Small Bus Econ (2024) 62:411–434
https://doi.org/10.1007/s11187-023-00779-x

RESEARCH ARTICLE

Estimating the innovation benefits of first-mover and second-mover strategies when micro-businesses adopt artificial intelligence and machine learning

Ully Y. Nafizah · Stephen Roper · Kevin Mole

Accepted: 22 April 2023 / Published online: 29 May 2023

Abstract Digital technologies have the potential to transform all aspects of firms' operations. The emergence of advanced digital technologies such as Artificial Intelligence and Machine Learning raises questions about whether and when micro-businesses should adopt these technologies. In this paper we focus on how firms' adoption decisions on Artificial Intelligence and Machine Learning influence their innovation capabilities. Using survey data for over 6,000 micro-businesses in the UK, we identify two groups of adopters based on the timing of their adoption of Artificial Intelligence and Machine Learning. 'first movers' – early adopters of the new technologies - and 'second movers'- later adopters of the new technology. Probit models are used to investigate the innovation benefits of first and second mover adoption strategies. Our results suggest strong and positive impacts of adopting Artificial Intelligence and Machine Learning on micro-businesses' innovation outcomes and innovation processes. We highlight the differential benefits of first mover and second mover strategies and highlight the role of technology characteristics as the differentiating factor. Our results emphasize both the innovation enabling role of digital technologies and the importance of an appropriate strategic approach to adopting advanced digital technologies.

Plain English Summary Despite the powerful functions offered by advanced digital technologies, such as Artificial Intelligence and Machine Learning, it is unclear whether micro-businesses should adopt these technologies. In addition, micro-businesses are faced with two adoption strategy options: a first mover strategy by becoming an early adopter, or a second mover strategy by becoming a later adopter of the new technologies. Our study suggests that adopting Artificial Intelligence and Machine Learning enhances micro-businesses' innovation outcomes and innovation processes, highlighting the benefits of technology adoption on micro-businesses with limited financial and human resources. Interestingly, our study suggests the differential benefits of first mover and second mover strategies based on technology characteristics. The principal implication of this study is that micro-businesses should be encouraged to adopt Artificial Intelligence and Machine Learning to compensate for their resources and capabilities in the innovation process.

U. Y. Nafizah (✉) · S. Roper · K. Mole
Warwick Business School, The University of Warwick, Coventry, UK
e-mail: Ully-Yunita.Nafizah@warwick.ac.uk

S. Roper
e-mail: Stephen.Roper@wbs.ac.uk

K. Mole
e-mail: Kevin.Mole@wbs.ac.uk

Keywords Advanced digital technology · Artificial Intelligence · Digital adoption · Innovation · Machine Learning · Micro-Business · Timing Adoption

JEL Classification O31 · O33 · C12 · C20

1 Introduction

The emergence of advanced digital technologies in the last decade promises a fourth industrial revolution, termed Industry 4.0, where firms adopt digital technologies to transform their business processes, product offerings, and inter-organizational relationships, so increasing competitiveness and profitability (Bharadwaj et al., 2013; Nambisan, 2017). Industry 4.0 requires digital adoption throughout the supply chain; yet prior literature highlights the complexity of the decision-making processes surrounding both the adoption of new technology and the timing of new technology adoption (e.g., Hoppe, 2000; Suarez & Lanzolla, 2007). Generally, the literature distinguishes two types of adoption strategies based on the timing of adoption: first mover and second mover strategies. In the first mover strategy, firms are the early adopters of new technology and may gain first mover advantages by exploiting their superiority in technology to achieve larger market shares and higher returns (Lieberman & Montgomery, 1988; Suarez & Lanzolla, 2007). Meanwhile, in the second mover strategy, firms delay adoption due to uncertainty about the value of any new technology and adoption costs (Hoppe, 2000). Second movers accrue advantages from better information about the value and costs of the technology and, thus, have lower risk (Yoon, 2009).

To date, the extant literature is vague concerning technology adoption by micro-businesses. Prior literature suggests the potential benefits of adopting digital technologies to compensate for the capability and resource constraints that smaller firms often face (e.g., Ainin et al., 2015). The literature also suggests that digital technologies can enhance firms' innovation processes and innovation outcomes (e.g., Niebel et al., 2019; Raymond et al., 2009), which is important because micro-businesses typically report lower innovation activity and innovation outcomes than larger firms (Baumann & Kritikos, 2016). On the other hand, micro-businesses have more barriers to technology adoption due to limited financial and human resources leading to lower adoption rates (Jones et al., 2014; Kelliher & Reinl, 2009). Micro-businesses also have difficulty valuing the potential benefits of technology adoption (Simmons et al., 2008), leading to late adoption of new technology (e.g., Dorrington et al., 2016; Macgregor & Vrazalic, 2005). This suggests that the decision-making process on the adoption and the timing of adoption of digital technologies are more complex for micro-businesses.

This study explores the innovation benefits and the best adoption strategy when micro-businesses adopt digital technologies. We compare the benefits of first mover and second mover strategies in adopting Artificial Intelligence and its subset, Machine Learning, for firms' innovation capability, measured by firms' ability to perform innovation processes and to introduce innovation outcomes. We use a micro-business survey covering 6,254 firms in the UK collected in 2018 which provides data on the adoption of Artificial Intelligence and Machine Learning before and after 2012 and firms' innovation activity and innovation outcomes during 2015 – 2018. The structure of the data allows us to identify two groups of adopters based on the timing of their technology adoption: 'first movers' that adopted advanced digital technology before 2012, and 'second movers' that adopted advanced digital technology between 2012–2015. We then consider the impact of each adoption strategy on innovation capability, measured by whether firms perform internal research and development (R&D) activity, and whether firms introduce product innovation and radical innovation, during the later 2015–18 period.

Our study makes two main contributions. First, we explore how advanced digital technology adoption strategies impact innovation capability. While the prior literature has provided insights into how both first movers and second movers benefitted from their strategies in market share and competition (Hoppe, 2000; Lieberman & Montgomery, 1988), we connect adoption strategies to firms' innovation processes and innovation outcomes. Understanding this linkage seems essential given the growing questions around the nature of advanced digital technologies and the increasing emergence of Industry 4.0. Second, our study focuses on digital technology adoption in micro-businesses. While the prior literature has examined the impact of digital technology adoption on larger firms (e.g., Steiber et al., 2021) and SMEs (e.g., Giotopoulos et al., 2017; Li et al., 2018), micro-businesses are often excluded from innovation surveys and related analyses, (e.g., the UK Innovation Survey, UK E-Commerce survey). Although smaller firms comprise over 95% of all businesses (BEIS, 2020), smaller firms tend to have limited awareness of the benefits of adopting new technology, leading to lower technology adoption rates compared to their larger counterparts (Jones et al., 2014; Simmons et al., 2008). Understanding the effects of digital technology adoption on micro-businesses seems imperative to provide evidence of the adoption benefits and encourage digital technology adoption.

The paper is organized as follows. Section 2 provides the conceptual framework drawing on the theoretical literature and empirical evidence on technology adoption strategy and its relation to innovation. In Section 3, we present our hypotheses drawn from previous studies on technology adoption, the timing of adoption decisions, and the complementarity of innovation. Section 4 describes the data and statistical approach, and Section 5 describes the probit estimation results. Last, in Section 6, we discuss the results, the contribution, the implications, and the limitations of this study.

2 Conceptual development

Based on the theoretical lens of the resource-based view, the adoption of new technology is considered as a resource-picking and capability-building mechanism to create sustained competitive advantage (e.g., Wu et al., 2006). Within the resource-based view, Barney (1991, p.105) proposed that valuable resources enable firms to "exploit opportunities and/or neutralize threats in a firms' environment". In other words, resources are considered valuable due to their resource value and resource risk considerations (Toms, 2010). Since the adoption decision also carries with it technology uncertainty and risks, and resources required to adopt new technologies (e.g., Hoppe, 2000; Yoon, 2009), this implies the existence of risk-reward considerations behind advanced digital technology adoption. To analyse this issue, we explore the value of Artificial Intelligence and Machine Learning adoption in micro-businesses and the risk-reward balance of advanced digital technology adoption based on the literature of first mover and second mover advantage.

2.1 Adoption of artificial intelligence and machine learning in micro-business

Artificial Intelligence (AI) and its subset technology, Machine Learning, offer various powerful cognitive and decision-making functions to enhance firms' capabilities, performance, and competitiveness. Artificial Intelligence (AI) is defined as a system's ability to imitate human cognitive functions to learn from data, perform learning and solve problems (Haenlein & Kaplan, 2019), with various AI techniques being introduced in the literature including decision support systems, intelligent agents, and expert systems (Chen et al., 2021). Loureiro et al. (2021) also highlight Artificial Intelligence capabilities for natural language processing, information storing, automated reasoning, and Machine Learning to learn from patterns. In its application, Artificial Intelligence may support firms in automating their digital and physical tasks, enable pattern detection in vast volumes of data and data interpretation, and the cognitive engagement between firms and their employees and customers (Davenport & Ronanki, 2018). Meanwhile, Machine Learning is defined as a subset technology of AI with the ability to self-learn from data patterns and perform an assigned task without human intervention (Brynjolfsson & Mcafee, 2017). In its application, Machine Learning provides a higher level of cognitive insights by mimicking the human brain to recognize patterns, make predictions, and produce new data for better analysis (Davenport & Ronanki, 2018). These reasons suggest that Artificial Intelligence and Machine Learning have the potential to act as complementary or substitute cognitive resources to traditional human resources to accelerate business function, which is aligned with the resource-based view (e.g., Bag et al., 2021; Wade & Hulland, 2004).

The potential benefits of Artificial Intelligence and Machine Learning to improve firms' capabilities, performance and competitiveness raises questions about whether and when firms should adopt these technologies. Linking to the resource-based view, digital technologies can serve as strategic resources to enhance firms' competitiveness, growth, and survivability (e.g., Hartmann & Henkel, 2020). However, Ghobakhloo and Ching (2019) argue that the decision process of adoption in smaller firms differs from larger firms due to their limited financial, human, and organizational resources (Hewitt-Dundas, 2006). Micro-businesses with less than 10 employees may experience more barriers to technology adoption, supported by empirical evidence of lower digital technology adoption rates in micro-businesses than their larger counterparts (Jones et al., 2014).

In addition to resource limitations, prior literature also highlights other barriers that hamper digital technology adoption in small businesses and micro-businesses. For instance, the literature highlights cost-benefit considerations as key determinants of technology adoption decisions in micro-businesses. Small firms may have perceptions of the high cost of adoption (Dorrington et al., 2016) as well as difficulties valuing the potential benefits (Simmons et al., 2008), and a more general lack of information (Macgregor & Vrazalic, 2005). These findings suggest that micro-businesses are often not convinced of the benefits of technology adoption and, therefore, delay their adoption to collect more information before reconsidering adoption.

