R&D MANAGEMENT

Technological sensing and response capabilities as drivers for radical innovation in the context of apocalyptic uncertainty

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This paper introduces a new conceptual model to examine the impact of technological opportunism (technology sensing and response capabilities) on the adoption of incremental and radical technological innovation by small and medium enterprises (SMEs). We tested our hypotheses with data from 228 Indian SMEs using a symmetric method of partial least square structural equation modeling (PLS-SEM) and the asymmetric method of fuzzy–set qualitative comparative analysis (fsQCA) followed by sensitivity analysis done by an artificial neural network (ANN) modeling. PLS-SEM results highlighted the roles of technology sensing and response capabilities as key drivers of both incremental and radical product innovations and the strengthening of these relationships by market uncertainty triggered by external events and crises. Apart from this, the results of fsQCA demonstrated multiple configurations of dimensions associated with the adoption of technological innovations by SMEs. This paper extends the current literature by exploring the process by which SMEs may adopt different types of technological innovation. Our findings also have useful implications for SMEs aiming to adopt technological innovations.

1. Introduction

The recent COVID-19 pandemic has devastated the global economy by slowing down economic activity and it may result in years of economic stagnation (Dimson et al., 2020). The impact of Covid-19 has been particularly severe on small and medium enterprises (SMEs) in emerging economies, due to their limited financial, technological, and, other resources, and institutional constraints (Kottika et al., 2020), as seen from widespread business closures, layoffs, employee attrition, and loss of regular customers (Eggers, 2020). On a more positive note, SMEs may play a positive role in the recovery of the global economy as key providers of many essential goods and services (Deng and Zhang, 2018; Matsuzaki et al., 2021), using their agility to navigate through major economic crises (Kottika et al., 2020). Thus, we need to identify and understand the factors that may help SMEs use technological innovations to not only recover from economic downturn but also improve their long-term productivity and capabilities (Petruzzelli et al., 2022; Martins and Singh, 2023).

Faced with the uncertain economic environment during the Covid-19 pandemic, many firms have to quickly configure their operations, by allowing their employees to work from home (Manroop and Petrovski, 2022), and relying on online platforms to engage with their customers (Brewer and Sebby, 2021). These changes highlight the importance of the ability of SMEs to adopt new and emerging technological innovations as one of the key drivers for their continued success. Active adoption of innovative technologies helps SMEs improve their capabilities and performance (Cenamor et al., 2019; Hosseini et al., 2019; Magistretti et al., 2021). For example, Cenamor et al. (2019) show that entrepreneurial SMEs may enhance their performance using digital platforms by improving their network capabilities, which may be negatively (vs. positively) moderated by their exploitation (vs. exploration) orientations.

Hardwick and Anderson (2019) show that the use of collaborative innovation between suppliers and customers will lead to improved performance. Davcik et al. (2021) find that SMEs' technological and marketing capabilities have significant effects on their performance in the international marketplace. Others highlight the role of suitable human resource practices, organizational learning culture, and knowledge sharing (Naqshbandi et al., 2023) and the importance of disruptive business models (Schmidt and van der Sijde, 2022) in the adoption of innovative technologies by SMEs. However, despite growing evidence about the importance of adopting technological innovation to improve SMEs' overall performance, there is little research on the impact of the technological capabilities of SMEs on their ability to respond to unexpected economic crises (Sharma et al., 2020). A few studies examine the vital role of technological innovation in helping small businesses build resilience and grow their businesses (Dubey et al., 2021; Tajudeen et al., 2022; Lashitew, 2023) but relatively less is known about the adoption of technological innovation by SMEs.

In this paper, we view technological innovation used by SMEs to comprise both incremental and radical innovations, which are needed for sustainable long-term growth by firms operating in dynamic and challenging business environments (Hidalgo and Albors, 2008; Matsuzaki et al., 2021; Tian et al., 2021). However, most studies in this area explore the overall innovation process and not its critical determinants (Chau et al., 2020) such as technological opportunism (Lucia-Palacios et al., 2014). Moreover, current literature on the adoption and utilization of innovative technologies by SMEs mostly focuses on the developed economies with relatively less attention to the emerging economies (Yoon et al., 2021). We address calls for more research to identify factors that may impact these different types of innovations by SMEs more effectively (e.g., Cenamor et al., 2019; Hosseini et al., 2019; Casidy et al., 2020; Magistretti et al., 2021). To summarize this discussion, we address the following specific research questions in this paper:

RQ1. What is the impact of technological opportunism (sensing and response capabilities) on the adoption of technological innovation?

RQ2. Under what conditions does market uncertainty influence the relationship between technological opportunism and technological innovation?

To address these research questions, we look beyond the resource-based view of the firms and the dynamic capabilities perspective, to explore the impact of technological opportunism on the process by which SMEs adopt different types of technological innovation. As SMEs in emerging economies are the key drivers of economic growth (Bruton et al., 2008; Sayal and Banerjee, 2022), we need to study the impact of incremental and radical innovations by the SMEs. In this research, dynamic capabilities have been employed to explain the management of knowledge and resources in the process of innovation adoption. It suggests that firms need to be able to identify, acquire, and mobilize the resources necessary to develop and exploit new opportunities (Teece et al., 1997).

According to dynamic capabilities theory, management of knowledge as a vital resource is of utmost importance in the process of innovation adoption and firms need to be able to identify, acquire, and mobilize the resources necessary to develop and exploit new opportunities. The second most important theory used to provide a conceptual base to research context is the contingency theory, which emphasizes the importance of context and environment in the process of innovation adoption. It suggests that the success of an innovation strategy is contingent upon the specific conditions of the organization, the environment, and the resources available (Burns and Stalker, 1961). This theory is particularly relevant for SMEs in emerging economies as the conditions may differ significantly from those of more established firms.

