ISSN 1816-6075 (Print), 1818-0523 (Online)
Journal of System and Management Sciences
Vol. 12 (2022) No. 3, pp. 216-243
DOI:10.33168/JSMS.2022.0312

Social Media Usage, External Knowledge Search Breadth, and Product Innovation: A Case of Manufacturing Firms in Thailand

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Abstract: The purpose of this study is twofold. First, it aims to investigate the effects of social media usage on firms' product innovation, focusing on testing the curvilinear effects of social media usage. Second, it explores the complementary effects of social media usage and external knowledge search breadth on firms' product innovations. We use the Negative Binomial Regression to solve our research questions, employing the survey data of 302 manufacturing firms in Thailand. The key results are as follows. First, we find that although social media has a positive effect on innovations, its effect is curvilinear, suggesting that firms should be selective in using social media platforms to source knowledge for innovative activities. Second, we also find that the complementary effect between social media usage and search breadth only exists in the case of radical product innovation. This finding implies that for firms that pursue a radical innovation strategy, using various social media platforms to search for knowledge from multiple sources can be an option. The theoretical contribution of this study is that it extends the literature on external knowledge sourcing by analysing the role of social media platforms for knowledge search. This study contributes evidence to an ongoing debate regarding how firms should use social media to source knowledge for innovations. The managerial implication of the current study suggests that firm managers should have an appropriate social media-based innovation strategy. Each social media platform contains information that may or may not be relevant to firms' innovation. Therefore, managers should be selective in using social media for innovative activities. Finally, this study also suggests that firms can use many social media platforms to complement their search information from a wide range of sources when they pursue a radical innovation strategy.

Keywords: social media usage, external knowledge sourcing, product innovation, Thailand

1. Introduction

Firms pursuing open innovation strategy and sourcing external knowledge to augment their existing knowledge base tend to have superior innovation performance (West & Bogers, 2014). The open innovation paradigm and external knowledge sourcing literature[1] suggest that obtaining knowledge from various external sources enables firms to remain competitive in a world with rapid technological change and high market dynamism (Chesbrough, 2006; Vivas & Barge-Gil, 2015). As innovation is characterised by a combination of novel ideas, searching for knowledge from multiple actors allows firms to access various information, increasing the possibilities of knowledge combination (Chiang & Hung, 2010).

The past decade has witnessed an increased use of social media (hereafter, SM) in firms' innovation activities (Liu & Kop, 2015). Scholars have paid more interest in exploring the role of SM-based external knowledge acquisition in firms' innovation performance. However, as this research area is still in its infancy stage, there are some notable gaps in the existing literature (Bhimani et al., 2019; Testa et al., 2020). First, some scholars highlight the positive impact of SM on innovations (Cheng & Krumwiede, 2018; Mount & Martinez, 2014; Rautela et al., 2020), while others warn against its negative impact (Jalonen, 2015; Liu & Kop, 2015; Roberts & Candi, 2014). However, few studies investigate these relationships empirically, taking a quantitative research approach with large sample size. Second, various case-study research examines firms' use of SM in external idea sourcing for innovations, but few studies explore how SM can complement firms' external knowledge search strategy.

The present study contributes to the literature on external knowledge sourcing and SM-based innovation in two ways. First, it employs the survey data of 302 Thai manufacturing firms to examine the effect of SM usage on product innovations. We formulate hypotheses to test the linear and curvilinear relationship between SM usage and product innovations based on SM-based innovation studies. In other words, we aim to investigate whether a diminishing product innovation return on SM usage exists. Second, this study examines the complementarity between search breadth (i.e., sourcing ideas from various actors) and SM usage on product innovations. We attempt to illustrate whether firms introduce more product innovations when more SM is used to source information from various actors. Managerially, this investigation will answer whether SM can be used to complement the knowledge search breadth strategy.

This study is done in Thailand, where the use of SM by businesses and people has been widespread and has increased rapidly in recent years. The internet users in Thailand overgrew from 21.6 million in 2013 to 50.1 million in 2019. The hours each user spent on the internet rose from 4.5 to 11.5 hours per day in the same period. In

[1] Open innovation literature encompasses three research areas – inbound, outbound, and coupled open innovations. The focus of this paper is inbound open innovation, which draws heavily on external knowledge sourcing studies (West & Bogers, 2013).

2020, SM usage was on the top of internet users' objectives in using the internet, with 95.3% of users engaging in SM, followed by entertainment (85.0%) and information search (82.2%), respectively. Most popular SM platform was Facebook (98.2%), followed by YouTube (97.5%), Line (96.0%), Instagram (80.4%), and Twitter (71.9%). To search for information, most users used YouTube (86.5%), followed by Facebook (66.4%), websites/blogs (48.0%), and Instagram (47.2%) (ETDA, 2020).

Thailand has been the largest E-Commerce market in Southeast Asia since 2013. Its E-Commerce value in 2019 was 55.92 billion USD, much higher than Malaysia (46.19 billion USD) and Indonesia (17.52 billion USD), respectively, in the second and third places. Facebook, Google, and Line are among the most popular platforms for marketing activities (ETDA, 2021). Therefore, given a rapid increase in SM usage and growth of the online business via SM platforms, Thailand provides a good context for examining the role of SM in firms' innovation performance, which, to our knowledge, has not been done before. Also, as studies of SM-based innovations outside developed countries in European and USA regions are still limited (Bhimani et al., 2019), this study adds new empirical evidence of SM-based innovations in the context of Asian emerging economies.

The remaining part of this paper is structured as follows. Section 2 reviews the literature on SM-based product innovations and external knowledge souring to develop hypotheses for empirical tests. Section 3 describes data collection, variable construction, and analytical methods. Sections 4 and 5 present and discuss the results, respectively. Finally, we conclude in Section 6.

