in the scientific network (Borgatti, 2005; Li et al., 2013). Organizations can control knowledge flow and sharing within a global network when they have such a bridging function between subnetworks (Borgatti, 2005; Burt, 1992; Freeman, 1978). A high betweenness centrality value enables firms to get access to knowledge from different scientific domains, and to a variety of skills and experiences that are required for successful knowledge recombination (Gilsing et al., 2008). It allows firms to gather knowledge and information from diverse scientific subnetworks at lower costs, and to recombine it in a novel approach to their own interdisciplinary research. Moreover, through a central betweenness position, firms can find attractive potential collaboration partners, and may get insights in technological breakthroughs and valuable problem-solving approaches from multiple scientific fields (Lai, 2016). Thus, a network position with a high betweenness centrality can improve R&D efficiency (Guan et al., 2016). Interdisciplinary firms may therefore act as knowledge brokers and can better control various information flows, have increased bargaining power, and may hold valuable non-redundant knowledge from other diverse alliance partners (Gilsing et al., 2008). Therefore, we argue that a firm's central betweenness position in the scientific networks will support knowledge recombination in interdisciplinary research and will increase the efficacy of DoI.

However, sourcing knowledge from scientific subnetworks may result in a dilemma: integration of knowledge acquired beyond the boundaries of a firm demands additional actors to absorb the new knowledge, and a more intensive sharing of the acquired information within the firm's innovation processes. Thus, the level of complexity of knowledge integration increases. The complexity also increases due to a higher number of interdependent elements that have to be handled and decided on. Knowledge from cognitively distant, distinct homogeneous subnetworks needs to be combined with the firm's existing knowledge stock and with the industry specific requirements during the later stages of the innovation process. Based on these arguments, we claim that a firm's central betweenness position in the scientific network

can amplify the effect of DoI on the complexity of its outcome validation.

H6a. The positive effect of DoI on a firm's innovation performance will be strengthened by the firm's betweenness centrality position in scientific networks.

H6b. The positive effect of DoI on the complexity of a firm's activities of outcome validation will be strengthened by its betweenness centrality position in scientific networks.

Figure 1 demonstrates our research framework. To summarize: we expect that DoI of R&D activities will be positively associated with a firm's innovation performance. DoI will also be positively related to the level of complexity of activities of outcome validation in later stages of the innovation process, which in turn is negatively associated with a firm's innovation performance. Higher levels of financial slack allow for higher flexibility of knowledge integration and will positively moderate the DoI innovation performance and complexity relationships. Research collaborations with universities and a central betweenness position in scientific networks will lead to increased scope and efficiency of knowledge integration, and thus intensify the expected positive effect of DoI on both innovation performance and complexity of activities of outcome validation.

3 | DATA AND METHOD

The study is performed in the field of medical technology. The medical technology industry utilizes multiple medical and engineering domains of scientific knowledge and is highly dependent on interdisciplinary research (Chandra, 2013). The development of innovative medical devices relies on many different domains of technology and knowledge, such as biomedical engineering, biomedical physics, and biomedical computing, as well as various medical fields that are all grounded in the research knowledge from chemistry, physics, mathematics, computer science, and biology (Nüsslin, 2006). Hence, the integration of interdisciplinary knowledge turns out to be a crucial factor for the success of technological advancements and new product development in the medical technology industry.

3.1 | Dataset and data aggregation

To test our hypotheses, we used a list of the 100 largest medical device companies, based on market capitalization

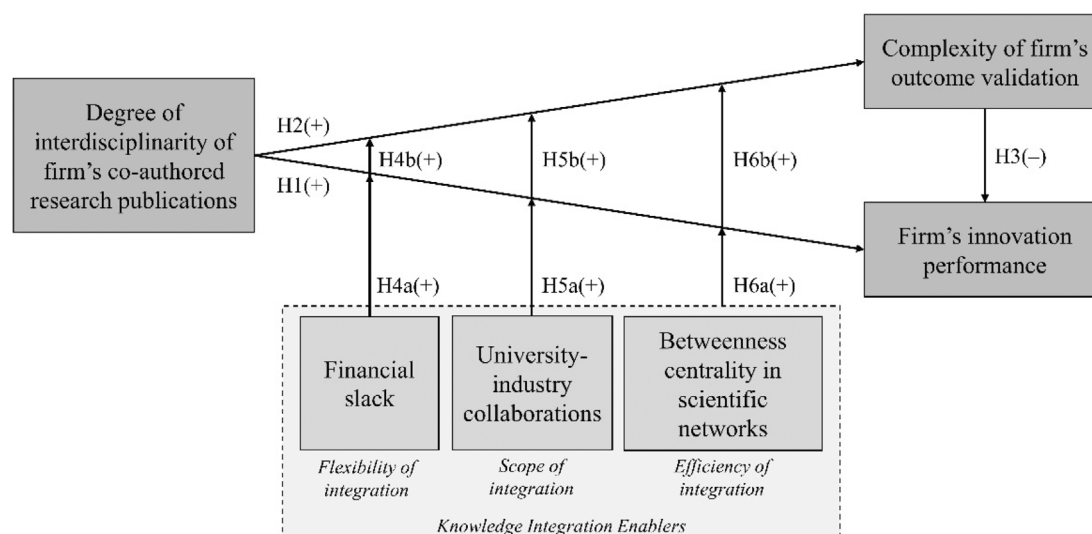


FIGURE 1 The research framework.

in 2017. We derived this list from the commercial quality management software platform *Greenlight Guru*, which specializes in data for and about medical device companies. To analyze the 100 companies, we collected a unique panel dataset comprising data on product approvals, as well as bibliographic, patent, clinical trial, and financial data from the period 1997 to 2021. One dataset selection criterion was a firm's existence as an independent firm for at least five consecutive years during that period. Another selection criterion was that mergers or divestitures should not have affected the firm's medical technology business unit. We excluded those firms for which product approvals, bibliographic, patent, and financial data were not available. Our final dataset contained 79 of the largest global medical device firms (Data S1A). All data were collected and aggregated at the firm and year level.

3.1.1 | Financial data

The companies' financial data, such as revenues, net profit, number of employees, and R&D expenditure, were extracted either directly from their annual reports, or from financial data internet portals, such as annualreports.com, nasdaq.com, morningstar.com, or last10k.com. As our sample contains non-U.S. firms, key financial figures were converted to U.S. dollars, applying the exchange rate as at the date of the company's fiscal year-end.

3.1.2 | FDA data

Market approvals for medical devices by national regulatory authorities represent the essential step to enter the

market with medical technology innovations. We used the data from the U.S. Food and Drug Administration (FDA) that regulates all medical technologies and devices on the U.S. market (Stern, 2017). The U.S. market is the biggest and most important single market for medical technology (Stern, 2017). The FDA classifies medical devices in three classes "based on the level of control necessary to assure the safety and effectiveness of the device" (FDA, 2020a). Class I and II devices are characterized by a low or moderate risk for patients. Class III devices, such as implantable pacemakers, heart valves, and stents are new devices that involve high risk for patients and are subject to a stringent regulation and review process (premarket approval PMA) before such devices can be launched on the U.S. market (Stern, 2017; Zuckerman et al., 2011). These devices can be considered as breakthrough innovative products (Kesselheim & Hwang, 2016). For Class I and II medical devices, the FDA requires firms to ensure that the devices are substantially equivalent in applied materials, use purpose, and mechanism of action to devices already on the market (premarket notification "510(k) review") (Zuckerman et al., 2011). Most Class I and some Class II devices are exempt from the PMA and 510(k) premarket notification process if they "are not required to provide reasonable assurance of safety and effectiveness for the device" (FDA, 2019). However, most Class II and some Class III devices which are not exempt from 510(k) premarket notification need to "demonstrate that the devices to be marketed are as safe and effective, that is, substantially equivalent, to a legally marketed device" (FDA, 2020b). For our analysis, we collected data on FDA PMA (original devices and supplements to the original devices) and 510(k) approvals (so called "clearances") for medical devices of the 79 medical technology firms. In total, we

obtained data on approximately 14,600 PMA and 510 (k) approvals (more details in Data [S1B](#)).