Further, this study demonstrates how some of the complex configurations of exogenous constructs (i.e., technology sensing capability, technology response capability, and market uncertainty) cultivate different impacts on an endogenous construct (i.e., incremental innovation adoption and radical innovation adoption) based on fuzzy-set qualitative comparative analysis (fsQCA). The remainder of the paper is organized as follows: Section 2 underpins the theoretical background and presents the hypotheses in detail. Section 3 describes the research methodology and setting, operationalization of constructs, sampling procedure, and other related details in a research context. Section 4 discusses the results obtained through PLS-SEM, fsQCA, and artificial neural network analysis. Section 5 comprises the discussion and implications of the research. Finally, the limitation and scope of future research are presented in Section 6.

2. Theoretical background and hypotheses

2.1. *Technology adoption by SMEs*

As the adoption of innovation is regarded as vital to the SMEs' performance (Biemans and Griffin, 2018), we also regard technology adoption as being an essential tacit element in the process of helping SMEs further their relationships with their customers. However, technology adoption by SMEs is also a multi-faceted phenomenon and is driven by many internal factors (Akpan et al., 2021). These may include the SMEs' ability to sense and respond to new technology (Hardwick and Anderson, 2019), knowledge integration capability, and innovation-based competitive strategy (Salunke et al., 2019). Similarly, network capabilities and exploitation (vs. exploration) orientations (Cenamor et al., 2019), sustainable competitive advantage, affective commitment and long-term orientation (Haddoud et al., 2021), and dynamic capabilities such as design thinking (Magistretti et al., 2021), technological, and marketing capabilities (Davcik et al., 2021) may also influence technology adoption by SMEs. Besides these internal influences, external factors, such as technological turbulence (Haddoud et al., 2021), informational and marketing barriers (Hosseini et al., 2019), open innovation (Grama-Vigouroux et al., 2020), digital servitization (Favoretto et al., 2022; Leminen et al., 2022), competitive intensity (Bachmann et al., 2021), and collaborative innovation (Hardwick and Anderson, 2019), may also influence technological innovation adoption by SMEs. Indeed, the extent to which decision-makers engage with or take the partners' views into account also helps underpin innovative adoption (Gao et al., 2012; Czakon et al., 2020).

2.2. *Contingency theory*

According to the contingency theory, organizations achieve the best and most sustainable performance when their structure and available resources are relevant to deal with the contingencies imposed by their size, technology, and the internal and external business environment (Despoudi, 2021). This theory views external contingencies as key determinants of the firm performance, which is particularly relevant during the ongoing COVID-19 pandemic that has forced SMEs to change their competitive strategies to deal with the demand- and supply-related uncertainties as a result of environmental turbulence caused by the business and government actions in response to the widespread disease and economic destruction. Economic crises require the organizational structure to become more flexible and adaptive by focusing on developing their capabilities to face external turbulence and not on simply acquiring additional resources (Dubey et al., 2021; Tajudeen et al., 2022; Lashitew, 2023). The contingency theory also highlights the firm behaviors necessary for survival, such as the adoption of innovative technologies by SMEs to identify and tap into new opportunities for the sustainable growth of their businesses (Dubey et al., 2021).

2.3. Dynamic capabilities

In the literature, dynamic capabilities are described as the firms' capacities to integrate, build, and reconfigure internal and external competencies in order to respond to quickly changing settings (Dubey et al., 2021; Magistretti et al., 2021; Messina et al., 2022). During the ongoing pandemic, we need to look beyond the resource-based view of the firm to pay attention to the dynamic capabilities perspective as it provides a more balanced approach between firm resources and the changing business environment in the adopting process (Kreye, 2022). Such an approach that considers both internal and external factors is suitable for examining innovation adoption by SMEs due to the challenge of simply internalizing the process (Homayounfard and Zaefarian, 2022). The strength of dynamic capabilities leads to durable competitive advantages by helping firms manage their existing resources more efficiently and facilitates the acquisition of fresh resources as well as dynamic marketing operations within the SMEs, if and when required (Mikalef et al., 2021).

2.4. Technological opportunism

Technological opportunism is depicted as a sense-and-respond capability of firms toward new technologies (Urban and Maphumulo, 2022) and includes both, the ability to understand and acquire knowledge about new technology developments (technology-sensing capability) and the willingness and ability to respond to new technologies (technology response capability). Under technological opportunism, when faced with new technologies, firms try to 'sense' information about the development of new technologies with the partner that could be the new source of development. They also 'respond' to innovative technologies and reformulate their business strategies to exploit the opportunities or reduce the threats posed by these new technologies (Bertello et al., 2022). Thus, technologically opportunistic firms perceive technology developments as potential sources of growth and accordingly respond proactively to adopt these (Bertello et al., 2022). Both these elements may help SMEs align their innovations and associated activities to their customers (Hidalgo and D'Alvano, 2014).

Technology-sensing capability is the capacity of an organization to learn about and comprehend new technological advancements (internal and external) relevant to its business operations. Strong technology sensing capabilities enable a company to continuously search for information on emerging technological possibilities and risks (Magistretti et al., 2021). The ability and desire of an organization to react to emerging technologies that it detects in its environment and believes may have an impact on the company is known as technology-response capability. An organization that detects emerging technologies may be ready or prepared to react to them. The capability and function of technological opportunism (i.e., sense and response capabilities to technological developments) enable organizations to incorporate new or emerging technologies into existing or new products or new markets while providing a competitive advantage for making proactive and well-informed strategic decisions in the marketplace (Flor and Oltra, 2005; Ngo et al., 2019).