2. Literature Review and Hypotheses

2.1. SM use and product innovation

SM-based innovation studies illustrate how SM can stimulate firms' product innovation performance. First, SM can be used as a market research tool, assisting firms in recognising public opinion, discussing with customers, networking with potential contributors, understanding market trends, and identifying locations of potential customers (Patino et al., 2012). SM-based market research is arguably better than traditional market research tools (e.g., interviews, open-ended surveys, and focus groups) in many aspects. It can be used to promote interaction with potential customers, generating reliable information and positive attitudes toward brands (Kim, 2022). With the internet, SM can lower the cost of accessing large samples of customers, allowing firms to gain instantaneous feedback from a vast network of people (Bartl et al., 2012). By using SM, firms can interact more frequently with customers and the public, permitting them to access in-depth and detailed information. Also, people's interactions in SM are not dictated by their affiliation; thus, information sourced from SM tends to be rich and reflect individual creativity that can provide firms with valuable insights (Hitchen et al., 2017). Moreover, as SM allows users to generate their content, it tends to contain diverse and novel insights. Thus, sourcing ideas from SM platforms enable firms to improve their products, services, and processes (Dong & Wu, 2015).

Second, SM can facilitate external knowledge sourcing activities. It provides firms with opportunities to form heterogeneous networks encompassing various actors with different knowledge and expertise. As a result, through SM-based networks, firms can be exposed to knowledge diversity, increasing their choices to recombine new insights with their existing knowledge base to produce innovations (Cheng & Shiu, 2020). Additionally, SM can stimulate frequent interactions between firms and external knowledge actors, increasing trust, mutual understanding, collective actions, and strength of knowledge networks (Choi et al., 2014). This is essential for transferring complex technological knowledge, resulting in superior innovation performance (Murphy & Salomone, 2013). Thus, using SM platforms to source ideas from various actors enables firms to improve their products, services, and processes (Dong & Wu, 2015).

Third, SM can be applied to engage key external actors (e.g., suppliers and customers) in the product development process (Liu & Kop, 2015). Firms using SM tools that support the integration of customers' insights into the NPD process tend to successfully develop new products (Rautela et al., 2020). Due to its interactive nature, SM helps firms to interact and exchange ideas frequently with their customers, enduring customers' active partnership in the NPD process (Sashi, 2012). When firms utilise SM to promote interactions with customers, it can build trust and mutual benefits and respond to customers' expectations that new products will meet their demand, leading to customer co-creation value and loyalty (Hidayanti et al., 2018). Moreover, besides customer engagement, SM tools can also facilitate suppliers' engagement in manufacturers' NPD activities. As a result, it accelerates knowledge sharing in supply chain networks and provides firms with greater access to complementary knowledge resources possessed by suppliers (Cheng & Krumwiede, 2018; Cheng & Shiu, 2020).

Fourth, SM can be employed to generate awareness and acceptance of new products and obtain feedback concerning new products, reinforcing the effectiveness of the new product launch strategy. By leveraging various functions of SM (e.g., hashtag, comments, share), companies can generate a social community where people with common interests are brought together to share ideas and perceptions about new products. Social publishing enables companies' managers to interact with consumers in real-time, facilitating a rapid spread of positive electronic word-of-mount and increasing awareness and acceptance of new products (Kim & Chandler, 2018). By engaging customers in collaborative efforts for a new product through SM platforms, firms can align the product with customer needs and bring it closer to the target audience, increasing the success rate of the new product launch (Mount & Martinez, 2014).

In sum, SM can be employed throughout the product innovation process. It can be used to source ideas and monitor market trends in the ideation stages. In addition, it can serve as a platform to promote the engagement of stakeholders (e.g., customers/users and suppliers) in the product development stage. Also, firms can use it for obtaining feedback and responding to requests in the launch stage (Zhan et al., 2020). Thus, we expect that when firms use SM more, they will likely introduce more product innovations. We then posit a hypothesis to test empirically.

Hypothesis 1: SM usage enhances firms' product innovation performance.

Despite considerable benefits stemming from SM, many studies demonstrate that using SM for innovations poses several challenges. Moe & Schweidel (2017) highlight the voluminous and unstructured data and representativeness of customers' insights as key challenges in conducting market research on SM platforms. As contents generated in SM platforms are voluminous and unstructured, firms tend to face difficulties collecting relevant data and preparing them for systematic analysis. In the SM world, market researchers have little control over the generated data and those who generate it. Some people may choose to participate in social media discussions than others or choose to generate content about specific aspects of products or brands based on their interests, potentially leading to sample and issue biases problems.

Jalonen (2015) brands SM as a paradoxical system consisting of "two poles pulling opposite directions" (p.14). On the one hand, SM provides firms with opportunities to explore new insights and thereby diversify firms' knowledge base. However, on the other hand, SM entails tremendous challenges such as information overload and information leakages, which may negatively affect firms' innovation performance. Liu & Kop (2015) warn that relying too much on SM tools for knowledge sourcing may incur a loss in tacit knowledge transfer. This is because the transfer of tacit knowledge requires direct and face-to-face interactions in which the co-presence of two actors at the same place is needed.

Some empirical studies highlight that using SM in innovation activities is still limited compared to using SM for other purposes like seeking market insights and advertising products. For instance, Roberts & Piller (2016) mention, based on their survey result from 453 companies in North America, Europe, and Asia, that although 82% of surveyed companies use SM for NPD, only 14.7% of them use it intensively. Bartl et al. (2012) show that perceived disadvantages like lack of target group orientation and inabilities of customers to articulate their requirements for new products negatively affect managers' attitudes and intention to virtually integrate customers into the NPD process. Roberts et al. (2016) find that companies that use SM exclusively to search for technical information to support their NPD process experience negative impacts of increasing the use of SM on NPD performance due to information overload.

Moreover, the attention-based view of the firm (ABV) argues that managerial attention is a valuable resource. Hence, superior performance will result from firm managers focusing on a few critical issues (Ocasio, 1997). This implies that too much engagement in using SM for knowledge acquisition may divert firms' attention to unnecessary or irrelevant issues, resulting in a decline in innovation performance.

Therefore, we argue that using SM may yield positive and negative effects on product innovation performance. Negative effects may occur due to the unstructured nature of data, reliability of the information, information overload, and complexities involved in information processing. Thus, hypothesise that the effect of SM usage on product innovations is curvilinear, taking an inverted U-curve form.

Hypothesis 2: The relationship between SM usage and product innovation performance takes an inverted U-curve pattern.

2.2. External knowledge search, social media usage and product innovation

The inbound open innovation literature holds that sourcing knowledge from external sources can complement firms' existing knowledge base, increasing firms' innovative capability (West & Bogers, 2014). Knowledge sourcing requires various tools to facilitate interactions and information exchange between a firm and its knowledge partners (Natalicchio et al., 2017). In this sense, SM can serve as a tool to promote interactions and facilitate external knowledge acquisition (Mount & Martinez, 2014). However, despite many studies examining the effects of external knowledge interaction on firms' innovativeness, there has been a scant effort to investigate the complementary effects of SM and external knowledge sourcing on innovations.

