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How do university-firm interactions affect firm innovation speed? The case of Chinese science-intensive SMEs

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ABSTRACT

This study examines how university-firm (U-F) interactions affect innovation speed in science-intensive small and medium-sized firms (SISMEs). We distinguish between formal and informal U-F interactions and build on dynamic capability theory to argue that (1) U-F R&D alliances enhance innovation speed through firm-level entrepreneurial orientation (EO), and (2) frequent U-F informal contacts weaken the effects of U-F R&D alliances on innovation speed. Analyzing a sample of 268 SISMEs from 10 science parks in China, the results of the partial least squares structural equation modeling (PLS-SEM) support our hypotheses. Furthermore, fuzzy-set qualitative comparative analysis (fsQCA) identifies various configurations of U-F R&D alliances, U-F informal contacts and EO, along with other organizational, science park and environmental conditions, that lead to higher or lower innovation speed in SISMEs. Our findings offer valuable theoretical and practical insights, advancing our understanding of the complex relationship between U-F interactions and innovation speed in SISMEs.

1. Introduction

Within the pharmaceutical industry, the development and launch of the COVID-19 vaccine underscores the critical role of innovation acceleration in securing strong market positions and generating substantial economic and social impacts (Cooper, 2021; Rosa, 2021). In fact, innovation speed is highly relevant in any science-intensive and high-tech market, where being first-to-market is paramount (Chen et al., 2012; Markman et al., 2005). Despite captivating the attention of researchers and practitioners for some time, the factors driving innovation speed remain one of the least understood aspects in innovation literature (Ferreras-Méndez et al., 2022). Our study seeks to enrich this literature by exploring the influence of University-Firm (U-F) interactions on innovation speed in science-intensive small and medium-sized enterprises (SISMEs).

SISMEs strive for competitiveness through rapid innovations by leveraging unique technical knowledge (George et al., 2002). However, their small size constrains their ability to develop internal resources and capabilities, posing challenges to their innovation efforts (Vanacker et al., 2014). To compensate, SISMEs often turn to universities as major sources of advanced knowledge (Mindruta, 2013) and initiate formal and/or informal U-F interactions to acquire scientific knowledge and technological resources (Díez-Vial and Montoro-Sánchez, 2016; Schaeffer et al., 2020). U-F formal interactions are established through contractual agreements, including R&D alliances and patent licensing (Azagra-Caro et al., 2017; Landry et al., 2010), whereas U-F informal interactions are comprised of non-contractual linkages, such as individual contacts between firm employees and university staff, and participation in academic events (e.g., seminars, conferences, workshops, etc.) (Azagra-Caro et al., 2017; Dahl and Pedersen, 2004; Diánez-González and Camelo-Ordaz, 2019).

Among these channels, U-F R&D alliances are most often utilized by science-intensive firms, and a substantial body of research acknowledges the significant relationship between such alliances and firm innovation (Caloghirou et al., 2021; Soh and Subramian, 2014). Nevertheless, the nature of this relationship remains ambiguous, yielding mixed findings that range from positive (Melnychuk et al., 2021; Soh and Subramian, 2014) to negative (Bruneel et al., 2010; He et al., 2021; Zhang et al., 2022b), with others suggesting a U-shaped relationship (Caloghirou et al., 2021). This inconsistency underscores both the complexity of the U-F R&D alliances-innovation relationship in SISMEs, and the need to examine this relationship more closely. Furthermore, while a few previous studies highlight the pivotal role of U-F informal interactions in knowledge transfer (Apa et al., 2021; Díez-

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Vial and Montoro-Sánchez, 2016), to date, we know little about how U-F informal interactions help to accelerate firm innovation. More critically, the interplay between these U-F informal interactions and formal R&D alliances in driving innovation speed remains underexplored (Azagra-Caro et al., 2017; Schaeffer et al., 2020).

We attempt to address these issues by developing a fine-grained framework to investigate how U-F interactions affect firm innovation speed. Grounded in dynamic capability theory (Teece et al., 1997), innovation speed can be conceptualized as the firm's ability to accelerate the innovation process from idea generation to commercialization (Cankurtaran et al., 2013; Markman et al., 2005). Moreover, dynamic capability theory highlights the importance of organizational resource-oriented mechanisms through which firms integrate and reconfigure both external and internal assets to generate innovative outcomes and seize opportunities in rapidly changing environments (Teece, 2007). Building on this logic, we initially investigate how SISMEs harness U-F R&D alliances to access advanced technical knowledge and employ entrepreneurial mechanisms to exploit these external resources effectively, thereby augmenting their innovation speed. We contend that firm-level entrepreneurial orientation (EO) represents such a mechanism because EO, characterized by innovativeness, risk-taking, and proactiveness, is a central function that allows firms to reconfigure and exploit critical resources inside and outside the organization (Brouthers et al., 2015; Wiklund and Shepherd, 2003) for innovation and changes to competitive positioning (Anderson et al., 2015; Covin and Slevin, 1991; Zhang et al., 2020). Subsequently, we explore the interplay between U-F informal contacts and U-F R&D alliances, proposing their substitutive effects on innovation speed.

Our study makes at least three significant contributions to the literature. First, we advance research on the U-F interactions-innovation relationship by emphasizing a specific indictor of innovation: innovation speed. Broadly, within the innovation literature, innovation can be comprised of two components and phases, early stage “innovation inputs” (e.g., results of R&D and human resources) and later stage “innovation outputs” (e.g., outcomes of product and process innovations) (Janger et al., 2017, p. 31; OECD, 2015). However, within this literature, prior research has primarily focused on how U-F R&D alliances affect input proxies of innovation, such as R&D performance (Melnychuk et al., 2021), number of patents (Chai and Shih, 2016; George et al., 2002), and technology newness (Wirsich et al., 2016), with only a few studies examining their effects on output proxies of innovation, such as the number of product and process innovations (e.g., Caloghirou et al., 2021; Díez-Vial and Montoro-Sánchez, 2016). Our study adds to this stream of literature by offering a novel perspective, namely the effects of U-F R&D alliances on innovation speed, which encompasses both innovation input (e.g., idea generation) and output efforts (e.g., commercialization).

Second, our study provides a deeper understanding of the interplay between U-F formal and informal interactions (Schaeffer et al., 2020) by illustrating how the effects of frequent U-F informal contacts substitute for the effects of U-F R&D alliances on innovation speed. While prior research shows that SISMEs emphasizing the utilization of specific knowledge and emerging technologies (Miozzo and DiVito, 2016) are more likely to benefit from the complementarity of formal and informal interactions with universities (Schaeffer et al., 2020), our analysis suggests an alternative perspective. Our findings show that a high frequency of U-F informal contacts may diminish the beneficial effects of U-F R&D alliances on innovation speed in SISMEs. Our results provide robust evidence for the broader argument that frequent U-F informal contacts may generate strong “interpersonal commitments and social exchange” (Jiang et al., 2021, p. 1796), leading firms to be over-embedded in such relationships (Anderson, 2013), thereby reducing the efficacy of formal U-F interactions (Landry et al., 2010).

Third, we contribute to the literature by identifying firm-level EO as an effective organizational mechanism for the U-F R&D alliances-innovation relationship. Specifically, our research extends beyond merely examining U-F interactions-innovation speed and EO-innovation speed relationships. Instead, we broaden our understanding by emphasizing how firm innovation is accelerated through the integration of U-F R&D alliances and EO, shedding light on how SISMEs “act entrepreneurially” (George et al., 2002) to reconfigure firm advanced technical resources to become competitive in the market. Our findings also help reconcile the debate regarding the relationship between U-F interactions and entrepreneurship (Diánez-González and Camelo-Ordaz, 2019), as well as between EO and innovation speed (Ferreras-Méndez et al., 2022; Shan et al., 2016). We achieve this by demonstrating the beneficial effects of U-F R&D alliances on EO and the positive impact of EO on innovation speed in the context of SISMEs.

Our analysis, drawing on data from 268 SISMEs located in 10 Chinese science parks, integrates symmetrical and asymmetrical approaches. Specifically, we initially employ the symmetrical approach in terms of the Partial Least Squares Structural Equation Modeling (PLS-SEM) to test our conceptual framework. Subsequently, asymmetrical analysis is conducted using Fuzzy-Set Qualitative Comparative Analysis (fsQCA) to explore distinct configurations of antecedents of innovation speed. This methodological amalgamation allows us to gain a holistic understanding of the catalysts and mechanisms affecting innovation speed in SISMEs.

2. Theoretical background and hypothesis development

2.1. Theory and conceptual framework

Innovation speed has garnered substantial attention in innovation research and various terms such as new product development speed, speed-to-market, time-to-market, and cycle time have been used to describe this concept (Bao et al., 2021; Chen et al., 2012; Clausen and Korneliussen, 2012). Despite varied terminologies, at its core, innovation speed captures the firm's ability to quickly move from initial idea generation to product commercialization (Cankurtaran et al., 2013; Markman et al., 2005). This capability-centric view can be underpinned by dynamic capability theory, where dynamic capabilities are defined as “the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments” for competitive advantage (Teece et al., 1997, p. 516). Reflected in the firm's innovation abilities (Helfat and Peteraf, 2003), innovation speed is thus the firm's capability to compress time from idea generation through product development, production, to commercialization by reconfiguring both external and internal resources and capabilities (Williamson, 2016; Wu et al., 2017).

Drawing on this capability perspective, prior research suggests that accelerated innovation enables a firm to reap the benefits of being the first mover (Fosfuri et al., 2013), maintain strong competitiveness and market positions (Cankurtaran et al., 2013; Kessler and Chakrabarti, 1996), and increase long-term survivability (Chen and Jin, 2023). Despite its recognized importance, research on the factors that drive innovation speed remains underdeveloped. Most studies focusing on elucidating such factors has been conducted at the project level (Ferreras-Méndez et al., 2022, p. 241), concentrating on specific project characteristics such as project investment (Menon et al., 2002), project complexity (Markman et al., 2005), technological newness and radicalness (Seidel, 2007), and knowledge sharing (Wang et al., 2016). Although insightful, prioritising project-level aspects may overlook the significance of organizational-level factors related to innovation speed, such as inter-organizational collaborations (Ma et al., 2012), strategic orientations (Clausen and Korneliussen, 2012), business models (Zhu et al., 2019), and absorptive capacity (Bao et al., 2021).

Moreover, due to their smallness, many SISMEs may only engage in one innovation project at a time, requiring them to dedicate a significant portion of their limited organizational resources to each initiative. In such scenarios, firm-level factors may have a more pronounced impact on innovation. To deepen our understanding of this phenomena, we develop a nuanced model that incorporates both external and internal firm-level factors as predictors of innovation speed in SISMEs. Specifically, we focus on the role of U-F interactions in accelerating SISMEs' innovation (Du et al., 2014). U-F interactions, serving as a critical external conduit for accessing advanced knowledge (Garcia-Perez-de-Lema et al., 2017; Jensen et al., 2007), are indispensable for SISMEs. They offer avenues for these firms to acquire and assimilate new technical knowledge (Melnychuk et al., 2021) and diverse technological resources (Wirsich et al., 2016) to improve their existing knowledge and resource bases (Caloghirou et al., 2021), ultimately bolstering the firm's innovative capabilities (Polidoro Jr et al., 2011; Polidoro Jr. et al., 2022).