We argue that the two aspects of technological opportunism (i.e., sensing and response capabilities) help drive the adoption of innovation by SMEs by bridging the knowledge gap with their customers. We do distinguish between incremental and radical innovation adoption in line with the literature (Sheehan et al., 2021; Tiberius et al., 2021). Radical innovations are products, processes, or services with unprecedented changes that have the capacity to either transform markets or industries or even create new markers (O'Connor and Rice, 2013, p. 3). Whilst technological opportunism is an important determinant of radical technological adoption (Srinivasan et al., 2002), we argue that in settings that involve partner firms, the adoption of this form of innovation is predicated by both the sensing and response capabilities of the supplier SME. We base this assertion on various empirical studies in the literature.

Many firms tend to place more emphasis on adopting one or the other form of innovation (i.e., radical versus incremental) – potentially at the expense of the other (Henderson, 1993); thus, we simultaneously examine the effects of both forms of technological opportunism on incremental innovation. This form of innovation comprises limited or smaller changes in technology, product, and/or service improvements by modifying and building on existing innovations (Sheng and Chien, 2016), so we anticipate this to have a less drastic impact on SMEs. Moreover, a firm's innovation activities (incremental and radical) are found to partially mediate the link between market and technology sensing capabilities and firm performance (Ngo et al., 2019) in a combined sample of B2B (70%) and B2C (30%) relationships. This indicates that the SMEs' technological innovation activity (radical and incremental adoption) is a function of technological opportunism. On that basis, we posit that both forms of technological opportunism (sensing and response capabilities) will independently impact each of the different types of innovation adopted, as follows:

H1 Technology sensing capabilities are positively associated with the adoption of (a) incremental and (b) radical technological innovation by SMEs.

H2 Technology response capabilities are positively associated with the adoption of (a) incremental and (b) radical technological innovation by SMEs.

2.5. Moderating effect of market uncertainty

Market uncertainty is depicted in the literature as a situation under which firms are unable to accurately forecast their future customer needs and preferences which in turn makes their own sales quite unpredictable (Zhang et al., 2021). As a result, it is very difficult for managers to understand and respond to market changes in an uncertain environment, and it requires some level of adaptation from the firm. High market uncertainty may also hamper the effective utilization of dynamic capabilities as it may make firms fail to recognize the need to alter their resources or take appropriate actions. Under high market uncertainty, firms may not have sufficient information about the ongoing and upcoming changes in customer needs and preferences, which may obstruct managers from making proper decisions (Zhang et al., 2021). Therefore, market uncertainty consists of market complexity and a lack of knowledge about the future direction of a given market, which may have a particularly severe impact on SMEs due to their limited capabilities and resources (Rodríguez et al., 2020).

Market uncertainty is a multidimensional concept that reflects 'the rate of change or the degree of instability of factors in an external environment' and is recognized as a crucial factor influencing the governance of buyer–supplier relationships (Dahlstrom et al., 1996). Therefore, it is likely to impact the type of innovation (i.e., radical versus incremental) being made by the SMEs due to the intrinsic risks faced by them. Moreover, environmental uncertainty influences opportunism in supply chain relationships of emerging markets and also reflects the market volatility and lack of information verifiability. Hence, eliminating opportunism in business relationships has long been the focus of scholarly activity (Zhao et al., 2021). In such a turbulent and rapidly changing business environment, rapid adoption of technological innovations, such as enterprise resource planning (ERP) and software application product (SAP), to allow firm to move faster and respond more quickly to market changes (Ahn, 2020). Firms need to trade off the benefits and risks associated with their partner firms acting opportunistically when they adopt innovations.

For example, uncertainty triggers innovation, especially in the context of SMEs, but performance in such settings depends largely on being able to adapt their offerings to the changing needs of their customers (Kottika et al., 2020). In response to market uncertainty, firms that are able to adopt and implement technological innovations are found to be relatively more successful (Kreye, 2022). Thus, many SMEs tend to become more resilient and are more likely to scout for innovative technologies to service their customers as that helps to improve their productivity when faced with market uncertainty (Ndubisi et al., 2020).

Due to the potential for partner opportunism, we posit that market uncertainty may moderate the link between technological opportunism and the technological adoption activities of the firm. We argue that market uncertainty may moderate the link between each form of technological opportunism (sensing and response capabilities) and technological innovation adopted (incremental and radical). For instance, radical innovation is associated with both technical and market uncertainty, and firms try to deal with this through the application of managerial discipline (O'Connor and Rice, 2013). The inference being that the ability to sense and respond to technological innovation and the type of innovation brought to the firm and its accompanying customer relationships is going to be a function of uncertainty.

As discussed earlier, the contingency theory postulates that firms may be able to achieve their best performance when their organization structure and available resources are in sync with the contingencies, such as size, technology, and the business environment (Despoudi, 2021). We use this theory to argue that the contingencies imposed by market uncertainty may trigger SMEs to leverage their technology sensing and response capabilities more efficiently by adopting both incremental and radical innovation. Such actions may be particularly useful during a socio-economic crisis, such as the ongoing COVID-19 pandemic, which has forced SMEs to come up with innovative business strategies to deal with the uncertainties caused by the business and government response to the devastating impact of the pandemic. There is growing evidence that many firms became more flexible in utilizing their capabilities and resources to deal with the uncertainty caused by the pandemic (Dubey et al., 2021; Tajudeen et al., 2022). The contingency theory may also explain the adoption of innovative processes and technologies by SMEs during the pandemic to help them create new opportunities for the survival of their businesses (Dubey et al., 2021). Thus, we hypothesize:

H3 Market uncertainty positively moderates (i.e., strengthens) the association between technology sensing capabilities and the adoption of (a) incremental, and (b) radical technological innovation by SMEs.

