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Bridging the 'Concept–Product' gap in new product development: Emerging insights from the application of artificial intelligence in FinTech SMEs

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ABSTRACT

Building on the literature on the concept-product gap in new product development, we examine how FinTech SMEs are developing Artificial Intelligence (AI)-based innovations and which organisational or project factors best contribute to the acceleration of AI innovation. The empirical evidence collected from interviews with key stakeholders, practitioners' forums, and public company documents yields two distinct approaches that differ in their potential for accelerating innovation and reducing the concept-product gap. From a contingency perspective, these two approaches are expanded into four distinct development process configurations, contingent on the business development stage, reliance on 3rd party platforms, availability of high volumes of data, investment level, organisational agility, and level of novelty. The resulting process typology could be used as a diagnostic tool for FinTech SMEs interested in effectively leveraging AI innovation. Using contingency theory, we further develop these insights into a new theoretical framework to explain how AI innovation development unfolds in FinTech SMEs and the rationale for different implementations. Our new process typology and theoretical model can help researchers investigate the mechanisms underlying technological innovation processes. We further identify the specific reasons why the potential of AI for creating new services and disrupting incumbents via digital startups has not been fully realised even in contexts with significant investment and support from public and private business development programmes. This field is still rapidly evolving, and thus, new areas for future research are also highlighted.

1. Introduction

This study explores the AI product development and innovation processes in FinTech SMEs and uncovers key factors that may contribute to their acceleration, and subsequently to the concept-product gap reduction. Our focus is on the producer side in Montreal, Canada, which offers an excellent environment for this study. Montreal has established itself as one of the main global AI knowledge hubs, leading to a surge of high-tech startups, particularly in FinTech.[1] The financial sector has been an early adopter of AI,[2, 3 and 4] and is among the most significant contributors to the global economy.

The concept-product gap has been extensively studied in the innovation literature (Cooper and Kleinschmidt, 1986; Cooper, 1994; Griffin, 1997; Grönlund et al., 2010; Cooper and Sommer, 2016), and its antecedents and consequences in different contexts have been identified (Chen et al., 2010; Cankurtaran et al., 2013). Several approaches for accelerating new product development (NPD) have been developed (Huang et al., 2017; Cooper, 2021) as well as guidelines for bridging the gap (Cooper, 2001; Kahn et al., 2006; Ettlie and Elsenbach, 2007; Cooper, 2008). However, most NPD studies have been based on large organisations (Moultrie et al., 2007; Berends et al., 2014) and a shortage of empirical research on NPD practices in SMEs, particularly in technological SMEs, has been highlighted in recent systematic reviews (Marzi et al., 2020; Iqbal and Suzianti, 2021). According to the World

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[1] https://www.stationfintech.com/en/read-news-and-publications/artificial-intelligence-is-making-its-way-in-the-quebec-financial-services-industry.
[2] https://www.forbes.com/sites/louiscolumbus/2020/10/31/the-state-of-ai-adoption-in-financial-services/.
[3] https://www.jbs.cam.ac.uk/faculty-research/centres/alternative-finance/publications/transforming-paradigms/.
[4] https://go.thoughtspot.com/white-paper-economist-ai-future-of-financial-services.html.

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Bank data[5] SMEs constitute the predominant portion of businesses worldwide and are significant contributors to job creation and global economic development. Understanding how to accelerate SMEs development processes will help increase their productivity and realise their full economic potential (Oliveira et al., 2018; Iqbal and Suzianti, 2021). Examining SMEs from the perspective of NPD can broaden the explanatory scope of the concept-product literature given that the characteristics and requirements of the NPD process in SMEs differ significantly from those in large companies (Marzi et al., 2020). SMEs have the potential to be more nimble, entrepreneurial and adaptable to market changes due to their sizes. However, they may also be less productive and less able to compete with the large organisations due to their informal processes and limited resources (Oliveira et al., 2018; Iqbal and Suzianti, 2021). This holds particularly true for firms developing AI products, which introduce significant differences to the NPD processes due to the unique and resource-intensive development stage (Davenport and Ronanki, 2018; Ransbotham et al., 2018; Brock and von Wangenheim, 2019; McCarthy et al., 2019). Furthermore, the research on developing AI innovation in FinTech SMEs lacks solid theoretical foundation, as noted in recent systematic reviews (Collins et al., 2021; Hendershott et al., 2021). Our study addresses these issues by exploring the process of AI innovation development within SMEs in the financial sector through the lens of contingency theory.

Data was primarily gathered from: (i) semi-structured interviews with AI in FinTech (AIFT) industry experts including senior executives from six AIFT companies, supplemented by email exchanges and phone calls after the interviews; (ii) key insights from Canadian FinTech forum including interviews and other exchanges with selected thought leaders; (iii) the websites of 28 AIFT companies and (iv) relevant news, public research and media reporting on these firms. These multiple sources enabled a comprehensive understanding of the AI product development and innovation processes in these FinTech SMEs. We used comparative process analysis to study these companies (Berends et al., 2014; Jiang and Rüling, 2019), in parallel and supported by thematic analysis of the collected data (Braun and Clarke, 2012), to unravel different innovation process configurations and understand the rationale for different AI development implementations.

This study contributes to our understanding of AI product development and innovation processes in FinTech. First, emerging from our data is a new typology of innovation development processes that can serve as a guide for understanding the factors contributing to differences in process configurations. SMEs interested in developing AI-based products can use this typology to understand their current development stage, where they want to be in the future, and how to get there.

Secondly, from the perspective of contingency theory we develop a new theoretical model for understanding the development process for AI innovation. It identifies key factors contributing to different process configurations and distinguishes between resource-driven and goal-driven process behaviours that are contingent on the investment level in AI and organisational agility. It shows that AI innovation development processes are fundamentally different from other innovation types, as the role of technology is increasingly superseded by the importance of data.

Finally, this study offers empirical observations on the current state of AI in FinTech. Although the expectations are that AI will create new opportunities for SMEs to challenge large organisations (Chalmers et al., 2021), it has not happened in the financial sector, where most SMEs still lag behind large financial institutions which have been more proactive in adopting AI and benefitting from it through efficiency gains, and improved product customisation (Jung et al., 2019). There are also specific reasons why the potential of AI in creating new services and disrupting incumbents via digital startups has not been realised even in a context where there is significant investment and support from public and private business development programmes.

The paper is organised as follows: the next section presents a critical review of the literature and the main theories underlying our research, followed by the description and justification of the empirical method. The data analysis and results are then presented. The paper concludes with a discussion of the main findings, their theoretical and practical implications, the study's limitations, and future research directions and opportunities.

2. Background and theoretical framework

This section offers review of relevant literature on the concept-product gap, NPD, and AI applications in FinTech as background, followed by a description and the rationale for using contingency theory to underpin the research. The resulting conceptual model, presented in Fig. 1, is used to guide our empirical effort.

2.1. The concept-product gap

In the context of technological innovation, the concept-product gap is the time it takes an organisation (or individual) to progress from proof of concept to delivering a fully deployable product (Ng, 2021) and implies a potentially laborious process of 'bridging the gap' marked by inherent uncertainties, as the process does not always lead to success (Castellion and Markham, 2013). This challenge is especially pronounced in the context of AI innovation (outside consumer internet businesses) which, according to practitioners is difficult to successfully deploy beyond pilot programmes (McCormick, 2020; Ng, 2021; Davenport and Mittal, 2023). In the academic literature, the concept-product gap is closely related to organising and accelerating the development phase in technological innovation processes (Salerno et al., 2015).

The research on innovation processes is multidisciplinary, comprising the literature on NPD (Cooper and Kleinschmidt, 1986; Cooper, 1994; Griffin, 1997; Grönlund et al., 2010; Cooper and Sommer, 2016), and also drawing from marketing, operations research, strategy and other disciplines (Nambisan, 2003). In the context of technological innovation in SMEs, previous studies have extensively leveraged literature from entrepreneurship and information system (IS) domains. Both offer valuable insights into different aspects of the product innovation process and thus suitable to be 'reference disciplines' (Nambisan, 2003) in our study.

2.2. New product development (NPD)

NPD is essential for the success and survival of firms in fast-paced competitive markets (Brown and Eisenhardt, 1995). The research on NPD can be traced back to early studies on both stepwise and Stage-Gate models (Booz, 1982; Cooper and Kleinschmidt, 1986) that view the development processes as a series of well-defined stages (or steps), each ending with a 'stage gate', a decision point for progressing to the next stage. This model has guided new product development in practice, particularly in large organisations (Griffin, 1997; Barczak et al., 2009) and closely aligns with software development and project management frameworks commonly used, such as waterfall[6] and PRINCE2.[7] These traditional NPD models focus on the product development process at a higher level of granularity, which involves a predefined sequence of NPD stages, such as idea generation, selection, development, and launch/diffusion/sales (Salerno et al., 2015). A growing number of scholars are also recognising that different types of NPD should be managed differently, especially given different levels of novelty

[5] https://www.worldbank.org/en/topic/smefinance.

[6] www.forbes.com/advisor/business/what-is-waterfall-methodology/.

[7] https://www.axelos.com/certifications/propath/prince2-project-management.

(O'Connor, 2012; O'Connor and Rice, 2013). Despite this aspect and other criticisms, such as being time consuming, overly bureaucratic and detrimental to performance (Grönlund et al., 2010; Ahmad et al., 2013; Bianchi et al., 2020), the Stage-Gate model continues to be adapted and used in contemporary technological innovation practice via open innovation, user-centric, and agile hybrids (Grönlund et al., 2010; Cooper and Sommer, 2016; Edwards et al., 2019; Bianchi et al., 2020).