Firms develop U-F interactions through either formal collaborations or informal contacts, distinguished by the presence or absence of contractual agreements (Azagra-Caro et al., 2017). U-F R&D alliances, considered as the most utilized form of formal U-F interactions (Caloghirou et al., 2021; George et al., 2002; Soh and Subramian, 2014), typically focus on the creation of codified novel knowledge (Garcia-Perez-de-Lema et al., 2017; Scillitoe and Chakrabarti, 2010). These alliances often lead to an increase in patents and products under development but do not necessarily lead to marketable products (George et al., 2002). Despite the numerous benefits of U-F R&D alliances for innovation (Melnychuk et al., 2021; Soh and Subramian, 2014), they also pose challenges due to the mismatched orientations of firms, which aim for marketable innovation, and universities, which prioritize the creation of scientific knowledge (He et al., 2021). Moreover, it is argued that merely having network resources does not guarantee enhanced innovation, instead, it requires the effective configuration of external and internal knowledge and resources (Wei et al., 2012, p. 383). More importantly, innovation speed is often an "entrepreneurial and risky endeavor" that necessitates entrepreneurial mechanisms (Clausen and Korneliussen, 2012; Ferreras-Méndez et al., 2022, p. 241). Therefore, we propose that firm-level EO plays a pivotal role in connecting U-F R&D alliances with innovation speed in SISMEs.

Firm-level EO is conceptualized as a strategic attribute and capability that encompasses specific "processes, practices, and decision-making activities", including engaging in product-market innovation, venturing into somewhat risky enterprises, and exploring and exploiting opportunities (Covin and Slevin, 1991; Lumpkin and Dess, 1996, p. 136). EO manifests in three interconnected dimensions: (1) organizational innovativeness, marked by creativity and experimentation in new products/services introductions; (2) risk-taking, characterized by bold actions in uncertain environments; and (3) proactiveness, which involves pursuing novel opportunities and initiatives ahead of competitors (Covin and Slevin, 1989; Covin and Wales, 2012, 2019). Firms with a strong EO stand out for their ability to innovate, embrace risks, and proactively capitalize on opportunities, setting themselves apart from traditional firms (e.g., Brouthers et al., 2015; Wiklund and Shepherd, 2003), which prioritize stability, risk aversion, and adhering to established procedures. However, possessing EO does not imply a lack of rules or structure within a firm. Rather, it signifies a strategic posture and decision-making framework that guides organizational strategies to form supportive structures for entrepreneurial behavior and empower employees to contribute to innovation, thus improving firm performance (e.g., Engelen et al., 2014; Patel et al., 2015). As such, EO enhances a firm's capacity to integrate external and internal resources (Kollmann and Stöckmann, 2014; Zhang et al., 2020) to forge new "internal firm capabilities" (Boso et al., 2013, p. 77), and ultimately, to drive innovation (Arzubiaga et al., 2018).

On the other hand, U-F informal contacts also contribute to knowledge transfer (Díez-Vial and Montoro-Sánchez, 2016). Unlike their formal counterparts, U-F informal contacts are not bounded by contracts but thrive within an informal *doing*, *using*, and *interacting* (DUI) mode (Jensen et al., 2007) through interpersonal bonds (Garcia-Perez-de-Lema et al., 2017). Such informal DUI modes prioritize learning of tacit knowledge elements such as "know-how" and "know-who", which are pivotal for enhancing individuals' problem-solving capabilities (Fernández-Esquinas et al., 2016; Jensen et al., 2007). As such, informal contacts are often considered an essential component of innovation strategies (Garcia-Perez-de-Lema et al., 2017) that influence innovation outcomes in SMEs (Apa et al., 2021).

Given the importance of both U-F formal and informal interactions in acquiring diverse knowledge and cutting-edge technologies from universities (Dahlander et al., 2016; Scandura, 2016; Soh and Subramian, 2014; Zhang et al., 2022b), understanding their interactive effects is crucial for firms focused on innovation (Azagra-Caro et al., 2017; Landry et al., 2010). However, the literature presents inconclusive findings regarding the interactive effects of U-F formal alliances and informal contacts. While some studies indicate that these interactions can generate complementary effects (e.g., Díez-Vial and Montoro-Sánchez, 2016; Schaeffer et al., 2020), other studies suggest trade-offs in their effects on innovation (e.g., Toole and Czarnitzki, 2010). This divergence underscores a gap in our understanding of their interactive effects on innovation, and specifically whether they influence innovation in a complementary or substitutive manner. To this end, our study proposes that frequent U-F informal contacts may weaken the effects of U-F R&D alliances on innovation speed. We detail these relationships as discussed above in our conceptual model, illustrated in Fig. 1.

2.2. EO as a mediating mechanism between U-F R&D alliances and innovation speed

Building on the theoretical foundation explored previously, we suggest that EO serves as a pivotal mechanism through which U-F R&D alliances boost innovation speed. This assertion stems from the goal asymmetry between U-F R&D alliances and firm innovation. Specifically, while U-F R&D alliances grant firms access to novel knowledge and inventions, these outcomes are often more scientific in nature and may not directly correspond with a firm's commercial goals (Soh and Subramian, 2014). In contrast, innovation speed, as a critical component of a firm's time-to-market capability (Bao et al., 2021), must align with the firm's commercial objectives. To benefit from novel technical knowledge gained through U-F R&D alliances, firms need to strengthen their ability to assimilate and apply such knowledge towards commercial ends. Indeed, this ability is significantly bolstered by a firm's EO, which prioritizes innovativeness and value creation through exploration and exploitation of market opportunities (Lumpkin and Dess, 1996). Specifically, EO adds in the synchronization of R&D outcomes with commercial objectives. It does so by promoting the exploration of cutting-edge technical knowledge for creating market value and improving the integration of market insights and opportunities with R&D efforts (Hughes et al., 2021), thereby propelling rapid innovation (Mehrabi et al., 2019). Furthermore, the potential goal misalignment between U-F R&D alliances and firm innovation also introduces uncertainty about the relevance and applicability of the acquired knowledge and resources for innovation. To navigate this uncertainty, firms need to adopt a *trial-and-error* approach to utilize these resources for innovation (Ganco, 2017), which requires a readiness to embrace risk. Thus, steering SISMEs towards risk-taking enhances their ability to quickly integrate and apply knowledge from U-F R&D alliances with their existing knowledge base, leading to accelerated innovation.

The mediating role of EO may also stem from the "potential risks of knowledge leakage and misappropriation" during knowledge transfer (Zhang et al., 2019a, p. 2640), especially when a university collaborates with multiple firms simultaneously. These risks potentially dilute the effectiveness of an individual firm's U-F R&D alliances (de Leeuw et al., 2019). Knowledge leakage refers to instances where proprietary knowledge intended for one firm through its U-F R&D alliances might unintentionally spread to and be utilized by other firms, including competitors, engaged with the same university, while misappropriation occurs when either party uses the other's knowledge without proper authorization (O'Dwyer et al., 2023). Such risks can discourage full

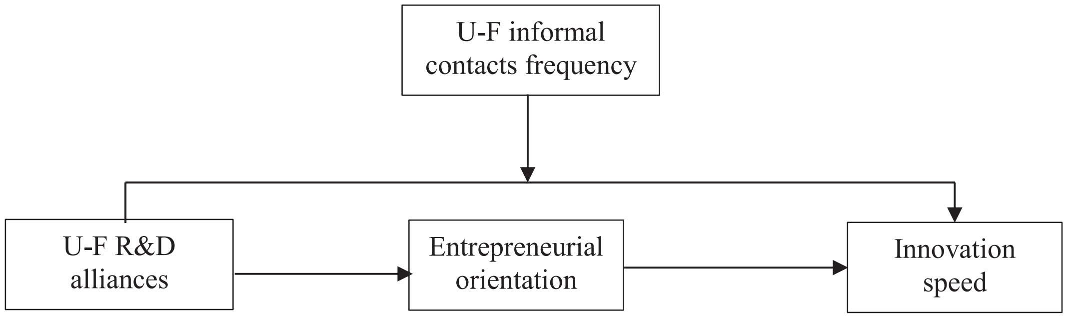

Fig. 1. Conceptual model.

engagement and effort in R&D alliances, "significantly jeopardizing the focal firm's innovation" prospects (Zhang et al., 2019a, p. 2639). Therefore, to help ensure U-F R&D alliances to enhance innovation speed, SISMEs need to be cognizant of such risks. They must proactively evaluate the outcomes from these alliances and develop forward-looking mechanisms to gauge the extent to which they can integrate knowledge and resources from these U-F R&D alliances with their own internal knowledge (Lumpkin and Dess, 2001). Given EO's emphasis on proactiveness, such adaptive and forward-looking mechanisms can be facilitated by adopting high degrees of EO. Thus, through EO, U-F R&D alliances may booster innovation speed more effectively.

Previous research has also provided empirical evidence supporting the direct impacts of U-F alliances on EO (e.g., Diánez-González and Camelo-Ordaz, 2019; Scillitoe and Chakrabarti, 2010) and, separately, the influence of EO on innovation speed (Clausen and Korneliussen, 2012; Ferreras-Méndez et al., 2022; Shan et al., 2016). These findings serve as a prerequisite for our argument regarding EO's mediating role in transforming the benefits of U-F R&D alliances into increased innovation speed. Specifically, U-F R&D alliances facilitate an increase in technical resource availability (Diánez-González and Camelo-Ordaz, 2019) by enabling firms to tap into a wider pool of codified knowledge from universities (Díez-Vial and Montoro-Sánchez, 2016). This enhanced resource availability can allow firms to more effectively pursue EO, as EO demands substantial resources as a strategic capability (Covin and Slevin, 1991; Wales et al., 2013, p. 1047), thereby leading to improved innovation outcomes (Bouncken et al., 2016). In turn, embracing EO enables firms to leverage the acquired knowledge and resources to achieve first-mover advantages (proactiveness), engage in the innovative and experimental introduction of new products/services (innovativeness), and explore new yet risky opportunities (risk-taking) (Wales et al., 2013; Wiklund and Shepherd, 2003). This approach ultimately culminates in accelerated innovation speed (Shan et al., 2016). Taken together, we hypothesize:

H1. EO mediates the relationship between U-F R&D alliances and innovation speed such that U-F R&D alliances facilitate EO, which in turn, leads to greater innovation speed in SISMEs.

2.3. The interactive effects of U-F informal contacts and R&D alliances on innovation speed

As previously discussed, while both U-F R&D alliances and informal contacts alone can increase firm innovation speed, their interactive effects on innovation speed can be complementary or substitute (Landry et al., 2010). For SISMEs, we argue that their effects on innovation speed are substitutive. Specifically, we posit that frequent U-F informal contacts may weaken the effects of U-F R&D alliances on innovation speed for several reasons. First, with a low frequency of U-F informal contacts, SISMEs might encounter limited options of informal channels for knowledge transfer, leading to increased reliance on formal interactions with universities to acquire the advanced knowledge and technologies necessary for innovation. As a result, the significance of U-F R&D alliances on innovation speed is heightened when U-F informal contacts frequency is low. Conversely, a high frequency of U-F informal contacts offers firms alternative, possibly more cost-effective ways to access university knowledge and resources, potentially enhancing the resource base for innovation more efficiently (Dahlander et al., 2016; Diánez-González and Camelo-Ordaz, 2019). Consequently, with abundant U-F informal contacts, firms may become less dependent on formal R&D alliances for accelerating innovation. This trade-off between engaging in U-F R&D alliances and frequent U-F informal contacts is especially pronounced in individual entrepreneurs and SMEs, where participation in one type of knowledge transfer activity might limit the capacity to engage in another (Landry et al., 2010, p. 1390).