H4 Market uncertainty positively moderates (i.e., strengthens) the association between technology response capabilities and the adoption of (a) incremental, and (b) radical technological innovation by SMEs.

Figure 1 shows our conceptual model with all the hypotheses.

3. Methodology

3.1. Measures

We adopted all the measures from the existing literature. The technological opportunism scale was adopted by Urban and Maphumulo (2022). Service innovation was operationalized using 10 items (five items each for incremental and radical service innovation) adopted from Johansson et al. (2019). The three-item market uncertainty scale was adopted from Zhang et al. (2021). All the scales use seven-point Likert-type scales (1 = strongly disagree and 7 = strongly agree). In line with Brislin (1970), the questionnaire was initially developed in English and then translated into Hindi before being back translated into English with minor adjustments to ensure that it retained the meanings of all the scale items. There were two sections to the questionnaire: Section 1 contained information about the respondents' demographics, and Section 2 contained all the scale elements.

3.2. Sampling and procedure

This study was carried out in two stages using the SMEs listed in the database of a private university's entrepreneurship incubator center in the Northern Capital Region (NCR) of India as its sampling frame. These SMEs represent well-established businesses and act as mentors for student entrepreneurs. First, we vetted our conceptual model using in-depth interviews with a small sample of entrepreneurs ($N = 24$) from the same target population as our main study. A semi-structured research protocol was used to guide each of the interviews, which took an average of 30 min to complete. Interviews were recorded and transcribed. In addition, the 24-hr rule (Eisenhardt and Bourgeois, 1988; Ellis and Pecotich, 2001) was used to capture the interviewee's impressions in the field that were translated into detailed field notes to help ensure the information gathered was accurate. We used these interviews to confirm the relevance of all the constructs included in our conceptual model and to seek a preliminary validation of our hypotheses (Hulland et al., 2018).

Next, we conducted our main study using an online self-administered survey with a purposive

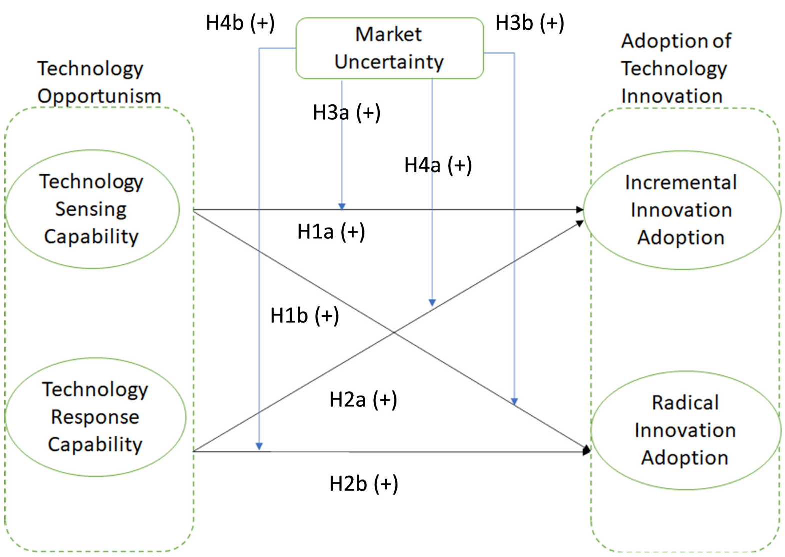

Figure 1. Conceptual model.

sampling approach (Sarstedt et al., 2018; Cheah et al., 2021) with a sample of SMEs ($N = 228$) from the same database as our pilot study. Prior to the main analysis, a pre-test of the sample ($N = 12$) to test the research instrument showed that all the questions were considered adequate for the survey and were well understood by the targeted respondents. As we aimed to test factors that contribute to the adoption of technologies deemed important in the relationship that SMEs have with their customers, key informants in each organization were asked to think about an important relationship when answering each of the questions. Given innovation also encompassed the degree to which decision-makers took supplier suggestions into account (Gao et al., 2012), the degree of partner engagement was captured by asking the respondents to take this into account when answering the survey questions.

Accordingly, a total of 350 Indian SMEs were contacted through both online and offline sources, and out of these, 228 (65.14%) completed questionnaires were received. To ensure the generalizability of our findings, we used a cross-industry sample of SMEs operating in six industries, including computer hardware manufacturers, software service providers, footwear manufacturers, light manufacturers, entertainment/media service providers, and market research agencies. All the participating SMEs serve other businesses, such as large computer hardware and software manufacturers, footwear wholesalers, large manufacturing industries, entertainment and media agencies, and major business firms, respectively. We selected the SMEs for our study using the Indian Ministry of Micro, Small and Medium Enterprises (https://msme.gov.in/know-about-msme) criteria; Small firms have an investment in plant and machinery or equipment of less than Rs. 10 crore (100 million) and an annual turnover of less than Rs. 50 crore (500 million), while medium firms have an investment in plant and machinery or equipment of less than Rs. 50 crore and an annual turnover of less than Rs. 250 crore (Rs. 2.5 billion). Table 1 illustrates a sample profile.

4. Data analysis (PLS-SEM and fsQCA)

4.1. *Common method bias*

We used data collected from a single source in this study; hence, it might suffer from common method bias, which we minimized using two approaches. First, we used a marker variable that was conceptually unrelated to both our predictor and outcome variables (Casidy et al., 2020). All the coefficients in our regression model remained significant after adding this marker variable. Thus, the marker variable did not make any difference to our results. Second, we added a method factor with signs for all the constructs. We found that the ratio of substantive variance to method variance was more than 100:1, and most method loadings were not significant (Bachmann et al., 2021), ruling out common method bias as a concern.