Complementarity can be understood as increasing returns from doing two things (Milgrom & Roberts, 1995). In this sense, the effects of SM usage and external knowledge sourcing on innovations are complementary when using more SM, and souring knowledge from more actors results in better innovation performance. Most studies focus on firms' use of SM to source ideas for new product development from customers (Bhimani et al., 2019; Liu & Kop, 2015; Testa et al., 2020). However, apart from customers, other knowledge actors can also provide insightful information for firms' innovativeness, such as firms' business competitors (Gnyawali & Park, 2011), suppliers (Johnsen, 2009), knowledge-intensive business service providers (KIBS) (Shearmur & Doloreux, 2013), universities, public research organisations (PROs) (Tödtling et al., 2009), and governmental agencies (Hsing et al., 2013). Laursen & Salter's (2006) concept of external knowledge search breadth captures a broad set of actors from which firms can source valuable knowledge. Some studies illustrate that when firms obtain knowledge from multiple actors (i.e., adopting a search breadth strategy), they are likely to achieve superior innovation performance (Chiang & Hung, 2010; Love et al., 2014; Patel & Van der Have, 2010).

There are some explanations why search breadth can strengthen innovative performance. First, searching for knowledge from multiple sources can reduce uncertainties by enlarging the knowledge elements used to manage uncertainties (Patel & Van der Have, 2010). As the payoff from external knowledge search is not known in advance, searching for knowledge from a broad set of actors can increase the chance that the right information will be attained (Love et al., 2014). Second, knowledge diversity is crucial for innovations. Firms that succeed in introducing innovations are those capable of blending diverse pieces of information to generate new knowledge (Basit & Medase, 2019). Thus, firms with multiple links with various knowledge actors can increase the probability of discovering a new combination of ideas and developing novel insights (Radicic, 2020; Yang & Wang, 2017). This is especially the case for firms pursuing radical innovations in which the diversity of information is deemed necessary (Radicic, 2020).

Therefore, success in open search strategies increases when firms interact and obtain knowledge from various actors having different knowledge bases. In this sense, SM can act as a tool to facilitate knowledge search breadth and increase the possibility of obtaining various insights from heterogeneous actors for innovative activities (Jalonen, 2015). Thus, we assume that SM usage and search breadth have a complementary effect on product innovations. Firms that use SM to source knowledge from various actors will tend to succeed in introducing product innovations. We propose the following hypothesis.

Hypothesis 3: the effects of SM usage and external knowledge search breadth on firms' product innovations are complementary.

3. Research methodology

3.1. Data collection

The data collection involves questionnaire development, sample selection, survey administration, and data screening and sampling bias check.

3.1.1. Questionnaire development

We developed a draft questionnaire based on related theories and empirical studies that we reviewed. Then, we sent the draft questionnaire to five scholars regarded in Thailand as experts in innovation studies and innovation management. We requested them to check and make comments on our draft questionnaire regarding its validity, consistency with related theories, and understandability of language and contents. Then, we revised our questionnaire based on their comments and suggestions.

3.1.2. Sample selection

This study focused on firms in high-tech manufacturing industries, as they are more likely to introduce innovations than firms in low-tech sectors. This study covers eight high-tech sectors, including machinery, automobiles, auto parts, metal products, electronics, computers, chemicals, and medical products. The complete data source in Thailand that provides information on firms in these sectors is the Department of Industrial Work's list of registered manufacturing firms. This data source provides necessary information for the survey, especially the firm's name, contact persons, and postal address. This list has been frequently updated, adding newly registered firms and removing dissolved firms from the list.

As of June 2020, there were 10,204 population firms in the list of eight high-tech sectors that we targeted. We applied the random sampling procedures using Microsoft Excel to select 3,000 firms from the list. First, we listed all 10,204 firms in Excel, including their names, contact persons, and postal addresses. Then, we generated the random number for each firm using the built-in random function in Excel. Finally, we chose the customised sorting of random numbers and selected the first 3,000 firms on the list. Based on these steps, all population firms are equally likely to be chosen.

After having sample firms, we determined the sample size to be used for analysis. This is an important step in designing data collection strategies. We determined the sample size range based on a widely used Yamane's (1967) formula[2]. We expected our sample size to fall between the marginal errors of 0.05 and 0.10. Applying Yamane's formula, we came up with the sample size range between 385 (error = 0.05) and 99 (error = 0.10).

3.1.3. Survey administration

We conducted a postal survey in two rounds. The first round took place in July-August 2020, where we sent questionnaires to 3,000 sample firms with a cover letter requesting the firms' CEO or senior managers to complete them. By the end of August 2020, only 217 questionnaires (7.22%) were returned. Although this sample size falls into our sample size range, we decided to increase the sample size by conducting the second survey round. In the second round (September-October 2020), we resent questionnaires to 1,000 firms that did not respond in the first-round survey. We also followed up by making telephone calls and emailing the firms (in cases where telephone numbers and emails are available) to ensure more return rate. By the end of October 2020, we received additional 104 questionnaires. Thus, we received returned questionnaires from 323 firms in both survey rounds.

3.1.4. Data screening and sampling bias check

We screened all returned questionnaires and checked for the completeness of the information. After carefully screening, 21 questionnaires were removed due to incomplete data. Thus, there are 302 questionnaires retained, forming a sample size of 302 firms (10.07% net response rate). The low response rate may be attributable to the

[2] $n = N/(1+Ne^2)$, where n = sample size, N = population size, and e = the margin of error.

Thai government's lockdown measures from March-August 2020 in response to the Covid-19 pandemic.

We examined the non-response bias by comparing the characteristics of early and late respondents regarding age, sales, employees, employees with higher education, export share, and R&D expenditure using a two-tailed t-test (Lahaut et al., 2003). The differences are not statistically significant for all variables, suggesting that non-response bias is not problematic in this study.

We also checked for common method bias that might occur due to using a single data gathering method or a single indicator for a concept (Huang & Li, 2009). To do so, we employed 18 Likert-scale questions measuring firms' knowledge management capabilities that are included in the questionnaire but not used in this paper. We performed Harman's one-factor test by running the exploratory factor analysis (EFA). The EFA result shows no single factor accounting for the majority of the total variance, indicating no common method bias in our data (Fuller et al., 2016; Podsakoff & Organ, 1986).