2.2 First mover and second mover adoption strategy

The timing of adoption decisions therefore reflects firms' consideration of costs, risks, and potential benefits, with prior literature identifying two types of adoption strategy based on firms' response to the emergence of new technology: first mover and second mover strategies. A first mover adoption strategy reflects firms' decision to become an early adopter of a new technology to gain first mover advantages by exploiting their superiority in technology to compete with their rivals, achieve larger market share, and earn higher economic profits (Lieberman & Montgomery, 1988; Suarez & Lanzolla, 2007). A first mover adoption strategy reflects a pre-emptive competitive strategy with the assumption that firms win when they introduce better innovations (by exploiting the technology) at the earliest time (e.g., Riordan, 1992). Suarez and Lanzolla (2007) identify three sources of first mover advantage: economic advantages, internal capability advantages, and market environmental advantages. First, first movers gain economic advantages by monopolizing production resources, achieving economic of scale, or capitalizing on the patents of their innovations (e.g., Dixit, 1980; Gilbert & Newbery, 1982). Second, consistent with the resource-based view, first movers enhance their internal competence and capabilities earlier and, therefore, may have specialized or superior capabilities than their competitors (e.g., Klepper & Simons, 2000; Rosenbloom & Cusumano, 1987). Third, market environment advantages accrue since by introducing better innovations before others, first movers may initiate market evolution and technology evolution and, therefore, benefit from technology leadership (e.g., Suarez & Lanzolla, 2007).

On the other hand, a first mover adoption strategy is higher risk due to the cost of investments and technological uncertainty. For instance, Lieberman and Montgomery (1988) suggest first movers may be harmed by free rider effects, i.e., the imitation of adoption by later adopters at lower costs, technology uncertainty of the "dominant design", and market shifting. These first mover disadvantages, therefore, become the advantages captured by second movers.

In the second mover strategy, firms delay adoption to benefit from information spillovers and lower adoption costs (Hoppe, 2000; Yoon, 2009). Later adopters, further, aim to gain information about technology adoption by observing early adopters' experience to reduce technological uncertainty and adoption risks (Tran et al., 2012; Yoon, 2009). However, in adopting a second mover strategy firms' trade-off greater information though delaying technology adoption against lower potential profits. Yoon (2009) suggests that the more firms adopt the same technology, the lower the potential profit due to competition. Prior literature on second mover advantages, therefore, focuses on the waiting game of adoption. For instance, Hoppe (2000) proposes a duopoly model of new technology adoption based on technology uncertainty and costs of adoption and suggests a small increase in the probability of success may transform the waiting game into a pre-emptive game. Meanwhile, Yoon (2009) argue that better informed firms are aware of the intention of less-informed firms and, therefore will delay adoption to prevent information spillovers and propose an equilibrium model based on the cost of delaying adoption. These findings highlight the complexity of adoption strategy based on the information characteristics, potential profit, and costs of adoption.

3 Hypothesis development

The potential benefit of adopting advanced digital technology raises questions about whether micro-businesses should adopt these technologies and which adoption strategy works best for micro-businesses. Next, we investigate first mover advantages and second mover advantages in the micro-businesses case.

3.1 How artificial intelligence and machine learning influences micro-businesses' innovation processes and innovation outcomes

The literature suggests a close relationship between digital technology and innovation. Digital technologies potentially transform innovation outcomes: first by enabling the development of new products based on the recombination of physical and digital components (Yoo et al., 2010); and second by altering the spatial and temporal boundaries of the innovation process (Nambisan, 2017). To illustrate these two effects of digital technologies' role in innovation, the literature introduces two perspectives: product-centric and process-centric development. The product-centric perspective defines digital innovation as a new type of product innovation, i.e., the combination of physical and digital products enabled by the properties of digital technologies to offer new opportunities for products and services (Yoo et al., 2010, 2012). Meanwhile, the process-centric perspective on digital innovation emphasizes the use of digital technologies to orchestrate market offerings, business processes, and innovation processes (Agostini et al., 2020; Nambisan, 2017). From the process-centric view, digital technologies can act as both operand resources, i.e., enabler or facilitator, and operant resources, i.e., initiator or actor, in firms' innovation process. In other words, the process-centric view of digital innovation argues that the adoption of digital technology will enhance firms' innovation process. In this study, we explore both product-centric and process-centric views of digital innovation and, therefore, analyse the impact of advanced digital technology adoption on both firms' capability to undertake innovation and to achieve enhanced innovation outcomes.

We propose that the adoption of Artificial Intelligence and Machine Learning positively influences innovation capability and enhances the innovation process and improves firms' ability to achieve innovation outcomes. Firstly, both technologies potentially reduce innovation barriers, improve efficiency, and accelerate the innovation process that is traditionally performed by humans. As suggested by Haefner et al. (2020), both technologies support the stage of idea generation and idea development by overcoming information processing and knowledge search barriers. The growing availability of data and information due to technological advancements challenges the limit of human cognitive capacity to absorb and process information. Artificial Intelligence enables firms to identify more problems and opportunities for new idea identification and assess more information for idea development (Haefner et al., 2020). Next, Artificial Intelligence eases the acquisition of external information and knowledge; therefore, it reduces knowledge search limitations and supports firms in identifying more exploratory problems/opportunities leading to the generation of more novel ideas (Haefner et al., 2020; Paschen et al., 2019). In addition, the adoption of Artificial Intelligence allows firms to learn from customer data and, thus, improve the prediction accuracy of customer preferences and market segmentation (Angermann & Ramzan, 2016; Farazzmanesh & Hosseini, 2017). These adoption benefits may help firms identify and develop innovation outcomes based on the specific market segment's preferences and needs, which improves the success of innovation outcomes. Both Artificial Intelligence and Machine Learning allow firms to undertake more precise forecasting based on a vast amount of data, leading to less risky decision-making (Srinivasan, 2014). These potential benefits of Artificial Intelligence and Machine Learning are particularly relevant to the idea evaluation stage, where firms may evaluate possible ideas based on the prediction of customers' demand. Second, both Artificial Intelligence and Machine Learning technology can be recombined into the existing solutions, thus, leading to a new application of ideas (Davenport & Ronanki, 2018). For instance, embedded Artificial Intelligence enables self-driving cars, customer-bots, and personal assistants, e.g., Alexa or Siri. These reasons suggest that Artificial Intelligence and Machine Learning can improve firms' ability to undertake internal innovation processes and achieve enhanced innovation outcomes.

These effects may be particularly important for resource constrained micro-businesses. To begin with, empirical evidence suggests that micro-businesses, i.e., firms with fewer than ten employees, tend to have a lower probability of performing innovation activity and, therefore, have less product and process innovation than larger firms (Baumann & Kritikos, 2016). Micro-businesses have limited amounts of internal capital and ability to invest in innovation (Audretsch et al., 2020). However, advanced digital technologies help small firms compensate for their limited internal resources enabling their innovation activity (Li et al., 2018). In our case, Artificial Intelligence and Machine Learning technology may enhance small firms' cognitive and decision-making capability and compensate for their human resource limitations. Linking to the resource-based view, Artificial Intelligence and Machine Learning, can thus be considered strategic resources enabling firms to develop their internal capabilities and achieve competitive advantage through innovation. Therefore, we argue that adopting these technologies enhances micro-businesses' innovation capability to perform innovation processes and leverage their innovation outcomes (Fig. 1).

H1a: The adoption of Artificial Intelligence positively affects micro-businesses' innovation outcomes.
H1b: The adoption of Artificial Intelligence positively affects micro-businesses' innovation processes.
H2a: The adoption of Machine Learning positively affects micro-businesses' innovation outcomes.
H2b: The adoption of Machine Learning positively affects micro-businesses' innovation processes.

3.2 Second mover strategy as the best adoption strategy for micro-businesses

Whether it is more advantageous to be a first mover, or a second mover is the subject of discussion in prior literature. To date, the literature provides conflicting empirical evidence and is unable to provide conclusive evidence on the relative strength of first mover and second mover advantages. One stream of literature highlights the impact of first mover advantages on various measures of firm performance. Lambkin (1988) provides empirical evidence that first movers enjoy higher share values and longer profit advantages to compensate for higher investments using 129 firms from the PIMS database. Shepherd (1999) highlights that first movers have a higher probability of survival than second movers based on the 1995 Australian Venture Capital Guide. Similarly, Robinson and Min (2002) provide evidence that first mover advantages offset technological uncertainty and risks and enhance firms' survivability through temporary monopoly using the 1999 *Thomas Register* of US manufacturers. Using data from the *Strategic Planning Institute's STR2 database* of US manufacturers, Robinson et al. (1992) also highlights that first

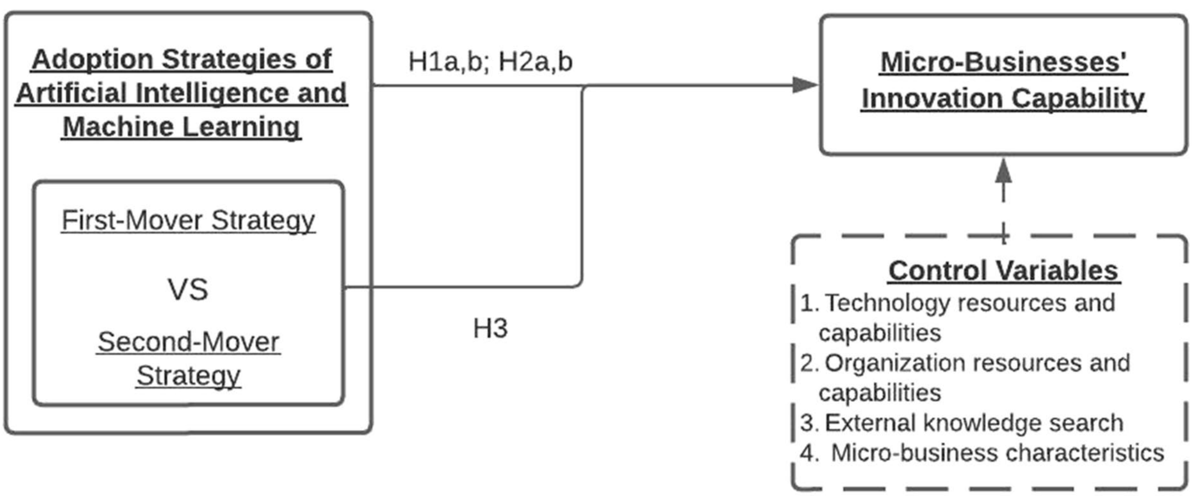

Fig. 1 Conceptual Model

movers have stronger intrinsic skills and resource profiles than second movers.