4.2. *Measurement model*

We tested the construct reliability and validity using composite reliability (CR), Henseler's rhoA, and average variance extracted (AVE) for each construct (Anderson and Gerbing, 1988). All the composite reliabilities were above 0.80. All the rhoA values were also above the limit of 0.70 and the AVE were above 0.50 (Hair et al., 2010). As shown in Table 2, all the standardized outer loadings were higher than the cut-off value of 0.60 and statistically significant ($P < 0.001$) with no major cross-factor loadings, which showed convergent validity (Hair et al., 2019). Next, we found that the square roots of all the AVE values for all the constructs were higher than their correlations with each of the other constructs as shown in Table 3, which confirmed discriminant validity (Fornell and Larcker, 1981). We also found all the Hetero-trait Mono-trait (HTMT) ratios higher than 0.85 (Voorhees et al., 2016) as shown in Table 4, which confirms discriminant validity.

4.3. *Structural model*

We used partial least square structural equation modeling (PLS-SEM) to test our hypotheses using a structural model with all the direct and interactive effects, as it is suitable for studies with smaller sample sizes and a focus on predicting variance in outcome variables. We found that all the variance inflation factor (VIF) values were below the threshold level of five (Table 5), thus multi-collinearity was not a serious concern in our data. The results were summarized in Table 6, including standardized path coefficients, coefficient of determination (R^2), effect size (F^2), and predictive relevance (Q^2) (Hair et al., 2019). We found support for all four hypothesized direct relationships (H1-H2), as shown in Table 6. Specifically, technology sensing capability had a significant positive impact on the adoption of both, incremental (H1a: $\beta = 0.389$, $P < 0.01$) and radical (H1b: $\beta = 0.375$, $P < 0.01$)

Table 1. Sample profile

SME characteristics			Participant characteristics		
Industry type	*N*	%	**Gender**	*N*	%
Computer hardware manufacturers	48	21.1%	Male	178	78.1%
Computer software services providers	54	23.7%	Female	50	21.9%
Footwear manufacturers	28	12.3%	**Age**		
Light manufacturers	39	17.1%	Below 25	43	18.9%
Entertainment/Media services providers	22	9.6%	25 to 44	155	68.0%
Market research agencies	37	16.2%	45 to 64	24	10.5%
			65 and above	6	2.6%
No. of employees					
Below 25	63	27.6%	**Education**		
25–50	98	43.0%	High school and below	43	18.9%
50–75	42	18.4%	Graduation	36	15.8%
75–100	16	7.0%	Post-graduation	39	17.1%
Above 100	9	3.9%	Technical/Vocational training	78	34.2%
			Others	34	14.9%
Year of establishment			**Experience**		
Less than 3 years	34	14.9%			
3–5 years	65	28.5%	Up to 12 months	47	20.6%
6–8 years	83	36.4%	13 to 24 months	47	20.6%
8–10 years	33	14.5%	25 to 36 months	74	32.5%
More than 10 years	13	5.7%	More than 36 months	60	26.3%

N, number of responses; %, percentage of responses.

innovations. Similarly, technology response capability also had a significant positive impact on the adoption of both, incremental (H2a: $\beta=0.224$, $P<0.01$) and radical (H2b: $\beta=0.106$, $P<0.01$) innovations. Thus, both H1-H2 were supported.

Next, we used bootstrapping with 5000 iterations to test the moderating effects of market uncertainty (Hair et al., 2017). As shown in Table 7, market uncertainty did not moderate the link between technology sensing capability and incremental innovation adoption (H3a: $\beta=0.029$, $P>0.619$) but had a significant positive moderating effect on the link between technology response capability and radical innovation adoption (H3b: $\beta=0.128$, $P<0.05$). Similarly, market uncertainty had a positive moderating effect on the link between technology sensing capability and incremental innovation adoption (H4a: $\beta=0.087$, $P<0.05$) but had a surprising negative effect on the link between technology sensing capability and radical innovation adoption (H4b: $\beta=-0.103$, $P<0.05$).

To further support our findings, firm size and age were considered as control variables for the adoption of technological innovation by small- and medium-sized enterprises (SMEs). The control variables were included in the PLS path model as single-item constructs. The results indicated that the adoption of technological innovation was found to be significantly impacted by firm size for incremental ($\beta=0.011$, $P<0.01$) and radical ($\beta=0.006$, $P<0.01$). Firm age also significantly affected adoption of both types of innovation (incremental: $\beta=0.023$, $P<0.01$ and radical: $\beta=0.007$, $P<0.01$). Therefore, adoption of technological innovation was significantly influenced by both the firm size and firm age.

In order to find unobserved heterogeneity in the inner structural model as the final step of the structural model evaluation, we used the finite mixture partial least squares (FIMIX-PLS) approach in SmartPLS (Hahn et al., 2002). After analyzing their segment sizes, the metrics produced diverging solutions, which showed that the intended solution had a smaller segment size than the minimal segment size. As a result, the FIMIX-PLS results demonstrated that unobserved heterogeneity had no impact on the model's data (Hair et al., 2012). However, to strengthen the PLS-SEM model's findings, we also employed the fsQCA method, which enhanced our comprehension of the obtained results.

4.4. *fsQCA*

The fsQCA method helps identify a variety of cases that illustrate a particular phenomenon in complex situations (Ragin et al., 2008; Fiss, 2011).