3.2. Variable construction

3.2.1. Dependent variable

The dependent variable in this study captures firms' product innovations. The concept of product innovation is adopted from the Oslo Manual's (OECD/Eurostat, 2018) conceptualisation of product innovations. In the questionnaire, we asked firm managers to indicate the number of new products their firms introduced into the market in the past three years. Accordingly, we use the data on the number of firms' new products to measure firms' product innovation. Our dependent variable – product innovation – is a count variable consisting of non-negative integers. The questionnaire also asked about the numbers of new-to-firm and new-to-market products. Based on this information, we also create two additional counts variables that capture the degree of novelty in product innovations:

(1) Incremental product innovation: the number of new-to-firm products.

(2) Radical product innovation: the number of new-to-market products.

Table 1 shows the number and percentage of sample firms according to innovative products. One hundred seventy-seven firms (58.61%) indicated that they did not introduce any new products in the past three years. The number of firms decreases as the number of innovative products increases, which is common in the studies of innovation count. Both incremental and radical product innovations also follow the same pattern. The mean values for new, new-to-firm, and new-to-market products are 3.01, 2.42, and .59, respectively.

Table 1: Number and percentage of sample firms by innovative products (n = 302)

# New products	# Firms	%
0	177	58.61
1 to 5	97	32.12
6 to 10	14	4.64
11 to 15	4	1.32
16 to 20	1	.33
More than 20	1	.33
# New-to-firm products		
0	194	64.24
1 to 5	86	28.48
6 to 10	10	3.31
11 to 15	3	.99
16 to 20	3	.99
More than 20	6	1.99
# New-to-market products		
0	256	84.77
1 to 5	38	12.58
6 to 10	3	.99
11 to 15	2	.66
16 to 20	1	.33
More than 20	2	.66

3.2.2. Independent variables

(a) SM usage

The variable "*SM usage*" measures the number of SM platforms firms used in the past three years. We focus on eight SM platforms that are widely used in Thailand, including Facebook, YouTube, Line, Twitter, Instagram, WeChat, LinkedIn, and others (e.g., Skype, Pinterest, and Snapchat). We asked the firms to specify their social media use in the last three years. The question is: *to what extent your firm has used the following SM platforms (Facebook, YouTube, Line, Twitter, Instagram, WeChat, LinkedIn, and others) for marketing and external knowledge sourcing activities in the past three years?* For each SM platform, there are four mutually exclusive choices expressed in four-point Likert scale: 1 = never or rarely; 2 = sometimes; 3 = often; 4 = regularly). We assign a binary code for each SM platform, coding zero if firms never or rarely used the platform and one if they used it sometimes, often, or regularly. Then, we sum across all SM platforms to generate an SM usage variable measured as a number between zero (no SM platform used) to eight (all SM platforms used). The Cronbach's alpha coefficient for this construct is 0.76, suggesting acceptable reliability (Ahdika, 2017). To test for the curvilinear effect of social media use on product innovations, we use the square of SM usage (*SM usage squared*). If Hypothesis 1 and Hypothesis 2 hold, we expect the coefficients of SM usage to be positive and its square to be negative.

Our data reveals that firms' most popular SM platform is Line, followed by Facebook and YouTube. On the other hand, Instagram, Twitter, WeChat, LinkedIn, and others are not quite popular among sample firms, as the number of firms that used each of these platforms is well below the number of firms that did not use them (Figure 1). Twenty-two firms (7.28%) did not use any SM platform over the past three years, and only one firm (0.33%) used all platforms. The number of firms increases with the number of platforms used and peaks at three platforms (Figure 2). On average, our sample firms used 2.86 platforms.

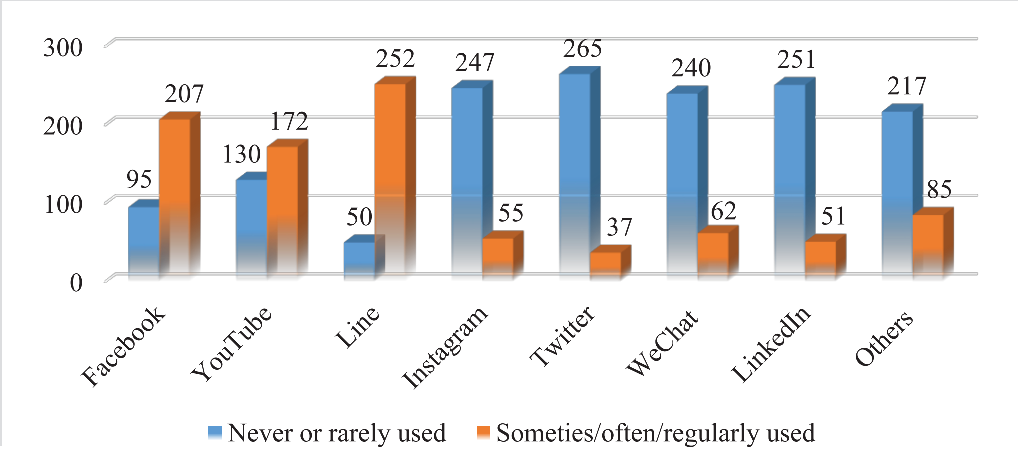

Fig. 1: Number of firms using SM platforms by the extent of use (n = 302)

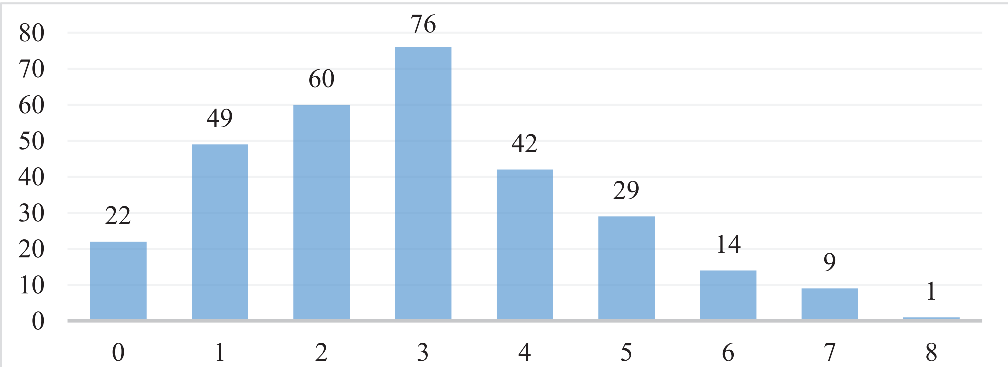

Fig. 2: Number of firms by number of SM platforms (n = 302)