In recent years, agile development, and project management approaches, such as Scrum, have become a de facto standard in the software industry and technology firms. These methodologies are based on Agile Manifesto[8] principles and characterised by their iterative, time-boxed development processes and focus on delivering products both incrementally and frequently. They also emphasise the specification of process aspects during development iterations like planning, development, and review (Dybå and Dingsøyr, 2008). These multiple iterations of goal setting (review and planning) followed by resource commitment (implementation) activities are some of the defining characteristics of agile development. Compared to Stage-Gate, the Agile model of innovation is more applicable to dynamic environments characterised by high market and technology uncertainties (Bianchi et al., 2020; Paluch et al., 2020). Recently, the Agile–Stage-Gate hybrid model (Cooper and Sommer, 2016) has shown promise for accelerating development in manufacturing SMEs (Edwards et al., 2019). However, its impact on software industry is less favourable, as the effects of traditional gating system on NPD performance remain negative; therefore an Agile-only approach may be a better option for technology firms not already using Stage-Gate model, including new ventures (Bianchi et al., 2020). This highlights the necessity of further research on technology-based SMEs' NPD processes (Iqbal and Suzianti, 2021).

The research on NPD and innovation processes is primarily focused on success-factors/variance studies, as well as strategic and stakeholder involvement issues, particularly in large organisations (Moultrie et al., 2007; Berends et al., 2014; Marzi et al., 2020). Within the SME NPD literature the emphasis lies on strategic, ICT and quality issues (Iqbal and Suzianti, 2021). However, with a few notable exceptions (e.g., Berends et al., 2014; Salerno et al., 2015), the process perspective on new product development in SMEs is largely missing (Marzi et al., 2020). Berends et al.'s (2014) study on innovation processes in small manufacturing firms (5–150 employees) suggests that the traditional linear NPD model does not always fit well with SMEs, the behaviour of which tends to be driven by resource constraints and quick time-to-market requirements, and the structural differences between the innovation processes in these firms stem from various project contingencies, such as length of the product life cycle, maturity of market and technologies, R&D expenditure, role of the client, and time-to-market. Salerno et al. (2015) made a similar argument in a broader context by using firms of different sizes from different sectors to emphasise the necessity for firms to adopt non-linear NPD processes to adapt to market and technology uncertainties. Emerging from their data are different (innovation) process configurations, each addressing a specific context and other contingencies. Further, they highlight specific differences in the SMEs approaches to NPD, including making creative use of resources, scoping innovation to what is affordable with available resources, extensive use of external resources and the iterative nature of innovation processes.

While these studies do provide valuable insights into how innovation processes may unfold in SMEs, their context is not specific to AI technologies, and their focus is not the development stage of innovation processes. As shown later in this study, AI development produces additional complexities, uncertainties, and unique challenges; therefore, it is worth studying it separately from other forms and stages of technological innovation. Recently, several new reviews have emerged centring on the intersection between innovation and AI (Haefner, et al., 2021; Truong and Papagiannidis, 2022), as well as the link between AI and business strategy (Borges et al., 2021). However, it is important to highlight that in our study, AI is the primary product to be developed, rather than serving primarily as a supportive technology for assisting innovators or strategy developers.

2.3. *Artificial intelligence in FinTech (AIFT)*

Although there is still no commonly accepted definition of AI, one of the most frequently cited sources is Russel and Norvig's book, *Artificial Intelligence: A Modern Approach,* and its editions (Collins et al., 2021). They define AI as a study field that concentrates on general principles of rational agents and the components for constructing them (Russel and Norvig, 2016: p.5). This definition moves away from the 'human behaviour' definitions of AI so common in cognitive sciences and the 'strong vs. weak AI' debates and toward a more rationalist approach based on mathematics and engineering. It is more suited for our study, which focuses on AI use for solving specific problems and support human activities. Moreover, this study focus on data-driven AI variant, which is most frequently used in business and financial sectors and includes software technologies, such as machine-learning (ML), deep learning (DL), reinforcement learning (RL), and natural language processing (NLP) (Jung et al., 2019; Collins et al., 2021; Mariani et al., 2022).

The crucial difference between AI and other software innovation is having as a starting point data and no algorithm. Initially, an algorithm (or model) is created through an iterative construction process using a training dataset. Subsequently, this resulting algorithm is deployed on a new set of data to produce the outputs. It is a process known as ML Development Pipeline (Jung et al., 2019, p. 21). Its high dependence on data from the training and production environments calls for adapting generic NPD models to the AI-specific development environment. Several authors (Verganti, et al., 2020) put forward a proposition in a context of data-driven AI, traditional design process then becomes a data-enabled 'problem solving loop', wherein the development and deployment stages iterate and overlap because of the need to continuously tune the algorithm (the trained model) in the target environment. Numerous examples are reported in the literature and press demonstrating that the AI deployment step rarely works according to expectations. Many practitioners (Benbya et al., 2020; Ng, 2021) have thus been calling for a more disciplined approach to AI development and deployment, namely, the MLOps, or ML Operations, arguing that managing AI development differs from traditional software development operations (DevOps). However, little is yet known on how these development processes are structured in actual practice, especially in the context of SMEs as many, outside consumer internet business, lack data, infrastructure, or skills found in large organisations (Ng, 2021).

As one of the early AI adopters, the financial sector offers a rich context for researching AI innovation. In 2020[2], 70% of all financial firms utilised ML for tasks such as cash flow prediction, credit scores refinement and fraud detection. The adoption of AI innovation has further accelerated in response to COVID-19.[9]

Technological innovation in financial services is commonly referred to by the acronym FinTech. While traditionally FinTech has been used in backend systems of established FIs for fraud detection, risk management, and pricing, more recently it is starting to enable client-side applications, such as loans, payments, asset management, and crowdfunding. Additionally, FinTech has extended its reach into other sectors, including retail, travel, and education among others. It is known as 'embedded FinTech' or 'embedded financial services.' While there has been a shift in the focus of 'FinTech' in the press from innovation to disruption (Zavolokina et al., 2016) particularly due to the use of digital

[8] The agile manifesto at https://agilemanifesto.org.

[9] https://www.bankofengland.co.uk/quarterly-bulletin/2020/2020-q4/the-impact-of-covid-on-machine-learning-and-data-science-in-uk-banking.

Table 1
AI business values (adapted from Davenport and Ronanki, 2018).

Key term	Automation	Engagement	Data insights
Definition	Automation of business processes	Engagement of customers and employees	Detection and interpretation of patterns from vast volumes of data
Level of novelty	Low	Medium	High
Business area	Back-office	•Customer management •Employee information system	•Customer management •Risk management •New product development
AI function	Data curation	Prediction and classification of customer behaviour	•Pattern detection ("analytics on steroids") •Discovery of new data for better analytics
Technologies	NLP	NLP and ML	ML and DL
General usecases	•Transferring data from e-mail and call centre systems •Extracting information from multiple documents	•24/7 customer service •Employee helpdesk and IT support •Product and service recommendation systems	•Fraud detection •Automating personalised targeting of ads •Predicting customer buying intentions •Market predictions
FinTech usecases	•Extracting information from financial documents (e.g. invoices)	•Assets management (recommendations) •Financial/robo-advisors	•AML and fraud detection •Stock predictions •Risk assessment/ underwriting •Pricing predictions •Propensity modelling •Assets management (insights)

currency and blockchain technologies that promote new business ecosystems (Hendershott et al., 2021, p.2), this study assumes a wider meaning of FinTech, to denote (digital) technology-based innovation in financial services. Although this innovation type can be sourced in all three types of financial companies, namely, FinTech SMEs, big technology companies (e.g., Google, Amazon, and others) and traditional FIs, such as banks and insurance companies, the focus of this study is on SMEs.

In the FinTech context, it is also useful to consider the potential business value of the AI innovation, such as, automating business processes, engaging with customers and employees, and gaining insights through data analysis (Davenport and Ronanki, 2018). Table 1 provides a summary of the defining characteristics of these three AI innovations building blocks and some examples of its use in the FinTech domain.

The research on AI in business has been dominated by practitioner-focussed literature that is investigating potential and evaluating the experience with AI adoption in large organisations (e.g., Davenport and Ronanki, 2018; Brock and von Wangenheim, 2019; McCarthy et al., 2019). While there have been suggestions that learning from successful implementations of 'AI factories', which are organisations extensively utilising AI in their operating models, such as Netflix, Tesla and Airbnb (Iansiti and Lakhani, 2020), could be a way forward for any firm looking to incorporate AI into their own business models (Verganti, et al., 2020), little is still known whether this practice is actually realised, particularly in the context of SMEs outside the consumer internet businesses, where resource limitations present significant barriers to AI implementation.

2.4. *Theoretical approaches to innovation development*

The research on innovation management draws from diverse theoretical perspectives (Mariani et al., 2022; Steele and Watts, 2022) including, diffusion of innovation (Rogers, 1995), open innovation (Chesbrough et al., 2006), knowledge-based theory of the firm (Nonaka, 1994), technology acceptance model (Davis, 1989), and dynamic capabilities (Teece and Pisano, 2003). Most focus on the antecedents or outcomes of innovation, rather than the actual innovation processes. Paraphrasing McKelvie and Wiklund (2010), we argue it is necessary to better understand the "how" and "why" aspects of innovation before turning attention to how much or how fast firms can benefit from it. In this study, we thus adopt contingency theory as the starting point for understanding innovation processes in organisations to explain *how* innovation development processes are structured, and *why,* i.e., under which specific conditions these processes exhibit particular configurations.