Meanwhile, another strand of literature highlights evidence of first mover disadvantages, inter alia supporting second mover advantages. Golder and Tellis (1993) use historical analysis to provide evidence that first movers have a 47% failure rate, and only 11% of first movers become the market leaders of their respective industries. Similarly, Boulding and Christen (2001) use the PIMS database from 1930 to 1985 to provide empirical evidence of the cost disadvantages of first movers. Boulding and Christen (2001) highlight that first movers have less profit in the long term than second movers as the cost penalty outweighs the potential revenue. These differences in empirical evidence suggest that both first mover strategy and second mover strategies can provide potential benefits for firms. Suarez and Lanzolla (2007) further propose that the success of entry timing strategy is affected not only by firm-level enablers, such as firms' resources and capabilities, but also by the environmental dynamics of markets and technology evolution.

In this study, we propose that the second mover strategy is the best adoption strategy for micro-businesses for two reasons: competitive strategy and limited internal resources. First, a second mover strategy fits with micro-businesses' competitive strategy. As suggested by Parnell and Carraher (2001), early adopters are identical to "the prospectors" in Miles and Snow's (1986) typology who utilize innovation to actively engage with fast-changing environments, while second movers link to "the analysers" who focus on maintaining stability and react to the dynamic started by first movers, although both "prospectors" and "analysers" are associated with high entrepreneurial orientation that enables small firms to benefit from innovation, risk-taking, and proactiveness (Tang & Tang, 2012). Evidence from Brazil and Ghana show "analysers" as the most common strategy for small firms (Agyapong et al., 2016; Gimenez, 2000). Micro-businesses, therefore, are better to adopt second mover adoption strategy as part of their competitive strategy.

Second, micro-businesses have limited internal resources to devote to the adoption of new technologies and capitalize on technology benefits. Firms' ability to capitalize on their technology superiority to achieve economies of scale is critical for a first mover strategy (e.g., Dixit, 1980; Gilbert & Newbery, 1982). Micro-businesses have few permanent employees (or even none), limited access to financial resources, and therefore limited capacity to utilize scale economies (Liberman-Yaconi et al., 2010). Micro-businesses are vulnerable to risk and, therefore, first mover strategy with more technological uncertainty is less suitable for micro-businesses. Next, using 577 retail companies in the USA, Parnell and Carraher (2001) find that micro-businesses with limited R&D activity will have a less effective first mover strategy. Given that micro-businesses are less able to gain innovation benefits from the first mover strategy, we propose that the second mover strategy by delaying the adoption of advanced digital technologies is superior to the first mover strategy to enhance micro-businesses innovation process and outcomes.

H3: Second mover strategy leads to higher micro-businesses' innovation capability compared to a first mover strategy

4 Data and methods

For our empirical analysis, we use the Micro-business Britain Survey 2018 that provides information on established micro-businesses in the UK. The Micro-business Britain Survey includes information on digital adoption before 2012, between 2012–2015, and after 2015, and innovation activity between 2015 and 2018. The survey also provides information on micro-businesses' key business characteristics and business strategies making it a suitable dataset to study the links between business characteristics, business strategy and digital adoption. The survey covers established micro-businesses: firms with 1–9 employees and had been operating for at least three years. The survey excludes micro-businesses that are subsidiaries of larger firms, charities, or part of the public sector. The Micro-Business Britain survey was undertaken by telephone interview with either the owner or business manager between February and May 2018. The survey's response rate is 9.3 per cent in the UK survey. Although the survey tried to gain representative samples by sector and region within the firm's size band, there is an oversampling for firms in the

5–9 size band to prevent small sample sizes in the specific groups. In this study, we use the UK survey sample with a total of 6,254 micro-businesses.

4.1 First and second movers

The Micro-Business Britain Survey 2018 provides information on advanced digital technology adoption, such as Artificial Intelligence and Machine Learning. For each technology, the survey asks whether firms used each advanced digital technology, and this is used for our adoption variables (*Adopt:AI* and *Adopt:ML).* The survey also asks whether firms had adopted these technologies in the last three years (between 2015–2018), 3–6 years ago (between 2012–2015), or before 2012.

Based on the timing of their adoption of advanced digital technology, we identify two groups of adopters: first movers and second movers. 'First movers' are firms who adopted either Artificial Intelligence or Machine Learning before 2012. Meanwhile, 'second movers' are firms who adopted any of the two advanced digital technologies during 2012–2015. We, thus, come up with four variables of adoption strategy: first mover strategy and second mover strategy of adopting Artificial Intelligence (*Adopt:AI-First Mover* and *Adopt:AI-Second Mover)* and Machine Learning (*Adopt:ML-First Mover* and *Adopt:ML-Second Mover*). While we use 2012 as the cut-off point for first movers' and second movers' analysis due to data limitations, interestingly, this timing also coincides with the period when Industry 4.0 was introduced as a high-tech strategy by the German government (Kagermann et al., 2013).

Appendix Table 1 reports the proportion of advanced digital technology adopters in the UK. By 2015, 2% of UK's micro-businesses had adopted Artificial Intelligence and 6% of them had adopted Machine Learning. This seems related to the fact that Machine Learning is a subset of computational techniques of Artificial Intelligence, which is easier to adopt (Brynjolfsson & Mcafee, 2017). Interestingly, almost half of Artificial Intelligence and Machine Learning adopters are first movers: 1.42 per cent of first movers compared to 0.68 per cent of second movers for Artificial Intelligence, and 4.28 per cent of first movers compared to 2.68 per cent of second movers for Machine Learning.

4.2 Dependent variables

The Micro-business Britain survey includes questions about micro-businesses' innovation activity in the last three years, i.e., between 2015 and 2018. The survey follows the core questions of the Community Innovation Survey (CIS) to provide information on innovativeness by different types of innovation, and innovation performance. We focus on innovation questions that measure micro-businesses' capability to introduce innovation outcomes and perform innovation activities. The innovation outcome is measured by product innovation, a question on whether they introduced *'any new or significantly improved products or services'* and a radical innovation question on whether '*the new or improved products or services introduced were new to the market and/or introduced before their competitors'*. Meanwhile, innovation activity is measured by whether micro-businesses conduct internal research and development (R&D) activities.

Each innovation question is answered in Yes/No format and, therefore, makes our dependent variables binary. Overall, 33% of UK micro-businesses introduce product innovations, 11% of UK micro-businesses introduce radical innovations, and 12% of UK micro-businesses performed internal R&D activity during 2015–2018. However, first movers tend to have a higher propensity to introduce product innovations, radical innovations and to perform R&D activity compared to second movers: 5.53 per cent of first movers introduced product innovations compared to 1.12 per cent of second movers, 0.72 per cent of first movers introduced new-to-the market innovations compared to 0.48 per cent of second movers, and 1.12 per cent of first movers performed internal R&D activity compared to 0.6 per cent of second movers.

4.3 Control variables

Following the resource-based view, firms' capabilities are contingent on and built using their set of organizational resources (Sirmon et al., 2007). In addition, the resource-based view suggests that firms' strategic resources and capability to integrate, deploy, and utilize these resources will determine their performance, highlighting the role of both resources and capabilities as sources of competitive advantage (Barney, 2001). While technology adoption is considered as a resource-picking and capability-building mechanism, prior literature has shown the importance of complementary organizational resources and capabilities, along with the technology itself, to fully realize the benefits of technology investment (Mikalef & Gupta, 2021; Mikalef et al., 2018).

We therefore include some control variables in our analysis in relation to complementary organization resources and capabilities. First, we include technology assets and technology skills since the literature suggests that previous adoption of related technology increases firms' stock of knowledge, enhances digital skills (Bourke & Roper, 2016), and acts as the pre-condition for developing firms' capability to both improve existing technology and to create new technologies (Romijn & Albaladejo, 2002). We identify technology assets based on all of the digital technologies adopted by micro-businesses. The survey provides information on digital technology adoption, such as customer relationship management (CRM) systems, e-commerce, web-based accounting software, computer-aided design software, and cloud computing. Here, 55 per cent of UK micro-businesses have adopted at least one digital technology by 2015. Next, we determine technological skills through specific training to develop new products /services in micro-businesses. The survey suggests that only 14.5 per cent of micro-businesses in the UK conducted specific training for innovation. Second, we include human resource assets and capabilities. We include human resource management practices and organizational innovation practices as complementary to innovation capability within the micro-businesses. As suggested in the literature, the adoption of technological innovation alone is insufficient to enhance firms' innovativeness. It requires other managerial and innovation practices (Battisti & Iona, 2009; Battisti & Stoneman, 2010). The survey suggests that 66 per cent of micro-businesses in the UK performed human resources practices, while only 23 per cent of them undertook organizational innovation. Third, we include external knowledge search activity as another resource-picking and capability-building mechanism to enhance innovation capability, since the literature highlights technological innovation's success through integrating both the internal capabilities of inventiveness and external knowledge (Cassiman & Veugelers, 2002). We control for micro-businesses' external activities: whether firms collaborate with external partners on their innovation activities and whether firms are members of formal business organizations or network members. The survey shows that, on average, micro-businesses in the UK collaborated at least with one external party to innovate, and 47 per cent of micro-businesses have an engagement with a business network.

We also include micro-businesses characteristics as control variables. We include standard control variables such as firms' age based on operating years as well as industry dummies. On average, micro-businesses in the UK 3–4 years of experience operating in the businesses. The adopters of advanced digital technology predominantly come from sector G (retail, wholesale), followed by sector M (professional, scientific) and sector JKL (information, finance, real estate). Considering the importance of human resources elements in technology adoption and innovation activity (e.g., Battisti & Stoneman, 2010), we incorporate employee characteristics measured by the number of employees with a degree or above. Next, following the work of Bourke and Roper (2016), we controlled for business ambition based on questions of the importance "to build national and/or international business" and "to keep business similar to how it operates now". Based on the data, we find that only 22 per cent of micro-businesses in the UK agree that 'building a national or international building' was important. Appendix Table 2 in the Appendix shows the list of variable definitions, while Appendix Table 3 provides descriptive statistics of each variable.