3.1.3 | Bibliographic data

We extracted bibliographic data for the 79 medical technology firms from the scientific publication database Web of Science (WoS). We used bibliographic metadata to measure our independent variable DoI. For this purpose, we first identified medical technology journals in the WoS database, from which we extracted the most frequent keywords. Then we manually processed the keywords list and removed keywords that were either too general or too specific to other industry sectors, such as biotech, pharmaceutical, or electronics industries, since the focal firms may have had business units in these sectors as well (more details in Data [S1C](#)). We used the revised medical technology keywords list and filtered the focal firms' scientific publications for these keywords to identify only publications related to the medical technology industry. In total, we identified more than 30,500 medical technology publications produced by the 79 focal firms. We also identified around 20,600 publications by the focal firms in which universities were co-authors, and labeled these as university–industry collaborations (UIC). These bibliographic data of co-authored scientific publications present a tangible, verifiable indicator for university–industry collaborations (Abramo et al., 2011; Jong & Slavova, 2014; Wirsich et al., 2016). We also collected a total of around 45,500 scientific publications by firms outside the medical technology area (more details in Data [S1D](#)).

3.1.4 | Patent data

Protecting inventions with the help of patents is a vital competitive instrument in the medical device industry (Rothaermel & Ku, 2008). Patent application data were collected from the PATSTAT database. We simplified the names of focal medical technology firms by removing business entity extensions and special characters in the names of the firms. We used a manual process to mostly eliminate false positives. To focus on the development of medical technology, we used only the focal firms' patent applications in the medical technology field that belong to the following subclasses of international patent classification (IPC) class A61 “Medical or veterinary science; hygiene”: A61B, A61C, A61F, A61H, A61L, A61M, A61N (Data [S1E](#)). Only patent applications that have at least one of these IPC codes were included in the dataset. In total, the dataset contains over 44,000 patent application families.

3.1.5 | Clinical trials data

New medical products, especially high-risk Class III medical devices, must undergo rigorous scrutiny by the regulatory bodies, such as the FDA, which demand significant evidence of the safety and effectiveness of the new product candidates (Stern, 2017). Since novel medical device products can be technologically very complex, and the regulatory bodies need to understand the causal mechanisms of the medical outcomes of such devices, their safety and efficacy must be confirmed via results of clinical trials on humans (Stern, 2017). We therefore consider clinical trials as the central step of outcome validation. We collected the information on clinical trials of the focal firms from the database [ClinicalTrials.gov](#), curated by the U.S. National Library of Medicine. To concentrate on medical device clinical trials, we included only clinical trials with intervention type “device” in the sample. Our dataset contains information on approximately 3000 clinical trials (Data [S1F](#)).

3.2 | Measurement

3.2.1 | Dependent variable – Innovation performance

We measured innovation performance as the outcome of R&D activities of medical technology firms. Fernald et al. (2017) and Fernald et al. (2015) operationalize innovation performance as the number of new drugs approved by the FDA. While Chatterji and Fabrizio (2016) measure medical device firms' innovations as the number of FDA-approved medical devices (medical devices approved through both pre-market notification (510 k) process and the more rigorous pre-market approval (PMA) process, with an exclusion of supplemental filings), Onur and Söderberg (2020) differentiate between radical innovations (the number of original PMA approvals) and incremental innovations (the number of PMA supplements). Similarly, we measured a firm's innovation performance as the number of FDA PMA and 510(k) approvals for medical devices for each firm and each year. In Table 1 we provide an overview of all concepts and measurements included in our conceptual and empirical design.

3.2.2 | Independent variable: Degree of interdisciplinarity

Following Yegros-Yegros et al. (2015), and their conceptualization of DoI as a three-dimensional concept of diversity, we focus on the most challenging diversity dimension of DoI, namely the level of difference

TABLE 1 Concept definitions and measures of the study's variables.

Variable name	Conceptual definition	Operationalization	Data source
Innovation performance	Innovation performance is an outcome of the R&D activities of medical technology firms measured by the number of new products introduced to the market. Chatterji and Fabrizio (2016) define medical device firms' innovations as the number of FDA-approved medical devices (medical devices approved through both premarket notification (510 k) process and the more rigorous premarket approval (PMA) process, with an exclusion of supplemental filings). Onur and Söderberg (2020) define radical innovations as the number of original PMA and incremental innovations as the number of PMA supplements.	The number of FDA PMA and 510(k) approvals for medical devices for each firm and each year	U.S. FDA website
Degree of interdisciplinarity	The degree of interdisciplinarity is based on the interdisciplinary research concept suggested by Yegros-Yegros et al. (2015). Our DoI conceptualization puts the disparity dimension of interdisciplinary research in focus because the disparity dimension represents high cognitive efforts of a knowledge combination from different scientific fields (Yegros-Yegros et al., 2015). Moreover, a disparity dimension of interdisciplinary research is closely related to research novelty (Uzzi et al., 2013) which can have a high impact for technological and industrial applications.	A novel method of DoI measurement based on a machine-learning approach applied to bibliographic data that determines a scientific field similarity (Melnychuk et al., 2023)	Web of Science database
Complexity of outcome validation	The complexity of outcome validation refers to the complexity of potential product market testing. We ground our complexity concept on the definition of complexity through the number of elements in a system and the level of interdependencies of these elements (Maleki & Rosiello, 2019).	The average number of countries in which clinical trials are conducted, per firm and per year	ClinicalTrials.gov website
Financial slack	Financial slack is related to sufficient financial resources that a firm can invest in R&D activities, if necessary.	A positive revenue growth rate (financial performance >0 compared to the previous year) and a negative revenue growth rate (financial performance <0 compared to the previous year) (Quéré et al., 2018)	Firms' annual reports or internet portals (annualreports.com, Nasdaq.com, morningstar.com, or last10k.com)
university–industry collaborations intensity	University–industry collaborations refer to R&D collaborative activities between employees of the focal firms and universities. Bibliographic metadata of co-authored research publications present a tangible indicator for university–industry collaborative activities (Abramo et al., 2011; Jong & Slavova, 2014; Wirsich et al., 2016).	A ratio of the number of each focal firm's publications co-authored with universities (including publications without a medical technology focus) to the firm's medical technology publications in the same year	Web of Science database

TABLE 1 (Continued)

Variable name	Conceptual definition	Operationalization	Data source
Betweenness centrality position in scientific networks	A betweenness centrality position represents a bridging function in heterogeneous social networks that allows to control knowledge flows between the heterogeneous subnetworks (Burt, 1992; Freeman, 1978; Gilsing et al., 2008).	A fraction of the shortest paths connecting a pair of actors in a scientific network passing through the focal firm	Web of Science database
Firm size	Firm size indicates whether a firm has enough human, financial, technological, manufacturing, and marketing resources to develop and launch a new product.	The number of employees per firm and per year	Firms' annual reports or internet portals (annualreports.com , Nasdaq.com , morningstar.com , or last10k.com)
Firm total assets	Firm total assets refer to a firm R&D capacity suggesting that a firm's R&D investments depend on the firm assets (Huang et al., 2018).	Firm total assets per firm and per year	Firms' annual reports or internet portals (annualreports.com , Nasdaq.com , morningstar.com , or last10k.com)
Net profit margin	Net profit margin displays the prior financial performance of a firm and presents a firm's financial health.	The ratio of a firm's net profit and revenues for each focal firm per year	Firms' annual reports or internet portals (annualreports.com , Nasdaq.com , morningstar.com , or last10k.com)
Technological performance	Technological performance is the output of technological activities of a firm in specific technological domains that can improve a firm's innovation performance (Fernald et al., 2015).	The number of patent application families applied for in the subclasses of the IPC class A61 per firm and per year	PATSTAT database
Scientific medical technology focus	Scientific medical technology focus refers to a focus of a firm's R&D activities on medical technology fields.	A firm's number of medical technology publications divided by its total number of publications	Web of Science database
Diversity of medical science fields	The diversity of medical science fields is a breadth/diversity of medical technology applications embedded in the scientific research of focal firms.	1—Herfindahl–Hirschman Index of the WoS research categories of medical technology publications per firm per year	Web of Science database
R&D intensity growth	R&D intensity represents a firm's internal R&D activities along the complete R&D process chain.	The yearly growth rate of a firm's R&D expenditure divided by revenues per firm and per year	Firms' annual reports or internet portals (annualreports.com , Nasdaq.com , morningstar.com , or last10k.com)