Table 2. Scale items and psychometric properties

Scale items	λ	M	SD	VIF
Incremental innovation (Johansson et al., 2019) (α=0.876)				
1. Regular adaptation of existing services	0.799	4.10	0.763	2.029
2. Improved efficiency of providing services	0.841	3.98	0.795	2.337
3. Expanding services for existing clients	0.761	3.88	0.892	1.771
4. Using improvised ways of providing services	0.838	3.97	0.826	3.007
5. Introducing continuous improvements in services for local markets	0.852	3.85	0.941	3.147
Radical innovation (Johansson et al., 2019) (α=0.863)				
1. Using advanced technology to produce service	0.775	4.69	0.589	1.745
2. Creating totally new services	0.777	4.15	0.304	1.824
3. Changing customers' buying behavior through new services	0.845	4.65	0.034	2.360
4. Using new ways of evaluating quality of services	0.849	3.90	0.931	2.490
5. Prompt addition of new service features compared to competitors	0.773	3.65	0.023	1.725
Market uncertainty (Zhang et al., 2021) (α=0.784)				
1. Managing inventory is very difficult	0.852	3.58	0.436	2.035
2. Setting prices is very difficult	0.879	3.34	0.303	2.084
3. Determining profit margins is very difficult	0.775	3.59	0.552	1.358
Technology response capability (Urban and Maphumulo, 2022) (α=0.644)				
1. We generally respond very quickly to technological changes in the environment	0.643	3.36	0.336	1.432
2. This business unit lags behind the industry in responding to new technologies	0.766	3.64	0.374	1.407
3. For one reason or another, we are slow to respond to new technologies	0.771	3.28	0.143	1.987
4. We tend to resist new technologies that cause our current investments to lose value	0.791	3.40	0.245	1.997
Technology sensing capability (Urban and Maphumulo, 2022) (α=0.0733)				
1. We are often one of the first in our industry to detect technological developments that may potentially affect our business	0.743	3.43	0.320	1.568
2. We actively seek intelligence on technological changes in the environment that are likely to affect our business	0.705	3.63	0.126	1.589
3. We are often slow to detect changes in technologies that might affect our business	0.841	3.59	0.478	1.691
4. We periodically review the likely effect of changes in technology on our business	0.678	3.56	0.458	1.342

M, mean; SD, standard deviation; VIF, variance inflation factors; α, Cronbach's alpha; λ, standardized outer loadings.

Table 3. Discriminant analysis: Fornell-Larcker criteria (1981)

Constructs	1	2	3	4	5
1. Incremental innovation adoption	*0.904*				
2. Market uncertainty	0.625	*0.915*			
3. Radical innovation adoption	0.583	0.628	*0.897*		
4. Technology response capability	0.450	0.444	0.520	*0.835*	
5. Technology sensing capability	0.531	0.502	0.603	0.523	*0.863*
Mean (M)	3.956	3.503	4.208	3.420	4.553
Standard deviation (SD)	0.843	0.430	0.376	0.275	0.346
Average variance extracted (AVE)	0.817	0.837	0.805	0.677	0.745
Composite reliability (CR)	0.876	0.771	0.873	0.782	0.797

Values in italics on the diagonals are square roots of AVEs and the off-diagonal values are the bivariate correlations between constructs.

Table 4. Discriminant analysis: Hetero-trait mono-trait (HTMT) ratio

Construct	1	2	3	4	5
1. Incremental innovation adoption					
2. Market uncertainty	0.096				
3. Radical innovation adoption	0.754	0.085			
4. Technology response capability	0.118	0.769	0.144		
5. Technology sensing capability	0.092	0.859	0.168	0.835	

Table 5. Model fit indices

Constructs	R^2	F^2	Q^2
Technology sensing capability	0.392	0.341	–
Technology response capability	0.307	0.301	–
Incremental innovation	–	–	0.534
Radical innovation	–	–	0.436

Given the predictive focus of this study, using the fsQCA method with PLS-SEM strengthens the findings through adequate configurations of antecedents toward casual combinations (Rasoolimanesh et al., 2021; Marzi et al., 2023). As fsQCA assumes proximity and asymmetry between exogenous and endogenous constructs, it offers detailed insight into variables configuration to determine that may also lead to the right decision for the adoption of technological innovations by SMEs.

Following the 5-step methodology recommended by Rasoolimanesh et al. (2021) for the fsQCA method utilizing PLS-SEM, the score for each construct was initially calculated. First, all the scores were rescaled to values between 0 and 1, wherein 0 refers to non-membership and 1 to full membership based on the PLS-SEM construct scores. Second, truth tables were developed to investigate all possible configurations and to enable the fsQCA application to eliminate rows with two or fewer cases and consistency less than 0.80 (Olya et al., 2020). Third, in order to calculate the consistency and coverage of all possible configurations, the intermediate solution was chosen to define consistency (Pappas and Woodside, 2021).

Fourth, all possible configurations' consistency and coverage were calculated by identifying the sufficient configurations with coverage >0.2 and consistency >0.80 (Pappas and Woodside, 2021; Rasoolimanesh et al., 2021). Fifth, to increase the credibility of the fsQCA's findings, we applied the criteria outlined by Pappas and Woodside (2021) and performed an analysis to ascertain the predictive validity of the proposed model. We divided the total sample into two groups and then used the data from the second subsample to investigate the causal configurations derived from the first subsample. This evaluation revealed that there were no substantial differences between the two groups.

The results of fsQCA demonstrated adequate configuration of dimensions of adoption of technological innovation by SMEs. The results established sufficient configuration for all two cases to generate outcome (Table 8). Both sets of solutions presented high levels of coverage and consistency, in line with the methodological requirements of Ragin et al. (2008) which provided more heterogeneous combinations than PLS-SEM results. As shown in Table 8, the overall solution coverage for the cases associated with the willingness to adopt incremental innovation adoption was able to explain 91% of the cases (coverage 0.914). In the case of the adoption of radical innovation, the overall coverage explained 87% of the cases (coverage of 0.872). The four configurations for incremental and radical innovation showed high levels of coverage and consistency by themselves, presenting different paths to achieve high levels of willingness to adopt technological innovation.