(b) External knowledge search breadth

Conceptually, search breadth captures the scope in which firms source knowledge from external actors, indicating how broad the set of knowledge actors/sources from which firms obtain knowledge is (Laursen & Salter, 2006). We follow Laursen & Salter's (2006) seminal work to measure search breadth regarding the number of knowledge actors from which firms sourced knowledge. The questionnaire asked about the degree that firms sourced knowledge from six types of knowledge actors (suppliers, clients, competitors, KIBS, universities and PROs, and governmental agencies) located in three locational settings (local, national, and overseas)[3] in the past three years. Thus, we have 18 potential knowledge actors (local suppliers, national suppliers, overseas suppliers, local clients, national clients, overseas clients, and so on). The degree that firms sourced knowledge from these actors is measured using a six-point Likert scale (0 = none; 1 = lowest; 2 = low; 3 = medium; 4 = high; 5 = highest). We apply a binary coding with zero, denoting that the firm did not source knowledge from an actor or otherwise. Then, we sum across to create a variable "*Search breadth*", which is the number between zero (no actor sourced) and eighteen (all actors sourced). The Cronbach's alpha for this variable is remarkably high at 0.90, indicating strong reliability (Ahdika, 2017).

3.2.3. Control variables

We include four variables (*Size*, *Skill*, *Export,* and *R&D*) and five industry dummies (machinery and metal products, automobile and auto parts, electronics and computers, chemical products, and medical products) as control variables. *Size* is measured as the number of full-time employees. It captures available resources to invest in innovative activities. It is assumed that larger firms possess more resources to mobilise for innovations. With more resources, they can also tolerate risks associated with investing in innovative activities (Shefer & Frenkel, 2005). *Skill* is the percent share of employees holding at least a bachelor's degree. This variable captures human capital that may positively affect firms' innovative capability (Lund Vinding, 2006). *Export* is the percent share of export in firms' sales. Theoretically, this variable may influence firms' innovativeness in two ways. First, as the competitive pressure in the export market is intense, exporting firms have to innovate to thrive in the export market. Second, there can be learning effects from export. Exporters can learn from best practices or experiences in the world market (Cai *et al*., 2020). *R&D* accounts for firms' internal knowledge generation and absorptive capacities, which are crucial to firms' innovativeness (Cohen & Levinthal, 1990). Variables *Size*, *Skill*, *Export* and *R&D* are transformed into logarithms to reduce the degree of dispersion in the data. Finally, industry dummies are binary variables (coding 0 or 1), where the medical products sector is a base category.

3.3. Analytical method

Our dependent variable – product innovation – has some remarkable characteristics. It is a count of innovative products with many zeros and right-skewed distribution (see Table 1). With these characteristics, applying the standard linear statistical method,

[3] The local setting refers to the area within a radius of 90 kilometres from a firm. The national setting denotes other areas in Thailand. The global setting refers to other countries.

such as the Ordinary Least Square (OLS) Regression, is inappropriate and will result in inefficient and unreliable estimators (Long, 1997). Some statistical methods are specifically designed to deal with the analysis of count variables. One is the Poisson Regression (PR), where a Poisson distribution is used to determine the probability of a count, and the mean of the distribution is a function of independent variables. The PR model assumes equality of conditional mean and variance. Thus, it may not produce reliable results if the conditional mean and variance are not equal. The alternative method is the Negative Binomial Regression (NBR), which is not based on the conditional mean-variance equality assumption. The NBR tends to produce more robust results than the PR when the sample variance exceeds its mean, which is likely to occur in social science studies due to the unobserved heterogeneity in the sample (Long, 1977). In this study, we employ the NBR for data analysis. However, it is recommended that the dispersion (alpha) parameter should be produced to check whether the sample distribution violates the mean-variance equality assumption (Long, 1997). Accordingly, we produced the dispersion parameter in parallel with the NBR analysis. We found that α parameters are statistically significant for all model specifications (see Tables 3 and 4), indicating that mean and variance are not equal and justify NBR use.

4. Empirical Results

Descriptive statistics and bivariate correlations of all independent variables are displayed in Table 2 (only significant correlations are reported). All pairs of independent variable correlation do not exhibit strong correlations, showing no sign of a multicollinearity problem. We also checked for the presence of multicollinearity statistically. We found that the variance inflation factor (VIF) statistics for all independent variables are lower than the cut-point of ten (Wooldridge, 2016), indicating no severe multicollinearity problem in our data. Note that we mean-centred variables *SM usage*, *SM usage squared*, and *Search breadth* to remedy a structural multicollinearity problem that might arise with the inclusion of interaction and square terms (Frost, 2019). A mean-centred transformation reduces the magnitude of bivariable correlations among these variables and their VIF values.

Table 2: Descriptive statistics and bivariate correlations of independent variables (*p values* are in parentheses

	1	2	3	4	5	6	7	8	9	10	11	12
1. SM usage	1											
2. SM usage squared	.33(.000)	1										
3. Search breadth	.23(.000)		1									
4. Size			.19(.001)	1								
5. Skill	.14(.014)		.17(.003)		1							
6. Export			.14(.014)	.315(.000)	.	1						
7. R&D	.22(.000)		.22(.000)	.314(.000)	.27(.000)		1					
8. Machine & Metal						-.13(.025)		1				
9. Automobile	-.15(.010)				-.12(.045)		-.17(.003)	-.32(.000)	1			
10. Elect & Comp					-.12(.039)			-.26(.000)	-.24(.000)	1		
11. Chemical					.15(.012)		.17(.003)	-.27(.000)	-.25(.000)	-.20(.000)	1	
12. Medical	.19(.001)				.14(.013)		.27(.000)	-.27(.000)	-.25(.000)	-.29(.000)	-.21(.000)	1
Mean	2.86	11.18	11.80	4.39	2.91	1.71	6.16	0.25	0.22	0.16	0.17	0.17
SD	1.73	11.82	5.05	1.46	1.09	1.79	7.31	0.43	0.42	0.37	0.37	0.38
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	8.00	64.00	18.00	8.56	4.60	4.61	19.51	1.00	1.00	1.00	1.00	1.00