Second, and more significantly, U-F informal contacts may promote deeper learning and the exchange of tacit knowledge (Fernández-Esquinas et al., 2016), potentially accelerating the development of problem-solving competencies (Jensen et al., 2007). For example, U-F informal contacts may boost individuals' absorptive capacity in SISMEs, improving the effectiveness of knowledge transfer from universities (Díez-Vial and Montoro-Sánchez, 2016; Uzzi, 1996). Such benefits could lead to reduced engagement in other formal relationships and diminish the advantages of diversification (Anderson, 2013). As a result, a high level of U-F informal contacts may decrease SISMEs' reliance on U-F R&D alliances, thereby diminishing their role in facilitating university knowledge transfer for innovation purposes (Polidoro Jr. et al., 2022), and affecting innovation speed.

Third, while frequent U-F informal contacts offer significant benefits, an excessive frequency of U-F informal contacts may result in individuals becoming overly embedded in these interactions, which also hinders the pursuit of alternative partnerships (Elfenbein and Zenger, 2017; Uzzi, 1997). Specifically, while embeddedness, which denotes deep and cohesive relationships characterized by social and interpersonal ties (Granovetter, 1985; Greve et al., 2010), is generally beneficial for fostering innovation-related collaborations (Lioukas and Reuer, 2020; Uzzi, 1997), it may cause a cognitive lock-in for SISMEs (Lavie and Drori, 2012) when such relationships become too frequent or intense, resulting in over-embeddedness (Granovetter, 1985). This situation can lead to a constrained and dominant focus on acquiring and exchanging tacit knowledge through close interpersonal connections (Jiang et al., 2021), thus making firms hesitant to explore or leverage the benefits of other U-F formal interactions (Uzzi, 1997) essential for rapid innovation. Consequently, a high frequency of U-F informal contacts might reduce the beneficial effects of U-F R&D alliances on innovation speed. Drawing from the above discussion, we propose the following hypothesis:

H2. Frequent U-F informal contacts weaken the relationship between U-F R&D alliances and innovation speed in SISMEs.

3. Methods

3.1. Sample and data collection

Following prior studies on U-F interactions (e.g., Caloghirou et al., 2021; He et al., 2021; Lee and Miozzo, 2019), we utilized survey data to test our conceptual model. We conducted a questionnaire survey targeting SISMEs located in 10 national science parks across Guangdong, Zhejiang, Jiangsu, and Fujian provinces in China. These science parks were selected for their strategic importance. First, they are in regions known for their rapid growth and active entrepreneurial climates, thus conducive to fostering innovation through new ventures (De Oliveira et al., 2022). Second, their proximity to elite universities and research institutions enhances the prospects of firms accessing the R&D resources and intellectual capital that are essential for innovation and business development (Armanios et al., 2017). Third, while prior research on China's science parks has predominantly focused on the Beijing Zhongguancun Science Park (ZSP), the inclusion of multiple parks aims to mitigate potential selection bias.

Aligning with prior research on firms within Chinese science parks (Filatotchev et al., 2001; Zhang and Guan, 2021), our sample was comprised of SISMEs from science-intensive and high-tech industries, as officially categorized by China's High-Tech Industry Classification. This includes sectors such as pharmaceuticals, biotechnology, information technology, and more. These firms, often established as university spin-offs or founded by scientists, have a strong R&D focus, and emphasize the advanced skills and specialized knowledge of their employees. Moreover, we define SMEs as firms with 500 or fewer employees, reflecting that "about 99% of SMEs in China have less than 500 employees (OECD, 2022)" (Zhang et al., 2022a, p. 8).

The questionnaire for data collection, which was based on validated items from existing literature, was initially drafted in English. To ensure linguistic accuracy in the Chinese version, a translation-back-translation procedure was utilized. This translated questionnaire underwent a pretest by four Chinese academics and a pilot test with 70 CEOs or top managers of SMEs in two science parks, ensuring its reliability, validity, and clarity. Feedback from these tests led to further refinement of the questionnaire.

For the initiation of data collection, a member of the research team visited each of the 10 science parks to engage with park administrators and discuss the research objectives. With their support, we employed the key informant approach (Kumar et al., 1993), sending personalized emails to the CEOs of SISMEs within these parks. Four weeks following the initial contact, a reminder email was sent to those who had not yet responded. The study resulted in 296 responses, from which a usable sample of 268 firms was derived after discarding responses with significant data missing for questions related to key constructs. This sample had firms of varied size and age and included firms from eight science-intensive and high-tech industries. Descriptive statistics for these distributions are detailed in Table 1.

Table 1
Basic statistics of the sample.

Variable	Description	Frequency (% of firms)	Mean	S.D.
Firm age	Logarithm of the difference between the year that the survey was conducted and the establishment year of the firm		2.37	0.61
Firm size	Categories of the average number of fulltime employees over the latest two years		2.78	1.24
	1: ≤ 10 employees	11.2		
	2: 11–50 employees	41.8		
	3: 51–100 employees	19.4		
	4: 101–300 employees	12.7		
	5: 301–500 employees	14.9		
R&D intensity	% of R&D expenditure to total sales		25.9%	6.2%
High-skilled employees	Categories of the % of employees with a graduate degree		3.31	1.74
	1: 0%	5.1		
	2: 0% - 5%	39.6		
	3: 5% - 10%	15.3		
	4: 10% - 25%	15.3		
	5: 25% - 50%	11.6		
	6: 50% - 75%	4.5		
	7: >75%	8.6		
Development stage	The firm's stage when it first entered the science park		2.70	1.48
	1: R&D/planning: developing product prototype	31.0		
	2: Pre-revenue: product prototype but still developing the product	18.3		
	3: Early revenue: finished product shipped to at least one customer	19.4		
	4: Initial profits: sales just surpass costs	12.7		
	5: Growth: 5% or more profitability	18.7		
Exports experiences	Firms report if they have exported products/services 1: yes, 0: no		0.61	0.49
Science park size	Number of resident organizations (categorical)		4.70	1.92
	1: <50	6.3		
	2: between 50 and 100	14.6		
	3: between 100 and 200	8.6		
	4: between 200 and 400	9.7		
	5: between 400 and 600	13.8		
	6: between 600 and 1000	28.4		
	7: >1000	18.7		
Industry	Inudustries that the usable sample operates in:			
	1: Information technology (e.g., devices, computer systems, networks databases)	17.5		
	2: Software development (e.g., coding, testing, and developing software)	9.3		
	3: New and renewable energy	15.3		
	4: Electronics	15.7		
	5: Telecommunication	13.4		
	6: Biotechnology	14.2		
	7: Pharmaceutical	8.2		
	8: High-tech in agriculture	6.3		

3.2. Measures

To increase the validity of measurement, we used well-established items from prior research to measuring our key constructs. We elaborate on the detail of these measures below.

3.2.1. Innovation speed

Drawing on prior research (Acharya et al., 2020; Markman et al., 2005; Shan et al., 2016; Wang et al., 2016), we measured innovation speed using three 11-point Likert scale items. These items assess the firm's ability to conduct rapid innovation in comparison to major competitors ($\alpha = 0.914$), as detailed in Table 2.

3.2.2. U-F R&D alliances

Informed by previous studies on R&D alliances, we developed three items to gauge U-F R&D alliances. Participants evaluated the extent to which their firm engages with and partners with universities/research institutes for R&D projects based on a contract (e.g., Caloghirou et al., 2021), fosters and maintains constructive relationships with these entities (e.g., D'Este et al., 2019), and commits to U-F joint R&D projects. These items were rated on a 7-point scale from 1 = strongly disagree to

Table 2
Constructs measurement.

Constructs	Loadings	Weights
Innovation speed (e.g., Acharya et al., 2020; Markman et al., 2005; Shan et al., 2016; Wang et al., 2016) (α = 0.914, CR = 0.946, AVE = 0.853)		
Our firm is quick in new product/process development than that of key competitors	0.925***	0.391***
Our firm is always capable of conducting innovation at a high rate compare with key competitors	0.930***	0.346***
Our firm's innovation "on-time performance" is often ahead of the assigned schedule	0.915***	0.346***
University-firm R&D alliances (e.g., Caloghirou et al., 2021; D'Este et al., 2019) (α = 0.876, CR = 0.924, AVE = 0.802)		
Our firm always uses and partners with universities/research institutes for R&D projects	0.904***	0.373***
Our firm develops and maintains good contractual relationships with universities/research institutes for R&D projects	0.914***	0.370***
Our firm always has high commitment and trust to joint R&D projects with universities/research institutes.	0.868***	0.373***
University-firm informal contacts frequency (5-point Likert scale ranges from 1 = one or less than one contact annually; 2 = on average, one contact every six months; 3 = on average, one contact every two months; 4 = on average, one contact every two weeks; 5 = one and/or multiple daily contacts) (e.g., Diánez-González and Camelo-Ordaz, 2019; He et al., 2021; Scillitoe and Chakrabarti, 2010).		
Entrepreneurial orientation (Covin and Slevin, 1989; Ferreras-Méndez et al., 2021; George, 2011) (α = 0.937, CR = 0.949, AVE = 0.760)		
Innovativeness (α = 0.867, CR = 0.938, AVE = 0.882)		
In general, our firm favors a strong emphasis on R&D, technological leadership, and innovations	0.936***	0.518***
In the last five years, our firm has marketed many new product lines or services (removed)	–	–
In our firm, changes in product or service lines have usually been quite dramatic	0.943***	0.546***
Risk-taking (α = 0.889, CR = 0.947, AVE = 0.900)		
In general, my firm has a strong proclivity for high-risk projects (with chances of very high return)	0.946***	0.514***
In general, our firm believes that owing to the nature of environment, wide-ranging acts are necessary to achieve the firm's objectives.	0.951***	0.540***
When confronted with decision-marking situations involving uncertainty, our firm typically adopts a bold, aggressive posture in order to maximize the probability of exploiting potential opportunities (removed)	–	–
Proactiveness (α = 0.880, CR = 0.943, AVE = 0.893)		
In dealing with its competitors, our firm typically initiates actions to which competitors then respond (removed)	–	–
In dealing with its competitors, our firm is very often the first business to introduce new products/services, operating technologies, etc.	0.946***	0.536***
In dealing with its competitors, our firm typically adopts a competitive, "undo-the-competitors' posture	0.944***	0.523***
Environmental dynamism (Jansen et al., 2006) (α = 0.882, CR = 0.918, AVE = 0.738)		
Environmental changes in our local market are intense.	0.873***	0.280***
In our local market, changes are taking place continuously.	0.789***	0.222***
Our customers constantly ask for new products and services.	0.888***	0.328***
In our market, products and services to be delivered change fast and often.	0.880***	0.328***

Notes: α: Cronbach's alpha; CR: composite reliability; AVE: Average variance extracted; Loadings: Standardized indictor loadings; Weights: Coefficients in the regression of the corresponding construct on its indictors. Significant level: ***: $p < 0.001$, **: $p < 0.01$, *:$p < 0.05$, †:$p < 0.10$.