Contingency theory suggests that there is no one best way to structure an organisation, i.e., an organisation's structure and process should fit its unique context in order to survive and perform well (Drazin and Van de Ven, 1985). This theory has dominated the study of organisational design for nearly sixty years (Woodward, 1965; Lawrence and Lorsch, 1967) and drawn from the situational approach to management and leadership (Fiedler, 1967). The contingency approach has been applied in innovation research as a way of coping with the uncertainty that is intrinsically a part of every new project (Salerno et al., 2015; Gama et al., 2022). The interpretation of contingency theory in this same context relies on the view of the (innovation development) projects as being temporary organisation and open systems (Cleland and Kerzner, 1985; Turner and Müller, 2003). The theory suggests that there is more than one way of managing innovation development, or 'bridging the

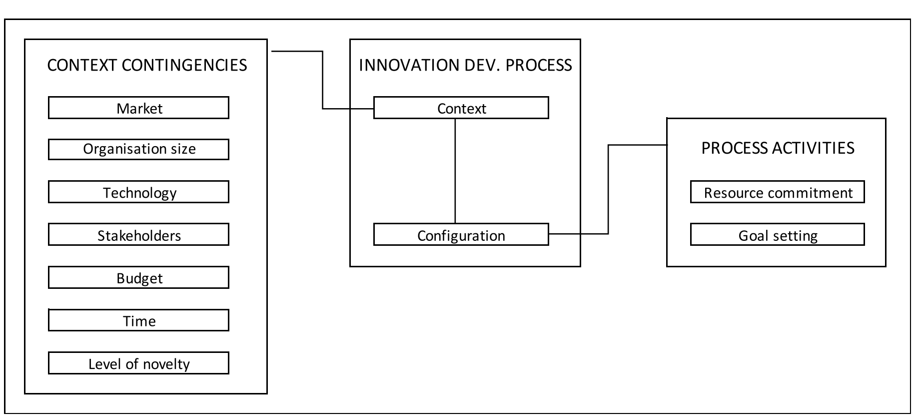

Fig. 1. The conceptual framework of technological innovation processes.

concept-product' gap; and tailoring innovation development processes to fit their environment can reinforce project performance (Lee et al., 2021). The way taken depends on various environment factors, including market, technologies, time, budget, stakeholders, and degree of novelty (Ernst, 2002; Salerno et al., 2015). Further still, organisation size plays an important role in differentiating innovation processes, with SMEs often noted for their distinct behaviour, exhibiting more iterative and resource constrained approaches compared to large organisations (Berends et al., 2014; Salerno et al., 2015). However, contingency theory does not go as far as providing insight into the innovation process building blocks, or configurations. A focus on the specific characteristics of digital technologies, including AI, may hold potential for offering a more fine-grained theoretical foundation for developing digital innovation (Nambisan, 2017).

2.5. Research questions and conceptual framework

The literature review helped us identify the gaps and thereby further refine the aims of our study into the following two research questions: (1) how do SMEs develop new AIFT products? and (2) which organisational or project factors contribute to an acceleration of AI innovation?

The conceptual framework that guided this research is summarised in Fig. 1. The contingency lens is represented by Context attributes (market, technology, stakeholders, and others) and a dependency relation between Innovation Development Process and Context concepts. To complement the contingency theory and enable a view inside the innovation development processes, this research focuses on a more granular, process activity level and borrows from effectuation theory in distinguishing between resource commitment and goal setting Process Activities (Sarasvathy, 2001; Fisher, 2012; Berends et al., 2014; Jiang and Rüling, 2019). These activities are then combined into a configuration to provide a structure to an Innovation Development Process. Moreover, this framework indicates that different process configurations are contingent on specific Context variables (Ernst, 2002; Salerno et al., 2015), as represented with the arrow between the context and configuration attributes of the Innovation Development Process. This framework provides the starting point for our data analysis, with some of the Context variables as fixed (financial *market*, SME *organisation size*, AI *technology* and development teams as *stakeholders*) and others (budget, time, level of novelty) varying in different processes. Our study further extends and refines this framework using the new concepts, relationships, and attributes emerging from the empirical data on AI innovation in FinTech.

3. Research design

Our research design was influenced by several important factors. First, the focus was on the "how" questions (Eisenhardt and Graebner, 2007), which involved uncovering the detailed steps, interactions, and factors contributing to various process configurations for innovation development; second, the challenge of accessing data, and third, the lack of previous studies or theories directly applicable to our two research questions. These factors suggested the need for an in-depth exploration of the phenomenon in question within a specific real-life context, using multiple sources of data, and the aim of expanding the existing theory to provide a broader view of the phenomenon being studied. Therefore, our study is based on the exploratory case-study approach (Yin, 2009), where the phenomenon under investigation is 'the AI product development and innovation processes in FinTech' with a focus on the SME producers of AIFT innovation. The empirical evidence for our research is provided by the AIFT SMEs that are operating in Montreal, a global financial centre and one of the leading AI-innovation hubs in the world. Our research design utilises multiple data sources, including primary data gathered through interviews with AIFT experts and decision-makers, secondary data from select AIFT organisations, and primary and secondary data gathered from a national FinTech forum and various research reports. These data were employed in various ways, primarily for categorising AIFT development processes within these organisations, classifying different types of AIFT SMEs, and providing a broader context for process analysis and other empirical findings, respectively. The total size of the dataset collected for the analysis was 1749 pages of Ariel, 12 pt, single-spaced text comprising of four distinct subsets of data as shown in Tables 4 and 5.

3.1. Data collection methods

A search performed in September and October of 2021 of various reputable Canadian AI and FinTech business and academic platforms (Canada FinTech Forum, Fintech Cadence, IVADO Labs, Mila, Mitacs, NextAI, and Station FinTech Montreal) produced a list of 238 active private businesses operating in Montreal with potential AI or FinTech capabilities. After checking these companies' websites, the list was reduced to 46 (19.33%), using specific selection criteria: company's public description mentions AIFT capabilities, the company is not a big tech (e.g., Google) or financial institution (e.g., Bank of Montreal), and the company is part of the Montreal AIFT ecosystem. After further information was gathered from public sources and in some cases vie emails exchanged with company representatives, 16 (34.78%) companies were excluded from the study, as they have only limited AI or FinTech capabilities within their core business portfolios. Typically, a website of an organisation will claim that their products are powered by AI, but email responses would clarify that the company is not using enough AI at this point in time. Another example are those companies that were recently acquired by big organisations (e.g., Dataperformers acquired by Deloitte). Finally, two more firms were removed from the data sample for this study due to their sizes (500–1000), as the focus was on small and medium sized companies (fewer than 250 employees).

The remaining 28 firms thus formed the basis for this research and were included in further analysis, initially using publicly available information online from their and other websites, including crunchbase.com, appengine.ai, croft.co, Station FinTech Montreal, LinkedIn, twitter, and others. A summary of these FinTechs is shown in Table 2 and Table 3.

The sample included 16 (57.14%) startups and 12 (42.86%) more mature firms that were in the process of scaling up their operations and generating revenue. It is important to emphasise here that the startups were at different stages of development and included firms that were already testing their pilots with many subscribers (e.g., C13) and business partners (e.g., C3, C10). Most of the firms were operating as B2B entities (82.14%), primarily in the financial sector (53.57% including insurance) or the IT sector (42.86%), with one example being an 'embedded FinTech' in the construction industry (C13). These firms covered a variety of AI and FinTech functions, ranging from AI capabilities for automating business processes, including NLP-based text recognition and ML-based document classification (25.00%), financial and insurance models (28.57%), cognitive data insights, and recommendations for business development and engagement of customers (17.86%), with a few developing more advanced AI capabilities, such as deep learning, responsible AI, and natural language understanding. These AI capabilities have enabled diverse FinTech functions in the prospective organisations, including standard functions like asset and wealth management (21.43%), payments and loans (14.29%), risk and compliance (14.29%), but also newer IT capabilities, such as InsureTech, AutoAI, BaaS, and MLOps. Four (14.92%) of these firms were IT providers of customised AI solutions to financial clients.

A systematic approach was applied for the collection of secondary data and the gathering of relevant information from diverse sources including (i) academia (e.g., IVADO, MILA); (ii) government (e.g., Canadian register of companies, Mitacs), (iii) business consortiums (e.g., finance-montreal.com); (iv) market research and consulting firms (e.g., crunchbase.com, appengine.ai, croft.co); and (v) social media (e.g., LinkedIn, twitter). In addition to their study relevance, all the

Table 2
Participating companies' AI and FinTech functions and state of development.

Company ID	Founding year	Industry	Company size	Business stage	Business model	Total funding	Financial (business) function	AI capability
C1	2017	IT	11–50	Startup	B2B	NA	Financial risk management	ML models
C2	2016	IT	101–250	Growth	B2B	NA	Customised solutions for FS clients	Responsible AI
C3	2019	Financial	1–10	Startup	B2B&B2C	NA	Asset management	General (3rd party)
C4	2015	IT	1–10	Startup	B2B	$250K	Financial models management	Support for MLOPs
C5	1997	Financial	101–250	Mature	B2B	NA	Treasury	ML-based models (3rd party)
C6	2017	IT	11–50	Startup	B2B	NA	Customised solutions for FS clients	Deep learning & computer vision
C7	2020	Financial	1–10	Startup	B2B	NA	Customised solutions for FS clients	Sentiment analysis
C8	2017	Financial	1–10	Startup	B2B	$425K	Asset management	ML models
C9	2015	IT	11–50	Startup	B2B	NA	Financial risk management & compliance	Responsible AI
C10	2020	Financial	11–50	Startup	B2B	NA	BaaS	ML models
C11	2017	Financial	11–50	Startup	B2B	NA	Payments	ML models
C12	2016	Financial	101–250	Growth	B2B	$93 M	Financial infrastructure	ML, data insights
C13	2016	Construction	11–50	Startup	B2B	$1.8 M	Embedded FinTech (payments and loans)	NLP, text recognition
C14	2017	IT	1–10	Startup	B2B	$12 M	Financial data processing/ automation	NLU, voice & text recognition
C15	2018	Financial	1–10	Startup	B2B&B2C	NA	Financial Education	Big data analytics, data insights
C16	2017	Insurance	11–50	Growth	B2B	NA	InsureTech	NLP
C17	2019	IT	11–50	Startup	B2B	NA	Insurance advising	NLP, text recognition
C18	2018	Financial	11–50	Growth	B2B	$2 M	Wealth management	NA, building AI capacity
C19	2016	Financial	51–100	Growth	B2C	$10.5 M	Wealth management	Big data analytics, data insights
C20	2018	Financial	11–50	Mature	B2C	$71.4 M	Loan/Mortgage advisors	ML, recommendations
C21	2018	IT	51–100	Growth	B2B	$10.3 M	Data security& fraud prevention	ML, classification
C22	2017	IT	1–10	Growth	B2B	$4.5 M	Financial documents processing/ automation	NLP, ML, classification
C23	2017	Financial	1–10	Startup	B2B	NA	Payments	NLP, text recognition
C24	2012	IT	51–100	Growth	B2B	$26.8 M	Investment management support	ML, data insights
C25	2014	Financial	1–10	Startup	B2B&B2C	NA	Payments	ML, recommendations
C26	2018	IT	11–50	Startup	B2B	NA	Financial risk management	Big data analytics, data insights
C27	2018	IT	11–50	Growth	B2B	NA	Customised solutions for FS clients	General
C28	2016	Insurance	51–100	Growth	B2B	$16 M	InsureTech (recommendation engine)	NLP, ML, Responsible AI

information was assessed for its reliability through a triangulation of multiple sources, resulting in a dataset that comprised 45 press releases, 80 social network posts and profiles, 27 emails and other documents ranging in size from 100 words (e.g., short emails), to 400 words (e.g., press release) and resulting in the first subset of data consisting of 107 pages (Ariel, 12 pt, single-spaced) of text gathered for analysis (see Table 5).