The NBR results for overall product innovations (the number of new products in total) are displayed in Table 3. We report three model specifications. The first specification is a baseline specification comprising control variables only. The second one adds variables *SM usage* and its square term, and the third specification includes all variables. Regarding model summary statistics, the Likelihood-Ratio (LR) Chi-Square statistic is statistically significant ($p < .010$) for all specifications, suggesting that all variable coefficients are significantly different from zero. Pseudo R^2 increases as we move from specification 1 to specification 3, indicating the improvement of specifications as we add independent variables from the baseline specification (specification 1). A statistical significance of the alpha values ($p < .010$) means that the mean-variance equality assumption does not hold, hence justifying that the NBR is more appropriate than the Poisson regression in our case.

The variable *SM usage* has positive coefficients and strong statistical significance in both specification 2 and specification 3, suggesting that using social media for marketing and information sourcing activities increases the likelihood of firms introducing product innovations. This result supports Hypothesis 1 and conforms with previous studies (Cheng & Krumwiede, 2018; Rautela et al., 2020). Conversely, *SM usage squared* is negative and significant ($p < .050$) in both specifications, indicating a decreasing innovation return on SM usage. Specifically, firms that use SM for marketing and knowledge sourcing activities can introduce product innovations at some point. Still, as they use it more, the product innovation performance decreases. The negative effects of *SM usage squared* support Hypothesis 2, which states that the relationship between SM use and product innovations is curvilinear, taking an inverted U-curve form.

The coefficient for *Search breadth* is positive and statistically significant ($p < .010$), suggesting that firms tend to introduce more product innovations as they obtain knowledge from numerous external sources. This result is consistent with other studies (Love et al., 2014; Patel & Van der Have, 2010). However, the interaction term (*SM usage*Search breadth*) is not statistically significant. Thus, this study cannot establish the complementary effect of SM usage and search breadth. In other words, increasing SM usage and sourcing knowledge from more actors do not necessarily improve product innovation performance. Therefore, Hypothesis 3 cannot be supported by the result of this analysis.

For control variables, only *Size* and *R&D* are positive, statistically significant, and robust in all model specifications. This indicates that large firms and firms investing more in R&D stands have a good chance to achieve better product innovation performance than small firms and those not investing in R&D.

Table 3: Regression results for product innovation (overall)

	Dependent variable: Product innovation					
	1		2		3	
	Coefficient (SE)	p values	Coefficient (SE)	p values	Coefficient (SE)	p values
Constant	-2.35(.76)	.002	-2.17(.76)	.004	-2.00(.76)	.008
SM usage			.24(.09)	.005	.18(.09)	.043
SM usage squared			-.08(.03)	.010	-.08(.03)	.011
Search breadth					.07(.03)	.007
SM usage*Search breadth					.01(.02)	.715
Size	.31(.10)	.002	.29(.10)	.004	.27(.10)	.006
Skill	.30(.13)	.026	.26(.14)	.055	.25(.14)	.068
Export	-.04(.07)	.550	.02(.07)	.829	-.01(.07)	.888
R&D	.13(.02)[a]	.000	.12(.02)	.000	.11(.02)	.000
Industry Dummies (Medical = 0)						
Machinery & metal	-.79(.36)[b]	.029	-.60(.36)	.097	-.72(.36)	.045
Automobiles	-.04(.38)	.923	.07(.38)	.946	.04(.38)	.909
Electronics & computers	-.25(.39)	.530	.04(.40)	.929	.05(.40)	.903
Chemicals	-.24(.37)	.520	-.17(.36)	.641	-.16(.35)	.656
Alpha	2.85(.37)	.000	2.69(.36)	.000	2.55(.34)	.000
LR Chi-Square (df)	104.40(8)	.000	113.28(10)	.000	120.44(12)	.000
Log likelihood	-487.87		-483.43		-479.85	
Pseudo R^2	.10		.11		.11	
n	302		302		302	

We also report NBR results for incremental and radical product innovations in Table 4. The model summary statistics in this table show statistical outputs consistent with those in Table 3. Remarkably, the alpha coefficient is statistically significant for all specifications, suggesting that NBR is more appropriate than Poisson regression as an estimation method.

In the *Incremental product innovation* model, the results are generally similar to those of *Product innovation* model (in Table 3). This means that using SM for marketing and knowledge sourcing improves firms' incremental product innovation performance. *SM usage squared* is negative and statistically significant ($p < .050$) in specifications 2 and 3, suggesting that using SM is subject to decreasing product innovation returns. *Search breadth* is positive and statistically significant ($p < .050$), suggesting that sourcing knowledge from various external actors enhances firms' ability to introduce incremental product innovations. However, the interaction term (*SM usage*Search breadth*) is not statistically significant. Thus, complementary effects on incremental product innovation of SM usage and search breadth cannot be established.

Regarding control variables, *Size* and *R&D* are still positive, statistically significant, and robust in all specifications ($p < .010$). Thus, bigger firms and firms investing in R&D activities still stand a better chance to introduce incremental product innovations. *Skill* is also positive and significant in this analysis, though at a moderate significance level ($p < .100$) in specification 3. Thus, firms with a high share of skilled workers will likely perform well in incremental product innovations.

For *Radical innovation* model, the results are somewhat different from the two earlier analyses. First, *SM usage* is positive and statistically significant, though at a moderate level ($p < .100$) in specification 3. This means using SM for marketing and external knowledge sourcing activities is good for radical product innovations. Similar to earlier results, *SM usage squared* is also negative and statistically significant ($p < .100$), indicating an inverted U-curve relationship between SM use and radical product innovations. Although *Search breadth* is not statistically significant in this model, its interaction with *SM usage* is positive and statistically significant ($p < .050$). This result indicates that using more SM platforms and sourcing knowledge from a greater number of actors is important for radical product innovations. In other words, the complementary effect of SM use and external knowledge search breadth prevails in the case of radical product innovations. Finally, regarding the effects of control variables on radical product innovations, only *R&D* is positive and statistically significant. Thus, investing in R&D is essential for all types of product innovation.