7 = strongly agree ($\alpha = 0.876$).

3.2.3. U-F informal contacts frequency

Drawing from prior research (Diánez-González and Camelo-Ordaz, 2019; He et al., 2021; Scillitoe and Chakrabarti, 2010), U-F informal contacts frequency was assessed by querying the frequency of interactions firm managers and members have with universities, such as attending seminars/conferences, personal interactions, and communications with academics, etc. This was measured on a 5-point scale ranging from 1 = one or fewer contacts annually; 2 = on average, a contact every six months; 3 = on average, one contact every two months; 4 = on average, one contact every two weeks; 5 = one and/or multiple daily contacts.

3.2.4. Entrepreneurial orientation (EO)

We measured EO as a second-order construct composed of three dimensions: innovativeness, risk-taking, and proactiveness (Ferreras-Méndez et al., 2021; George, 2011). We administered the widely adopted nine-item measure of EO developed by Covin and Slevin (1989) to measure these three dimensions with 3 items each on a 7-point Likert scale. The results in Table 2 show that an item was removed from each dimension given their poor factor loadings (< 0.40). Consequently, innovativeness (α = 0.867), risk-taking (α = 0.889) and proactiveness (α = 0.880) are each measured with 2 items. The second-order construct of EO is then measured by these three dimensions (α = 0.937).

3.2.5. Control variables

We included control variables at three levels: firm, science park, and industry level. At the firm level, as demonstrated in Table 1, we first controlled for *firm age* and measured it as the "logarithm of the difference between the year that the survey was conducted and the establishment year of the firm" (Caloghirou et al., 2021; p. 6; Soh and Subramian, 2014). Second, *firm size* was included, measured by the average number of full-time employees over the latest two years, categorized as follows: 1 ≤ 10 employees; 2 = 11 to 50 employees; 3 = 51 to 100 employees; 4 = 101 to 300 employees; 5 = 301 to 500 employees (e.g., Ferreras-Méndez et al., 2022). Third, due to its direct impact on innovation speed, we included *R&D intensity* and operationalized it as the ratio of R&D expenditures to total sales (Bao et al., 2021). Fourth, considering the influence of *highly skilled employees* on innovation in science parks (Filatotchev et al., 2001), we categorized the percentage of employees with a graduate degree relative to the total number of employees into 7 groups: 1 = 0%; 2 = 0% to 5%; 3 = 5% to 10%; 4 = 10% to 25%; 5 = 25% to 50%; 6 = 50% to 75%, and 7 = >75%). The fifth control variable, *development stage*, adopted from Armanios et al. (2017), is measured based on the firm's stage at the time of entry into the science park (e.g., "[1] R&D/planning...[5] growth: five percent or more profitability") (p. 1380). The last firm-level control variable is *export experience*, coded as 1 if the firm has exported technology, products, or services, and 0 if not (Filatotchev et al., 2001).

At the science park level, following Ng et al. (2019)'s study, which underscores the importance of the size of the science park for firms' business and innovation activities, we measured *science park size* based on the number of resident organizations: (1) <50, (2) 50 to 100, (3) 100 to 200, (4) 200 to 400, (5) 400 to 600, (6) 600 to 1000, or (7) >1000 (p. 721).

At the industry level, prior research on science parks (e.g., Zhang et al., 2019b) and innovation (e.g., Chaudhuri et al., 2023; Zhang et al., 2020) has indicated that industry and market environmental dynamism significantly affects innovation, including innovation speed (Bao et al., 2021). We therefore controlled for *environmental dynamism* using four items adopted from Jansen et al. (2006) on a 7-point scale (1 = strongly disagree to 7 = strongly agree) with good reliability and validity (α = 0.882), as detailed in Table 2. Finally, industry dummies for various industries, as listed in Table 1, were included to account for potential heterogeneity related to industry types (Caloghirou et al., 2021).

3.3. Analytical models

We employed both symmetrical and asymmetrical approaches to develop a comprehensive understanding of the phenomenon—the

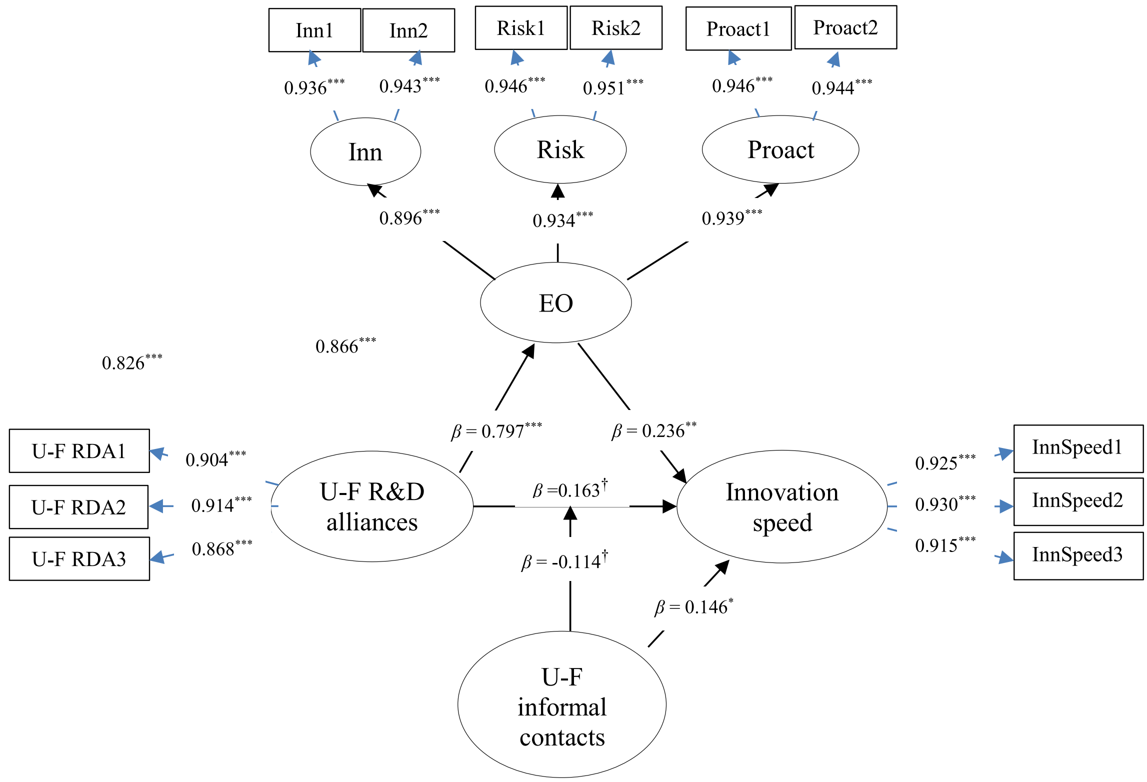

Fig. 2. Results of PLS-SEM analysis
Notes: Inn: innovativeness; Risk: risk-taking; Proact: proactiveness; EO: entrepreneurial orientation; U-F RDA: U-F R&D alliances; InnSpeed: innovation speed. Rectangular nodes represent observed variables; circles or ellipses represent latent constructs. Significant level: ***: p < 0.001; **: p < 0.01; *: p < 0.05; †: p < 0.10.

relationship between U-F interactions, EO, and innovation speed (Belitski et al., 2019; He et al., 2021). Recent studies in innovation have frequently utilized PLS-SEM (e.g., García-Granero et al., 2020; Hung, 2017) and fsQCA (e.g., Renko et al., 2020; Speldekamp et al., 2020; Subrammanian et al., 2022) to address the complexity of causal conceptual models. Drawing from these studies, we initially utilized PLS-SEM (Ringle et al., 2015) to test our hypotheses and then adopted fsQCA (Fiss, 2011; Ragin, 2000) to gain complementary insights (Pappas and Woodside, 2021).

On the one hand, PLS-SEM as a symmetrical approach provides the most appropriate estimation for complex causal relationship frameworks with latent constructs (Hair et al., 2017; Hair et al., 2020). Being a variance-based approach, it offers “much greater flexibility compared to CB-SEM” (Hair et al., 2020, p. 102), enabling a bootstrapping approach to test complex moderated mediation relationships, as is the case in this study. Specifically, PLS-SEM allows us to estimate two sub-models: (1) the measurement model and (2) the structural model, addressing both measurement errors and issues associated with regression models (García-Granero et al., 2020). However, a drawback of PLS-SEM is that it is based on a set of mean-centered regressions, where explanatory variables compete in producing an outcome, leading to an “incomplete picture of the effects” (Rasoolimanesh et al., 2021, p. 1572).

On the other hand, fsQCA, as an asymmetrical approach, accounts for causal conjunction, asymmetry and equifinality of configurations (Haefner et al., 2021). It posits that the same outcome can result from several non-linear configurations of conditions (Fiss, 2007). Therefore, it

Table 3
Fornell-Larcker Criterion.

Construct	1	2	3	4	5	6	7	8	9	10	11	12
1 Innovation speed	**0.923**											
2 U-F R&D alliances	0.423***	**0.895**										
3 Entrepreneurial orientation	0.463***	0.797***	**0.872**									
4 U-F informal contacts frequency	0.181**	0.061	0.148**	**1.000**								
5 Firm Age	0.061	−0.047	−0.031	0.006	**1.000**							
6 Firm Size	0.103	−0.095	0.024	0.251	0.453***	**1.000**						
7 R&D intensity	0.057	−0.012	0.038	0.235**	−0.096	0.043	**1.000**					
8 High skilled employees	0.104	0.043	0.119†	0.436***	0.073	0.179**	0.158*	**1.000**				
9 Development stage	−0.082	−0.086	−0.122*	0.006	0.005	−0.060	0.011	−0.172**	**1.000**			
10 Exports experiences	0.246***	0.171**	0.206***	0.133*	−0.037	0.180*	0.187**	0.149*	−0.153*	**1.000**		
11 Science park size	0.118*	0.055	0.073	0.055	−0.093	0.051	−0.054	0.097†	−0.032	0.144*	**1.000**	
12 Environmental dynamism	0.322***	0.700***	0.653***	0.058	−0.036	−0.030	0.037	0.007	−0.037	0.047	0.054	**0.859**

Notes: Values in bold on the diagonal are the square root of Average variance extracted (AVEs). Significant level: ***: p < 0.001, **: p < 0.01, *: p < 0.05, †: p < 0.10.

Table 4
Heterotrait-Monotrait ratios of constructs (HTMT).