The resulting 28 FinTechs provided the variety of context that was necessary for observing differences in innovation process patterns; however, further data collections were necessary for more in-depth analysis that focused on the research questions and the theoretical framework established through the literature review (see Fig. 1). To examine these questions further and validate some of the preliminary findings emerging from the data, 12 semi-structured interviews were conducted with top AIFT decision-makers including the CEOs, COOs, Heads of AI development from six selected FinTech companies (which belonged to our sample of 28 firms), and other FinTech and AI industry experts (see Table 4). The companies included in the interviews provided the variety of context necessary for observing the differences in innovation process patterns with some replication across the parameters, such as business type, size, and stage of development to enable corroboration of the findings. They have been selected to cover a variety of AI and FinTech functions. These ranged from AI capabilities for automating business processes, such as, NLP- based text and document recognition (C13, C28), cognitive data insights for business development (C19) and further engagement of customers (C25), predictions and recommendations (C10, C28) and MLOps support functions (C4). In addition to the six direct AIFT company representatives, the interviews also included subject domain experts (P1-4, P8, and P12) with deep knowledge of development processes within organisations that form the Montreal AIFT ecosystem.

AI has been integrated into diverse FinTech capabilities in these organisations for standard operations, such as payments, loans, asset management, and propensity modelling, but also some newer InsureTech and IT products, including AutoAI (C28), BaaS (C10) and MLOps management (C4). The lead author here organised and conducted the interviews from September 30, 2021 to December 15, 2021 using the otter.ai application for recording and transcription. To ensure that all language issues were resolved and to anonymise the text, the transcripts were reviewed and compared to the recorded audio. The total duration of the interviews was 596 min (an average of 50 min per interview) which yielded the second subset of data consisting of 152 pages of text (Ariel, 12 pt, single space) for further analyses (see Table 4). The interview transcripts were also sent to the participants to check for misunderstandings and ensure no confidential information was included. The interviews were followed up with emails and phone calls for clarification. All data management and ethics requirements were fully addressed according to the ethics protocols of the authors' respective Universities.

Additional data were also collected from Canada FinTech Forum (CFF)[10], gathered in Montreal between the 27th and October 29, 2021. The forum provided a very rich source of contextual data, extracted from presentations and interviews with leading Canadian FinTech

[10] https://www.forumfintechcanada.com/en/2021-edition.

Table 3
Summaries of participating companies (C1–C28).

Company characteristics	Frequency	%
Founding year		
1997–2015	5	17.86%
2016–2018	19	67.86%
2019–2020	4	14.29%
Industry		
Financial	13	46.43%
IT	12	42.86%
Insurance	2	7.14%
Other	1	3.57%
Company size		
1–10	9	32.14%
11–50	12	42.86%
51–100	4	14.29%
101–250	3	10.71%
Business model		
B2B	23	82.14%
B2C	2	7.14%
B2B & B2C	3	10.71%
Business stage		
Startup	16	57.14%
Growth	10	35.71%
Mature	2	7.14%
Finance (business) function		
Asset/wealth management	6	21.43%
Customised solutions for FS clients	4	14.29%
Payments & Loans	4	14.29%
Risk, compliance, fraud & ALM	4	14.29%
InsureTech	3	10.71%
Financial data automation	2	7.14%
Financial infrastructure & BaaS	2	7.14%
Embedded FinTech	1	3.57%
Financial education	1	3.57%
Treasury	1	3.57%
AI capability		
ML	8	28.57%
NLP/NLU	7	25.00%
Big data insights	5	17.86%
Responsible AI	2	7.14%
General AI	2	7.14%
Deep learning, computer vision.	1	3.57%
MLOPs	1	3.57%
Sentiment analysis	1	3.57%
NA, building AI capacity	1	3.57%

practitioners, including representatives from 17 of the 28 firms from our sample (60.71%). The otter.ai application was used for recording and transcribing the relevant forum sessions (total duration 5:26 h) resulting in the third subset of data comprising 70 pages of text (Ariel, 12 pt, single space) for further analyses (see Table 5). The transcripts were reviewed for information only relevant to the research topic, resulting in 34 directly relevant 'quotes' from these sessions. Throughout the rest of this paper, quotes from the CFF[10] will be referred to by their number, i.e., from Q1 to Q34. Primary data from the interviews were supplemented with information from 16 online chats and emails exchanged with FinTech company representatives from the CFF[10]. The CFF data were used to triangulate and supplement the findings from the FinTech organisations providing a broader context for their analysis. This enhances the research quality and, as a result, strengthens its validity and reliability.

Table 5 summarises the additional secondary data collected, outlining how it was utilised in the research to support process analysis (as described in Table 6) and contribute to the findings in Section 4. This includes the typology of AI innovation processes presented in Table 7.

3.2. Data analysis approach

The unit of analysis used in this research is the organisation, as commonly accepted in SMEs and entrepreneurship research (Fisher, 2012). The data were analysed using thematic and process analysis approaches, wherein for each participating organisation, we were considering a single specific process of AI development. To begin, we characterised the AIFT organisations using our initial sample, resulting in Tables 2 and 3, to gain a better understanding of the types of AIFT capabilities being developed by them. Next, we performed a thematic analysis of the data within the context of out predefined conceptual framework depicted in Fig. 1. The code tree shown in Fig. 2, served as a tool to align the emerging (first and second order) themes with our theoretical concepts (third order themes seen in Fig. 2) and helped connect the data to the pre-established conceptual framework. The themes resulting from this analysis (type of process activities and other contextual factors) were then used to inform our process analysis and answer the specific research questions.

Finally, we conducted a process analysis, as described in Table 6, utilising data from the interviews, emails, and discussions at the CFF[10] with AIFT experts and the decision-makers from the participating 28 SMEs.

Data collection, processing and analysis were all conducted in an iterative fashion. Each iteration began with new data collection, followed by updates to the codes and categories in a thematic analysis of data (Braun and Clarke, 2012) or updates to the definitions for the processes of the specific organisation (Berends et al., 2014; Jiang and Rüling, 2019). This incremental process of data analysis enabled a systematic identification and comparison of all the related process activities and process configurations across different organisations (Jiang and Rüling, 2019). The codes and categories emerging from the thematic analysis were then used to provide a context for a full process analysis and any needed further explanations of the justifications for process variations. These process analysis steps for each individual organisation, are outlined in Table 6.

The start and end point of each process was identified as being the founding year of the corresponding firm and the end date for the data collection process (December 2021), respectively. The process activities were categorised as either goal setting (G) or resource commitment (R) activities (Fisher, 2012; Berends et al., 2014). Unlike Berends et al. (2014), 'idea generation' activities were not considered separately and

Table 4
Description of the interviews and interview data.

Participant ID	Relevant experience/role	Education (level)	Industry	Duration (mins)	Transcript (pages)
P1	Professor/FinTech researcher	PhD	Education	50	9
P2	Director/AI specialist	PhD	Financial services	50	15
P3	Data science/AI consultant	PhD	IT	63	14
P4	AI in FinTech programme director	MSc	Financial services	29	12
P5	Head of data science (company C28)	BSc	InsureTech	65	15
P6	CEO (company C25)	MBA	Fintech	32	12
P7	COO for (company C19)	BSC	Fintech	46	13
P8	AI business development mentor	BSc	Government	40	12
P9	CEO (company C13)	BSc	Fintech	43	12
P10	CEO (company C4)	MSc	Fintech	63	11
P11	Head of analytics (company C10)	PhD	Fintech	55	16
P12	Insurance consultant	BSc	Insurance	60	11

Table 5
Description of the secondary data.

Data source	Data type	Data amount in pages[a]	Data use
Public research reports	Articles from academic sources on the state of AIFT implementation, including systematic reviews of literature (SLRs), reports from major FIs including BoE, BMO, CIBC, RBS, Scotiabank, and TD, and relevant publications from Forbes, McKinsey, WEF, The Economist, IDC, IIF.	1420 pages of text, consisting of 26 MB of PDF files from 10 SLRs, and 9.5 MB of PDF files from 11 FI reports and 10 other public reports.	1. To provide background information and the business context for understanding, validating and analysing the data collected from the participating organisations and interviews. 2. To support empirical observations on AIFT in Section 4.3.
Canada FinTech forum (CFF)	Videos of relevant CFF panels discussing the implementation and scaling of AI innovation in financial services, featuring representatives from 17 of the 28 firms in our sample (60.71%). Additionally, there are demos from FinTech startups' CEOs and interviews with leading Canadian FinTech decision-makers.	70 pages of transcript corresponding to 286 min of video, encompassing 5 panel sessions, 8 demos, and 5 interviews.	1. To provide a broader context for process analysis (see Table 6), including the types of AIFT development resources, goals, and context variables (steps 2–4 in the process analysis method outlined in Table 6). 2. To triangulate and supplement the findings from the AIFT SMEs (step 7 in the process analysis method detailed in Table 6).
Selected websites, news and media articles	Information about the 28 selected AIFT SMEs (see Table 2) obtained from their websites, and from the websites of related organisations, including academia (e.g., IVADO, MILA), government (e.g., Canadian Register of Companies, Mitacs), business consortiums (e.g., finance-montreal.com), market research and consulting firms (e.g., Crunchbase, AppEngine, Croft), and social media platforms (e.g., LinkedIn, Twitter). Additionally, internal documents from some of the AIFT SMEs obtained through personal contacts.	107 pages of text comprising information from 28 SMEs' profiles, 45 press releases, 80 social media posts, and 24 public documents, along with 3 internal documents.	In addition to the above: 1. To classify different types of AIFT SMEs (see Tables 2 and 3). 2. To gain a better understanding of the types of AIFT capabilities developed by the participating SMEs (see Section 4.1 & Table 7). 3. To understand the rationale, contingencies, challenges, and opportunities for different AI development implementations (see Table 7 & Fig. 3).