4.4 Modelling strategy

This study analyses the effect of advanced digital technology adoption on firms' innovation capability, measured by whether firms introduce product innovation and radical innovation and whether firms perform R&D activity. The innovation capability variables used as our dependent variables are binary, and therefore estimation models such as *logit* or *probit* would be appropriate (Greene, 2000). In this study, we follow López-Mielgo et al. (2009) *using a probit model* to analyze innovation capabilities as the likelihood of firms' performing innovation. We define innovation capability ($Innov_i$) as: 1) firms' propensity to introduce any product innovation (*Innov:Prod*); 2) firms' likelihood to introduce any radical innovation

(*Innov:New*); and 3) firms' probability to perform any internal research and development (R&D) activity (*Innov:RnD*) within the last three years. We model each aspect of innovation capability ($Innov_i$) using the same univariate probit model to test our first and second hypotheses as follows:

$$Innov_i = \beta_0 + \beta_1 Adopt : AI_i + \beta_2 Adopt : ML_i + \beta_3 Cont_i + \varepsilon \tag{1}$$

Where $Adopt{:}AII_i$ and $Adopt{:}ML_i$ are vectors of independent variables that reflect the adoption Artificial Intelligence and Machine Learning. Next, $Cont_i$ is a vector of control variables consisting of complementary resources and capabilities and micro-businesses' key characteristics. In addition, $Innov_i$ measures firms' propensity to innovate, i.e., whether innovation occurs or not, such that:

$$Innov_i = \begin{cases} 1 \ if Innovi^* > 0 \\ 0 \ if Innovi^* \leq 0 \end{cases} \tag{2}$$

The third hypothesis explores two adoption strategies: first movers who adopt either Artificial Intelligence or Machine Learning before 2012, and second movers who adopt either technology between 2012 and 2015. We include an additional model to estimate the effects of these adoption strategies on innovation capability by partitioning the adoption variables using the baseline univariate probit model as seen in Eq. 3. The model, thus, allows us to test the hypothesis using the total sample with greater precision compared to a group test analysis where groups are defined by adoption strategy.

$$\begin{aligned} Innov_i = \beta_0 &+ \beta_1 Adopt : AI - FirstMovers_i \\ &+ \beta_2 Adopt : AI - SecondMovers_i + \beta_3 Adopt : ML - FirstMovers_i \\ &+ \beta_4 Adopt : ML - SecondMovers_i + \beta_5 Cont_i + \varepsilon \end{aligned} \tag{3}$$

For a better approximation of the probability change produced by explanatory variables, we also calculate the marginal effects and, this allows us to compare degrees of change between variables.

5 Empirical results

This study includes two models based on the adoption strategy, as seen in Appendix Table 5. The first model analyses the impact of technology adoption on innovation, while the second model explores the impact of adoption strategy on innovation with illustrative split by adoption strategies. Appendix Table 4 report the correlation coefficients, which suggest low correlations (less than 0.01) between technology adoption and innovation capabilities. The low correlations suggest that there are no serious issues of multicollinearity. In addition, we use different time periods to analyse the effect of technology adoption on innovation capability. We use data on the adoption of technology before 2012 as the first movers group and data of the adoption of technology between 2012 and 2015 as the second movers group, while we use data on innovation activity between 2015 and 2018. The structure of the data enables us to avoid the potential issues of reverse causality between technology adoption and innovation. Appendix Table 5 summarizes the probit estimation results with marginal values calculated at variable means. Appendix Table 5 also reports the VIF to check the multicollinearity and Harman's single factor test across three groups of adopters to check the variance. The maximum variance inflation factor (VIF) associated with each independent variable for each group of adopters is 1.04, 1.08, 1.06, and 1.11, respectively, which is below the 10-cut-off recommended (Neter et al., 1989) and indicates little influence of multicollinearity. Next, Harman's single factor test yields between 9.5% and 11.62% across different models explaining the variance in the data. This low result suggests that the measures are unlikely to result from common method bias (Podsakoff et al., 2003).

Based on Appendix Table 5, we find that adopting Artificial Intelligence positively affects firms' capability to introduce innovation outcomes, while adopting Machine Learning negatively affects firms' propensity to introduce innovations. For all micro-businesses, the adoption of Artificial Intelligence is associated with 7.4% higher propensity to introduce product innovation and 5.7% higher propensity to introduce new-to-the market innovation. Meanwhile, Machine Learning adoption is linked with 4.5% lower probability to introduce product innovation (see Appendix Table 5). In addition, we do not find any significant association between the adoption of Artificial Intelligence and Machine Learning and research and development (R&D) activity, suggesting no significant association between adopting these technologies and firms' innovation process. Therefore, we provide support only for H1a.

We also explore the effect of adoption based on group sizes of micro-businesses: very small micro-businesses with 1–4 employees and larger micro-businesses with 5–9 employees. The survey shows that very small micro-businesses have higher adoption rates than larger micro-businesses (very small micro-businesses 4 per cent and larger micro-businesses 3 per cent). Both size groups have a similar proportion of first movers and second movers, i.e., around 2 per cent for very small micro-businesses and 1 per cent for larger micro-businesses. Interestingly, we find that advanced digital technology affects very small micro-businesses and larger micro-businesses differently. For very small micro-business, the adoption of Artificial Intelligence and Machine Learning does not affect the capability to introduce product innovation and perform internal research and development (R&D). Meanwhile, for larger micro-businesses, the adoption of Artificial Intelligence increases the firms' propensity to introduce innovation outcomes, and the adoption of Machine Learning increases the firms' propensity to conduct R&D activity. These results support only H1a and H2b, suggesting that the adoption of advanced digital technology positively affects the micro-businesses innovation outcome and the innovation process only for larger micro-businesses with 5–9 employees.

Next, we test our third hypothesis that a second mover strategy leads to higher micro-businesses' innovation capability compared to a first mover strategy. We include F-tests to evaluate the equality of the coefficients on the partitioned adoption strategy variables, as reported in Appendix Table 6. The F-tests suggest a significant difference between first mover strategy and second mover strategy for both adoption of Artificial Intelligence and Machine Learning, highlighting the different impacts of technology adoption strategy on innovation capability. Based on the probit estimation results (see Appendix Table 5), we find the different effects of technology adoption strategies on innovation capability. First, Artificial Intelligence adoption is associated with innovation outcomes for second movers. The adoption of Artificial Intelligence by second movers is associated with a 17% higher propensity to introduce product innovation and a 9% higher propensity to introduce radical innovation, as seen in Appendix Table 5. Second, we find that Machine Learning adoption by first movers positively affects their innovation capability to perform internal R&D activity, while Machine Learning adoption by second movers negatively affects firms' propensity to introduce product innovation. For instance, the adoption of Machine Learning by first movers is associated with 3% higher propensity to perform R&D activity, while the adoption of Machine Learning by the second movers is associated with 7% lower propensity to introduce product innovation (Appendix Table 5). Our findings suggest that our third hypothesis (H3) is supported for Artificial Intelligence adoption but not for Machine Learning.

We identify the effect of complementary organization resources and capabilities to develop innovation capability as the control variables. First, the literature suggests that technology assets and capabilities affect firms' ability to perform innovation activities (e.g., Wang et al., 2008; Zhou and Wu, 2010). Here, technology assets measured by total adoption of digital technology, positively links with firms' innovation capability to introduce innovation outcome and to perform R&D activity for both first movers and second movers (Appendix Table 5). Next, Romijn and Albaladejo (2002) also highlight the role of technology skills on firms' ability to introduce innovation. In our sample, technology skills show a consistent and strong association with firms' innovation outcomes and R&D activity across all three different groups of adopters, as seen in Appendix Table 5. Second, the literature highlights the importance of human resources and capabilities in innovation activities (e.g., Kianto et al., 2017). We find that human resource practices and organizational innovation practices are positively associated with R&D activity, while organizational innovation practices are negatively associated with firms' propensity to introduce product innovation (Appendix Table 5). Thirdly, consistent with the literature (e.g., Cassiman & Veugelers, 2002), we find that micro-businesses partnerships with external parties have a consistent positive association with innovation capability on introducing innovation outcomes and performing R&D activity for all micro-businesses, for both first movers and second movers, as seen in Appendix Table 5. However, the involvement of business networks shows no association with innovation capability across different types of adopters. Overall, the result suggests that various complementary organization resources and capabilities influence micro-businesses' innovation capability.

The key characteristics of micro-businesses as the control variables provide mixed results. Firm age is negatively associated only with the propensity to introduce product innovation, while employees' graduate status is positively associated with innovation capability to perform R&D activity. Business ambition was also strongly linked with a higher propensity to introduce innovation outcomes and perform internal R&D activities across different types of adopters. This result indicates that micro-businesses characteristics link to innovation capability.

5.1 Robustness tests

As a robustness test, we conduct group tests based on the timing of advanced digital technology adoption strategy, reported in Appendix Table 7. The first analysis focuses on first movers: micro-businesses which adopted either Artificial Intelligence or Machine Learning before 2012. Meanwhile, the second analysis focuses on second movers: micro-businesses which adopted either Artificial Intelligence or Machine Learning between 2012 and 2015. For the first and the second groups, we include the non-adopters of Artificial Intelligence and Machine Learning in the analysis as the baseline for comparison. Estimation results are very similar to our main analysis, providing only partial support for Hypothesis 3. Second movers strategy of adopting Artificial Intelligence is consistently associated with a higher probability of innovation outcomes.

6 Discussion and conclusion

6.1 Discussion

The paper examines the impact of the adoption of advanced digital technologies, such as Artificial Intelligence and Machine Learning, on innovation capability. Using a dataset from the Micro-Businesses Britain Survey, we identify two groups of UK adopters based on the timing of technology adoption. The first group is 'first movers' that adopt new technology at the earliest time. The second group is 'second movers' that delay the adoption of new technology. In general, four key findings emerge.

We find evidence that the adoption of advanced digital technologies, such as Artificial Intelligence and Machine Learning, enhances micro-businesses' innovation capability. Our findings reaffirm the benefits of advanced digital technology on innovation. For instance, our study confirms the role of Machine Learning to enhance service innovation and the design process as highlighted by Antons and Breidbach (2018) and the role of Artificial Intelligence to enable new methods of invention as proposed by Cockburn et al. (2019). Our findings, thus, reaffirm the finding of Battisti and Stoneman (2010) that the adoption of technologies can be regarded as a technological innovation that leads to positive innovation complementarity. Our results suggest the role of Artificial Intelligence and Machine Learning as strategic resources to leverage firms' innovation capability, highlighting the role of technology adoption as a capability-building mechanism, as suggested by the resource-based view.