Construct	1	2	3	4	5	6	7	8	9	10	11	12
1 Innovation speed												
2 U-F R&D alliances	0.472 [0.33, 0.60]											
3 Entrepreneurial orientation	0.499 [0.36, 0.62]	0.880 [0.80, 0.94]										
4 U-F informal contacts frequency	0.190 [0.07, 0.31]	0.066 [0.02, 0.18]	0.154 [0.06, 0.26]									
5 Firm Age	0.064 [0.01, 0.19]	0.082 [0.04, 0.19]	0.033 [0.03, 0.17]	0.006 [0.002, 0.13]								
6 Firm Size	0.104 [0.04, 0.23]	0.101 [0.03, 0.23]	0.032 [0.02, 0.16]	0.251 [0.13, 0.36]	0.453 [0.35, 0.55]							
7 R&D intensity	0.058 [0.02, 0.18]	0.053 [0.03, 0.14]	0.054 [0.03, 0.16]	0.235 [0.11, 0.36]	0.096 [0.01, 0.22]	0.043 [0.003, 0.17]						
8 High skilled employees	0.107 [0.02, 0.24]	0.046 [0.02, 0.18]	0.123 [0.04, 0.26]	0.436 [0.32, 0.55]	0.073 [0.004, 0.20]	0.179 [0.05, 0.31]	0.158 [0.03, 0.29]					
9 Development stage	0.084 [0.03, 0.21]	0.092 [0.02, 0.22]	0.125 [0.04, 0.24]	0.006 [0.002, 0.14]	0.005 [0.002, 0.14]	0.060 [0.003, 0.18]	0.011 [0.002, 0.13]	0.172 [0.06, 0.28]				
10 Exports experiences	0.255 [0.14, 0.37]	0.183 [0.06, 0.31]	0.212 [0.11, 0.33]	0.133 [0.02, 0.25]	0.037 [0.002, 0.16]	0.180 [0.07, 0.29]	0.187 [0.06, 0.31]	0.149 [0.03, 0.26]	0.153 [0.04, 0.27]			
11 Science park size	0.122 [0.03, 0.24]	0.059 [0.02, 0.17]	0.075 [0.03, 0.19]	0.055 [0.003, 0.16]	0.093 [0.01, 0.21]	0.051 [0.03, 0.16]	0.054 [0.003, 0.18]	0.097 [0.01, 0.20]	0.032 [0.002, 0.15]	0.144 [0.03, 0.26]		
12 Environmental dynamism	0.350 [0.21, 0.48]	0.759 [0.67, 0.89]	0.715 [0.59, 0.82]	0.119 [0.06, 0.20]	0.076 [0.05, 0.19]	0.053 [0.03, 0.18]	0.048 [0.03, 0.15]	0.063 [0.04, 0.17]	0.049 [0.03, 0.16]	0.047 [0.03, 0.17]	0.058 [0.02, 0.18]	

Notes: [,]: 95 % confidence interval.

allows us to move beyond symmetric analyses to explore how multiple configurations of factors contribute to specific levels of innovation speed. In fact, the joint use of PLS-SEM and fsQCA not only aligns well with our research objectives but also provides us with opportunities to better assess our "model's predictive power" and generate more insightful "managerial recommendations" (Rasoolimanesh et al., 2021, p. 1573).

4. Results

4.1. Evaluating measurement model

We evaluated our measurement model in several ways. First, we examined the indicator loadings and weights (coefficients representing "each indicator's relative importance" in the regression of a construct on its indicators) and their statistical significance using a nonparametric bootstrapping procedure with 5000 subsamples (Hair et al., 2017, p. 323). The results, displayed in Table 2 and Fig. 2, indicate that all standardized indicator loadings to their corresponding constructs are greater than 0.708 ($min(L)$ = 0.789) (Hair et al., 2020) with a significance level of $p < 0.001$, and all indicator weights are also strongly significant ($p < 0.001$). Together, these results ensure a significant contribution of items to construct score (Hair et al., 2020). We also checked outer variance inflation factors (VIFs) for all constructs to see if there is a collinearity issue. The results reveal that the highest VIF value among indictors is 4.318, which is below the threshold of 5 (Hair et al., 2017), indicating outer collinearity is not a concern in our measurement model.

Second, we assessed the reliability of both the first- and second-order constructs using Cronbach's alphas (α) and composite reliability (CR). All alphas' ($min(\alpha)$ = 0.867; max(α) = 0.937) and CRs' values ($min(CR)$ = 0.918; $max(CR)$ = 0.949) shown in Table 2 surpass the threshold of 0.70 and are below 0.95, suggesting construct reliability (Hair et al., 2020). Third, the results in Table 2 also demonstrate that the Average Variance Extracted (AVE) scores for all first- and second-order constructs ($min(AVE)$ = 0.738) exceed the cutoff level of 0.5 (Fornell and Larcker, 1981), confirming convergent validity.

Fourth, we assessed discriminant validity by the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT). As shown in Table 3, all square root values of AVE are greater than the corresponding correlations between constructs, adhering to the Fornell-Larcker's criterion. Moreover, the results in Table 4 demonstrate that the HTMT scores ($max(HTMT)$ = 0.880) for all construct pairs are below the conservative threshold of 0.90 (Henseler et al., 2015), and the bias-correlated bootstrap 95 % confidence intervals for all construct pairs did not include 1 ($max(UCI)$ = 0.94). Together, these results affirm discriminant validity for our constructs.

4.2. Accounting for common method variance

Following previous studies in innovation and entrepreneurship (García-Granero et al., 2020; Klein et al., 2021; Moore et al., 2021), our data collection was based on responses from single informants. However, this approach might raise concerns about common method variance (CMV). To mitigate this risk, we implemented several procedural remedies recommended by Podsakoff et al. (2003). Initially, before data collection, we selected validated items from existing literature and conducted a pre-test of our questionnaire design. Additionally, we informed survey participants about (1) the research purpose; (2) the absence of correct or incorrect answers; and (3) their responses remaining anonymous and confidential. We also designed the survey to separate scale items for explanatory variables from those for the dependent variable, minimizing participants' ability to discern direct linkages between these variables. Furthermore, we varied response formats for different constructs (e.g., semantic differential and Likert scales) and the number of points (e.g., 11-, 7-, and 5-point scales).

For statistical remedies for CMV, we followed the procedures by Lindell and Whitney (2001) and conducted a partial correlation analysis using a marker variable technique. We selected participants' family reasons for developing a business (family reason) (Chadwick and Raver, 2020) as the marker variable, which is theoretically unrelated. Respondents rated the importance of being respected by family in developing a business on a 5-point Likert scale ranging from 1 = "to no extent" to 5 = "to a very great extent". Correlations of the marker variable (family reason) with other constructs ranged from −0.091 to 0.068, none of which were significant (*min(p-value)* = 0.149). Next, we included family reason as an exogenous effect on each variable in the hypothesized relationships to "control for (partial out) method effects" (Podsakoff et al., 2003, p. 889). The results show that the inclusion of family reason didn't significantly change the results of any path estimates in the hypothesized relationships.

Moreover, following the recommended procedure by Liang et al. (2007), we further included a common method factor in our PLS model. This common factor encompassed all indicators of the principal constructs: innovation speed, U-F R&D alliances, innovativeness, risk-taking, proactiveness, and environmental dynamism, thus explaining each indicator's variance by both its principal construct (substantive variance) and the common method factor (method variance). If most method factor loadings are not significant and the indicators' method variances are substantially smaller than their substantive variances, the risk of CMV is not a concern (Liang et al., 2007). The results in Table 5 indicate that all method factor loadings are insignificant ($p > 0.05$), and the average substantively explained variance (0.818) is significantly greater than the average method variance (0.004).

Finally, in line with Klein et al. (2021) and Zhang et al. (2020), we conducted a full collinearity assessment (Kock, 2015) to determine the presence of pathological collinearity indicative of common method bias. The results in Table 6 show that the VIFs of all constructs (*max(VIF)* = 2.805) fall below the threshold of 3.3. Together, these results confirm that common method variance is not a serious concern in this research.

4.3. Evaluating structural model

Prior to hypothesis testing, we examined the inner Variance Inflation Factors (VIFs) for all variables in our model, with all values below 5 (*max(innerVIF)* = 3.511), indicating that inner multicollinearity is unlikely to be a concern in this study. The structural model's predictive power was assessed using the coefficient of determination (R^2) for endogenous constructs (Hair et al., 2017). As shown in Table 7, *adjusted* R^2 values for endogenous constructs of innovation speed ($R^2_{adj} = 0.245$, $p < 0.001$) and EO ($R^2_{adj} = 0.634$, $p < 0.001$) demonstrate strong in-sample predictive power (Hair et al., 2017).

Table 6
Full collinearity variance inflation factors (VIFs).

	Inner VIF values			
	1	2	3	4
1 Innovation speed		1.292	1.255	1.279
2 U-F R&D alliances	2.754		1.219	2.244
3 Entrepreneurial orientation	2.805	1.279		2.577
4 U-F informal contacts frequency	1.013	1.039	1.034	

To further estimate the model's predictive power, we conducted *PLSpredict* analysis (Shmueli et al., 2019), where the root mean squared error (RMES) was calculated to assess the predictive performance of the model for the constructs and indicators. The results, shown in Table 8, indicate that all indicators in the PLS-SEM have a Q^2 value greater than 0 ($Q^2_{predict} > 0$). Additionally, seven out of nine items of the first-order constructs in the PLS-SEM exhibit smaller prediction errors than those in a linear regression model (LM), suggesting medium predictive power (Shmueli et al., 2019). Moreover, the cross-validated predictive ability test (CVPAT) (Sharma et al., 2023) was conducted. The results in Table 8 reveal that the innovation speed model demonstrates a significantly lower average loss for both overall indicator averages ($CVPAT^{benchmark\_IA}_{overall}$: *difference of average loss* = −1.336, $p < 0.001$) and overall liner model prediction benchmarks ($CVPAT^{benchmark\_LM}_{overall}$: *difference of average loss* = −0.138, $p < 0.05$), confirming the strong predictive validity of the model.

4.4. The results of hypothesis testing

Hypothesis 1 predicts the mediating effects of EO on the relationship between U-F R&D alliances and innovation speed. The results in Table 7 support this hypothesis. Specifically, U-F R&D alliances are positively related to EO ($\beta = 0.797$, $p < 0.001$) with the effect size of $f^2 = 0.974$, and EO is significantly and positively associated with innovation speed ($\beta = 0.236$, $p < 0.05$; $f^2 = 0.024$), together leading to a positive and significant indirect effect of U-F R&D alliances on innovation speed through EO (*indirect effect* = 0.188, *standard deviation* = 0.077, p = 0.015, *95%CI* [0.031, 0.337]). Since the direct effects of U-F R&D alliances on innovation speed ($\beta = 0.163$, $p < 0.10$; $f^2 = 0.011$) are still significant when EO is included, the relationship between U-F R&D alliances and innovation speed is partially mediated by EO.

Hypothesis 2 posits the moderating effects of U-F informal contacts frequency on the relationship between U-F R&D alliances and innovation speed. As shown in Table 7, while U-F informal contacts frequency

Table 5
Common method bias analysis.

Construct	Indicator	SFL (L_1)	|t-value|	$(L_1)^2$	MFL (L_2)	|t-value|	$(L_2)^2$
Innovation speed (InnSpeed)	InnSpeed1	0.890***	25.738	0.792	0.049	1.627	0.002
	InnSpeed2	0.948***	65.187	0.899	−0.025	1.038	0.001
	InnSpeed3	0.933***	44.711	0.870	−0.025	0.963	0.001
	U-F RDA1	0.907***	10.687	0.823	0.001	0.002	0.000
	U-F RDA2	0.994***	12.393	0.988	−0.110	1.083	0.012
U-F R&D alliances (U-F RDA)	U-F RDA3	0.764***	8.878	0.575	0.117	1.391	0.014
	Inn1	0.930***	19.182	0.865	0.010	0.194	0.000
Innovativeness (Inn)	Inn2	0.949***	21.959	0.901	−0.010	0.194	0.000
	Risk1	0.911***	30.754	0.830	−0.073†	1.867	0.005
Risk-taking (Risk)	Risk2	0.886***	23.204	0.785	0.073†	1.868	0.005
	Proact1	0.972***	21.813	0.945	−0.031	0.655	0.001
Proactiveness (Proact)	Proact2	0.918***	22.490	0.843	0.031	0.656	0.001
	EnDyn1	0.925***	14.992	0.856	−0.060	0.848	0.004
	EnDyn2	0.877***	11.476	0.769	−0.079	1.013	0.006
	EnDyn3	0.841***	16.982	0.707	0.047	0.870	0.002
Environmental dynamism (EnDyn)	EnyDy4	0.798***	10.868	0.637	0.085	1.163	0.007
Average				**0.818**			**0.004**

Notes: Significant level: ***: p < 0.001, **: p < 0.01, *:p < 0.05, †:p < 0.10. SFL: Substantive factor loading; MFL: Method factor loading.