(similarity) of scientific disciplines from the cognitive perspective. Disparity, as a dimension of DoI, reflects not only the benefits of scientifically and technologically distant knowledge integration, but also the cognitive efforts required for knowledge integration (Yegros-Yegros et al., 2015). The concept of disparity of interdisciplinary research is closely related to the concept of research novelty which can be achieved through an atypical combination of knowledge pieces (Uzzi et al., 2013). Uzzi et al. (2013) suggest that research novelty can result from a

combination of contextually distant knowledge. The more recent study by Fontana et al. (2020) examines the conceptual and measurement discrepancies of research novelty and confirmed that the research novelty measurement offered by Uzzi et al. (2013) and the disparity dimension of interdisciplinary research are highly correlated. Based on this finding, we decided to focus on the disparity dimension of the degree of interdisciplinarity for two reasons. First, by measuring only the disparity dimension, we attempt to capture the high cognitive

efforts required for the recombination of existing knowledge from distant scientific disciplines. Second, disparity is related to research novelty and has therefore a high relevance for new product development. We defined DoI as a broad-level diversity construct that specifically reflects the cognitive distance between diverse scientific knowledge domains. This measurement can capture, to a large extent, the interdisciplinarity of the R&D activities of medical technology firms. We determined the DoI for each focal firm on a yearly basis.

For this purpose, we exploited a machine-learning method based on neural networks and graph approaches (Galke et al., 2019; Guo et al., 2012) and grounded our measurement method on the similarity/dissimilarity measure offered by Melnychuk et al., 2023, who show that machine-learning approaches employed on the bibliographic data graphs are capable of capturing contextual similarity/dissimilarity of diverse scientific fields, specifically in the life science context (Melnychuk et al., 2023). First, we used bibliographic metadata of scientific publications labeled as medical technology to generate a graph that contained authors at the organizational level (firms, universities, and other organizations), publication titles, journal titles, and keywords as nodes of the graph, and links between all these nodes. Data S1G provides details of the applied measurement approach. For the construction of the graph, we used standardized keywords (Keyword Plus[®] provided by the database Web of Science) that occurred at least 10 times throughout the whole dataset of medical technology publications by all medical device firms. These keywords allowed us to focus on the knowledge, methods, and techniques which are common to and relevant for the medical technology sector. The edges of the graph were defined as co-authorships of the same publication and according to co-annotation of a publication with multiple keywords.

To construct the training set of the model, we first used all publications labeled medical technology produced by all 100 largest medical device companies from our initial companies' dataset. These had around 174,000 author affiliations (such as firms, universities, research institutions, etc.) and around 5900 unique keywords as set by the WoS. These data were utilized for the construction of the graph, which in total contained 295,633 nodes and 730,345 edges. For the resultant graph, we applied a graph convolutional approach to learn vector representations for concepts (keywords) based on the information contained in the graph and its structure (Kipf & Welling, 2017). In Data S1G, we present a detailed description of this method, the validation of the chosen hyperparameter, and the robustness of the used trained model. As the final step, we measured DoI as the

maximum value of cosine distances between keywords of all publications by each firm and each year. This value represents the largest cognitive distance of a firm's interdisciplinary R&D activities at the firm level in a particular year.

3.2.3 | Mediator variable: Complexity of outcome validation

We focus on the later stages of new product development to measure the complexity of outcome validation and capture the high heterogeneity level of applied knowledge, as well as the high level of interdependencies of elements to be considered in the validation of intended outcomes (Zhang & Thomson, 2018). Clinical trials represent a major part of the late stages of new product development (Banerjee & Siebert, 2017; Stern, 2017). In the medical technology industry, testing of medical devices in clinical trials denotes the development of potentially technologically complex and new devices (Stern, 2017). In the case of highly complex validation steps, clinical trials studies may be multicentric, and several clinical trials need to be carried out in different countries to access the necessary number of patients and to cope with local requirements (Sahin et al., 2020). Hence, we use clinical trials information of the focal medical technology firms to access the *complexity of outcome validation*. We measured the average number of countries in which clinical trials are conducted, per firm and per year as a proxy for the complexity of outcome validation.

3.2.4 | Financial slack

The determination of the financial slack level may be influenced by the performance history of the organization (historical aspiration level), specifically if the organization holds a unique position within the market. We thus measured a firm's *financial slack* as the yearly growth rate of its revenues, following the study by Quéré et al. (2018). We defined financial slack as a positive growth rate (financial performance >0 compared to the previous year). In order to identify the effect of financial slack we also included negative financial performance as a negative growth rate (financial performance <0 compared to the previous year) in the model.

3.2.5 | University–industry collaborations

Following Abramo et al. (2011) and others, we investigated research collaborations between firms and

universities on the basis of their co-authored scientific publications. The benefit of this measurement is that it is a visible, verifiable, and quantifiable indicator of the joint research output between firms and their academic counterparts (Abramo et al., 2011; Wirsich et al., 2016). Hence, the *UIC intensity* was measured as a ratio of the number of each focal firm's publications co-authored with universities (including publications without a medical technology focus) to the firm's medical technology publications in the same year.

3.2.6 | Betweenness centrality position in scientific networks

Betweenness centrality in social networks is an indicator of the potential to control information and knowledge flows in heterogeneous networks (Freeman, 1978). Similar to Gilsing et al. (2008), we therefore defined betweenness centrality as a fraction of the shortest paths connecting a pair of actors in a scientific network passing through the focal firm, and calculated it as a relative betweenness centrality $BC_{rel}(k)$ according to Freeman (1978) as:

$$BC(k) = \sum_i^n \sum_j^n \frac{g_{ij}(k)}{g_{ij}}$$

$$BC_{rel}(k) = \frac{2 BC(k)}{n^2 - 3n + 2},$$

where $BC(k)$ is a betweenness centrality of the focal firm k ; $g_{ij}(k)$ is a number of shortest paths connecting actors i and j and passing through the focal firm k ; g_{ij} is a number of paths connecting actors i and j ; and n is the total number of actors in the network. We computed betweenness centrality by using the medical technology publications by the focal firms, co-authored with universities, research organizations, or other firms. Hence, we measured the betweenness centrality at the firm level, for each focal firm and each year.

