R&D MANAGEMENT

How does information technology capabilities affect business sustainability? The roles of ambidextrous innovation and data-driven culture

Voon-Hsien Lee[1], Yogesh K. Dwivedi[2,3,*], Garry Wei-Han Tan[4,5,6,7], Keng-Boon Ooi[4,5,8] and Lai-Wan Wong[9]

[1]Faculty of Business and Finance, Universiti Tunku Abdul Rahman, Kampar, Malaysia. leevh@utar.edu.my
[2]Digital Futures for Sustainable Business & Society Research Group, School of Management, Swansea University, Bay Campus, Fabian Bay, Swansea, UK.
[3]Department of Management, Symbiosis Institute of Business Management, Pune & Symbiosis International (Deemed University), Pune, India. y.k.dwivedi@swansea.ac.uk
[4]UCSI Graduate Business School, UCSI University, Kuala Lumpur, Malaysia, garrytanweihan@gmail.com, ooikengboon@gmail.com
[5]Faculty of Business, Design, and Arts, Swinburne University of Technology Sarawak Campus, Kuching, Malaysia, garrytanweihan@gmail.com, ooikengboon@gmail.com
[6]School of Economics and Management, Yunnan Normal University, Kunming, People's Republic of China.
[7]College of Business Administration, Adamson University, Manila, Philippines. garrytanweihan@gmail.com
[8]FORE School of Management, New Delhi, India. ooikengboon@gmail.com
[9]School of Computing and Data Science, Xiamen University Malaysia, Sepang, Malaysia. wlaiwan@cact.asia

This research investigates explicitly how Information technology capability (ITC) can be tailored to achieve business sustainability via ambidextrous innovation in a turbulent environment. Moreover, the moderating factor of a data-driven culture (DDC) is also being investigated. The research model was built on the theoretical foundations of the resource-based view (RBV), dynamic capabilities view and existing IT capabilities literature. Through a close-ended survey questionnaire from approximately 254 IT personnel in managerial positions working in the manufacturing industry, partial least squares-structural equation modelling-artificial neural network (PLS-SEM-ANN) is applied. Notably, the result indicated that ITC positively influences IT-enabled dynamic capabilities (ITDC), which

positively impacts ambidextrous innovations and helps manufacturing firms achieve business sustainability. Meanwhile, the moderating role of DDC between ITDC and exploitative innovation was also found. The results showed that ANN models A, B, C and D are consistent for both analysis. This study provides several novel additions to the literature on operations management and information systems (IS) researchers. IS researchers should focus on leveraging ITC to enable and support organisational capabilities rather than the direct effects of IT expenditures. Additionally, the importance of a DDC has seldom been explored together previously. Thus, this study fills gaps in existing knowledge, along with significant insights, specifically for future IT implementation. As for practical implications, this study provides corporate leaders and executives with insights about how to leverage their resources and customise their ITC in an unpredictable and volatile business environment.

1. Introduction

Environmental uncertainties have resulted in dynamic and complicated business environments (Nejatian et al., 2018). In response, enterprises have had to rapidly adapt to market challenges and exploit opportunities in order to survive and grow in a volatile business climate. Along with this, information technology capabilities (ITC) has grown in relevance in emerging economies during the last decade (Akram et al., 2018). Firms rely on ITC to become more involved in innovation (Lowry and Wilson, 2016) and to respond quickly to external forces (Pavlou and Sawy, 2010). The rapid change in technology and market dynamics have provided much evidence suggesting that a data-driven culture (DDC) is essential for firms' ambidextrous innovation (Liu et al., 2017; Iranmanesh et al., 2021) and subsequently enhancing business sustainability (Akram et al., 2018).

Prior studies have asserted ITC as key facilitator for improving a firm's capabilities, such as dynamic capabilities (Parida et al., 2016; Mikalef et al., 2021), knowledge management capability (Akram et al., 2018), and innovation capability (Ferreira et al., 2020; Ilmudeen, 2021). Furthermore, the literature on performance suggested that exploitative and exploratory innovation might have differing effects on firms' adaptability and performance, may be relatively indirect and requires additional investigation (Ferreira et al., 2020). Furthermore, little is known about how ITC affects the underlying processes that enable ambidextrous innovation and subsequently business sustainability, particularly in a tumultuous and fast-paced environment. It is critical to explore the internal reaction capabilities afforded by firms' development of IT solutions because a compromised sensing ability to detect new opportunities and dangers can have adverse consequence. For instance, firms would not be able to exploit the opportunities through coordinated actions that would otherwise enable them to sustain competitive advantage (Mikalef et al., 2021).