Table 7
Results of hypothesis testing.

Endogenous constructs	Adjusted R^2				
Innovation speed (InnSpeed)	0.245*** CI_{95}[0.185, 0.425]				
Entrepreneurial orientation (EO)	0.634*** CI_{95}[0.514, 0.737]				
Path	*Coefficients*	*STD*	*95 % CI*		f^2
			LCI	*UCI*	
U-F R&D alliances (U-F RDA) → EO	0.797***	0.036	0.718	0.859	0.974
EO → InnSpeed	0.236*	0.095	0.039	0.410	0.024
U-F RDA → InnSpeed	0.163†	0.094	−0.022	0.344	0.011
U-F informal contacts frequency (U-F ICFreq.) → InnSpeed	0.146*	0.069	0.012	0.281	0.020
U-F RDA × U-F ICFreq. → InnSpeed	−0.114†	0.058	−0.237	−0.007	0.014
Firm age → InnSpeed	0.076	0.062	−0.048	0.200	0.006
Firm size → InnSpeed	0.002	0.075	−0.146	0.147	0.000
R&D intensity → InnSpeed	0.017	0.056	−0.092	0.124	0.000
High-skilled employees → InnSpeed	−0.057	0.063	−0.179	0.069	0.003
Development stage → InnSpeed	−0.022	0.058	−0.138	0.091	0.001
Exports experiences → InnSpeed	0.259*	0.129	0.014	0.518	0.018
Science park size → InnSpeed	0.073	0.060	−0.042	0.191	0.007
Environmental dynamism → InnSpeed	0.005	0.083	−0.149	0.177	0.000
Industry dummies	Yes				
Indirect effects					
U-F RDA → EO → InnSpeed	0.188*	0.077	0.031	0.337	

Notes: STD: Standard deviation. CI_{95}[,]: 95 % confidence interval. LCI: lower limit of confidence interval. UCI: upper limit of confidence interval. Significant level: ***: $p < 0.001$, **: $p < 0.01$, *:$p < 0.05$, †:$p < 0.10$.

is positively and significantly associated with innovation speed ($\beta = 0.146$, $p < 0.05$; $f^2 = 0.020$), the interaction term between U-F R&D alliances and U-F informal contacts frequency is negatively associated with EO ($\beta = -0.114$, $p < 0.10$; $f^2 = 0.014$). Depicted in Fig. 3, the results of slope analysis illustrate that the positive relationship between U-F R&D alliances and innovation speed is more pronounced when U-F informal contacts frequency is low, supporting Hypothesis 2.

To further explore the effects U-F interactions, we conducted a multigroup analysis (MGA) among firms with different development stages upon entry into science parks (Armanios et al., 2017), categorizing the sample into three groups: (1) R&D stage group (G1) (development stages = 1 and 2), (2) market introduction stage (development stages = 3 and 4), and (3) market growth stage (development stage = 5). Prior to MGA, we assessed measurement invariances of composite models (MICOM) to ensure the measurement models to exhibit the same attributes under different conditions. The results in Table 9 show that all correlations (c) are close to 1 with insignificant permutation *p*-values of $p > 0.10$, confirming compositional invariance and indicating no significant differences in the means and variances of measures across groups. Consequently, full measurement invariance is established, enabling us to proceed with MGA. The results of MGA reveal a significant difference in the effects of U-F informal contacts frequency on innovation speed between firms at the market introduction stage and those at the market growth stage ($\Delta\beta = -0.594$, $p = 0.077$).

Table 8
PLS predict assessment.

	PLS		LM	PLS-LM
	RMSE	Q^2 *Predict*	RMSE	RMSE
InnSpeed1	2.019	0.156	2.569	−0.054
InnSpeed2	2.047	0.113	2.677	−0.089
Innspeed3	2.033	0.132	2.575	−0.069
Inn1	0.741	0.525	1.028	0.058
Inn2	0.831	0.457	1.307	−0.053
RiskT1	1.056	0.376	1.466	0.011
RiskT2	0.931	0.474	1.369	−0.078
Proact1	0.952	0.472	1.363	−0.053
Proact2	0.751	0.555	1.182	−0.065

Cross-validated predictive ability test (CVPAT)		
	Average loss difference	|t-value|
$CVPAT^{benchmark\_IA}_{overall}$	−1.336***	5.511
$CVPAT^{benchmark\_LM}_{overall}$	−0.138*	2.522

Notes: LM: linear regression model; RMSE: the root mean squared error; RMES: the root mean squared error; IA: indicator averages. LM: Linear model. InnSpeed: Innovation speed; Inn: innovativeness; RiskT: risk-taking; Proact: proactiveness.

4.5. Robustness checks

We conducted two additional analyses to assess the robustness of our findings in PLS-SEM: endogeneity and unobserved heterogeneity.

4.5.1. Checking for endogeneity

In PLS-SEM, endogeneity often arises when the error term of the dependent construct correlates with the independent variables (Sarstedt et al., 2020). Considering PLS-SEM estimates partial model structures simultaneously, recent research by Hult et al. (2018) recommended a systematic procedure based on Park and Gupta (2012)'s Gaussian copula approach for testing endogeneity, which is particularly suitable for assessing potentially endogenous constructs that are not normally distributed in PLS-SEM.

Following this recommendation, we examined endogeneity for each of the main predictor constructs in PLS-SEM. Consistent with prior research (Sarstedt et al., 2020), we performed the Kolmogorov-Smirnov test with Lilliefors correction on the latent variable scores of these predictor constructs. For the mediator of EO, the main predictor construct is U-F alliances. Hence, we initially assessed its potential endogeneity for EO. The results of Model 1 in Table 10 show that the Gaussian copula for U-F alliances is insignificant (^{c}U-F RDA = 0.059, $p = 0.539$), confirming that endogeneity is not a concern for U-F R&D alliances in predicting EO. For the dependent construct of innovation speed, with three main predictor constructs - EO, U-F R&D alliances, and informal contact frequency - we evaluated the significance of their Gaussian copulas. The results in Table 10 demonstrate that Gaussian copulas yielded for EO (^{c}EO = −0.146, $p = 0.446$), U-F R&D alliances

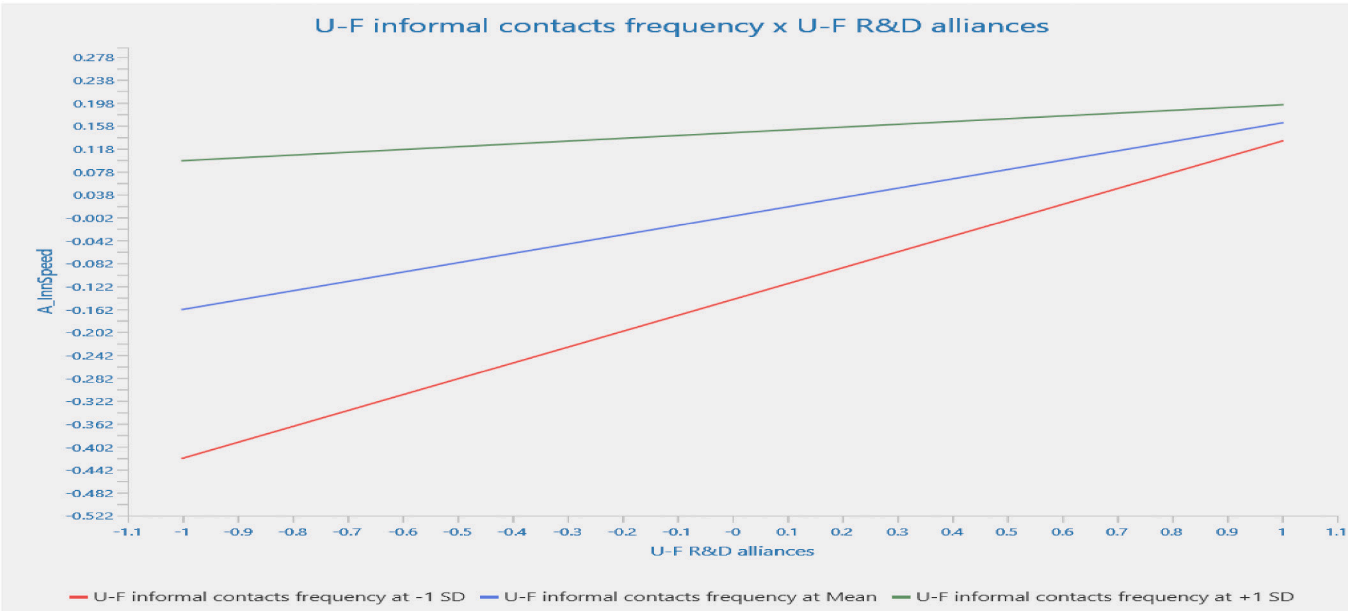

Fig. 3. The interactive effects of U-F R&D alliances and U-F informal contacts frequency.

Table 9
Results of MGA.

MICOM assessment									
Group	Construct	Com. invariance		PIM	Equal Mean Value		Equal Variances		FMI
		C (=1)	CI		Diff.	CI	Diff.	CI	
G1 vs G2	InnSpeed	1.000	[0.999, 1.000]	Yes	0.156	[−0.379, 0.376]	0.036	[−0.414, 0.505]	Yes
	U-F RDA	0.994	[0.995, 1.000]	Yes	0.082	[−0.379, 0.384]	−0.011	[−0.472, 0.491]	Yes
	EO	1.000	[0.999, 1.000]	Yes	0.012	[−0.402, 0.422]	−0.225	[−0.602, 0.701]	Yes
	U-F ICFreq.	1.000	[1.000, 1.000]	Yes	0.073	[−0.379, 0.434]	0.368	[−0.531, 0.728]	Yes
G1 vs G3	InnSpeed	1.000	[0.999, 1.000]	Yes	0.182	[−0.357, 0.346]	0.242	[−0.432, 0.453]	Yes
	U-F RDA	1.000	[0.999, 1.000]	Yes	0.257	[−0.328, 0.384]	−0.437	[−0.649, 0.644]	Yes
	EO	1.000	[0.999, 1.000]	Yes	0.182	[−0.322, 0.376]	−0.125	[−0.532, 0.604]	Yes
	U-F ICFreq.	1.000	[1.000, 1.000]	Yes	−0.031	[−0.353, 0.361]	0.203	[−0.491, 0.616]	Yes
G2 vs G3	InnSpeed	1.000	[0.998, 1.000]	Yes	0.025	[−0.441, 0.391]	0.210	[−0.697, 0.457]	Yes
	U-F RDA	0.996	[0.992, 1.000]	Yes	0.176	[−0.390, 0.420]	−0.432	[−1.024, 0.860]	Yes
	EO	1.000	[1.000, 1.000]	Yes	0.162	[−0.384, 0.427]	0.101	[−0.958, 0.538]	Yes
	U-F ICFreq.	1.000	[1.000, 1.000]	Yes	−0.114	[−0.387, 0.434]	−0.165	[−0.812, 0.546]	Yes

Path differences						
	G1-G2		G1-G3		G2-G3	
	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
U-F RDA → InnSpeed	−0.136	0.851	−0.180	0.563	−0.044	0.893
EO → InnSpeed	0.348	0.570	0.169	0.533	−0.179	0.783
U-F ICFreq. → InnSpeed	−0.400	0.209	−0.195	0.321	**−0.594**	**0.077**
Controls	Yes		Yes		Yes	

Notes: G1: group of firms at the R&D stage; G2: group of firms at the market introduction stage; G3: group of firms at the market growth stage; Com.: Compositional; C: correlation; CI: confidence interval; PIM: partial measurement invariance; FMI: full measurement invariance; InnSpeed: Innovation speed; U-F RDA: University-firm R&D alliances; EO: Entrepreneurial orientation; U-F ICFreq.: University-firm informal contacts frequency.