3.2.7 | Control variables

To control for firm-level characteristics for each firm, we measured *firm size* as the number of employees, *firm total assets*, and *net profit margin* as the ratio of a firm's net profit and revenues for each focal firm per year. We also controlled for a firm's technological performance, since its technological strength can positively affect its innovation performance (Fernald et al., 2015). Following

Fernald et al. (2015), we assumed that a firm's patent activity in a specific domain, such as medical technology, can bind R&D resources and foster innovative output in the respective technology domain. As such, we measured a *firm's technological performance* as the number of patent application families applied for in the subclasses of the IPC class A61 per firm and per year. Furthermore, to account for the medical technology focus in the firms' research activities, we measured *scientific medical technology focus* as a firm's number of medical technology publications divided by its total number of publications. We also controlled whether a firm has a broad and diverse portfolio of medical technology applications. For this purpose, we used WoS research categories to determine the science fields within which the medical technology publications were classified. Following Melnychuk et al. (2021), by employing the Herfindahl–Hirschman Index (HHI) as a concentration indicator, we modified it to $1 - \text{HHI}$, and measured *diversity of medical science fields* accordingly. R&D intensity is an indicator of a firm's internal R&D activities along the complete R&D process chain: from basic research through applied research to developed (unlaunched) products. R&D intensity not only captures successful knowledge recombination, but it also includes research failures that often occur in science-intensive industries (Khanna et al., 2016). Thus, we measured a firm's *R&D intensity growth* as the yearly growth rate of a firm's R&D expenditure divided by revenues per firm and per year.

3.3 | Estimation

To analyze whether the DoI has a direct effect on a firm's innovation performance, and whether the complexity of outcome validation mediates the underlined relationship, we estimated three models, following the approach for the mediation analysis of panel dataset by Wahba and Elsayed (2015), based on the conceptual considerations related to a mediation relationship by Baron and Kenny (1986): We first regressed the mediator variable on the independent variable (Mediation Model), and then we regressed the dependent variable on the independent variable. In the third equation, we regressed the dependent variable on the independent variable and mediator (Total Model). The dependent variable in our panel dataset is a non-negative count variable. Due to overdispersion in the dependent variable that may bias standard errors (Molla & Muniswamy, 2012), we employed a negative binomial model specification that allows for overdispersion. We further controlled for unobserved heterogeneity at the firm level by including a firm's dummy variables to create fixed-effects. This approach allows us to account

for factors that cannot be observed directly, such as the firm's technological strategy or organizational culture, which might have an impact on its innovation performance. We also controlled for time-varying effects that could have influenced the whole medical technology industry during the analysis period by including respective year dummy variables (Wooldridge, 2016). Allison and Waterman (2002) suggest that the conditional fixed-effects negative binomial method might not control for all explanatory variables. In following their suggestion, we applied the unconditional fixed-effects negative binomial model. Furthermore, due to residuals' heteroscedasticity issues, we used the Huber-White sandwich estimator to compute robust standard errors (Wooldridge, 2010). We also applied fixed-effects model to estimate the effect of the independent variable on the mediator variable, since the Hausman specification test was significant (Hausman, 1978); and we employed the Huber-White sandwich estimator to calculate robust cluster standard errors (Wooldridge, 2010).

We assume that the knowledge generated by a firm's interdisciplinary projects first should be assimilated by and internalized and integrated in new product development; thus, the effect of DoI could be visible only after a certain period. In addition, the approval processes may require long-lasting substantial testing in clinical trials, as well as a long average FDA review time of 18 to 23 months for new high-risk products (Stern, 2017). Therefore, we applied a time lag of 5 years to the independent variable and all moderator and control variables. The mediator variable was not lagged, since the FDA can approve the medical device products soon after the completion of clinical trials. Since firms that show high levels of innovation performance might invest more in the diversification of their future knowledge portfolio and conduct research projects with a higher degree of interdisciplinarity, we assumed that applying time lags can reduce potential negative effects of possible endogeneity and reverse causality. Owing to high heterogeneity values of medical technology firms leading to outlier variable values that could bias the estimations, we excluded observations with extreme values under the 1% percentile and over the 99% percentile for the dependent variable and all explanatory and control variables. Due to our use of a time lag of 5 years and the exclusion of outliers, our unbalanced dataset contained 618 observations.

4 | EMPIRICAL RESULTS

We present descriptive statistics and pairwise correlations for the variables in Tables 2 and 3. Pairwise correlations among explanatory variables are low or

moderate. Moreover, the results of the calculation of the variance inflation factors (VIFs) don't reveal multicollinearity issues, since all VIFs <2.0 and the mean VIF value is 1.37 (Allison, 1999). Additionally, owing to the application of a fixed-effects model for controlling for firm-specific effects, the potential multicollinearity caused by a moderate correlation between the predictors can be neglected when estimating both models.

4.1 | The direct and moderating effects of DoI on the complexity of a firm's activities of outcome validation

We present the results of the analysis of the effect of DoI on complexity of outcome validation in Table 4. We compared results of six distinct models. Model 1 represents a baseline model with only control variables. Model 2 comprises the effect of DoI. Models 3 to 5 contain the interaction effects of three moderators: financial slack, UIC intensity, and betweenness centrality position in scientific networks. Model 6 (full model) includes the influence of DoI and all moderator effects.

In Table 4, we show that technological performance has a positive effect on the complexity of outcome validation ($\beta = 1.41, p < 0.001$), implying that breadth of technological knowledge creates opportunities for knowledge diversity and recombination for knowledge application (Xu, 2015), and it indeed enhances the complexity of outcome validation. Furthermore, collaborations with universities foster exactly such a breadth of acquired knowledge and increase the complexity of outcome validation ($\beta = 0.89, p < 0.001$). The inclusion of DoI in Model 2 shows that DoI of R&D activities has a positive significant effect on the complexity of outcome validation ($\beta = 0.42, p < 0.05$). Thus, H2 is supported. A likelihood ratio test (LRT) supports the inclusion of DoI, because it improves the model's fit (4.60, $p < 0.05$) significantly. In Model 3, both interaction effects of the financial growth trend are negative but insignificant. Therefore, H4b needs to be rejected. In H5b, we expected that collaborations with universities will enhance the effect of DoI. In Model 4, we find support for H5b, since the interaction effect of UIC intensity is positive and significant ($\beta = 2.01, p < 0.01$). The fit of the model is significantly improved (12.27, $p < 0.001$), which confirms the integration of the UIC intensity. The interaction effect of DoI and betweenness centrality is also positive and significant ($\beta = 14.78, p < 0.01$). Thus, H6b is confirmed. The LRT provides support for the inclusion of the betweenness centrality moderator (8.21, $p < 0.01$). The results of the full model (Model 6) show that the effects of DoI and moderators

TABLE 2 Descriptive statistics.

Variables	Mean	SD	Min	Max
(1) Number of FDA approvals	23.709	50.963	0.000	358
(2) DoI	0.896	0.215	0.149	1.249
(3) Complexity of outcome validation	0.855	1.043	0.000	5.5
(4) Firm size	0.034	0.053	0.000	0.327
(5) Firm total assets	0.127	0.478	0.000	4.067
(6) Net profit margin	0.086	0.177	−1.368	2.824
(7) Technological performance	0.071	0.114	0.001	0.641
(8) Scientific medical technology focus	0.614	0.227	0.125	1
(9) Diversity of medical science fields	0.456	0.284	0.000	0.844
(10) R&D intensity growth	−0.012	0.238	−4.399	0.649
(11) Financial slack (FPGR >0)	0.091	0.096	0.000	0.679
(12) FPGR <0	−0.015	0.065	−1.039	0
(13) UIC intensity	0.761	0.194	0.167	1
(14) Betweenness centrality	0.022	0.049	0.000	0.364

Note: Firm size was divided by 1000; technological performance was divided by 1000; firm total assets were divided by 10,000,000.

Abbreviations: DoI, degree of interdisciplinarity; FPGR, financial performance growth rate; UIC, university–industry collaborations.

remain significant. The improved model fit confirms this finding (16.75, $p < 0.01$).