[a] (Ariel, 12 pt, single-spaced).

Table 6
The process analysis method (adapted from Berends et al., 2014; Jiang and Rüling, 2019).

Step	Description
1	Identifying the process start and end points
2	Identifying the process activities and their order in time
3	Labelling the activities according to the themes emerging from the data (Fig. 2)
4	Categorising the activities as either goal setting or resource commitment
5	Updating the process definition and the process map
6	Comparing the process characteristics with those found in other SMEs.
7	Interpreting the process characteristics relative to the themes emerging from the literature (Fig. 1) and data (Fig. 2)

were subsumed within either resource commitment or goal setting activities, as the focus of this particular research was development rather than the 'ideation' phase of a firm's lifecycle. Initially, Davenport and Ronanki's (2018) AI business value types were used for further characterising process activities. In cases where they were not applicable, new categories emerging from the data were applied (Fig. 2). The final three steps in the process analysis enabled the discovery of common patterns in process behaviours and their configurations across different organisations, as well as the specific contingencies associated with each process group.

The thematic analysis followed a standard process of coding/re-coding and grouping/re-grouping of data until no new information could be generated (Braun and Clarke, 2012).

The preliminary results were then reviewed and validated by the second author and discussed with the interview participants, thereby contributing to fine-tuning the ongoing research process and strengthening the reliability and validity of the findings. All disagreements were resolved by reviewing the data to ensure shared understanding and by revisiting assumptions and approaches to analysis. Data from different sources allowed for triangulation to augment external validities (Eisenhardt, 1989), guard against observer bias (Miles and Huberman, 1994), enable replication logic (Yin, 2009) and support the development of new theoretical explanations of the observed phenomenon (Lee, 1999). To mitigate potential biases related to retrospective sensemaking and impression management (Eisenhardt and Graebner, 2007), the data were collected by interviewing multiple respondents with different perspectives. Retrospective and real-time data were then triangulated with archival and secondary data, verified by selected informants and in subsequent interviews. Hence, such biases were minimised.

4. Analysis and results

In this section, we analyse and compare the AI innovation processes from different organisations that participated in the research and discuss the contingencies, implementation challenges, and the ways forward to develop AIFT capabilities in these firms. Our data analysis resulted in a typology of AI innovation processes and their trajectories as illustrated in Table 7 and Fig. 3, respectively, and a new theoretical model for innovation processes shown in Fig. 4. We also considered certain wider AIFT ecosystem issues discovered in our data, leading to an overall critical assessment of the state of AI implementation in FinTech SMEs.

4.1. Process analysis

Our comparison of the process characteristics across different organisations and relative to the categories emerging from the thematic analysis of data (Fig. 2) yielded four different process configurations (Table 7). The rest of this section offers a more detailed description of the resulting processes, illustrated with representative quotes from the interviews and supplemented by links to theory, i.e., via the specific contingencies related to each process type.

Early startup FinTech with aspirational AI - These are FinTech startups at a very early stage of development that aspire to use AI and are preparing for it, but not yet focusing on implementation, as they have many more critical problems to solve, such as developing the MVP and securing funding. Their process pattern for AI innovation thus *starts* with one or more resource commitment activities, such as building the dataset and developing the infrastructure around it; these activities are followed by planning and the selection of AI capabilities suitable for their products (i.e., one or more goal setting activities):

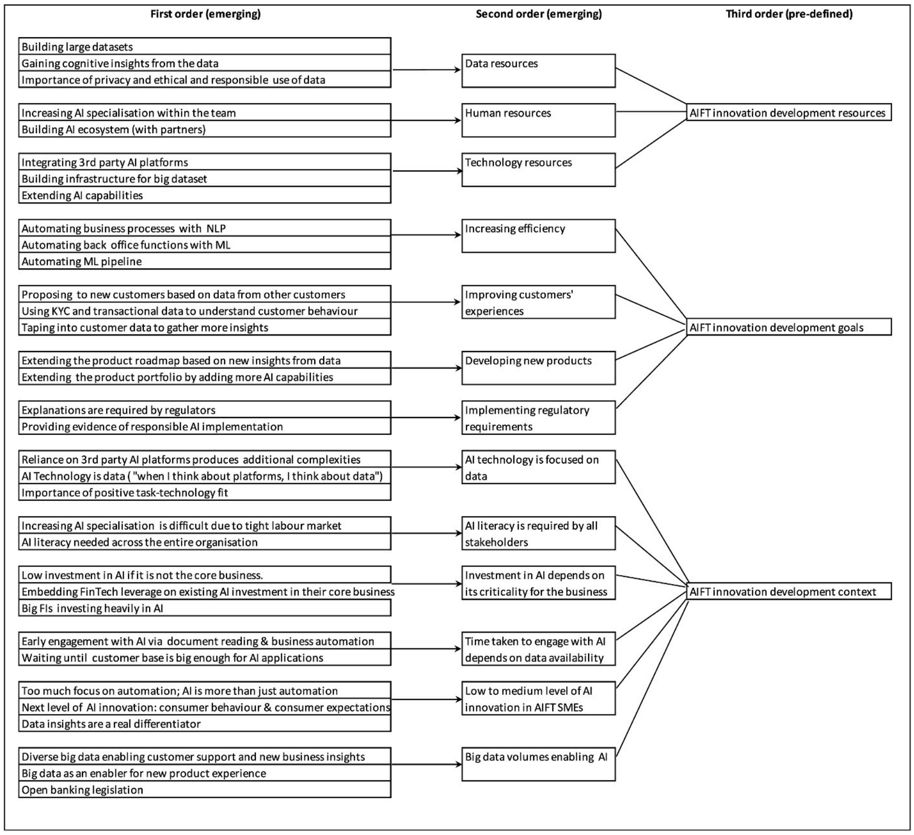

Fig. 2. Code tree.

> The first step is really to have the good dataset inside our system to collect the data before going in the direction of really using AI. So, what we did is, building our database based on what we wanted to do with the data. We started by selecting all the information needed and being sure that they are all correctly collected. Our next step will be to develop the algorithms that we'll be able to use the data to give us insights to understand their (customer) behaviour and then adapt our communication and the communication among the merchants also (P6, C25's CEO).

The specific contingencies associated with this group are an early stage of business development, high reliance on 3rd party AI platforms, low level of AI specialisation within the team, a low level of investment in AI, low data volumes, late engagement with AI, and a low-medium level of novelty for their planned AI applications. The last corresponds to automation and customer engagement capabilities (Davenport and Ronanki, 2018), as was the case for C15 and C25, respectively.

Providing these firms survive financially, develop the MVP, and find the first customer, the next step in their AI innovation trajectory (Fig. 3) may be to use AI for automation (e.g., C28 started their AI journey using NLP for 'document reading'). Another option would be to continue growing their customer base and transactional datasets while focusing on their core service and thereby transforming into a data-driven business (as in the case of C19). To avoid misalignment between what many nascent entrepreneurs think they can do with the technology and what ultimately proves to be possible (Chalmers et al., 2021) these firms should critically assess whether AI Is a good technology fit for their particular business problem:

> That seems to be a challenge, at least with some of the models that have come out in Montreal, where you've had companies that have a strong AI focus, but the business problems that they're solving for are less well defined (P8).

Data-driven FinTech with aspirational AI - For these particular firms, data is fundamental for their business, so AI is seen as a complementary and a longer-term opportunity. For example, C19 started by developing a data-driven product with no AI capabilities first (resource commitment), and then, building on the large dataset of 'know your customer' and transactional information enabled planning product extensions with AI-like features (goal setting):

> That rich data set that we have access to is through tapping into the transactional bank data. From that foundation, we were enabling a few other product experiences to provide more value to the users. The first of those was we have financial planners, i.e., building something which provides a recommendation or prediction for the user that they can interact with and take action on. This is taking it one step further because it's extrapolating information about the user's financial profile, and then exposing it to the user and the app (P7, C19's COO)

While rich and large datasets are essential for AI implementation, equally important are the skills to acquire, manage, and analyse these data (Brock and von Wangenheim, 2019). For AI to provide value to users, an increase in investment is required, starting with growing the AI specialisation within the team (resource-commitment):

> What changed was more in relation to additional investment in specific data skills, for example, initially, the data engineering work was handled by a pool of back-end engineers who would be assigned tasks as opposed to taking overall responsibility for ensuring the integrity of the data pipeline and improving it over time. And as the company grew, we were able to assign dedicated resources only to that, so having a dedicated data engineer, and greater specialisation within the team (P7, C19's COO).

Initially, C19 use of AI was 'aspirational', as their core business function (asset management) was implemented using expert knowledge,

Table 7
Typology of AI innovation processes in FinTech SMEs and specific contingencies related to stage of business, technology, stakeholders, budget, time, level of novelty, and data volumes.