(^{c}U-F RDA $= -0.277$, $p = 0.114$) and informal U-F contact frequency (^{c}U-F ICFreq. $= 0.480$, $p = 0.486$) are all insignificant ($p > 0.10$) (Model 8). We also assessed all other possible combinations of Gaussian copulas (Model 2 to Model 7 in Table 10) and found that none of these copulas is significant (*min(p)* $= 0.126$). These results together confirm that endogeneity is not present in our PLS-SEM analysis.

Given EO's dual role as both a predictor construct for innovation speed and a dependent construct with U-F R&D alliances as its predictor, we conducted another endogeneity test by using Heckman and Robb (1985)'s two-stage control function (CF) approach to ensure the robustness of our results. In the first stage, EO was estimated as a function of instrumental variables. We used *previous experience* of knowledge sharing and learning from failure as instrumental variables, along with the same control variables used in the PLS-SEM model, to estimate EO. Drawing on studies that argue a relationship between knowledge sharing (De Clercq et al., 2013) and learning from failure (Covin et al., 2006) with entrepreneurial orientation, we measured these experiences on a 7-point Likert scale with nine items each. The results indicate that both knowledge sharing experience ($\beta = 0.643$, $p < 0.001$) and learning from failure ($\beta = 0.242$, $p < 0.001$) are significantly

Table 10
Assessment of endogeneity using the Gaussian copula approach.

Test model	Construct	Coefficient	p-value
Gaussian copular of Model 1	U-F RDA	0.728	0.000
(Key endogenous variables: U-F RDA)	^{c}U-F RDA	**0.059**	**0.539**
Gaussian copular of Model 2	EO	0.313	0.163
(Key endogenous variables: EO)	U-F RDA	0.166	0.090
	U-F ICFreq.	0.133	0.033
	^{c}EO	**−0.035**	**0.855**
Gaussian copular of Model 3	EO	0.797	0.000
(Key endogenous variables: U-F RDA)	U-F RDA	0.070	0.768
	U-F ICFreq.	0.144	0.009
	^{c}U-F RDA	**−0.206**	**0.233**
Gaussian copular of Model 4	EO	0.277	0.004
(Key endogenous variables: U-F ICFreq.)	U-F RDA	0.172	0.079
	U-F ICFreq.	−0.182	0.732
	^{c}U-F ICFreq.	**0.395**	**0.554**
Gaussian copular of Model 5	EO	0.442	0.046
(Key endogenous variables: EO, U-F RDA)	U-F RDA	−0.139	0.560
	U-F ICFreq.	0.148	0.018
	^{c}EO	**−0.155**	**0.415**
	^{c}U-F RDA	**0.265**	**0.126**
Gaussian copular of Model 6	EO	0.303	0.183
(Key endogenous variables: EO, U-F ICFreq.)	U-F RDA	0.172	0.081
	U-F ICFreq.	−0.174	0.746
	^{c}EO	**−0.024**	**0.902**
	^{c}U-F ICFreq	**0.385**	**0.568**
Gaussian copular of Model 7	EO	0.277	0.004
(Key endogenous variables: U-F RDA, U-F ICFreq.)	U-F RDA	0.081	0.737
	U-F ICFreq.	−0.265	0.627
	^{c}U-F RDA	**0.222**	**0.206**
	^{c}U-F ICFreq	**0.513**	**0.453**
Gaussian copular of Model 8	EO	0.435	0.052
(Key endogenous variables: EO, U-F RDA, U-F ICFreq.)	U-F RDA	0.145	0.545
	U-F ICFreq.	−0.235	0.669
	^{c}EO	**−0.146**	**0.446**
	^{c}U-F RDA	**−0.277**	**0.114**
	^{c}U-F ICFreq	**0.480**	**0.486**

Notes: InnSpeed: Innovation speed; U-F RDA: University-firm R&D alliances; EO: Entrepreneurial orientation; U-F ICFreq.: University-firm informal contacts frequency. Values in bold are Gaussian copulas.

associated with EO. In the second stage, the residuals (r_e) from the first-stage model were included as an additional regressor in the innovation speed model. We found that EO is significantly associated with innovation speed ($\beta = 0.346$, $p < 0.01$), while the effects of r_e ($\beta = 0.085$) are insignificant ($p = 0.206$), providing evidence against the presence of endogeneity and supporting the robustness of our results.

4.5.2. *Checking for heterogeneity*

We employed the finite mixture partial least squares (FIMIX-PLS) procedure on the data (Hair et al., 2017) to account for unobserved heterogeneity. Consistent with prior research (Carlson et al., 2019; Gelhard et al., 2016; Matthews et al., 2016), we utilized the stopping criterion of $10^{-10} = 1.0\text{E-}10$, a maximum number of iterations of 5000 and the number of repetitions of 10 for each of segments ($g = 1$ to 5) proceeded by the FIMIX-PLS algorithm. The Akaike information criterion (*AIC*), modified *AIC*$_3$ and *AIC*$_4$, Bayesian information criterion (*BIC*), heuristic consistent *AIC* (*CAIC*), minimum description length with factor 5 (*MDL*$_5$) and normed entropy statistics (*EN*) (Carlson et al., 2019; Gelhard et al., 2016) were used to determine the appropriate number of segments. As indicated in Table 11, the results suggest AIC$_3$ and CAIC point to the same number of segments, a five-segment solution. However, MDL$_5$ suggests a one-segment solution, indicating that more than one segment should be extracted (Hair et al., 2017). Taken together, these findings imply that fsQCA should be conducted to further explore unobserved heterogeneity (Carlson et al., 2019).

4.6. *fsQCA*

We took several steps to conduct fsQCA. In the first step, we calibrated our measures of variables defined previously into a 0–1 scale with multiple scores in between by using three qualitative thresholds: fully-in, the crossover point, and fully-out membership (Fiss, 2011). Adhering to the guidelines of Rasoolimanesh et al. (2021), we extracted standardized PLS-SEM latent variable scores from the original model's PLS-SEM algorithm, and following the majority of studies in the innovation and entrepreneurship literature, we adopted the direct approach to set the thresholds for membership categorization at the 95th percentile for "fully-in", the 50th percentile for the crossover point, and the 5th percentile for "fully-out" (Pappas and Woodside, 2021). To

Table 12
Solutions for the innovation speed.

	High innovation speed		Low innovation speed			
	C1	C2	C3	C4	C5	C6
U-F R&D alliances	●	●	⊗	⊗	⊗	⊗
Entrepreneurial orientation	●	●	⊗	⊗	⊗	⊗
U-F informal contacts frequency	⊗	●	⊗	⊗	⊗	⊗
Firm Age		●	●	●	⊗	●
Firm Size	●		⊗	⊗	⊗	●
R&D intensity	⊗	⊗	⊗	⊗	●	⊗
High-skilled employees	⊗	●	⊗	⊗	●	●
Development stage	⊗	⊗	⊗	●	⊗	⊗
Exports experiences	●	●	⊗	⊗	●	●
Science park size	●	●	⊗	●	●	●
Environmental dynamism	●	●	⊗	⊗	⊗	⊗
Consistency	0.984	0.981	0.960	0.987	0.984	0.972
Raw coverage	0.151	0.116	0.097	0.092	0.127	0.108
Unique coverage	0.071	0.036	0.034	0.034	0.044	0.025
Overall coverage	0.187		0.282			
Overall consistency	0.976		0.969			

Note: ● = peripheral condition present; ⊗ = peripheral condition absent. Blank spaces indicate the condition may not be either present or absent. Consistency cutoff: 0.91, frequency cut: 3, PRI > 0.75. 95th percentile.

Table 11
FIMIX-PLS.

S	AIC	AIC$_3$	AIC$_4$	BIC	CAIC	MDL$_5$	EN	Relative segment size g = 1	g = 2	g = 3	g = 4	g = 5
1	1931.113	1959.113	1987.113	2031.661	2059.661	2657.851	–	1.00				
2	1387.166	1444.166	1501.166	1591.853	1648.853	2866.598	0.838	0.62	0.39			
3	1030.768	1116.768	1202.768	1339.593	1425.593	3262.862	0.882	0.43	0.37	0.20		
4	918.209	1033.209	1148.209	1331.173	1446.173	3903.027	0.897	0.41	0.30	0.20	0.09	
5	646.194	790.194	934.194	1163.296	1307.296	4383.705	0.952	0.47	0.20	0.12	0.11	0.10

Notes: S: segments; AIC: Akaike information criterion, AIC$_3$: modified AIC; BIC: Bayesian information criterion: CAIC: heuristic consistent AIC: Bayesian information criterion; MDL$_5$: minimum description length with factor 5; EN: normed entropy statistics.

address methodological challenges, a constant of 0.001 was added to measures with a calibrated score of exactly 0.5, as recommended by Fiss (2011).

Next, we examined necessary conditions for innovation speed, which exists if it has a consistency value greater than 0.90 (Greckhamer et al., 2018). Our analysis found no necessary conditions for innovation speed (*max(consistency)* = 0.773159).

Finally, we conducted a sufficiency analysis using the fsQCA truth-table algorithms for fuzzy sets (Ragin, 2008), which listed 2^k logically possible configurations, where k is the number of conditions. We obtained a truth-table with $2^k = 2048$ ($k = 11$) logical combinations of causal conditions. Given that our sample of 268 exceeded 150, we applied a frequency cut-off of 3 cases (Fiss, 2011) to ensure that only substantial configurations are assessed (Kimmitt et al., 2020). In accordance with prior research in innovation (Marzi et al., 2023; Xie and Wang, 2020), we set the raw consistency threshold at 0.9 or higher and, following Ragin's (2008) recommendation, set proportional reduction in inconsistency (*PRI*) at $PRI \geq 0.75$.