4.2 | The direct, mediator and moderator effects of DoI on a firm's innovation performance

The findings of the total model for innovation performance are reported in Table 5. We compared results of eight distinct models. Model 7 is a baseline model containing only control variables. Model 8 integrates the effect of the mediator complexity of outcome validation. Model 9 includes the effect of DoI on innovation performance. Model 10 presents the mediation effect of complexity and a direct effect of DoI. Models 11 to 13 include the interaction effects of DoI and three moderators: financial slack, UIC intensity, and betweenness centrality position in scientific networks. Model 14 (full model) integrates the influence of DoI of R&D activities, the complexity of outcome validation as mediator, and all moderator effects.

In Table 5, we summarize the results for the firm's innovation performance. These show that the innovation performance of a firm is positively affected by firm size ($\beta = 13.91$, $p < 0.001$), indicating that large firms are more capable of bringing innovations to the market—a finding that is in line with prior research (Jong & Slavova, 2014). Net profit margin also has a positive effect on innovation performance ($\beta = 0.45$, $p < 0.05$),

indicating that a firm's profitability supports the development of new products. R&D intensity growth also has a positive effect on innovation performance ($\beta = 0.40$, $p < 0.01$), indicating that science-intensive firms indeed depend on their capabilities to absorb, assimilate, and exploit internal and external knowledge in order to generate innovations, which is also in line with existing research (Belderbos et al., 2016; Lin et al., 2012).

Integration of the mediator complexity of outcome validation in Model 8 shows its negative significant association with a firm's innovation performance ($\beta = -0.12$, $p < 0.05$). Thus, H3 is confirmed. The fit of the model is improved (4.30, $p < 0.05$), confirming the integration of the mediator. Including DoI of R&D activities in Model 9 reveals its positive significant direct effect on innovation performance ($\beta = 0.48$, $p < 0.05$). Thus, H1 is supported. An LRT supports the integration of the main predictor, since it improves the model's fit (2.88, $p < 0.1$). To examine whether a competitive mediation effect exists (Zhao et al., 2010), we included both DoI and complexity in the model (Model 10). Both effects remained significant, revealing that the direct positive effect of DoI of R&D activities is indeed negatively mediated by the complexity of outcome validation. In H4a, we expected that financial slack will positively moderate the relationship between DoI and innovation performance in the case of performance gains; and the interaction effect of high financial slack is indeed positive and significant ($\beta = 4.84$, $p < 0.05$), hence H4a is supported. The LRT of Model 11 (12.31, $p < 0.05$) compared to Model 7 confirms

TABLE 3 Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Number of FDA approvals	1.000													
(2) DoI	0.274*	1.000												
(3) Complexity of outcome validation	0.386*	0.390*	1.000											
(4) Firm size	0.101*	0.373*	0.170*	1.000										
(5) Firm total assets	-0.064	0.001	-0.104*	0.378*	1.000									
(6) Net profit margin	0.067	0.196*	0.100*	0.090*	-0.063	1.000								
(7) Technological performance	0.261*	0.292*	0.335*	0.203*	0.301*	0.033	1.000							
(8) Scient. medical tech. focus	-0.001	-0.101*	0.042	-0.239*	-0.076	-0.044	0.042	1.000						
(9) Diversity of medical science fields	0.084*	0.407*	0.101*	0.332*	0.162*	0.173*	0.196*	-0.264*	1.000					
(10) R&D intensity growth	0.015	-0.025	0.052	0.007	0.026	0.116*	0.021	-0.095*	0.032	1.000				
(11) Financial slack (FPGR >0)	-0.010	-0.074	-0.038	-0.180*	-0.100*	-0.083*	-0.090*	0.128*	-0.103*	-0.197*	1.000			
(12) FPGR <0	-0.093*	-0.058	-0.011	-0.113*	-0.058	0.038	-0.048	0.085*	-0.055	-0.013	0.218*	1.000		
(13) UIC intensity	-0.063	-0.119*	0.029	-0.291*	-0.225*	-0.049	-0.148*	0.295*	-0.369*	0.000	0.066	0.012	1.000	
(14) Betweenness centrality	0.293*	0.459*	0.274*	0.506*	-0.026	0.134*	0.215*	-0.247*	0.343*	0.000	-0.098*	-0.088*	-0.183*	1.000

Note: $p < 0.05$; firm size was divided by 1000; technological performance was divided by 1000; firm total assets were divided by 10,000,000.

Abbreviations: DoI, degree of interdisciplinarity; FPGR, financial performance growth rate; UIC, university-industry collaborations.

TABLE 4 Mediation model: Effects of DoI on complexity of outcome validation of medical technology firms (average number of countries of clinical trials per year).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Firm size	1.18 (0.812)	0.77 (0.874)	0.77 (0.875)	1.10 (0.805)	1.26 (0.782)	1.66 (0.686)
Firm total assets	−0.20 (0.427)	−0.21 (0.406)	−0.21 (0.402)	−0.18 (0.434)	−0.21 (0.365)	−0.19 (0.387)
Net profit margin	−0.27 (0.471)	−0.28 (0.462)	−0.28 (0.464)	−0.27 (0.484)	−0.28 (0.461)	−0.26 (0.490)
Technological performance	1.41*** (0.000)	1.30*** (0.001)	1.30*** (0.001)	1.29** (0.001)	1.29*** (0.001)	1.27** (0.002)
Scientific medical technology focus	0.08 (0.693)	0.05 (0.803)	0.05 (0.800)	−0.00 (0.991)	0.06 (0.778)	−0.00 (0.992)
Diversity of medical science fields	0.11 (0.646)	0.08 (0.760)	0.08 (0.761)	0.08 (0.746)	0.08 (0.744)	0.08 (0.732)
R&D intensity growth	0.12 (0.341)	0.13 (0.278)	0.13 (0.286)	0.13 (0.262)	0.14 (0.273)	0.14 (0.270)
Financial slack (FPGR >0)	−0.01 (0.974)	−0.02 (0.938)	0.31 (0.767)	0.01 (0.974)	−0.04 (0.894)	0.18 (0.866)
FPGR <0	0.31 (0.146)	0.35 [#] (0.096)	0.79 (0.501)	0.35 [#] (0.075)	0.44 [#] (0.054)	0.12 (0.899)
UIC intensity	0.89*** (0.000)	0.86*** (0.000)	0.86*** (0.000)	−0.77 [#] (0.075)	0.85*** (0.000)	−0.86* (0.050)
Betweenness centrality (BC)	−7.30 [#] (0.054)	−7.92* (0.030)	−7.94* (0.030)	−7.64* (0.030)	−24.52** (0.002)	−26.10*** (0.001)
<i>Direct effect</i>						
DoI		0.42* (0.035)	0.45* (0.037)	−1.22* (0.019)	0.33 [#] (0.093)	−1.38* (0.016)
<i>Interaction effects</i>						
DoI × FPGR <0			−0.40 (0.695)			0.31 (0.707)
DoI × Financial slack (FPGR >0)			−0.39 (0.759)			−0.21 (0.875)
DoI × UIC intensity				2.01** (0.001)		2.11** (0.001)
DoI × BC					14.78** (0.009)	16.44** (0.003)
Constant	0.16 (0.551)	−0.12 (0.690)	−0.15 (0.622)	1.23** (0.003)	−0.05 (0.848)	1.36** (0.002)
Log-likelihood	−585.99	−583.70	−583.63	−579.86	−581.89	−577.62
Likelihood ratio test	Base	4.60*	4.72	12.27***	8.21**	16.75**
AIC	1193.99	1191.39	1195.27	1185.72	1189.78	1187.24

Note: Fixed-effects regression; firm-specific and year dummies were included; unstandardized coefficients; robust standard errors; *p* values in parentheses; all predictors and interaction effects were lagged (lag *t* = −5); all variables were winsorized; firm size was divided by 1000; technological performance was divided by 1000; firm total assets were divided by 10,000,000; *n* = 618. [#]*p* < 0.1, **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

Abbreviations: AIC, Akaike information criterion; BC, betweenness centrality; DoI, degree of interdisciplinarity; FPGR, financial performance growth rate; UIC, university–industry collaborations.