Process group		Contingencies	Process pattern description	Participating company ID
Data-first group		Low investment in AI Slow engagement with AI innovation	Selecting goals achievable with the existing resources	
	Early startup FinTech with aspirational AI	Early stage of business development High reliance on 3rd party AI platforms Low level of AI specialisation within the team Low level of AI investment Slow engagement with AI Low-medium level of AI novelty Low data volumes	Resource commitment followed by goal setting activities	C4, C8, C10, C11, C15, C25
	Data-driven FinTech with aspirational AI	Growth stage of business development Low reliance on 3rd party AI platforms Growing AI specialisation within the team Low level of AI investment Slow engagement with AI Medium level of AI novelty High data volumes	Resource commitment followed by one or more iterations comprising goal setting followed by resource commitment activities	C18, C19, C20, C24
AI-first group		Early engagement with AI innovation Medium-high level of AI investment	Selecting resources to achieve pre-specified goals	
	AI-automated FinTech	Early stage of business development High reliance on 3rd party AI platforms Medium level of AI specialisation within the team Medium level of AI investment Early engagement with AI Low level of AI novelty Growing data volumes	Goal setting followed by resource commitment activities	C3, C5, C13, C16, C23
	AI-augmented FinTech	Growth stage of business development Low reliance on 3rd party AI platforms High level of AI specialisation within the team Medium-high level of AI investment Early engagement with AI Medium-high level of AI novelty High data volumes	Multiple iterations comprising goal setting followed by resource commitment activities	C12, C28

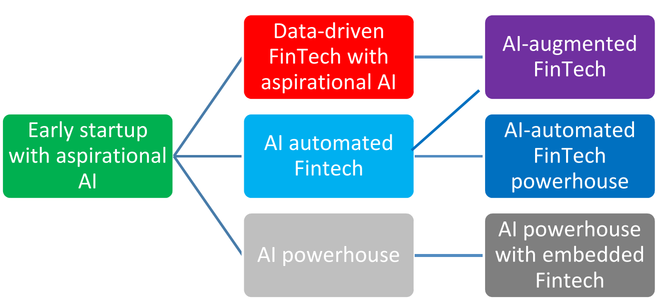

Fig. 3. Pathways to AI innovation in FinTech.

rather than learning from data. The main issue with lagging AI implementation in these firms was not the 'task-technology' fit, as many traditional asset management tasks are also suitable for AI implementation (Davenport and Ronanki, 2018), but rather that AI is seen as a complementary activity, while the investment is focused on the core business:

> I've seen a lot of companies come through there and I see that, for some of them AI is a bit of a secondary, consideration, and that's not the core of what they're building. And it's hard to do well, right? It's hard to really extract the full potential of it if it's not the main thing that you're doing (P8).

This group is characterised by a growth stage of business development, low reliance on 3rd party AI platforms, a growing AI specialisation within the team, a low investment in AI, a low-medium level of AI novelty, late engagements with AI, and high data volumes. Some of these characteristics are project-specific (Salerno et al., 2015) while others are new and related to the AI-innovation context. If not acquired by bigger firms (as was the case with C19 later in 2021) the next step for these firms could be to start investing more heavily in AI development, which given the size and readiness of their datasets, could lead to their transformation into more significant AI firms (Q10). The main barrier during this journey might be the tight AI labour market (Brock and von Wangenheim, 2019), which they could try to overcome by partnering with an AI service provider or by developing their AI expertise internally as was the case with C3 and C18, respectively.

AI-automated FinTech - This group is exemplified by the company C13, an 'embedded FinTech' startup from the construction industry and already using AI to automate invoicing and create more capacity and efficiency for financial services embedded in their applications, such as budgeting and accounting. Other examples include startups (C3, C23), growing (C16) and mature FinTech businesses (C5); all are using low-level AI capabilities (automation) to optimise payments, insurance, and treasury services, and mostly relying on 3rd party AI providers. The AI development process for this group thus starts with plans to build data models to increase productivity i.e., goal setting:

> It was only until we started building our company that we started to really think about using data models. And, and particularly for the focus about company, gathering data that could be used to help create predictive data models in the construction space for from a performance productivity perspective (P9, C13's CEO).

Planning for predictive AI is followed by resource commitment activities, including the integration of external AI infrastructure services, and the development and integration of NLP capability for text parsing, using internally developed synthetic data:

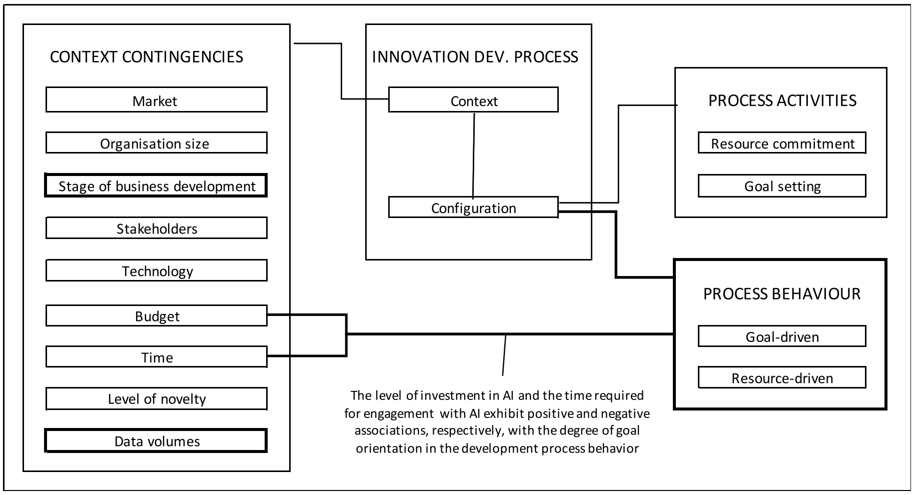

Fig. 4. New theoretical model for technological innovation development processes. New concepts and relations are shown in boldface.

> From an infrastructure standpoint, we leverage every service out there essentially, AWS, Google, authentication services. What we do build ourselves are the natural language processing micro services, the payments micro services, things like that. In terms of third-party data, we don't ingest third party data today, we have that in house. This data really doesn't exist out there. We have to build it ourselves (P9, C13's CEO).

The main contingencies associated with this group are early engagement with AI, enabled by using synthetic or public datasets, 3rd party AI infrastructure and services, and a low level of AI novelty (automation). Although at their early stage of development, these firms are already investing in AI capabilities by growing their AI specialisation and their data volumes with transactional and customer data (like C28).

The main challenge they experience is talent recruitment of AI software integrators.

AI-augmented FinTech – These are firms with a mature implementation of AI where AI/ML is seen not as complementary, but as a core business component that offers new solutions not previously possible.[11] Examples from sample include B2B FinTechs C12, and C28 with more than 11,000 business clients and millions of individual customers respectively. The process pattern for AI innovation in these companies proceeds through a series of alternating goal setting with resource commitment activities, following an iterative agile implementation pattern (Cooper and Sommer, 2016). i.e., defining iteration goals first, followed by implementing them (i.e., resource commitment):

> Our business goal is to enhance the end user experience for our direct customers, which are insurance and banks. To do so, we start with automatising some basic tasks, like for example, to read accident reports, to recognise information within the official documents, identity card, driving licence, also some information about medical service.

> Our system user usually is the insurer advisor. The aim is to make the path for the user, as smooth and efficient as possible. Next was our assistant tool will provide him with selections of the insights about the customer, let's say a certain propensity for product A or product C and not for product B. That's a recommendation.

> The same way, to ease the work of the advisor allowing him to type down a question in natural language to get the answer without having to search a question answering solution is also provided.

> And the last thing we're working which helps to get a summary of the discussion and also point out some points of interest to the user is voice recognition (P5, C28's Head of AI).

Finally, C28 started addressing some advanced objectives, such as providing explanations, responsible AI reporting, and automating their ML pipeline by using a mixture of resources, such as in-house expertise ('skunk work'), external expertise (PhD internships), and open innovation:

> What we did is to automatise as much as possible the ML pipeline. We did internally and we even develop what we call a standard data model, that basically, with the experience we gather with, we have like 15 clients, insurance, bank the big ones (P5, C28's Head of AI).

Like Google's 'AI-first' approach, which is not only about advancing the ML use in the company, but also enabling third parties, C28 has started 'paving the way for the ecosystem', by publishing their open-source standard for ethical AI data collection and developing domain-specific AutoML capabilities.

Being early adopters of AI innovation and in a more mature phase of business development, the companies in this group are facing some of the standard AI implementation challenges, such as data not been 'clean' at the source, managing 'data drift', and educating clients on understanding the ML model results. Other contingences specific to this group include low reliance on 3rd party platforms and relatively high levels of AI novelty, investment in AI, volumes of transaction data, and AI specialisation within the team. Moreover, these companies have a potential not only for sustaining their AI innovation, but for developing it further beyond their current business models (e.g., C28 could expose their 'AutoML' API for use by other InstureTechs), and thereby potentially disrupting the market. For example, C12's Open banking API has recently begun to be utilised by other FinTech SMEs allowing them to access the FI's consumer data and gain greater leverage in data-driven innovation (P4). These companies then have the potential to challenge established FIs by not only offering new products and services, but also introducing new business models, thereby promoting potentially game-changing business ecosystems (Gomber et al., 2017; Hendershott et al., 2021).

4.2. Summary of results of the process analysis

To address our research questions, we summarised the four distinct types of AI development processes derived from our data along with their associated configurations and contingencies into the process typology presented in Table 7. This typology, however, does not include the IT firms that are providing AI services to financial clients and other

[11] In 2017 Google introduced a term 'AI-first': https://youtu.be/5WRJYEA-mwY.

FinTech firms (n = 11, 39.28%).

The ‘Data-first’ process group exhibits behaviour that starts with resource commitment activities (e.g., building large dataset of customer data), followed by goal setting activities to select outcomes achievable within the available resources (e.g., increase customer engagement or increase efficiency through automation). In more mature firms, this process sequence iterates via alternating resource and goal activities. Examples include early startups, but also more mature businesses, with a different level of the FinTech focus: FinTech core business and IT support for financial firms. The main contingencies related to this group are low investment in AI and slow engagement with AI innovation. This group comprises two sub-groups in different stages of business development, namely, early startups, and growing data-driven FinTech businesses.