The results also suggest that each advanced digital technology corresponds to a different innovation capability. Machine Learning adoption increases firms' propensity to perform internal R&D activity, while Artificial Intelligence adoption increases firms' propensity to introduce both product innovation and radical innovation (see Appendix Table 5). This finding is also relevant to the key features of each advanced digital technology. For instance, Machine Learning serves as a decision aiding technology based on big data, particularly in the idea generation and idea development phases (Frank et al., 2019; Haefner et al., 2020). This suggests that Machine Learning fosters firms' capability to perform internal R&D based on data, highlighting the role of Machine Learning as the driver of data-driven innovation (e.g., Trabucchi et al., 2017; Trabucchi & Buganza, 2019). For instance, Machine Learning helps firms to decide which products to develop and at which market to aim.

While previous literature has suggested that advanced digital technology enables all firms (e.g., Trabucchi & Buganza, 2019), our results highlight the positive impacts of advanced digital technology adoption on innovation capability only for larger micro-businesses with 5–9 employees. This result potentially links to the characteristics of advanced digital technologies. The application of Machine Learning and Artificial Intelligence depend more on employees' technical know-how, and these reasons hamper the adoption of Machine Learning and Artificial Intelligence in the smallest firms (e.g., Bauer et al., 2020 and Iftikhar & Nordbjerg, 2021). Whilst overall, our findings highlight the benefit of adopting advanced digital technology on micro-businesses innovation process and innovation outcomes, significant differences emerge for different sizes of micro-businesses making outcomes specific to size.

We find strong evidence of both first mover advantages and second mover advantages of adopting advanced digital technologies on micro-businesses' innovation capability. The results also suggest that each advanced digital technology has a different optimal adoption strategy linked to the characteristics of each advanced digital technology. The adoption of Artificial Intelligence by both first and second movers increases the propensity of micro-businesses to innovate. This finding shows that Artificial Intelligence improves the innovation capability of micro-business regardless of the type of adoption strategy. On the contrary, the adoption of Machine Learning by first movers leads to a more significant and positive impact on innovation capability than the adoption by second movers. This finding suggests that a first mover strategy, becoming an early adopter of Machine Learning, works better for micro-businesses. In our case, first movers may benefit from the superior capability to utilize Machine Learning in their internal research and development activity. This finding reaffirms the first mover advantages of micro-businesses to gain internal capability advantages, as suggested by Suarez and Lanzolla (2007). Interestingly, these findings, therefore, highlight the benefit of first mover and second mover strategy for each advanced digital technology. This finding also shows that first mover and second mover advantages are not only relevant to firms' economic profitability (e.g., Hoppe, 2000; Yoon, 2009) but also to firms' innovation capability. To sum up, our findings highlight the role of technology characteristics as one determinant of technology adoption strategy.

We also find evidence that various complementary organization resources and capabilities affect micro-businesses' innovation capability. Linking to the resource-based view, our findings highlight the importance of complementary organization resources and capability to leverage innovation. First, our results suggest that technology assets and technology skills positively influence micro-businesses' propensity to innovate both for first movers and second movers. Our results confirm the importance of technology assets and skills as firm-level enablers to capture the potential benefits of first movers (Suarez & Lanzolla, 2007). Next, we find that human resource practices and organizational innovation are positively associated with micro-businesses' propensity to perform internal R&D activity. Meanwhile, organizational practices negatively influence micro-businesses' propensity to innovate, which may be consistent with micro-businesses' organizational limitations due to limited employees (Liberman-Yaconi et al., 2010) and the balancing focus between innovation activity and organizational activity (Battisti et al., 2015). Our findings also highlight external knowledge search activity as another resource-picking and capability-building mechanism to enable innovation (Cassiman & Veugelers, 2002). To sum up, our findings suggest the importance of alignment between firms' internal and external forces both in the context of innovation activity and technology adoption. Our results highlight that the success of technology adoption strategy and innovation strategy are contingent on firms' overall strategy and context.

6.2 Implications

The main theoretical contribution of this paper is to shed light on whether the adoption of advanced digital technologies by micro-businesses leads to higher innovation capability. First, our study suggests the strong and positive impact of advanced digital technology adoption on micro-businesses' innovation outcomes and innovation process. From the perspective of innovation management, this paper contributes by adding empirical evidence on technological factors that drive the innovation process. Secondly, our results highlight both first mover advantages and second mover advantages of adopting Artificial Intelligence and Machine Learning to develop innovation capability. These findings highlight the role of technology characteristics as one determinant for the technology adoption decision. Third, our findings reaffirm the role of advanced digital technology as one innovation complementarity. Fourth, our results suggest that the success of technology adoption strategy and innovation process are contingent on firms' overall strategy and contextual factors. Therefore, our study emphasizes the importance of a strategic approach to both digital adoption and innovation.

Our results suggest three practical implications for technology adoption and innovation processes in micro-businesses. First, our findings highlight the adoption benefits of advanced digital technologies in enhancing micro-businesses' innovation capability and potentially increasing their competitiveness and profitability. Micro-businesses, particularly larger micro-business with 5–9 employees, could be encouraged to adopt advanced digital technology to compensate for their resources and capability in the innovation process. Second, our findings highlight both first mover advantages and second mover advantages for the adoption of advanced digital technologies. The practical implication is that if micro-businesses intend to adopt specific technology, firms need to consider the characteristics of each technology, including the complementary technology. Our suggestion is that technology needs to be adopted within an overall strategic framework for the micro-business. Third, our findings also provide evidence of the role of complementary resources in shaping both technology adoption and innovation in micro-businesses. The implication is that micro-businesses need to fit the technology adoption strategy and innovation strategy with their overall strategy to enhance competitiveness and increase profitability.

The results have implications for two areas in public policy. First, this study provides an evidence base for policy to develop digital transformation programs on micro-businesses. As highlighted in our research, the adoption of advanced digital technologies positively impacts micro-businesses' innovation outcomes and innovation processes. The first policy implication is that micro-businesses should be included as a priority in national digital transformation programs. To date, national digital policies are commonly targeted toward SMEs and often exclude micro-businesses. For example, the UK's Made Smarter pilot program focuses on supporting digital diffusion in manufacturing SMEs. Our study suggests that the government should also target micro-businesses for policies aiming to increase digital skills, technology awareness, and digital adoption. Various forms of support can be used to foster digital transformation in micro-businesses, such as direct financial support through grants for firms' uptake of advanced digital technology, indirect financial support through tax relief for technology investment, or non-financial support through counselling or mentorship services to guide digital transformation. Secondly, this study provides an evidence base for national innovation policy, notably to support micro-businesses' innovation. Our study suggests that digital technology serves as one enabler of the innovation process. The second policy implication is that government should align innovation policy with digital policy. This implication links to the current trends of digital economy policy priorities to foster innovation in digital technologies, or so-called digital innovation (OECD, 2020). As suggested by OECD (2019), the government should respond to the emerging digital innovation trend by developing data access policies, digital technology adoption promotion policies, and digital technology sectoral application policies.

6.3 Limitation

Nevertheless, this study has some limitations. First, while the UK Micro-business Britain survey 2018 had questions relating to the timing of technology adoption, it was a cross-sectional survey. The survey only provides data on the timing adoption in the last three years (between 2015 and 2018), three-six years ago (between 2012 and 2015), and earlier (before 2012). Therefore, the survey has some limitations for the timings cut-off that potentially impacts the study's result, particularly in comparing the adoption strategy between first movers and second movers (H3). While 2012 coincidently links to the timing of the emergence of Industry 4.0, using 2012 as the cut-off was based on the practical reason to reduce the risk of reverse causality, i.e., timing of adoption must precede micro-business' innovation activities. We are aware of the potential impacts on our result if the timing cut-off is different, as we will have different sample groups of first movers and second movers. Second, innovation variables in the survey are binary yes/no question, i.e., whether firms introduce product innovation, whether firms introduce new-to-the-market innovation, and whether firms perform internal R&D activity. Therefore, our findings are measured by firms' propensity to innovate rather than innovation intensity, e.g., the number of product innovations introduced by firms. Future studies may be interested in exploring the impact of advanced digital technology adoption on innovation intensity. Third, our analysis is focused only on the UK, which limits the generalizability of the findings. It would be interesting to extend our empirical results to other countries to seek the impact of advanced digital technology adoption in micro-businesses. Fourthly, our study only covers two types of advanced digital technology, i.e., Artificial Intelligence and Machine Learning. Meanwhile, other advanced digital technologies exist, such as Big Data Analytics, the Internet of Things, and Robotic technology. Future studies of different types of advanced digital technology and their impact on innovation could make a valuable contribution.

Appendix

Table 1 The Adoption of Advanced Digital Technology in the UK before 2012

	All Micro-Businesses	First Movers (Early Adopters)	Second Movers (Later Adopter)
Artificial Intelligence	2.07%	1.42%	0.68%
Machine Learning	6.68%	4.28%	2.68%

Table 2 Variable Definition

Variable Name	Variable Definition
$Innov_i$	**Innovation capability** that is measured by the probability of firms to introduce innovation outcome and to perform innovation activity **during 2015–2018**
Innov:Prod	A binary variable taking value 1 where the business introduced any new or significantly improved products or services during 2015–2018
Innov:New	A binary variable taking value 1 where the business introduced any new or significantly improved products or services that is new to the market during 2015–2018
Innov:RnD	A binary variable taking value 1 where the business undertakes R&D within your firm during 2015–2018
$Adopt_i$	**The adoption of advanced digital technology**, such as Artificial Intelligence and Machine Learning technology
Adopt: AI	A binary variable taking value 1 where the business adopts Artificial Intelligence
Adopt:AI- First Movers	A binary variable taking value 1 where the business adopted Artificial Intelligence before 2012
Adopt:AI-Second Movers	A binary variable taking value 1 where the business adopted Artificial Intelligence during 2012–2015
Adopt:ML	A binary variable taking value 1 where the business adopts Machine Learning technology
Adopt:ML-First Movers	A binary variable taking value 1 where the business adopted Machine Learning technology before 2012
Adopt:ML- Second Movers	A binary variable taking value 1 where the business adopted Machine Learning technology during 2012–2015
$Cont_i$	**A set of control variables included in the model**
Tech:Assets	The number of total digital technologies adopted by each firm, such as CRM system, e-commerce, web-based accounting, CAD (apart from the advanced digital technology), and Cloud Computing. The variable ranges from 0 to 5
Tech: Skills	A binary variable taking value 1 where the business has specific training related specifically to develop new products/services
Org: HR practices	A binary variable taking value 1 where the business has any human resources practices
Org: Organizational Innovation	A binary variable taking value 1 where the business introduces any organizational innovation
Ext:Partners	Total number of partner types with which the firm is collaborating for innovation
Ext:Network	A binary variable taking value 1 where the business is a member of business network
Age	When the business built (interval: up to 3 years ago, 3–5 years ago, 5–10 years ago, 10–20 years ago, more than 20 years ago)
Employees characteristics	Number of employees with degree or equivalent qualification
National/International Ambition	Binary variable taking value 1 where the firm said the objective to build national/international business was either important or very important
Keep Business State	Binary variable taking value 1 where the firm said the objective to keep business similar to how it operates was either important or very important
Sector (Dummy)	Dummy variable of industry sector. 1 = ABDE primary, 2 = C-manufacturing, 3 = F-construction, 4 = G-retail, wholesale, 5 = HI- transport, accommodation, food, 6 = JKL- information, finance, real estate, 7 = M-professional scientific, 8 = N-administrative service, 9 = PQRS-other services
Size (Dummy)	Dummy variable of size, 1 = very small micro, 2 = larger micro-business