TABLE 5 Total model: Effects of DoI and complexity of outcome validation on innovative performance of medical technology firms (#FDA approvals for medical technology products).

	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Firm size	13.91*** (0.000)	13.53*** (0.000)	13.88*** (0.000)	13.50*** (0.000)	12.89*** (0.000)	14.41*** (0.000)	14.17*** (0.000)	14.66*** (0.000)
Firm total assets	0.10 (0.775)	0.05 (0.895)	0.12 (0.736)	0.06 (0.858)	0.08 (0.827)	0.09 (0.802)	0.06 (0.862)	0.10 (0.770)
Net profit margin	0.45* (0.029)	0.48* (0.021)	0.43* (0.028)	0.45* (0.020)	0.42* (0.028)	0.47* (0.014)	0.45* (0.024)	0.44* (0.022)
Technological performance	0.28 (0.686)	0.31 (0.649)	0.19 (0.778)	0.22 (0.741)	0.30 (0.650)	0.24 (0.721)	0.27 (0.696)	0.36 (0.585)
Scientific medical technology focus	-0.06 (0.747)	-0.05 (0.787)	-0.11 (0.562)	-0.11 (0.595)	-0.08 (0.675)	-0.22 (0.297)	-0.10 (0.629)	-0.19 (0.350)
Diversity of medical science fields	0.11 (0.470)	0.13 (0.384)	0.08 (0.587)	0.11 (0.495)	0.13 (0.402)	0.09 (0.559)	0.10 (0.526)	0.10 (0.508)
R&D intensity growth	0.40** (0.005)	0.39** (0.008)	0.41** (0.002)	0.40** (0.004)	0.39** (0.002)	0.41** (0.004)	0.42** (0.005)	0.42** (0.002)
Financial slack (FPGR >0)	0.59 (0.162)	0.65 (0.132)	0.54 (0.200)	0.60 (0.163)	-3.64* (0.037)	0.59 (0.166)	0.58 (0.177)	-3.63* (0.036)
FPGR <0	-0.10 (0.638)	-0.07 (0.762)	-0.04 (0.871)	0.00 (0.994)	0.88 (0.690)	0.03 (0.913)	0.10 (0.718)	-0.04 (0.987)
UTC intensity	0.11 (0.573)	0.21 (0.291)	0.08 (0.655)	0.18 (0.335)	0.21 (0.286)	-1.67* (0.029)	0.18 (0.344)	-1.83* (0.024)
Betweenness centrality (BC)	5.41 [#] (0.050)	4.13 (0.128)	4.87 [#] (0.078)	3.53 (0.190)	3.21 (0.223)	4.18 (0.126)	-15.40 [#] (0.056)	-20.24* (0.012)
<i>Mediation effect</i>								
Complexity of outcome validation		-0.12* (0.025)		-0.12* (0.021)	-0.12* (0.023)	-0.14* (0.012)	-0.12* (0.023)	-0.14* (0.013)
<i>Direct effect</i>								
DoI			0.48* (0.025)	0.50* (0.021)	0.05 (0.862)	-1.29 [#] (0.082)	0.39 [#] (0.079)	-2.04* (0.017)
<i>Interaction effects</i>								
DoI × FPGR <0					-0.86 (0.651)			0.10 (0.958)

TABLE 5 (Continued)

	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
DoI × Financial slack (FPGR > 0)					4.84* (0.028)			4.83* (0.028)
DoI × UIC intensity						2.19* (0.015)		2.40* (0.012)
DoI × BC							16.76* (0.021)	21.41** (0.004)
Constant	0.51 (0.206)	0.49 (0.214)	0.18 (0.657)	0.16 (0.699)	0.59 (0.144)	1.70* (0.016)	0.29 (0.469)	2.45** (0.001)
Log-likelihood	−1866.40	−1864.25	−1864.96	−1862.68	−1860.25	−1860.85	−1861.35	−1856.49
Likelihood ratio test	Base	4.30*	2.88 [#]	7.45*	12.31*	11.11*	10.10*	19.83**
AIC	3950.81	3934.50	3949.92	3943.35	3944.49	3945.70	3946.71	3940.98

Note: Unconditional negative binomial model; firm-specific and year dummies were included; unstandardized coefficients; robust standard errors; all predictors and interaction effects, except for complexity of outcome validation, were lagged (lag $t = -5$); all variables were winsorized; firm size was divided by 1000; technological performance was divided by 1000; firm total assets were divided by 1000,000; $n = 618$; $^{\#}p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Abbreviations: AIC, Akaike information criterion; BC, betweenness centrality; DoI, degree of interdisciplinarity; FPGR, financial performance growth rate; UIC, university–industry collaborations.

the improved model fit. H5a anticipated that collaborations with universities will strengthen the positive effect of DoI on innovation performance. As expected, the interaction effect is positive and significant ($\beta = 2.19$, $p < 0.05$). Thus, H5a is also supported. In H6a, we expected that the betweenness centrality in scientific networks will positively moderate the relationship between DoI and innovation performance. The interaction effect of betweenness centrality is positive and significant ($\beta = 16.76$, $p < 0.05$), hence H6a is confirmed. The model fit is improved (10.10, $p < 0.05$), which supports the inclusion of betweenness centrality as a moderator. The full Model 14 reveals that the direct and indirect relationships between DoI and innovation performance, as well as all the moderation effects of financial slack, UIC intensity, and betweenness centrality in scientific networks, remain significant. The LRT (19.83, $p < 0.01$) reveals that the full model's fit is significantly improved, which supports the integration of moderators in the model. The total effect (as the sum of both direct and indirect effects) of the DoI on the firm's innovation performance is 0.43 ($p < 0.01$), indicating that the negative effect of complexity reduces the positive role of DoI, but only to a limited extent. Finally, we performed several alternative estimations to check the robustness of the results and report these together with additional analyses in Data S1H. These results underline the validity of our results.

4.3 | Visualization of results

To illustrate the estimated results, Figure 2 presents the predicted number of FDA approvals for medical devices as a function of DoI of R&D activities at mean, low, and high levels (one standard deviation above and below the mean) of financial slack, UIC intensity, and betweenness centrality in scientific networks. For these calculations, all other explanatory variables were set to their mean values. Figure 2 demonstrates that the relationship between DoI and innovation performance depends on the levels of financial slack, UIC intensity, and betweenness centrality. Firms that have insufficient financial resources (Figure 2a) are incapable of absorbing, exploring, and recombining interdisciplinary knowledge for the development of new products. Financial slack improves flexibility of knowledge integration, and firms can explore and develop novel solutions to complex technical problems based on the linkages between their diverse knowledge sets.