4.5. *Artificial neural networks technique*

We also used Artificial Neural Networks (ANN) technique with the Multi-Layer Perceptron (MLP) method-training algorithm in SPSS. We used root mean square error (RMSE) values to check how accurate the network model was. Ninety percent of the data was used to train the ANN model, and ten percent of the data was used to test how accurate the trained model was (Chong and Bai, 2014; Syam and Sharma, 2018). The best way to test a neural network is to change the number of hidden nodes from one to ten. We did ten cross-validations and used the exogenous factors that were important in the SEM analysis as covariates in the ANN model. Specifically, we used technology sensing and response capabilities as covariates in the input layer of the network model. The output layer of the model had incremental innovation and radical innovation as the dependent variables. The RMSE results for the 10 validations are shown in Table 9. The average values of the RMSE of the training model and the testing model were 0.5011 and 0.5305, respectively. Similarly, the

Table 6. Hypothesis testing

Path relationship	O	M	STDEV	T	*P*
H1a: Technology sensing capability → Incremental innovation adoption	0.389	0.389	0.056	6.899	0.000
H1b: Technology sensing capability → Radical innovation adoption	0.375	0.377	0.068	5.518	0.000
H2a: Technology response capability → Incremental innovation adoption	0.224	0.225	0.073	3.068	0.002
H2b: Technology response capability → Radical innovation adoption	0.106	0.104	0.077	1.384	0.007
Firm size → Incremental innovation adoption	0.011	0.314	0.056	2.135	0.000
Firm size → Radical innovation adoption	0.006	0.218	0.043	3.139	0.001
Firm age → Incremental innovation adoption	0.023	0.189	0.058	1.673	0.000
Firm age → Radical innovation adoption	0.007	0.164	0.092	2.862	0.000

O, original sample; M, sample mean; STDEV, standard deviation; T, T-statistic; *P*, *P*-values.

Table 7. Moderation analysis

Relationship	O	M	STDEV	T	*P*
H3a: Technology sensing capability × Market uncertainty → Incremental innovation adoption	0.029	0.042	0.057	0.498	0.619
H3b: Technology sensing capability × Market uncertainty → Radical innovation adoption	0.128	0.135	0.053	2.399	0.017
H4a: Technology response capability × Market uncertainty → Incremental innovation adoption	0.087	0.098	0.060	2.056	0.040
H4b: Technology response capability × Market uncertainty → Radical innovation adoption	−0.103	−0.107	0.051	2.003	0.046

O, original sample; M, sample mean; STDEV, standard deviation; T, T-statistic; *P*, *P*-values.

Table 8. Sufficient causal configurations

Configurations	Row coverage	Unique coverage	Consistency
Incremental innovation adoption = f(TSC, TRC and MA)			
~TSC*TRC*MC	0.565	0.014	0.911
TSC*TRC~MC	0.519	0.004	0.916
TSC*TRC*MC	0.575	0.010	0.915
TSC~TRC*MC	0.766	0.243	0.947
Solution coverage: 0.914; solution consistency: 0.867			
Radical innovation adoption = f(TSC, TRC and MA)			
~TSC*TRC*MC	0.769	0.053	0.894
TSC*TRC~MC	0.597	0.006	0.905
TSC*TRC*MC	0.568	0.014	0.913
TSC~TRC*MC	0.671	0.002	0.920
Solution coverage: 0.872; solution consistency: 816			

~; Negation, *; Logical conjunction.
MU, market uncertainty; TRC, technology response capability; TSC, technology sensing capability.

standard deviation values were 0.0336 for the training model and 0.0554 for the testing model. These values indicated a consistent model fit and showed the relationship between independent and dependent variables. Finally, Table 10 presents the sensitivity analysis results in the ANN model with the technology response capability showing a higher average importance (0.5263) to predict the adoption of technology, compared to technology sensing capability (0.4010).

5. Discussion and implications

5.1. *Theoretical contributions*

This study investigates the link between technological opportunism and the adoption of technological innovation by SMEs and the moderating impact of market uncertainty on this link by applying two different quantitative analysis software (i.e., PLS-SEM and fsQCA). Our analysis of data collected from a sample of Indian SMEs confirms the positive association between technological opportunism (conceptualized as technology sensing and technology response capabilities) and the adoption of technological innovation (incremental and radical). In addition, our study responds to the call of the previous studies (e.g., Sheng and Chien, 2016; Marzi et al., 2023) to quantitatively validate their findings. Importantly, it examines how

Table 9. bb Values through neural networks

Network	Training model	Testing model
ANN1	0.553	0.466
ANN2	0.501	0.431
ANN3	0.512	0.470
ANN4	0.443	0.517
ANN5	0.475	0.551
ANN6	0.503	0.597
ANN7	0.553	0.529
ANN8	0.477	0.581
ANN9	0.473	0.593
ANN10	0.521	0.570
Mean	0.5011	0.5305
SD	0.0336	0.0554

Table 10. Sensitivity analysis

Constructs	Relative importance
Technology sensing capability	0.4010
Technology response capability	0.5263

various configurations of exogenous and endogenous constructs influence endogenous constructs differently from symmetric and asymmetric perspectives.