Combining the results from product innovation (overall), incremental product innovation, and radical product innovation analyses, we conclude as follows. First, SM usage is crucial for all types of product innovation. This evidence confirms Hypothesis 1. Second, the square term of SM usage is negative and statistically significant for all types of product innovation, meaning that increasing the use of SM for marketing and knowledge sourcing may incur a decreasing product innovation return. Thus, Hypothesis 2 is supported. Third, the complementary effect of SM use and external knowledge search breadth is found only in the case of radical product innovations. Thus, Hypothesis 3 is partly supported. The following section provides more detailed discussions regarding these findings.

Table 4: Regression results for incremental and radical product innovations

	Dependent variable: Incremental product innovation						Dependent variable: Radical product innovation					
	1		2		3		1		2		3	
	Coeffcient (SE)	p value	Coefficient (SE)	p value	Coefficient (SE)	p value	Coeffcient (SE)	p value	Coefficient (SE)	p value	Coefficient (SE)	p value
Constant	-2.90(.90)	.001	-2.69(.91)	.003	-2.51(.90)	.005	-3.74(1.18)	.002	-3.30(1.13)	.003	-2.82(1.11)	.011
SM usage			.19(.09)	.042	.16(.10)	.114			.52(.18)	.004	.35(.17)	.052
SM usage squared			-.08(.03)	.014	-.08(.04)	.027			-.08(.07)	.260	-.10(.06)	.088
Search breadth					.06(.03)	.033					.07(.05)	.170
SM usage*Search breadth					-.01(.02)	.746					.07(.03)	.036
Size	.40(.12)	.001	.38(.12)	.002	.35(.12)	.004	.11(.13)	.387	.08(.13)	.522	.03(.12)	.782
Skill	.33(.15)	.028	.30(.15)	.049	.29(.16)	.063	.11(.26)	.664	.00(.25)	.995	-.01(.25)	.959
Export	-0.04(.08)	.598	.01(.08)	.876	-.02(.08)	.836	-.09(.12)	.439	-.07(.12)	.555	-.10(.12)	.378
R&D	.17(.02)	.000	.10(.02)	.000	.10(.02)	.000	.20(.04)	.000	.18(.04)	.000	.17(.03)	.000
Industry Dummies (Medical = 0)												
Machinery & metal	-.87(.40)	030	-.72(.41)	.077	-.79(.40)	.049	.04(.60)	.948	.18(.57)	.753	-.20(.56)	.720
Automobiles	.04(.43)	.919	.08(.43)	.845	.14(.43)	.753	-.42(.74)	.568	-.08(.68)	.911	-.21(.65)	.752
Electronics & computers	-.36(.44)	.470	-.04(.44)	.927	.03(.44)	.943	.46(.64)	.477	.19(.69)	.784	-.39(.67)	.563
Chemicals	-.37(.41)	.362	-.30(.41)	.466	-.26(.40)	.524	.49(.56)	.385	.60(.52)	.247	.37(.50)	.461
Alpha	3.56(.50)	.000	3.41(.48)	.000	3.29(.47)	.000	5.35(1.21)	.000	4.22(1.01)	.000	3.56(.88)	.000
LR Chi-Square (df)	83.87(8)	.000	90.03(10)	.000	94.64(10)	.000	57.36(8)	.000	67.07(10)	.000	74.80(12)	.000
Log likelihood	-435.25		-432.17		-429.87		-193.72		-188.87		-185.01	
Pseudo R^2	.09		.09		0.10		.13		.15		.17	
n	302		302		302		302		302		302	

5. Discussion

5.1. Theoretical implication

Social media (SM) as an enabler and driver of innovation is an emerging area of research (Bhimani et al., 2019). This study contributes to the existing studies on SM-based innovations in two ways. First, it empirically examines the positive and negative impacts of SM usage on product innovations. Although much SM-based innovation literature discusses both the positive and negative effects of using SM for innovation (Bhimani et al., 2019; Testa et al., 2020), empirical evidence is still scarce. Second, we examine how SM use complements search breadth in determining success in product innovations. Despite numerous studies showing that sourcing knowledge from multiple actors (i.e., search breadth) enhances firms' innovation performance (West & Bogers, 2014), none of them explores how SM can complement the process of external knowledge sourcing. Given that SM has considerable advantages in linking firms with multiple sources of ideas, it is interesting to investigate whether SM use complements the search breadth strategy in sourcing external knowledge for innovations.

The first remarkable finding is that SM has a positive impact on product innovations, but increasing the use of SM may yield decreasing product innovation returns. Many studies highlight the potential of SM as an effective tool to enhance firms' innovativeness (Bhimani et al., 2019; Liu & Kop, 2015; Testa et al., 2020). SM can be used in various stages of the innovation process, from ideation (Mount and Martinez, 2014), product development (Cheng & Krumwiede, 2018; Rautela et al., 2020), to new product launches (Roberts et al., 2017). Due to some advantages like allowing users to generate their content, accelerating the rapid flow of information, and facilitating instantaneous interactions, SM can be used to source novel ideas, identify market needs, collaborate for product development, and receive and respond to markets' feedback (Liu & Kop, 2015). The positive effect of SM in the present study is in line with these studies, indicating that SM can be used for innovation activities, particularly for obtaining information and insights.

However, some scholars warn against intensively using SM for innovation activities (Liu & Kop, 2015). When firms use SM to source ideas for innovations, they may encounter various problems such as risks of listening to the wrong audience (Roberts & Candi, 2014), information overload and information leakage (Jalonen, 2015). As data available in SM is large, diverse, disconnected, and unstructured, firms tend to face difficulties in data screening and analysis (Roberts & Piler, 2016). Following the ABV, when firms engage too much in SM-based knowledge sourcing activities, the costs of diverting attention from valuable issues may increase, deteriorating their innovation performance (Ocasio, 2010). The negative coefficient of the square term in this study is consistent with these cautions, indicating that as firms increase the use of SM platforms for market and knowledge sourcing activities, the likelihood of introducing product innovations reduces. Unfortunately, only a few studies empirically investigate the curvilinear effect of SM on innovation performance. Notable works are Cheng & Krumwiede (2018) and Roberts et al. (2016), which find the inverted U-shaped effect of SM on NPD performance. Thus, our finding is consistent with their finding.