The behaviour of the ‘AI-first’ process group begins with goal setting activities (e.g., increase efficiency though automation), followed by resource commitment activities for achieving those goal (e.g., build specific datasets to enable application of document classification algorithms or purchase software for text-recognition). This iteration pattern is repeated in more mature firms, including startups and growing businesses with different levels of FinTech focus (embedded FinTech as well as FinTech core businesses). The main differentiators are the early implementation of AI innovation and a medium-high level of AI investment. Compared to the ‘Data-first’ group, this group is characterised by more successful businesses as evidenced by their total investment value, number of subscribers, active customers, and established partnerships (see Table 2). All demonstrate accelerated implementation of AI innovation and a reduced product-concept gap.

The AI innovation development in FinTech SMEs starts either with the gradual building of large transactional datasets or an immediate use of AI for automating business processes using internal data. This leads to delayed implementation of AI in the former group and its rapid implementation in the latter group. The rapid implementation of low novelty AI (automation) is also characteristic of more successful firms, regardless of the level of their business development and firm size. Early engagement with AI implementation in these firms contributes to the growth of internal capabilities. This is particularly important in a competitive job market where AI experts are often recruited by large financial and big tech firms. (P3, P7, P10, P11).

Our process analysis resulted in a new framework for developing AI innovation in FinTech, based on increasing the level of business development and investment in AI (Fig. 3). Thus, for example, a FinTech startup aspiring to use AI can begin by developing automation capabilities that initially rely on synthetic or 3rd party data, while gradually building higher volumes of customer and transactional data. These early successes will, in turn, facilitate the implementation of AI capabilities with greater business value. Alternatively, the businesses could focus on their FinTech core applications and continue to use data for enhancing internal efficiencies, as demonstrated by FinTech powerhouse, WealthSimple:

> We had to scale to meet that demand. And we use a lot of Machine Learning in our back office, figuring out the optimal ways i.e., at the best possible prices for our client to route the funds and to read request for funds has been a huge application of Machine Learning in our business (Q14, WealthSimple CEO).

Which way business will go will depend on a number of organisational, project, and environment factors. Our process typology (see Table 7) does not include the growing number of data-driven AI non-financial businesses (e.g., Hopper, a Montreal-based unicorn) which in a later (more mature) stage of their development has started introducing FinTech capabilities. In these firms, data and AI are the core of their market fit, with financial services embedded into their applications by leveraging high volumes of data. Although not included in our sample because of their size, these firms could provide an effective alternative pathway for AI innovation in FinTech, as shown in grey in Fig. 3.

We then revisit and enhance the conceptual model for technological innovation process shown in Fig. 1 by (i) adding new contingencies (Data Volumes and Stage of Business Development) into the AI innovation context; (ii) clarifying the meaning of existing contingencies (Technology, Stakeholders, Budget, Time and Level of Novelty) in the AI technology context (Table 7); (iii) adding a new concept (Process Behaviour) which can be either Resource- or Goal-driven as exhibited by different AI development process configurations that emerge from our data; and (iv) proposing a new theoretical relationship between the constructs for Process behaviour and the Context variables of Budget and Time, to indicate a link between the level of investment and time that is taken to engage with AI innovation at one end, and the level of goal orientation in development process behaviour at the other end (see Fig. 4).

Emerging from our data were also specific AI innovation process activities (see Fig. 2), such as automation, building large datasets, customer engagement, cognitive insights, higher-order capabilities (explanations, responsible AI, AutoML), the development of AI-ecosystem, and integration AI infrastructure (e.g., AWS, Google AutoML) . All can be characterised as examples of resource commitment or goal setting behaviours (Fig. 4). Our data analysis has revealed that in addition to standard project resources, such as finances, knowledge, time, people, and partners, AI innovation processes also rely on data as a fundamental resource for constructing ML and NLP models. This, coupled with the need to address regulatory requirements (e.g., explanations, data ethics, responsible AI) distinguishes AI-based innovation from other types of technological innovation.

4.3. Other empirical observations on AI innovation in FinTech

Based on the evidence emerging from the companies that participated in this research, the current implementation of AI in FinTech is under–developed despite the already significant investment, in AIFT innovation, such as in Montreal.[12 and 13] This lack of development may be due to the lack of customer data (e.g., C25), businesses operating on a scale that does not require the ML approach (e.g., C20), AI being perceived as a complementary activity (e.g., C19), or the constraints being imposed by business partners (e.g., C13). The exception to this rule is companies like C12 and C28, which have positioned themselves as AI-augmented businesses. However, even in these companies, little ambition exists to go beyond automation, product recommendation, and predictive analytics in the AI applications. The AI-factory models of Netflix and Airbnb, which effectively generate user interfaces using real-time data (Verganti et al., 2020) appear to be only a very distant future for FinTech startups.

Whereas the COVID-19 pandemic might have increased interest in AI (Collins et al., 2021) and FinTech firms (Q10), the impact was less positive for the FinTech startups because of the increased uncertainty that affected their funding and resourcing (e.g., P3, P6, P10). Even in those firms with significant AI investment, there remains limited evidence of more sophisticated (planned of actual) AI applications, such as employing deep-learning across very complex data sets to generate new insights or using “one-click machine learning” research tools to predict customer reactions to new features or product pricing (Chalmers et al., 2021).

Further still, the predictions that the conservative approach to AI adoption by large organisations may provide more opportunities for smaller, more agile firms, or the development of “challenger business models” that will take full advantage of the AI technology without being

[12] https://www.investquebec.com/international/en/secteurs-activite-economique/technologies-information-communications/Montreal-s-Artificial-Intelligence-Hub.html.

[13] https://www.stationfintech.com/en/read-news-and-publications/copy—quebec-fintech-report—q3.

constrained by existing processes and capabilities (Chalmers et al., 2021) has not yet been realised in our context. A possible exception are the AI powerhouses with embedded FinTech, which due to their agility and innovativeness, do have the potential to challenge established financial service providers (Gomber et al., 2017).

Unlike FinTech SMEs who are cautious in their approaches to AI innovation, some of the large FIs have a long history of investing in predictive models in banking, and their current substantial investment, in AI is a continuation of those ongoing efforts:

> There's like probably 40 years or more history of building predictive models in banking. And those models are actually quite sophisticated. I lead the team for the model validation in the bank which is a part of risk structure. Nowadays we see (models based on) trees and neural networks for which the parameters are derived by iterating through the data (P2).

The top five Canadian banks, which are part of the Montreal AIFT ecosystem, all run their own AI initiatives either by acquiring AI startups (e.g., TD[14] and Layer 6), building internal Centres of Excellence (RBC[15] founded Borealis AI research institute, BMO's[16] partnership with University of Toronto), partnering with AI powerhouses (CIBC's[17] conversational AI-based Virtual Assistant powered by IBM Watson Assistant) or relaying on bottom-up innovation, as in Scotiabank's ML innovation teams[18] (P11).

In the Canadian context, the gap between the FIs and SMEs in their AI implementations is widened even more due to delays in passing open banking legislation.

> One of the factors that is held back that promise is that open banking has been really slow to emerge in North America. So, the impact of it is that just the quality of the data and the reliability of the data has been very poor. That's been a way in which the incumbents are able to block out the potential for smaller companies to really leverage that data to provide better consumer experiences (P8).

While some FinTechs are using this delay as a business opportunity (e.g., C12 has started to provide other FinTechs with a secure access to consumer data from the FIs (P4)), for other FinTech SMEs, it is a real hindrance when developing AI innovation.

5. Discussion

Extant research on the concept-product gap is clustered in the NPD and Information systems literature. The former provides a generic innovation process perspective, while the latter focuses on development and the diffusion stages of the innovation processes. In the context of AIFT innovation, academic research is still in a nascent stage and dominated by technical studies that focus on the antecedents and outcomes of AI innovation and lacking in key organisational and innovation development studies. The organisational aspects of AI innovation are mostly studied in the practice-oriented literature, which centres on the expectations and implementations of AI innovation in large organisations. Apart from a few notable exceptions (e.g., Berends et al., 2014; Salerno et al., 2015), the process perspective for product development in SMEs is largely absent in the literature. We build on the findings of these studies by focusing specifically on AI innovation rather than general technological innovation. This AI context presents new contingencies that could influence project trajectories beyond those identified by Salerno et al. (2015). Additionally, our study uncovers new development process behavioural patterns that are driven by goal setting or resource commitment activities, thereby complementing the configurations discovered by Berends et al. (2014). Overall, from a process perspective, our study has not only identified a number of emerging patterns but has also highlighted a more unified theoretical perspective for future studies to complement existing research.

5.1. Theoretical implications

Our theoretical model for technological innovation processes (Fig. 4) emphasises the rationale for variations in the structure of innovation development processes. This is the first model that has attempted to provide an 'outside and inside' perspective, thereby rendering a more rounded basis for understanding fully the 'why and how' of innovation processes in organisations.

While the model inherits the extant theoretical premises of contingency theory, it also adds new project and organisational contingencies, data volumes and a stage of development, respectively, for differentiating innovation processes' configurations (see Fig. 4). These attributes have not been found in the previous research on factors that are contributing to successful and accelerated NPD (Ernst, 2002; Chen et al., 2010; Salerno et al., 2015; Zhu et al., 2019). Our results further show that AI innovation processes in SMEs can be either resource- or goal-driven (corresponding to Sarasvathy's (2001) effectuation and causation entrepreneurial approaches), unlike other types of innovation in SMEs that tend to focus on what can be done with existing resources (Fisher, 2012; Berends et al., 2014; Salerno et al., 2015). This finding suggests that variations in process configurations are sensitive not only to the organisation's size, but also to the type of innovation. Further still, our data analysis reveals a new theoretical relationship between (development) process behaviours and organisational agility, thereby suggesting that firms that exhibit more resource-driven behaviours are less agile in their implementation of AI innovation and thus less likely to reduce the concept-product gap. This is due to the fundamental role of data in the AI development process and the "data disadvantage" of the SMEs outside the consumer internet business (Ng, 2021). Unlike them, goal-driven SMEs position AI at the centre of their operations ('AI-first' group), they invest more in their AI innovation implementation, they start early with the implementation using internal or synthetics data, all of which is enabling accelerated (AI) innovation. The sequencing within their process pattern aligns with the agile perspective on development, wherein multiple iterations comprising goal-setting (review and planning) followed by resource commitment (implementation) activities are performed.