Table 3 Descriptive Statistics of Variables

Variable Name	Mean	Standard Deviations
Innovation Capabilities Variables		
Innov:Prod (Product Innovation)	0.328	0.469
Innov:New (Radicalness of Innovation)	0.112	0.316
Innov:RnD (Research and Development Activity)	0.117	0.321
Adoption Variables		
Adopt:AI (Artificial Intelligence)	0.019	0.137
Adopt:AI- First Movers	0.013	0.116
Adopt: AI-Second Movers	0.005	0.075
Adopt: ML (Machine Learning)	0.062	0.241
Adopt:ML – First Movers	0.038	0.192
Adopt: ML – Second Movers	0.023	0.152
Tech:Assets	1.021	1.174
Tech: Skills	0.145	0.352
Org: HR practices	1.336	0.472
Org: Organizational Innovation	0.231	0.421
Ext: Partners	0.42	1.087
Ext:Network	1.525	0.499
Age	4.119	0.978
Employees characteristics	1.054	1.541
National/International Ambition	0.22	0.414
Keep Business State Ambition	0.73	0.443

See Table 2 for Variable Definitions. $N=5{,}968$

Table 4 Correlation between Digital Technology Adoption and Innovation Activity for All Micro-Businesses Samples in the UK

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Innov:Prod	1																		
2.Innov:New	0.51	1																	
3.Innov:RnD	0.38	0.33	1																
4.Adopt:AI	0.05	0.06	0.08	1															
5.Adopt:AI-First Mov	0.03	0.04	0.07	0.83	1														
6.Adopt:AI-Second Mov	0.04	0.04	0.04	0.53	-0.009	1													
7.Adopt:ML	0.02	0.02	0.07	0.2	0.13	0.16	1												
8.Adopt:ML-First Mov	0.01	0.01	0.06	0.13	0.16	-0	0.77	1											
9.Adopt:ML-Second Mov	0.02	0.03	0.03	0.14	0.001	0.26	0.6	-0.03	1										
10.Tech:Assets	0.05	0.07	0.12	0.13	0.17	-0.02	0.15	0.22	-0.04	1									
11.Tech: Skills	0.41	0.26	0.32	0.06	0.06	0.02	0.06	0.04	0.04	0.07	1								
12.Org: HR practices	-0.1	-0.05	-0.07	-0.03	-0.03	-0.02	-0.07	-0.04	-0.06	-0.06	-0.2	1							
13.Org:Organizational Innovation	0.18	0.13	0.3	0.04	0.04	0.01	0.04	0.02	0.04	0.03	0.33	-0.12	1						
14.Ext: Partners	0.36	0.27	0.35	0.06	0.05	0.01	0.05	0.01	0.06	0.09	0.34	-0.12	0.34	1					
15.Ext: Netw	-0.05	-0.02	-0.05	-0.01	-0.01	-0.05	-0.03	-0.01	-0.02	-0.04	-0.07	0.14	-0.08	-0.09	1				
16.Age	-0.11	-0.07	-0.08	-0.0002	0.012	-0.01	-0.002	0.03	-0.04	0.07	-0.11	0.08	-0.12	-0.12	-0.01	1			
17.Employees Characteristics	0.11	0.1	0.19	0.03	0.02	0.03	0.03	0.01	0.02	0.13	0.15	-0.16	0.12	0.16	-0.03	-0.1	1		
18.National/ International Ambition	0.18	0.17	0.19	0.04	0.02	0.03	0.04	0.02	0.03	0.09	0.1	-0.04	0.15	0.18	0.009	-0.13	0.18	1	
19.Keep Business State	-0.14	-0.12	-0.16	-0.01	-0.01	-0.01	-0.007	0.01	-0.02	-0.02	-0.11	0.04	-0.13	-0.16	0.009	0.12	-0.1	-0.14	1

Table 5 Probit Estimation based on Adoption Strategy

	All Adoption Strategies				Split by Adoption Strategy			
	VIF	Innov: Prod	Innov: New	Innov: R&D	VIF	Innov: Prod	Innov: New	Innov: R&D
Adoption								
Adopt: AI	1.06	0.074*	0.057**	0.033				
		(0.039)	(0.023)	(0.021)				
Adopt: AI-First Movers					1.04	0.032	0.043	0.026
						(0.046)	(0.028)	(0.026)
Adopt AI-Second Movers					1.08	0.17**	0.09**	0.052
						(0.071)	(0.04)	(0.037)
Adopt: ML	1.10	-0.045*	-0.021	0.016				
		(0.023)	(0.015)	(0.013)				
Adopt: ML- First Movers					1.06	-0.033	-0.022	0.031*
						(0.029)	(0.019)	(0.016)
Adopt ML- Second Movers					1.11	-0.07*	-0.023	-0.01
						(0.037)	(0.024)	(0.021)
Control								
Tech:Assets	1.20	0.01***	0.014**	0.013***	1.20	0.013***	0.013***	0.013***
		(0.004)	(0.003)	(0.003)		(0.004)	(0.003)	(0.003)
Tech: Skills	1.25	0.35***	0.107***	0.096***	1.25	0.351***	0.108***	0.096***
		(0.015)	(0.009)	(0.008)		(0.015)	(0.009)	(0.008)
Org: HR practices	1.15	-0.009	0.006	0.016*	1.15	-0.009	0.006	0.016*
		(0.012)	(0.009)	(0.008)		(0.012)	(0.009)	(0.008)
Org: organizational innovation	1.23	-0.03**	-0.005	0.08***	1.24	-0.036***	-0.005	0.08***
		(0.014)	(0.009)	(0.007)		(0.014)	(0.009)	(0.007)
Ext: Partners	1.28	0.09***	0.03***	0.028***	1.28	0.093***	0.03***	0.028***
		(0.005)	(0.003)	(0.002)		(0.005)	(0.003)	(0.002)
Ext:Network	1.04	-0.011	0.003	-0.011	1.05	-0.012	0.004	-0.012
		(0.011)	(0.007)	(0.007)		(0.011)	(0.007)	(0.007)
Age	1.09	-0.01**	-0.004	-0.003	1.10	-0.018**	-0.004	-0.004
		(0.005)	(0.004)	(0.003)		(0.005)	(0.004)	(0.003)
Employee Characteristics	1.32	0.005	0.003	0.012***	1.33	0.004	0.003	0.012***
		(0.004)	(0.002)	(0.002)		(0.004)	(0.002)	(0.002)
National/International Ambition	1.11	0.08***	0.059***	0.046***	1.12	0.084***	0.058***	0.046***
		(0.013)	(0.008)	(0.007)		(0.013)	(0.008)	(0.007)
Keep Business State	1.07	-0.05***	-0.03***	-0.03***	1.07	-0.05***	-0.03***	-0.03***
		(0.012)	(0.008)	(0.007)		(0.012)	(0.008)	(0.007)
Sector Dummy		Yes	Yes	Yes		Yes	Yes	Yes
Size Dummy		Yes	Yes	Yes		Yes	Yes	Yes
Constant		-0.405	-1.57	-1.65		-0.585	-1.57	-1.63
N		5,549	5,478	5,585		5,549	5,478	5,585
Chi-squared		1476.28	652.51	1123.28		1446.6	653.47	1125.84
P - value		0.00	0.00	0.00		0.00	0.00	0.00
R-squared		0.205	0.17	0.27		0.206	0.17	0.27
Log Likelihood		-2782.08	-1589.49	-1465.21		-2780.58	-1589.01	-1463.93
Harman's one factor test		10.93%	10.87%	11.62%		10.27%	9.5%	10.3%

1) Panel Probit model. 2) Reported coefficients are marginal values calculated at variable means, 3) All micro-business sample consists of the adopters before 2015 and the non-adopters, 4) Models includes sector and size dummies 5) Standard errors are in parentheses, 6) *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6 Marginal effects comparison for first movers and second movers

	First Movers	Second Movers	F-Test	Probability (p)
Innov:Prod				
Adopt:AI	0.032	0.17**	3.48**	0.031
Adopt:ML	-0.033	-0.07*	2.50*	0.082
Innov: New				
Adopt:AI	0.043	0.09*	4.98***	0.006
Adopt:ML	-0.022	-0.023	1.39	0.249
Innov: R&D				
Adopt:AI	0.026	0.051	3.70**	0.024
Adopt:ML	0.031*	-0.01	2.74*	0.064

Coefficients and F-tests based on models similar to those in Table 5 for each innovation capability. *$p<0.1$, **$p<0.05$, ***$p<0.01$

Table 7 Regression Result based on Sample Split (Robustness Test)