Table 12 presents the condition configurations for innovation speed, revealing two configurations associated with high innovation speed. They collectively exhibit an overall consistency (*ocons*) of 97.6% and an overall coverage (*ocov*) of 18.7%. Configuration 1 (C1), with a consistency (*cons*) of 98.4%, a raw coverage (*rcov*) of 15.1%, and a unique coverage (*ucov*) of 7.1%, applies to larger SISMEs lacking R&D intensity, with fewer high-skilled employees, in early development stages, having some export experiences, located in large science parks, and operating in dynamic industries and markets. These firms underscore the significance of both U-F R&D alliances and EO, especially when informal contacts with universities are less frequent. Configuration 2 (C2) (*cons* = 0.981, *rcov* = 0.116, *ucov* = 0.036) underscores the importance of U-F R&D alliances, EO, and frequent U-F informal contacts for older SISMEs lacking R&D intensity but with more high-skilled employees, in early development stages, having export experiences, located in large science parks, and operating in dynamic industry and market environments.

Using the same thresholds for consistency and frequency and calibrating low innovation speed as the inverse of high innovation speed, four configurations for low innovation speed (*ocons* = 0.969, *ocov* = 0.282) are found. As shown in Table 12, these four configurations (C3: *cons* = 0.960, *rcov* = 0.097, *ucov* = 0.034; C4: *cons* = 0.987, *rcov* = 0.092, *ucov* = 0.034; C5: *cons* = 0.984, *rcov* = 0.127, *ucov* = 0.044; C6: *cons* = 0.972, *rcov* = 0.108, *ucov* = 0.025) illustrate that the absence of U-F R&D alliances, EO and U-F informal contacts frequency are significant conditions that lead to low innovation speed. Interestingly, for new and small firms even with high R&D intensity and more high-skilled employees (C5), they have low speed of innovation if they engage in limited U-F interactions and pursue a low degree of EO.

These findings underscore the significance of U-F R&D alliances, U-F informal contacts, and EO, configured with other organizational, science park, and environmental conditions, in influencing innovation speed. They thus provide additional support for our conceptual model, which argues the integrative effects of U-F interactions and EO on innovation speed.

5. Discussion and conclusions

Drawing on the dynamic capability perspective and university-firm interaction literature, our study investigates the impact of U-F interactions on innovation speed within the context of SISMEs. We distinguish between U-F R&D alliances and U-F informal contacts. Our findings indicate that both forms of U-F interactions independently increase innovation speed within SISMEs. Notably, this study identifies firm-level EO as an effective mechanism through which U-F R&D alliances amplify innovation speed. Moreover, we discover that the interaction between U-F R&D alliances and frequent U-F informal contacts significantly influences innovation speed, with the latter potentially diminishing the positive effects of U-F R&D alliances on innovation speed. Our results also highlight that innovation speed results from multiple configurations of U-F interactions and EO, in conjunction with diverse organizational, science park, and environmental conditions.

5.1. Theoretical implications

Our research offers several important theoretical implications. First, it underscores the critical role of U-F interactions in enhancing innovation speed, particularly within SISMEs. In providing evidence that supports the positive and significant effects of both U-F R&D alliances and U-F informal contacts, our research addresses the call for a deeper understanding of the determinants influencing innovation speed (Cooper, 2021; Rosa, 2021). Specifically, although previous studies have acknowledged the value of U-F interactions in firm innovation (e.g., Caloghirou et al., 2021), much of the literature has centered around how inter-organizational collaborations with business entities (such as suppliers and customers) lead to rapid innovation and market success (Zhang and Wu, 2017). Our work enriches this narrative by delineating the significant effects of U-F interactions on firm innovation speed.

Second, our study advances the research on U-F interactions by distinguishing between the effects of formal and informal interactions and underscoring their interactive effects. While the existing body of work has largely concentrated on formal interactions, particularly those defined by contractual R&D alliances (Schaeffer et al., 2020), our exploration of both U-F R&D alliances and informal contacts deepens the understanding of how SISMEs can utilize these relationships to foster innovation speed. Their distinctive roles in innovation speed are also confirmed by the findings associated with SISMEs' development stage. Specifically, our findings demonstrate that the effects of U-F informal contacts on innovation speed are more pronounced for SISMEs at the market introduction stage than for those at the market growth stage. In contrast, the effects of U-F R&D alliances on innovation speed do not significantly vary across SISMEs at different development stages. These findings offer a novel insight that for SISMEs, U-F R&D alliances consistently serve as a key driver of rapid innovation, irrespective of their firm development stage. However, U-F informal contacts have greater effects on innovation speed for SISMEs at the market introduction stage than for those at the growth stage. Our study therefore highlights an avenue for future research to explore how the lifecycle of SISMEs influences the dynamics between U-F informal interactions and innovation.

More importantly, our research adds valuable insights to the ongoing debate regarding the dynamics between U-F formal and informal interactions (e.g., Landry et al., 2010; Schaeffer et al., 2020). Our analysis demonstrates that although U-F R&D alliances and frequent U-F informal contacts each independently contribute to enhancing innovation speed, their interactive effects do not always result in complementary benefits. Specifically, we find that the beneficial effects of U-F R&D alliances on innovation speed are more pronounced in SISMEs with less frequency in U-F informal contacts. Further insights from our fsQCA analysis indicate that this trade-off relationship is especially prominent in larger SISMEs with lower R&D intensity and a lack of high-skilled employees (as detailed in C1 in Table 12). This finding is pivotal as it underscores that the positive impact of U-F R&D alliances on innovation speed is influenced not just by how these alliances are managed but also by how effectively and frequently firms engage in informal interactions for knowledge transfer.

Last, our analysis sheds light on the pivotal role of firm-level EO in harnessing U-F R&D alliances to expedite innovation speed in SISMEs. On one side, by examining the relationship between EO and innovation speed, we demonstrate the importance of fostering EO within SISMEs, which might otherwise lack extensive market experience, to achieve market-oriented results such as rapid innovation. On the other side, the findings of the U-F R&D alliances-EO-innovation speed relationship provides insights into the nuanced outcomes of R&D alliances (Caloghirou et al., 2021). Specifically, our results from PLS-SEM analysis indicate that the integration of U-F R&D alliances with EO is an effective way to benefit from these alliances. Through its emphasis on innovativeness, risk-taking, and proactivity, EO empowers SISMEs to effectively leverage U-F R&D alliances, thereby accelerating their innovation.

The findings from fsQCA analysis also enrich our comprehension of the complex relationship between U-F interactions, EO and innovation speed. They not only solidify the necessity of integrating U-F R&D alliances and U-F informal contacts with EO to attain heightened innovation speed but also show how such integration operates synergistically with various organizational characteristics (e.g., firm age, size, development state, etc.), the influence of science parks, and environmental conditions (e.g., environmental dynamism). These findings contribute novel insights to the literature on dynamic capabilities by demonstrating how strategic resource configuration represents an important lever to expedite innovation (Zhang and Wu, 2017).

5.2. Managerial implications

Our research offers important insights for management practice, revealing that both U-F formal and informal interactions play a vital role in enhancing the speed of innovation within SISMEs. Consequently, SISMEs should deliberately participate in both types of interaction and develop strategies to maximize the effectiveness of their overall U-F interactions. Our findings underscore that U-F R&D alliances can significantly contribute to innovation speed, both directly and through the mechanism of EO. Thus, SISMEs should not only pursue R&D alliances but also carefully integrate these alliances with entrepreneurial behaviors to fully capitalize on their benefits for accelerating innovation. This approach is particularly crucial for SISMEs constrained by limited resources, such as modest R&D investments, a smaller pool of highly skilled employees, and sparse informal university contacts.

Additionally, our study underscores EO's pivotal role as a firm-level mechanism that enhances innovation speed and amplifies the impact of U-F R&D alliances on this speed. It is imperative for top management to embrace EO and foster an entrepreneurial culture in both U-F interactions and innovation initiatives. Echoing the sentiment that EO can "serve as the guidelines for firm-specific behavior" (Klein et al., 2021), our research advises SISMEs to cultivate an organizational climate that encourages entrepreneurial behavior towards resource integration and the acceleration of innovation. This includes promoting new ideas and experimentation, viewing failure as an opportunity for growth, fostering a forward-thinking mindset among employees, and more. Firms should consider adapting their structure and human resources policies to support decentralized decision-making and autonomous groups (Wales et al., 2011), thereby facilitating entrepreneurial learning and empowering staff to undertake entrepreneurial actions. The strong linkage between U-F R&D alliances and EO suggests that leveraging EO to boost innovation speed necessitates strategic management of U-F R&D alliance efforts.

Furthermore, our analysis via PLS-SEM reveals that U-F R&D alliances tend to be more advantageous for innovation speed when the frequency of informal U-F contacts is low. Therefore, SISMEs with fewer informal interactions are advised to intensify their formal interactions with universities through R&D alliances in order to accelerate innovation within their firm. Our fsQCA findings also show that the integration of U-F R&D alliances and informal contacts with other factors affects innovation speed. SISMEs should be mindful of the potential substitutive effects of U-F formal and informal interactions and the conditions leading to various U-F interaction configurations. Specifically, larger SISMEs facing human resource constraints, such as a lack of highly skilled employees, could strategically capitalize on university knowledge for innovation via their entrepreneurial processes. In contrast, well-resourced SISMEs might benefit from a blend of U-F R&D alliances and frequent informal contacts, coupled with an entrepreneurial orientation, to drive rapid innovation.

5.3. Limitations and future research

While our study provides valuable insights, its findings should be viewed in light of certain limitations that pave the way for future research. First, our research focused on EO as a firm-level mechanism, and the results have shown that EO is a strong but partial mediator in the relationship between U-F R&D alliances and innovation speed. This underscores the need for future studies to investigate additional mechanisms that could complement EO in elucidating the dynamics between U-F R&D alliances and innovation speed. For example, recent studies suggest that business model innovation plays a crucial role in the EO-innovation performance nexus (Ferreras-Méndez et al., 2021). Future research could incorporate business model innovation into our conceptual model to further explain the relationship between U-F R&D alliances and innovation speed. Second, our analysis was limited to a single characteristic of U-F informal contacts, its frequency, to examine the interactive effects of U-F formal and informal interactions. Considering the resource-intensive and complex nature of innovation in SISMEs, future inquiries could benefit from examining a broader spectrum of U-F interaction characteristics that might influence innovation speed. Third, like many previous studies in the innovation literature, our analysis is based on cross-sectional data. While it is plausible to assume the significance of U-F R&D alliances, EO, and U-F informal contacts for concurrent innovation speed, longitudinal research would provide insights into the evolving dynamics of these relationships and their impact on future innovation acceleration. Finally, our sample, drawn from science-intensive industries, may limit the generalizability of our findings to other sectors. Future studies could investigate the relevance of U-F R&D alliances and EO for innovation across a broader range of sectors.

In conclusion, our study addresses call for more research on how science-intensive SMEs can accelerate their innovation. We highlight EO as a pivotal mechanism through which SISMEs can leverage the benefits of U-F R&D alliances for rapid innovation under specific configurational conditions. Additionally, we uncover the substitution effects between U-F R&D alliances and U-F informal contacts on innovation speed. Our findings offer novel perspectives and recommend strategies to counterbalance the potential drawbacks of both U-F formal and informal interactions on innovation, thereby contributing to the broader discourse on enhancing innovation in science-intensive sectors.

CRediT authorship contribution statement

Jing A. Zhang: Conceptualization, Formal analysis, Methodology, Writing – original draft. **Conor O'Kane:** Writing – review & editing. **Tao Bai:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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