Figure 2b shows that firms with a low level of UIC intensity would underperform compared to those that rely on collaborations with universities. At high levels of

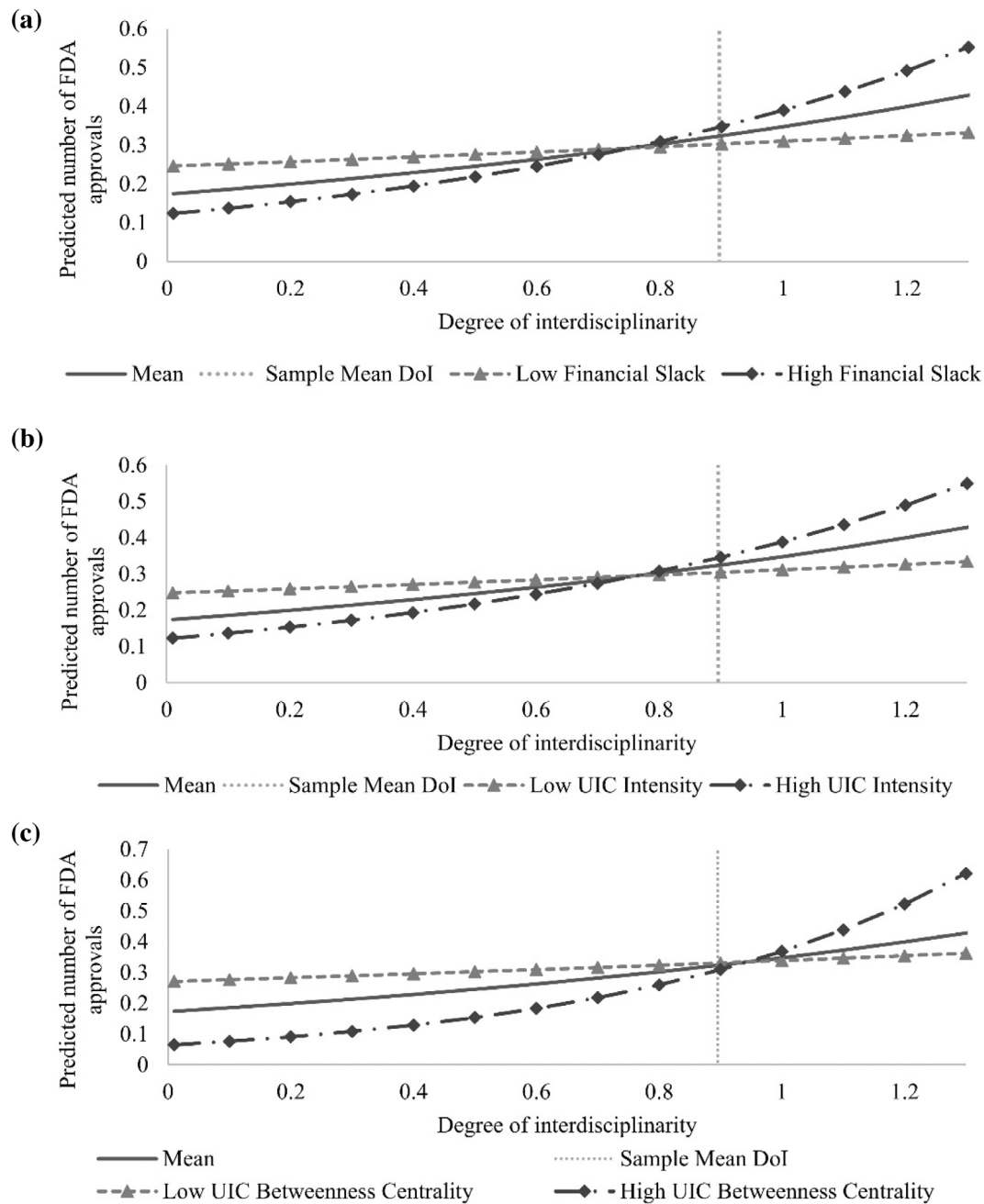


FIGURE 2 Predicted number of FDA approvals for medical devices, as a function of DoI at mean, high, and low levels of high financial slack, UIC intensity, and betweenness centrality in scientific networks. (a) The impact of financial slack on the relationship between DoI and innovation performance; (b) The impact of UIC intensity on the relationship between DoI and innovation performance; (c) The impact of betweenness centrality in scientific networks on the relationship between DoI and innovation performance.

UIC intensity, organizations are capable of profiting more from interdisciplinary R&D activities. Similarly, firms with low betweenness centrality (Figure 2c) may hardly derive any valuable new knowledge from their interdisciplinary R&D. A high betweenness centrality gives firms the advantage of controlling knowledge flows that enable easier access to non-redundant tacit knowledge from very heterogeneous scientific subnetworks at lower costs. We provide the visualization of estimated

results of interaction effects on the complexity of outcome validation in Data S1J.

5 | DISCUSSION AND CONCLUSION

In this study, we investigated the relationship between the degree of interdisciplinary R&D activities and a firm's

innovation performance in the medical technology industry under the mediation of complexity of necessary outcome validation. Our results reveal a positive association between the firm's DoI of R&D activities and its innovation performance. This finding is consistent with prior research, suggesting that interdisciplinary research provides multiple benefits for scientists and research organizations. However, our finding expands the prior literature by providing evidence that commercial organizations are also able to gain benefits from interdisciplinary R&D. Interdisciplinary R&D activities bridge ideas from various scientific domains, enable scientific breakthroughs, and promote scientific performance (Leahey et al., 2017; Schilling & Green, 2011).

In addition, our findings reveal that DoI of R&D activities also has attendant negative effects, as it increases the complexity of outcome validation. It fosters the diversity of knowledge needed for the later stages of the innovation process and increases the interdependencies between applied knowledge elements. Our results further show that this complexity leads to high coordination costs, and therefore decreases a firm's innovation performance. This finding is in line with prior research on knowledge domain complexity and its negative effect on a firm's innovation performance (Yayavaram & Chen, 2015). By establishing a competitive mediation relationship (Zhao et al., 2010), we additionally showed the trade-off between the knowledge diversity and recombination benefits of interdisciplinary R&D and its disadvantages due to the high complexity levels of validation step in the innovation process. However, despite the negative consequences of a higher complexity, the total effect of DoI of R&D activities is positive ($\beta = 0.43$).

We also analyzed the conditions necessary for DoI to affect the innovation performance of medical technology firms more positively. The results show a set of enabling resources and capabilities which promote the benefits of interdisciplinary research projects. We examined the moderating roles of a firm's financial slack as a resource facilitating the flexibility of knowledge integration. We also investigated a firm's collaborations with universities as a capability to improve the scope of interdisciplinary knowledge integration. We finally assessed a betweenness centrality position in scientific networks as a capability for promoting efficiency of interdisciplinary knowledge integration.

Our results suggest that larger financial slack promotes the association between DoI and a firm's innovation performance, but does not strengthen the relationship with the complexity of outcome validation. A firm's financial performance may provide the relevant resources needed for a more flexible knowledge integration in new commercially viable products. Even though knowledge recombination from multiple knowledge

domains is very risky (Taylor & Greve, 2006), firms investing their surplus financial resources in interdisciplinary projects can benefit by extending their organizational capability. The financial slack is most likely unabsorbed and not committed to specific expenditure programs, and firms may allocate these free budgets to risky projects with high expected returns (Herold et al., 2006). Our results may also reflect the challenges of investments in explorative R&D during environmental threats (Voss et al., 2008) as under the condition of a declined financial performance providing financial resources shows no supporting effect on the efficacy of interdisciplinary R&D activities. Due to a broad variety of unpredictable outcomes of exploratory interdisciplinary projects, these organizations may rather fail to translate the R&D results into successful innovation, which ultimately leads to a "failure trap" (Gupta et al., 2006).

The prior research suggests that technologically complex innovations are more likely to be developed by firms that have collaborative linkages to other market participants or public research institutions (Rothaermel & Deeds, 2004; Tether, 2002). Therefore, it is crucial for firms operating in interdisciplinary R&D to engage in research collaborations with external partners to build and extend their own capabilities regarding knowledge integration scope. Our results show that an organization's collaborations with universities do indeed foster benefits from interdisciplinary R&D activities. Our findings are consistent with prior research on the role of universities as knowledge spillover for organizations' innovation performance in regional technology clusters (Rothaermel & Ku, 2008). There are admittedly institutional collaborative challenges that can hinder the knowledge transfer and creative innovative output of such collaborations with universities (Bruneel et al., 2010). However, many firms have effective mechanisms to overcome challenges and barriers to collaborative interdisciplinary research with universities (Schultz et al., 2021), and create the favorable conditions for the development of trust, mutual common language, and intensive exchange between industrial and academic researchers in interdisciplinary projects (Groth et al., 2020). Collaborations with universities help to share failure risks and R&D costs with the academic institutions (George et al., 2002), and to cope with the long duration and extended efforts of interdisciplinary R&D (Leahey, 2018). Our results show that, with the help of universities, a more successful integration of a firm's interdisciplinary R&D projects in innovation processes also increases the complexity of the later stages of the innovation process. This again underlines the double-edged sword of successful interdisciplinary R&D.