	First mover (Early Adopters) Sample				Second movers (Later Adopters) Sample			
	VIF	Innov: Prod	Innov: New	Innov:R&D	VIF	Innov: Prod	Innov:New	Innov:R&D
Adopt								
Adopt: AI	1.05	0.041	0.048*	0.03	1.09	0.16**	0.09***	0.043
		(0.047)	(0.028)	(0.26)		(0.073)	(0.041)	(0.038)
Adopt: ML	1.08	-0.025	-0.018	0.03*	1.11	-0.068*	-0.021	-0.006
		(0.029)	(0.019)	(0.16)		(0.038)	(0.024)	(0.021)
Control								
Tech:Assets	1.16	0.002	0.008**	0.01***	1.16	0.013***	0.014***	0.014***
		(0.005)	(0.003)	(0.003)		(0.005)	(0.003)	(0.003)
Tech: Skills	1.25	0.352***	0.108***	0.097***	1.24	0.345***	0.105***	0.091***
		(0.015)	(0.009)	(0.008)		(0.016)	(0.01)	(0.008)
Org: HR practices	1.15	-0.012	0.005	0.015*	1.15	-0.007	0.006	0.012*
		(0.012)	(0.009)	(0.008)		(0.012)	(0.009)	(0.008)
Org: organizational innovation	1.24	-0.031**	-0.0007	0.078***	1.23	-0.035**	-0.003	0.078***
		(0.014)	(0.009)	(0.007)		(0.014)	(0.009)	(0.007)
Ext: Partners	1.27	0.093***	0.03***	0.028***	1.28	0.093***	0.02***	0.027***
		(0.005)	(0.003)	(0.002)		(0.005)	(0.003)	(0.002)
Ext:Network	1.04	-0.01	0.001	-0.01	1.04	-0.016	-0.003	-0.011
		(0.011)	(0.008)	(0.007)		(0.011)	(0.008)	(0.007)
Age	1.1	-0.022***	-0.008**	-0.007*	1.09	-0.018**	-0.004*	-0.002
		(0.005)	(0.004)	(0.003)		(0.005)	(0.004)	(0.003)
Employee Characteristics	1.32	0.005	0.004	0.012***	1.33	0.003	0.003*	0.011***
		(0.004)	(0.002)	(0.002)		(0.004)	(0.002)	(0.002)
National/International Ambition	1.11	0.088***	0.058***	0.046***	1.12	0.088***	0.06***	0.045***
		(0.013)	(0.008)	(0.008)		(0.013)	(0.008)	(0.008)
Keep Business State	1.06	-0.05***	-0.038***	-0.034***	1.07	-0.05***	-0.037***	-0.037***
		(0.012)	(0.008)	(0.007)		(0.012)	(0.008)	(0.007)
Sector		Yes	Yes	Yes		Yes	Yes	Yes
Size		Yes	Yes	Yes		Yes	Yes	Yes
Constant		-0.548	-1.48	-1.52		-0.557	-1.53	-1.6
N		5,402	5,332	5,438		5,275	5,209	5,308
Chi-squared		1397.07	609.33	1056.21		1341.6	610.85	1005.42
P - value		0	0	0		0	0	0
R-squared		0.205	0.16	0.27		0.201	0.16	0.26
Log Likelihood		-2703.72	-1539.77	-1431.69		-2648.6	-1495.4	-1361.79
Harman's one factor test		10.87%	10.12%	10.93%		11.37%	10.75%	11.43%

1) Panel Probit model. 2) Reported coefficients are marginal values calculated at variable means, 3) Reference groups of adopters refer to firms that adopted either Artificial Intelligence and Machine Learning, 4) First mover sample consists of the adopters before 2012 and the non-adopters, 5) Second mover sample consists of the adopters during 2012–2015 and the non-adopters, 6) Standard errors are in parentheses, 7) *$p<0.1$, ** $p<0.05$, *** $p<0.01$

Data availability statement The datasets generated during and/or analysed during the current study are not publicly available due to data ownership issue but are available from the corresponding author on reasonable request.

Declarations

The research was funded by the Indonesia Endowment Fund for Education (LPDP Scholarship).

References

Agostini, L., Galati, F., & Gastaldi, L. (2020). The digitalization of the innovation process: Challenges and opportunities from a management perspective. *European Journal of Innovation Management, 23*(1), 1–12. https://doi.org/10.1108/EJIM-11-2019-0330

Agyapong, A., Ellis, F., & Domeher, D. (2016). Competitive strategy and performance of family businesses: Moderating effect of managerial and innovative capabilities. *Journal of Small Business & Entrepreneurship, 28*(6), 449–477. https://doi.org/10.1080/08276331.2016.1217727

Ainin, S., Parveen, F., Moghavvemi, S., Jaafar, N. I., & Mohd Shuib, N. L. (2015). Factors influencing the use of social media by SMEs and its performance outcomes. *Industrial Management & Data Systems, 115*(3), 570–588. https://doi.org/10.1108/IMDS-07-2014-0205

Angermann, H., & Ramzan, N. (2016). TaxoPublish: Towards a solution to automatically personalize taxonomies in e-catalogs. *Expert Systems with Applications, 66*, 76–94. https://doi.org/10.1016/j.eswa.2016.08.058

Antons, D., & Breidbach, C. F. (2018). Big data, big insights? Advancing service innovation and design with machine Learning. *Journal of Service Research, 21*(1), 17–39. https://doi.org/10.1177/1094670517738373

Audretsch, D. B., Kritikos, A. S., & Schiersch, A. (2020). Microfirms and innovation in the service sector. *Small Business Economics, 55*(4), 997–1018. https://doi.org/10.1007/s11187-020-00366-4

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change, 163*. https://doi.org/10.1016/j.techfore.2020.120420

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Barney, J. B. (2001). Is the resource-based "view" a useful perspective for strategic management research? Yes. *Academy of Management Review, 26*(1), 41–56. https://doi.org/10.5465/amr.2001.4011938

Battisti, G., & Iona, A. (2009). The intra-firm diffusion of complementary innovations: Evidence from the adoption of management practices by British establishments. *Research Policy, 38*(8), 1326–1339. https://doi.org/10.1016/j.respol.2009.06.002

Battisti, G., & Stoneman, P. (2010). How innovative are UK firms? Evidence from the Fourth UK Community Innovation Survey on synergies between technological and organizational innovations. *British Journal of Management, 21*(1), 187–206. https://doi.org/10.1111/j.1467-8551.2009.00629.x

Battisti, G., Colombo, M. G., & Rabbiosi, L. (2015). Simultaneous versus sequential complementarity in the adoption of technological and organizational innovations: The case of innovations in the design sphere. *Industrial and Corporate Change, 24*(2), 345–382. https://doi.org/10.1093/icc/dtv003

Bauer, M., van Dinther, C., & Kiefer, D. (2020). Machine learning in SME: An empirical study on enablers and success factors. *AMCIS 2020 Proceedings*, 3. https://aisel.aisnet.org/amcis2020/adv_info_systems_research/adv_info_systems_research/3. Accessed 10 Oct 2022.

Baumann, J., & Kritikos, A. S. (2016). The link between R&D, innovation, and productivity: Are micro firms different? *Research Policy, 45*(6), 1263–1274. https://doi.org/10.1016/j.respol.2016.03.008

BEIS. (2020). Business population estimates for the UK and the regions 2020, Statistical Release, available at https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/923565/2020_Business_Population_Estimates_for_the_UK_and_regions_Statistical_Release.pdf, Accessed 27/08/2021

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: toward a next generation of insights. MIS quarterly, 471–482. https://doi.org/10.25300/misq/2013/37:2.3

Boulding, W., & Christen, M. (2001). First mover disadvantage. *Harvard Business Review, 79*(9), 20–21.

Bourke, J., & Roper, S. (2016). AMT adoption and innovation: An investigation of dynamic and complementary effects. *Technovation, 55–56*, 42–55. https://doi.org/10.1016/j.technovation.2016.05.003

Brynjolfsson, E., & Mcafee, A. N. D. R. E. W. (2017). Artificial intelligence, for real. *Harvard Business Review, 1*, 1–31.

Cassiman, B., & Veugelers, R. (2002). R&D cooperation and spillovers: Some empirical evidence from Belgium. *American Economic Review, 92*(4), 1169–1184. https://doi.org/10.1257/00028280260344704

Chen, L., Jiang, M., Jia, F., & Liu, G. (2021). Artificial intelligence adoption in business-to-business marketing: Toward a conceptual framework. *Journal of Business & Industrial*

Marketing., 37(5), 1025–1044. https://doi.org/10.1108/JBIM-09-2020-0448

Cockburn, I. M., Henderson, R., & Stern, S. (2019). *The impact of artificial intelligence on innovation: An exploratory analysis* (pp. 115–148). University of Chicago Press. https://www.nber.org/system/files/chapters/c14006/c14006.pdf. Accessed 26 Nov 2020.

Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the real world. *Harvard Business Review, 96*(1), 108–116.

Dixit, A. (1980). The role of investment in entry-deterrence. *The Economic Journal, 90*(357), 95–106. https://doi.org/10.2307/2231658

Dorrington, P., Lacan, F., Bigot, S. (2016). How are Micro Enterprises Adopting Emergent Technologies?. In Setchi, R., Howlett, R., Liu, Y., & Theobald, P. (Eds.), *Sustainable Design and Manufacturing 2016*, vol 52. Springer, Cham. https://doi.org/10.1007/978-3-319-32098-4_19

Farazzmanesh, F., & Hosseini, M. (2017). Analysis of business customers' value network using data mining techniques. *Journal of Information Systems and Telecommunication, 5*(3), 162–171. http://jist.ir/Article/15030.

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics, 210*, 15–26. https://doi.org/10.1016/j.ijpe.2019.01.004

Ghobakhloo, M., & Ching, N. T. (2019). Adoption of digital technologies of smart manufacturing in SMEs. *Journal of Industrial Information Integration, 16*, 100107. https://doi.org/10.1016/j.jii.2019.100107

Gilbert, R. J., & Newbery, D. M. (1982). Preemptive patenting and the persistence of monopoly. *The American Economic Review*, 514–526. http://www.jstor.org/stable/1831552. Accessed 20 Nov 2022.

Gimenez, F. A. (2000). The benefits of a coherent strategy for innovation and corporate change: A study applying Miles and Snow's model in the context of small firms. *Creativity and Innovation Management, 9*(4), 235–244. https://doi.org/10.1111/1467-8691.00197

Giotopoulos, I., Kontolaimou, A., Korra, E., & Tsakanikas, A. (2017). What drives ICT adoption by SMEs? Evidence from a large-scale survey in Greece. *Journal of Business Research, 81*, 60–69. https://doi.org/10.1016/j.jbusres.2017.08.007

Golder, P. N., & Tellis, G. J. (1993). Pioneer advantage: Marketing logic or marketing legend? *Journal of Marketing Research, 30*(2), 158–170. https://doi.org/10.1177/002224379303000203

Greene, W. H. (2000). *Econometric Analysis* (4th ed.). Prentice Hall.