This study supports the view that the adoption of technological innovation by SMEs is core to relationships with their customers and is a function of their capability to sense and respond to emerging technological changes in the environment. The rapid change in innovative technology has potential to uplift the relationship that SMEs have with their customers if adopted in a timely fashion. However, sensing the technological change is only the first step toward its adoption, and SMEs should have the willingness and the ability to further engage their partners in the process of adopting such innovations. Some SMEs may sense new technologies but may not respond to these new technologies, because of the fear that doing this may cannibalize their existing products, markets, and organizational relationships and result in high switching costs (Casidy et al., 2020).

Interestingly, in our sample, most of the SMEs are willing to adopt both incremental and radical innovations to leverage their technology sensing and response capabilities. Dynamic capabilities theory is used to understand the capabilities of the SME to sense and respond to technological changes in order to remain competitive (Teece et al., 1997). Furthermore, according to this theory, firms that have the ability to sense and respond to changes in their environment will be able to transform their capabilities to develop, use, and sustain new technologies, thus allowing them to remain competitive and successful (Sermontyte-Baniule et al., 2022). In summary, our findings support the dynamic capabilities theory, which suggests that firms must develop and maintain their capabilities to sense and respond to technological changes in order to remain competitive. SMEs possess the ability to sense and respond to changes in their environment, allowing them to transform their capabilities to develop, use, and sustain new technologies. This allows them to remain competitive and successful.

Our results also show that uncertain market conditions may generally hasten the adoption of technological innovation as a result of SMEs sensing capability and response capability. However, contrary to our expectation, we find the association between technology response capability and adoption of radical technological innovation becomes weaker under high market uncertainty. We believe this can be due to the perceived costs of adopting radical innovations, in terms of their monetary and non-monetary costs as well as the fear of losing their current products and services with the advent of new radical technologies. In this context, the contingency theory suggests that the relationship between organizational characteristics such as technology response capability and the success of various management strategies such as adoption of technological innovation may vary depending on the contextual factors. Our findings support this theory as we observe a weaker association between technology response capability and adoption of radical technological innovation under high market uncertainty. This result implies that SMEs should take into account the contextual factors such as market uncertainty when making decisions about technological adoption. Furthermore, our results suggest that SMEs should focus on strengthening their technology response capability, as it is still an important factor in their ability to adopt radical technological innovations under high market uncertainty.

5.2. *Managerial implications*

The findings of this study offer SME owners/entrepreneurs new insights on how to adopt new innovative technology in changing and difficult time with limited resources. The study suggests that SMEs should focus on developing an innovative mindset to identify the opportunities and challenges associated with technology adoption. They should also focus on creating a culture of innovation by establishing open communication channels and encouraging employees to come up with innovative ideas. Moreover, SMEs should be aware of the importance of external partners in the process of technology adoption, such as technology providers and government agencies. Finally, SMEs should take advantage of available resources to speed up their technology adoption process, such as online training and technology assessment tools.

With the growing rates of vaccination against COVID-19 and the gradual opening up of the global economy, businesses are expected to achieve the employment and productivity growth needed to pull us out of the economic decline during the pandemic. In this context, being the growth engines of most modern economies, especially in the emerging economies, SMEs need to push forward with efforts to grow their businesses once again and meet their aspirations of business expansion through the use of technological innovations. Global trends toward increasing digitization and automation, shifting supply chains, urbanization, rising incomes, and demographic shifts are all likely to give a boost to the post-COVID-19 pandemic economic recovery efforts. Irrespective of the size of their business, technological innovations have the potential to benefit the SMEs by helping them adapt their operations to match the changing needs of their customers, supply chain partners, and other stakeholders.

The firms' ability to sense and respond to new technologies is called technological opportunism, and it is expected to trigger the adoption of innovative technologies by SMEs. The results of the current study suggest that SMEs in emerging economies may not only possess technology sensing and response capabilities but also acts as a driving force that can enhance and improve their operations under the market uncertainty. Moreover, we test the impact of context-specific technological opportunism and innovation capabilities that are driven by dynamic capabilities of the SMEs, on the adoption of incremental and radical technological innovations in diverse business sectors. Better application of SMEs operations leads to radical development of products and new services, and, consequently, rapid problem solving. Our findings would help SME owners and managers understand the importance of their technology sensing and response capabilities and leveraging these to improve their adoption on both incremental and radical innovations, especially during uncertain market conditions, such as the ongoing COVID-19 pandemic.

6. Limitations and future research directions

This research has a few limitations that future research may address. First, we rely on a convenience sample of SMEs from six diverse industries through an Indian university's incubator to have a broadly representative sample, but our findings may not apply to other industries. Hence, future research may use a representative sample of SMEs in the emerging economies across industries, sizes, and geographical locations, to test the generalizability of our conceptual model and hypotheses. Second, we use a quantitative method to explore the relationship between technological opportunism and adoption of technological innovation by SMEs, and the moderating role of market uncertainty in this process, as all these are well-established constructs. However, it would be useful to adopt a mixed-method approach to better understand these complex relationships. Third, we did not consider the role of other factors, such as financial resources, to examine how technological opportunism may affect the firm performance through the adoption of innovative technology by SMEs as suggested by some researchers (e.g., Tiberius et al., 2021). Future research may add relevant financial resources measures and performance outcomes to our conceptual model to examine how the drivers (sensing and response capabilities) and the type of innovation adoption (radical versus incremental) may influence SME performance. Finally, this study focuses on the adopters and potential adopters of innovative technologies and ignores other types of SMEs that do not adopt technological innovation. However, studying the decision-making behavior of those types of entrepreneurs may provide insights into the obstacles hindering the acceptance of technological innovations by SMEs. Future research may address this limitation by studying both adoption and non-adoption of technological innovations.

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Data availability statement

The data used in this paper would be made available upon request.

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