Scientific networks are a valuable source for gleaning external knowledge from multiple diverse domains. By tapping into such scientific networks, firms can obtain

knowledge complementary to their own existing competences (Guan & Liu, 2016). Firms occupying a central betweenness position in such networks, and bridge sub-networks of specific knowledge areas that are otherwise not connected to each other (Burt, 1992), can obtain novel non-redundant information from distant network actors (Gilsing et al., 2008). In addition, the information flow rate and level of information control is higher for firms occupying high betweenness centrality positions and they can thus increase the efficiency of knowledge transfer and integration (Liebeskind et al., 1996). Our results extend the prior research by emphasizing that a high betweenness centrality in scientific networks allows a firm to recombine knowledge in interdisciplinary research projects, which leads to improved product innovations. Our insights are in line with the research of Gilsing et al. (2008) on the role of betweenness centrality in alliance networks for firms' explorative patents. However, our findings also suggest that efficiently transferred knowledge in scientific homogeneous subnetworks also fosters dependence on tacit knowledge from such subnetworks, which consequently facilitates the complexity of required validation steps of intended outcomes (Zhang & Thomson, 2018).

5.1 | Theoretical contributions

We make several contributions to the debate about the necessity and value of interdisciplinary research for a firm's innovation output. According to the knowledge-based view proposed by Grant (1996b), knowledge creation, transfer, and conversion into viable commercial products are crucial to a firm's competitive dimension. Our study shows that a firm's degree of interdisciplinarity can be a unique, non-imitable strategic resource that can be crucial for its competitive advantage that will lead to a higher level of innovativeness (Carnabuci & Operti, 2013). Our study sheds light on principal organizational knowledge recombination capabilities by offering empirical evidence that a firm's set of resources and capabilities is required for the integration of interdisciplinary R&D in new product development. The flexibility, scope, and efficiency of knowledge integration are the main pillars of these capabilities. A firm's financial slack may improve the flexibility of knowledge integration, while collaborations with universities foster the scope of integration, and betweenness centrality in scientific networks elevates its efficiency. All three elements improve the firm's implementation of interdisciplinary knowledge in successful innovation.

Our analysis thus bridges a gap in the prior research on the role of the degree of interdisciplinarity in

innovative output by providing empirical evidence that DoI facilitates a firm's innovations and not only academic research. Additionally, we extend the literature on recombinant knowledge (Fleming, 2001; Yayavaram & Chen, 2015) by providing empirical evidence of the trade-off between the advantages and disadvantages of DoI for a firm's innovation performance. We achieve this by disentangling a positive direct effect of DoI and a negatively mediated effect of complexity of outcome validation on a firm's innovation performance. Our study therefore contributes to the literature on the benefits and pitfalls of interdisciplinary research at the firm level. We developed an additional, novel measurement for the degree of interdisciplinarity based on machine learning techniques. Future research should adopt this approach to map the interdisciplinarity and related concepts based on bibliographic metadata of publications by science-intensive firms.

5.2 | Limitations and future research

First, we measured innovation performance as the number of PMA and 510(k) applications approved by the FDA. Future research can explore the extent to which DoI can contribute to the development of medical device products with different degrees of innovativeness, to determine the role of DoI in exploration and exploitation innovation performance. Future research should specifically also include innovation-related additional revenues as indicators for financial performance.

Second, we measured the DoI based on a firm's publications. This has the advantage of a very broad availability of valid data, but it may not reflect a firm's entire R&D portfolio. As the high number of publications shows, scientific publications appear frequently and are very relevant to medical technology firms. However, firms may have confidentiality issues, for example, that prevent them from publishing their R&D results. Future research may have access to internal documents reflecting the complete R&D project portfolio.

Third, co-authorships of publications indicate collaborations with universities. UICs do not necessarily lead to scientific publications. Such collaborations may result in technical reports, which were not included in our study. Moreover, co-authored publications don't indicate that such collaborations operated on a deep level, or that firms indeed managed to transfer knowledge from such R&D collaborations. Again, future research may have access to more detailed information on the project level. In addition, our analysis provided evidence that a firm's knowledge integration capabilities and resources foster the relationship between DoI and innovation

performance. However, our study did not explore the mechanisms of specialized knowledge integration during new product development. Future research can investigate those mechanisms that facilitate the application of diverse knowledge during risky interdisciplinary research projects in more detail. This should also include potential moderators of the relationship between complexity and innovation performance, reflecting potential coping mechanisms regarding complexity in the later stages of the innovation process. Finally, this study was designed for firms in the highly science-intensive medical technology industry. Therefore, the results of the study cannot be generalized for other, less knowledge-intensive industry sectors without further empirical research.

5.3 | Managerial implications and conclusion

Our study recommends that managers of high-technology firms should conduct interdisciplinary research to increase the knowledge base for successful knowledge recombination that will result in new product development. However, the results of our study suggest that DoI is a double-edged sword for a firm's innovation performance. On the one hand, we recommend that managers should develop and enhance DoI to foster a firm's innovativeness. On the other hand, DoI increases the complexity of required validation of intended outcomes, which diminishes a firm's innovation performance. Thus, we suggest that managers should be aware of this phenomenon and take measures to cope with the increasing complexity. Possible coping mechanisms may build on professional project management and the use of digital tools during a project's complex innovation stages (Kroh et al., 2018). Our study also suggests that management should actively seek interdisciplinary R&D projects during phases of financial prosperity. Additionally, our research advises that managers should not be afraid of collaborative and cognitive challenges while collaborating with universities. They should rather actively engage in collaborations with universities to explore and recombine knowledge from diverse distant knowledge domains. Our study also recommends that managers of science-intensive firms should engage with scientific networks, develop informal linkages in such networks, and build central betweenness positions in those networks that connect multiple subnetworks and thus provide heterogeneous knowledge. Utilizing a high betweenness centrality position in scientific networks, firms can access valuable non-redundant diverse knowledge sets residing in subnetworks containing specific homogeneous knowledge.

ACKNOWLEDGMENTS

The authors thank the editor-in-chief, the associate editor, the anonymous reviewers, and the participants of the 28th Innovation and Product Development Management Conference for their helpful feedback on earlier versions of the manuscript, and Dr. Lukas Galke for his valuable suggestions related to the graph convolutional algorithm. We also thank the German Federal Ministry of Education and Research (BMBF) (grant number 16WIK2101A), especially the FIZ Karlsruhe–Leibniz Institute for Information Infrastructure, for providing the access to the bibliographic database Web of Science and the German Network for Bioinformatics Infrastructure (de.NBI) for providing the computing infrastructure for conducting the training of models. Open Access funding enabled and organized by Projekt DEAL.

FUNDING INFORMATION

The authors declare the following funding was received in support of the research: This study was supported by the German Federal Ministry of Education and Research (BMBF) represented by the project executing organization Jülich (PtJ) within the framework of the Research Project BlueHealthTech under Grant 03WIR6203 within the funding line “WIR! Change through innovation in the region.”

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ETHICS STATEMENT

The authors have read and agreed to the Committee on Publication Ethics (COPE) international standards for authors.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Melnychuk, Tetyana, and Carsten Schultz. 2025. “Direct and Indirect Effects of Degree of Interdisciplinarity on Firms’ Innovation Performance: The Moderating Role of Firms’ Capabilities.” *Journal of Product Innovation Management* 42(2): 417–443. <https://doi.org/10.1111/jpim.12750>