The next important finding is that the complementary effect of search breadth and SM use is only confirmed in the case of radical product innovations. Studies on external knowledge sourcing argue that sourcing knowledge from various actors (i.e., search breadth) is important for radical innovations (Chiang & Hung, 2010; Xu, 2015; Zhou, 2012). It is mainly due to the nature of radical innovation and the characteristics of knowledge required to produce it. As radical innovation is characterised by the complexity and newness of knowledge components, the knowledge required to produce it tends to be complex and dissimilar to firms' existing knowledge base (Dewar & Dutton, 1986). Consequently, it requires firms to acquire knowledge from heterogeneous actors, increasing the diversity and novelty of information that can be used to complement firms' knowledge base, resulting in superior radical innovation performance (Chiang & Hung, 2010).

The significance of the complementary effect of search breadth and SM use in this study means that increasing SM usage and souring knowledge from various actors is crucial for radical product innovation. This informs the inbound innovation literature that SM can be used to access a wide range of knowledge actors and maintain the inflow of various ideas necessary for producing radical innovation. Moreover, a significant complementary effect also means that the problem of homophily in using SM for product development can be avoided. Intensive use of SM may increase the likelihood of having homogeneous networks (i.e., homophily), as the SM algorithm will help facilitate networking with those who share common characteristics or interests. This may result in decreasing knowledge variety and consequently reducing radical innovation performance. Thus, using more SM while searching for knowledge from many actors avoids the homophily problem and increases the possibility of introducing radical product innovation (Fischer et al., 2021).

5.2. Managerial implication

Key findings in this study offer some managerial implications. First, SM can be beneficial to firms' product innovation process. Especially it can facilitate the search for external information that can be used for product innovations. However, managers should be careful in using SM for product innovation because too much use of SM may give negative outcomes. Using SM for product innovation activities should be done selectively, focusing on some platforms most relevant to product innovations' knowledge requirement. Managers should develop an SM-based innovation strategy, mechanisms, and infrastructure necessary to foster staff and organisational capacity to manage SM for innovation activities. As SM can be utilised in different stages of product innovation, from idea sourcing, product development, and product launch (Mount & Martinez, 2014), various capacities should be developed to leverage its benefits in each stage. For instance, market research and data analytics capacities may be necessary for the early stage of sourcing ideas. In the development stage, strong communication and coordination skills should be enhanced, while in the product launch stage, abilities to respond to feedback and manage impacts of both positive and negative words of mouth must be fostered (Roberts & Piller, 2016).

Second, for firms that aim to pursue radical product innovations, SM can be employed to complement a broad knowledge search strategy. SM usage strategy should be developed along with an external knowledge search strategy to gain the most benefit from the search. For instance, managers need to analyse which SM platform should be applied for sourcing information from a particular type of knowledge actors at the basic level. At a more advanced level, a special sort of SM can be designed to engage a particular group of actors in the firm's innovation process (Bhimani et al., 2019). Sourcing information from multiple actors may require different SM tools and platforms.

5.3. Limitations and future research

This study has some limitations that should be highlighted as implications for future research. First, this study explores the inverted U-shape relationship between SM use and product innovations, but it doesn't investigate factors that might moderate this relationship. External knowledge sourcing studies also highlight the inverted U-shape relationship between external knowledge search and innovation performance (Laursen & Salter, 2006; Kobarg et al., 2019). However, some of them suggest firms' internal capabilities moderating this relationship, such as knowledge learned from previous sourcing activities (Love et al., 2014) or in-house research capabilities (Berchicci, 2013). Perceiving SM as a tool to search for external knowledge, some internal capacities are required to leverage SM for innovations (Roberts et al., 2016; Roberts & Piller, 2016). Thus, future research may explore firms' capacities that moderate the relationship between SM-based knowledge sourcing and innovation performance.

Second, this study focuses on the impact on product innovations of firms using SM for marketing and sourcing external ideas, but it does not differentiate the purposes of SM use. Arguably, firms may have different objectives in using SM. These objectives may affect firms' innovation performance differently (Roberts et al., 2016) or may affect innovations of different kinds (e.g., process, market, or organisational innovations). Thus, future research may explore the impacts of various purposes of SM usage on different types of innovations.

Finally, this study examines the effects of SM use on product innovation outcomes. It does not focus on the impact of SM use in various phases constituting the innovation process. Previous case studies highlight that various SM platforms and different modes of SM management can be leveraged for each phase of innovation (e.g., ideation, development, and commercialisation) (Mount & Martinez, 2014). However, there have been limited empirical studies undertaking statistical analysis on this issue. Therefore, future research may take a quantitative research approach to examine the role of SM in a different stage of innovation.

6. Conclusion

This study investigates whether firms' SM usage is crucial for product innovations and whether SM can complement firms' external knowledge search breadth in determining product innovation performance. The study contributes to the literature on social media-based innovation and inbound open innovation in two ways. First, drawing on studies that highlight the positive and negative sides of using SM for innovation activities, it empirically explores the curvilinear relationship between SM usage and product innovation, answering the question as to whether SM usage is subject to diminishing product innovation return. To date, this issue is less explored. Second, it explores the complementary effects between SM usage and external knowledge search breadth in determining product innovations, which has also been less studied.

We employ the data of 302 manufacturing firms in Thailand derived from our survey and use the negative binomial regression to analyse this data. The analysis reveals that SM can enhance product innovation performance, but its effect is curvilinear, exhibiting an inverted U-shape pattern and confirming our proposed hypotheses. This pattern occurs for all types of innovations we measure (overall product innovations, incremental product innovation, and radical product innovation). Thus, we suggest that SM may foster firms' innovative efforts; however, relying too much on SM can harm innovative outcomes.

Another important finding is that the interaction between external search breadth and SM usage is positive and statistically significant only in the case of radical product innovation. This finding partially supports our hypothesis that a complementary effect exists on product innovation of search breadth and SM usage. The finding also suggests that SM usage reinforces firms' efforts to search for novel ideas from various actors, which is crucial for radical product innovation. As SM enables firms to reach out to the mass public with relatively low costs, using various SM platforms to access multiple knowledge sources would be key to succeeding in radical product innovations.

In sum, we note that SM has many strengths to serve as a tool for achieving product innovations. However, its benefit will be optimised only when it is used appropriately. This poses many challenges to firms. Therefore, firms need to develop the necessary management capacities to deal with challenges and gain the most benefits from SM regarding product innovations.

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