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2020). Artificial Intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change, 162*, 120392. https://doi.org/10.1016/j.techfore.2020.120392

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review, 61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Hartmann, P., & Henkel, J. (2020). The rise of corporate science in AI: Data as a strategic resource. *Academy of Management Discoveries, 6*(3), 359–381. https://doi.org/10.5465/amd.2019.0043

Hewitt-Dundas, N. (2006). Resource and capability constraints to innovation in small and large plants. *Small Business Economics, 26*(3), 257–277. https://doi.org/10.1007/s11187-005-2140-3

Hoppe, H. C. (2000). Second mover advantages in the strategic adoption of new technology under uncertainty. *International Journal of Industrial Organization, 18*(2), 315–338. https://doi.org/10.1016/S0167-7187(98)00020-4

Iftikhar, N., & Nordbjerg, F. E. (2021). Adopting artificial intelligence in Danish SMEs: Barriers to become a data driven company, its solutions and benefits. In H. Panetto, M. Macchi, & K. Madani (Eds.), *Proceedings of the 2nd International Conference on Innovative Intelligent Industrial Production and Logistics*, IN4PL 2021 (pp. 131–136). SCITEPRESS Digital Library. https://doi.org/10.5220/0010691800003062

Jones, P., Simmons, G., Packham, G., Beynon-Davies, P., & Pickernell, D. (2014). An exploration of the attitudes and strategic responses of sole-proprietor micro-enterprises in adopting information and communication technology. *International Small Business Journal, 32*(3), 285–306. https://doi.org/10.1177/0266242612461802

Kagermann, H., Wahlster, W., & Helbig, J. (2013). *Securing the future of german manufacturing industry: Recommendations for implementing the strategic initiative INDUSTRIE 4.0; final report of the industrie 4.0 working group.* Forschungsunion Im Stifterverband Für Die Deutsche Wirtschaft e.V., Berlin.

Kelliher, F., & Reinl, L. (2009). A resource-based view of micro-firm management practice. *Journal of Small Business and Enterprise Development, 16*(3), 521–532. https://doi.org/10.1108/14626000910977206

Kianto, A., Sáenz, J., & Aramburu, N. (2017). Knowledge-based human resource management practices, intellectual capital, and innovation. *Journal of Business Research, 81*, 11–20. https://doi.org/10.1016/j.jbusres.2017.07.018

Klepper, S., & Simons, K. L. (2000). Dominance by birthright: Entry of prior radio producers and competitive ramifications in the US television receiver industry. *Strategic Management Journal, 21*(10–11), 997–1016. https://doi.org/10.1002/1097-0266(200010/11)21:10/11%3c997::AID-SMJ134%3e3.0.CO;2-O

Lambkin, M. (1988). Order of entry and performance in new markets. *Strategic Management Journal, 9*(S1), 127–140. https://doi.org/10.1002/smj.4250090713

Li, L., Su, F., Zhang, W., & Mao, J. Y. (2018). Digital transformation by SME entrepreneurs: A capability perspective. *Information Systems Journal, 28*(6), 1129–1157. https://doi.org/10.1111/isj.12153

Liberman-Yaconi, L., Hooper, T., & Hutchings, K. (2010). Toward a model of understanding strategic decision-making in micro-firms: Exploring the Australian information technology sector. *Journal of Small Business Management, 48*(1), 70–95. https://doi.org/10.1111/j.1540-627X.2009.00287.x

Lieberman, M. B., & Montgomery, D. B. (1988). First-Mover Advantages. *Strategic Management Journal, 9*(S1), 41–58. https://doi.org/10.1002/smj.4250090706

López-Mielgo, N., Montes-Peón, J. M., & Vázquez-Ordás, C. J. (2009). Are quality and innovation management conflicting activities? *Technovation, 29*(8), 537–545. https://doi.org/10.1016/j.technovation.2009.02.005

Loureiro, S. M. C., Guerreiro, J., & Tussyadiah, I. (2021). Artificial intelligence in business: State of the art and future research agenda. *Journal of Business Research, 129*, 911–926. https://doi.org/10.1016/j.jbusres.2020.11.001

MacGregor, R. C., & Vrazalic, L. (2005). A basic model of electronic commerce adoption barriers: A study of regional small businesses in Sweden and Australia. *Journal of Small Business and Enterprise Development, 12*(4), 510–527. https://doi.org/10.1108/14626000510628199

Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2018). Big data analytics capabilities: A systematic literature review and research agenda. *Information Systems and e-Business Management, 16*(3), 547–578. https://doi.org/10.1007/s10257-017-0362-y

Mikalef, P., & Gupta, M. (2021). Artificial Intelligence Capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 103434. https://doi.org/10.1016/j.im.2021.103434

Miles, R. E., & Snow, C. C. (1986). Organizations: New concepts for new forms. *California Management Review, 28*(3), 62–73. https://doi.org/10.2307/41165202

Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice, 41*(6), 1029–1055. https://doi.org/10.1111/etap.12254

Netter, J., Wasserman, W., & Kutner, M. H. (1989). *Applied Regression Models*. Richard D. Irwin, Homewood, IL.

Niebel, T., Rasel, F., & Viete, S. (2019). BIG data–BIG gains? Understanding the link between big data analytics and innovation. *Economics of Innovation and New Technology, 28*(3), 296–316. https://doi.org/10.1080/10438599.2018.1493075

OECD. (2019). *Digital innovation: Seizing policy opportunities*. OECD Publishing, Paris. https://doi.org/10.1787/a298dc87-en

OECD. (2020). *OECD Digital Economy Outlook 2020*. OECD Publishing, Paris. https://doi.org/10.1787/bb167041-en

Parnell, J. A., & Carraher, S. (2001). The role of effective resource utilization on strategy's impact on performance. *International Journal of Commerce and Management., 11*(3/4), 1–34. https://doi.org/10.1108/eb047425

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business & Industrial Marketing, 34*(7), 1410–1419. https://doi.org/10.1108/JBIM-10-2018-0295

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879.

Raymond, L., Croteau A.-M., Bergeron F. (2009). The Integrative Role of IT in Product and Process Innovation: Growth and Productivity Outcomes for Manufacturing. In *Enterprise Information Systems-Bk*, ed. J. Filipe and J. Cordeiro, 27–39. https://doi.org/10.1007/978-3-642-01347-8_3

Riordan, M. H. (1992). Regulation and preemptive technology adoption. *The Rand Journal of Economics*, 334–349. https://doi.org/10.2307/2555866

Robinson, W. T., & Min, S. (2002). Is the first to market the first to fail? Empirical evidence for industrial goods businesses. *Journal of Marketing Research, 39*(1), 120–128. https://doi.org/10.1509/jmkr.39.1.120.18938

Robinson, W. T., Fornell, C., & Sullivan, M. (1992). Are market pioneers intrinsically stronger than later entrants? *Strategic Management Journal, 13*(8), 609–624. https://doi.org/10.1002/smj.4250130804

Romijn, H., & Albaladejo, M. (2002). Determinants of innovation capability in small electronics and software firms in southeast England. *Research Policy, 31*(7), 1053–1067. https://doi.org/10.1016/S0048-7333(01)00176-7

Rosenbloom, R. S., & Cusumano, M. A. (1987). Technological pioneering and competitive advantage: The birth of the VCR industry. *California Management Review, 29*(4), 51–76. https://doi.org/10.2307/41162131

Shepherd, D. A. (1999). Venture capitalists' assessment of new venture survival. *Management Science, 45*(5), 621–632. https://doi.org/10.1287/mnsc.45.5.621

Simmons, G., Armstrong, G. A., & Durkin, M. G. (2008). A conceptualization of the determinants of small business website adoption: Setting the research agenda. *International Small Business Journal, 26*(3), 351–389. https://doi.org/10.1177/0266242608088743

Sirmon, D. G., Hitt, M. A., & Ireland, R. D. (2007). Managing firm resources in dynamic environments to create value: Looking inside the black box. *Academy of Management Review, 32*(1), 273–292. https://doi.org/10.5465/amr.2007.23466005

Srinivasan, V. (2014). A Call for Artificial Intelligence Tools to Support Manufacturing Innovation. *International Journal on Artificial Intelligence Tools, 23*(06), 1460025. https://doi.org/10.1142/S0218213014600252

Steiber, A., Alänge, S., Ghosh, S., & Goncalves, D. (2021). Digital transformation of industrial firms: An innovation diffusion perspective. *European Journal of Innovation Management, 24*(3), 799–819. https://doi.org/10.1108/EJIM-01-2020-0018

Suarez, F. F., & Lanzolla, G. (2007). The role of environmental dynamics in building a first mover advantage theory. *Academy of Management Review, 32*(2), 377–392. https://doi.org/10.5465/amr.2007.24349587

Tang, Z., & Tang, J. (2012). Entrepreneurial orientation and SME performance in China's changing environment: The moderating effects of strategies. *Asia Pacific Journal of Management, 29*(2), 409–431. https://doi.org/10.1007/s10490-010-9200-1

Toms, S. (2010). Value, profit, and risk: Accounting and the resource-based view of the firm. *Accounting, Auditing & Accountability Journal., 23*(5), 647–670. https://doi.org/10.1108/09513571011054927

Trabucchi, D., & Buganza, T. (2019). Data-driven innovation: Switching the perspective on Big Data. *European Journal of Innovation Management, 22*(1), 23–40. https://doi.org/10.1108/EJIM-01-2018-0017

Trabucchi, D., Buganza, T., & Pellizzoni, E. (2017). Give away your digital services: Leveraging big data to capture value new models that capture the value embedded in the data generated by digital services may make it viable for companies to offer those services for free. *Research-Technology Management, 60*(2), 43–52. https://doi.org/10.1080/08956308.2017.1276390

Tran, V. D., Sibley, D. S., & Wilkie, S. (2012). Second mover advantage and entry timing. *The Journal of Industrial Economics, 60*(3), 517–535. https://doi.org/10.1111/j.1467-6451.2012.00490.x

Wade, M., & Hulland, J. (2004). The resource-based view and information systems research: Review, extension, and suggestions for future research. *MIS quarterly*, 107–142. https://doi.org/10.2307/25148626

Wang, C. H., Lu, I. Y., & Chen, C. B. (2008). Evaluating firm technological innovation capability under uncertainty. *Technovation, 28*(6), 349–363. https://doi.org/10.1016/j.technovation.2007.10.007

Wu, F., Yeniyurt, S., Kim, D., & Cavusgil, S. T. (2006). The impact of information technology on supply chain capabilities and firm performance: A resource-based view. *Industrial Marketing Management, 35*(4), 493–504. https://doi.org/10.1016/j.indmarman.2005.05.003

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). Research commentary—the new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research, 21*(4), 724–735. https://doi.org/10.1287/isre.1100.0322

Yoo, Y., Boland, R. J., Jr., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science, 23*(5), 1398–1408. https://doi.org/10.1287/orsc.1120.0771

Yoon, Y. R. (2009). Endogenous timing of actions under conflict between two types of second mover advantage. *International Journal of Industrial Organization, 27*(6), 728–738. https://doi.org/10.1016/j.ijindorg.2009.04.001

Zhou, K. Z., & Wu, F. (2010). Technological capability, strategic flexibility, and product innovation. *Strategic Management Journal, 31*(5), 547–561. https://doi.org/10.1002/smj.830

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.