While our study confirms that Agile is a way to go for SMEs developing AI products, it also underscores the importance of examining NPD at a more detailed level of granularity. This entails gaining deeper insights into the various possible configurations within specific NPD phases and the factors influencing their selection. Our study was primarily concerned with the development phase of the NPD process, wherein AI introduces additional complexity due to the nature of machine learning algorithms and the need to handle large datasets. This complexity creates more uncertainty about how a product developed in a lab, trained with only one set of data, will perform once launched or deployed in a real-life scenario with a different set of data. This issue, in turn, widens the concept-product gap. To address this uncertainty, we employed a more granular perspective to understand how the development phase is configured for different types of contingencies, such as the stage of business development, technology, stakeholders, budget, time, level of novelty and data volumes. By considering all these factors, firms can better navigate the complexities of AI development during the

[14] Toronto Dominion Bank (TD) AI research lab https://layer6.ai/.

[15] Royal Bank of Scottland (RBC) AI research institute at RBC https://www.borealisai.com/.

[16] Bank of Montreal (BMO) R&D Lab at University of Toronto https://bmolab.artsci.utoronto.ca.

[17] Canadian Imperial Bank of Commerce (CIBC) CIBC's AI-based Virtual Assistant https://cibc.mediaroom.com/2020-12-10-CIBC-launches-AI-based-Virtual-Assistant-to-help-clients-bank-digitally.

[18] Bank of Nova Scotia (Scotiabank) Scotiabank ML Innovation teams https://www.scotiabank.com/ca/en/about/perspectives.articles.digital.2021-04-scotiabank-global-ai-platform.html.

NPD process and thereby improve their chances of success.

The unique characteristics of digital technologies render NPD processes that are less bounded (Salerno et al., 2015; Nambisan, 2017). With AI in particular, the boundaries between development and diffusion stages of NPD become more fluid due to the continuous nature of the AI model improvement process and its ongoing evolution in the target (deployment) environment. Consequently, the traditional NPD model, with its clearly separated high-level process stages, becomes less relevant and a more granular, fine-grained perspective may be a better option for addressing the uncertainty and complexity associated with the development of AI products.

5.2. Managerial implications

Emerging from our empirical data is a typology of the AI innovation processes in FinTech firms as shown in Table 7. AI innovation processes in FinTech SMEs can be 'Data-first' or 'AI-first', with the agility of AI implementation and the level of investment being the most prominent differentiator between the two groups. Further specialisation within these groups is contingent on the level of novelty of the AI implementation (ranging from none-low to medium-high), the stage of business development (startup, and growth), reliance on 3rd party AI technologies (from low to high), level of AI specialisation in the team (low to high) and the size of data volumes (low to high). Our data analysis suggests that those firms that follow an agile development pattern (multiple iterations of goal setting followed by resource commitment activities) engage early on with any of the (internal or external) data available for developing their AI capabilities (e.g., use of NLP and ML for 'document reading'). Consequently, these firms tend to develop their AI expertise faster and are in a better position to benefit from more significant AI implementation in their products and reduce the concept-product gap. Others, who delay their AI implementation either because they are waiting to capture more data from new customers or because they perceive AI as only a complementary, 'nice to have' activity, are reducing their potential for creating new AI-based services and disrupting incumbents.

AI development also involves a high level of uncertainty due to the cognitive complexities related to the nature of machine learning algorithms and large datasets. Our study found that the firms included in our research dealt with uncertainty in different ways. The 'AI-first' group exhibited a more explorative 'probe and learn' approach (O'Connor and Rice, 2013), while the 'Data-first' firms tended to be more cautious and adopt an exploitative 'wait and see' approach. Our results suggest that firms choose different process patterns that match their risk tolerance levels as well as their development goals.

Moreover, the results suggest possible trajectories for AI innovation implementation in FinTech (see Fig. 3), providing an effective diagnostic tool for the SMEs that are interested in implementing AI innovation in their portfolios. To challenge established FIs, SMEs should embrace a more agile approach toward the development of AI innovation in their product portfolios (i.e., AI-automated FinTech, followed by the AI-augmented approach). The potential for accelerated implementation of AI innovation thus lays in the abilities of 'AI-first' firms to continue to innovate and plan the expansion of their AI development beyond automation.

This research also provides a specific AI perspective on innovation process activities, using data as its fundamental resource for creating value for firms (Brock and von Wangenheim, 2019). Along with the AI business goals related to efficiency and business development (e.g., Davenport and Ronanki, 2018), our research emphasises the importance of considering regulatory requirements for AI innovation implementations (see Fig. 2). These relate to having responsible AI, such as providing explanations for the model's outcomes and ensuring the ethical use of data. These activities, while not adding immediate financial value to the business, are still necessary to prevent losses due to penalties that may incur or reputational damage.

5.3. Limitations and future work

We recognise there are some limitations with our study. The collection and analysing of the data were primarily led by just one researcher, which could have potentially introduced some bias in the interpretations. Two measures were applied to reduce this possibility. First, the sources of potential bias were identified at the start of the research process – for example, the lead author's background in practice from a technical discipline could lead to an overly positive perception of AI innovation as a force for good. Secondly, the emerging findings were reviewed and discussed at regular time intervals with the second author, in particular, for how they aligned with the relevant theory and practice.

The data collection approach may also be perceived as too complex due to its multi-method, multiple-sources nature. Yet that was necessary due to the fast-paced and complex nature of the AIFT domain itself. For example, soon after our study was finished six (21.42%) firms from our initial sample of 28 were either acquired or partnered with other firms. To further explore the processes and mechanisms within the companies included in our data set, additional interviews were conducted with the top decision-makers from these organisations and other AIFT experts from the Canada Fintech Forum[10]. Theses interviewees were selected so as to be representative of the 28 FinTech companies from our sample regarding the industry (financial, IT and embedded FinTech), company size (micro, small and medium), stage of business development (startups, growing and mature firms), business model (B2B and one B2C), AI capability (automation, financial models, propensity modelling, data insights and certain higher-order capabilities, such as responsible AI) and FinTech function (Wealth management, InsureTech, Payments, BaaS, and support for model management). This study could still benefit from more interviews and more comprehensive empirical data, but like every research effort, we were constrained by time and high-quality access to senior leaders and entrepreneurs, especially given the sensitive nature of the issues we were studying. The issue with using secondary data in research is well documented in the literature, however, there is also an increasing trend of the use of such data in innovation and IS research, due to the large amount of data already available.

This study does open up several new areas for future research. First, more empirical research is required to validate and further develop the theoretical model that emerged from our study for a larger sample of firms from different empirical contexts. We have already initiated the expansion of our research in London, Paris, and several other European cities with significant AIFT development. Identifying similarities and differences among these regions is an area for future research. This will help us further develop and validate the boundary conditions of our findings. However, more systematic empirical studies are still needed. Second, further research is required for identifying and empirically validating different process types and trajectories through which AI unfolds in financial services in different-sized firms and different markets around the world. This effort could further extend our findings and contribute more to the development of a more complete taxonomy of AI-enabled innovation processes in FinTech. Given that the NPD process in SMEs is typically coupled with entrepreneurship, employing effectuation–causation logic (Sarasvathy, 2001) in future process analysis studies may offer additional insights for accelerating innovation (Berends et al., 2014; Marzi et al., 2020). Finally, identifying and evaluating the links between the innovation processes emerging from this study and business performance through large-scale surveys in different markets would contribute additionally to the development of AIFT theory and practice.

6. Conclusions

This paper explores the AI development process in FinTech SMEs, a phenomenon of particular interest today due to the significance of AI and FinTech for the global economy. It addresses the lack of empirical evidence on how the AI innovation unfolds within organisations and the rationale behind their different implementations. The findings are the result of a comprehensive analysis of data gathered from various sources, including interviews with the senior executives in these organisations and insights from the interviews and presentations of industry experts; taken together, they provide inside and outside views of innovation processes in these organisations. Future studies could benefit from efforts to further identify the different process configurations and improve our understanding of why the differences actually occur and what are the consequences of different implementations. These new findings can then be used to inform theory development and provide contextualised insights for both business leaders and entrepreneurs when developing and implementing AI-enabled innovations.

By extending contingency theory with the process configuration construct, we identified two distinct behavioural patterns for AI innovation development processes that are contingent on the level of investment and organisational agility with AI implementation. These findings have been integrated into a new theoretical model for better understanding how AI-based innovation is implemented within FinTech SMEs and which factors contribute most to its accelerated implementation. Our typology of AI innovation processes and their trajectories could also serve as a practice and diagnostic tool for understanding and more effective utilisation of AI innovation in the FinTech sector.

Additionally, our theoretical model has potential for researchers studying the mechanisms involved in technological innovation processes. In a broader context, this study suggests that despite the enormous potential of AI to offer SMEs with opportunities to challenge big firms and disrupt the industry, this promise has not been realised in the financial industry, which was one of the early adopters of AI innovation. We have explored the reasons behind this lack of disruption and considered what can be done to address it. Overall, our study provides a useful guide for practitioners and presents a new theoretical model for studying AI innovation which requires further validation with more empirical data from various contexts.

CRediT authorship contribution statement

Marija Cubric: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing. **Feng Li:** Conceptualization, Methodology, Validation, Writing - review & editing.

Data availability

The authors do not have permission to share data.

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