This study draws on the theoretical perspectives of the resource-based view (RBV) (Barney, 1991), dynamic capabilities (DC) view (DCV) (Teece et al., 1997), and recent IT capabilities literature (Guo et al., 2021; Ilmudeen, 2021) to expound the effects of ITC as an enabler of the firm's overall dynamic capability *via* its underlying processes (i.e. IT-enabled dynamic capability or ITDC), which can then facilitate ambidextrous innovation (i.e. exploratory and exploitative innovation), resulting in improved sustainability performance. The moderating capacity of a DDC was also introduced to establish a specific environment that might either enhance or impede the proposed relationships.

This work significantly advances both theory and practical knowledge. Theorising dynamic capability towards ITC and ITDC, this paper first argues that businesses with excellent ITC can leverage more of the firm's innovative capability to accomplish superior sustainability performance. Next, the inclusion of DDC in this study demonstrates firms real behaviour, through which managers can make meaningful decisions on resource management during turbulent circumstances. Third, corporate leaders can devise strategies to develop a firm-wide ITC through rigorous examination of its business goals rather than merely investing in IT. The subsequent sections of this research is structured as follows. The theoretical framework is presented in Section 2, and the hypotheses are developed in Section 3. The research strategy is narrated in Section 4, while the empirical analysis and outcomes are discussed in Section 5. Sections 6 and 7 discuss and highlight the discussions and consequences.

2. Literature review

2.1. Underpinning theories

According to the RBV theory, company resources are the primary driver of business performance.

This theory posits that rent-yielding firm-level resources are valuable, rare, imperfectly imitable and non-substitutable (VRIN) and can survive competitive imitation (Jeble et al., 2018). IT infrastructure, trained human resources and relationships between the IT department and user departments are important resources viewed as rent-yielding (Ravichandran and Lertwongsatien, 2005). Existing IT capability research acknowledges that the ability to mobilise and deploy IT-based resources may provide a competitive advantage and help organisations stand out from their competitors (Mikalef et al., 2020).

Despite that, it is critical for businesses to move beyond IT-related technology and resources to focus on other requisite resources for an inimitable IT competence. A firm's DC is its capacity to alter its resource base to detect and capitalise on opportunities, as well as deal with challenges to enhance its competitiveness (Zhang et al., 2016). Hence, DC enables businesses to integrate, create and restructure resources and competencies in response to evolving situations (Mikalef and Pateli, 2017; Senaratne et al., 2021). In today's volatile environment, simply having a collection of resources is no longer enough to sustain competitive advantage (Wu, 2010). Accordingly, Teece et al. (1997) expanded the RBV and proposed that businesses adapt, restructure and remodel their resources and skills regularly to handle any dynamic environmental changes (Ilmudeen, 2021).

Additionally, there is strong consensus that innovation is imperative for organisational survival, competitiveness and performance (Berraies and Bchini, 2019; Zuraik and Kelly, 2019). This notion is characterised as an iterative and multistage process through which businesses effectively transform ideas into improved or new processes, products or services that are successfully disseminated to stakeholders (Wong et al., 2017). This study presents innovation ambidexterity as a crucial DC that allows for the pursuit of both short and long-term gains, leading to optimal performance (Wong et al., 2017; Zuraik and Kelly, 2019; Ben Rejeb et al., 2020).

As per the insights of RBV and DCV, IT capabilities supplement innovative capabilities, helping firms to attain their desired performance and business sustainability. Additionally, McAfee and Brynjolfsson (2012) emphasise the significance of cultivating a data-driven decision-making culture where managers make judgements based on insights rather than instinct. According to Mikalef et al. (2020), firms need to manage their business analytics departments and ensure alignment of analytic skills with company strategy in their quest to become data-driven.

2.2. *IT capability*

ITC, is defined in terms of company's capacity to organise its IT-based resources in conjunction with or in addition to other resources and skills (Mikalef et al., 2020). ITC has been frequently utilised in attempting to assess the commercial return of investments. The capacity of a corporation to buy, deploy, combine and reconfigure its IT resources function to realise an IT ability to achieve its intended need is referred to as ITC (Lu and Ramamurthy, 2011). In line with previous research, ITC in this study is conceptualised as a composite construct comprising of IT infrastructure flexibility, IT human capital and IT partnership quality (Ravichandran and Lertwongsatien, 2005). IT infrastructure flexibility is the extent to which a company's IT infrastructure can supply and integrate various hardware, software and communications technologies to quickly and efficiently deliver technical solutions (Byrd and Turner, 2000). IT human capital refers to how adept a company's IT employees are in terms of business, technical and managerial competence, as well as firm-specific knowledge such as a thorough comprehension of the company's business processes, routines and culture (Guo et al., 2021). Thirdly, the quality of an organisation's IT department's partnerships with other functional units, vendors and IT service providers is referred to as IT partnership quality (Ravichandran and Lertwongsatien, 2005). ITC encapsulates the similarity shared by all three aspects. A company with outstanding ITC is anticipated to excel in all three of the aforementioned aspects.

2.3. *IT-enabled dynamic capabilities*

Through ITDC, firms can sense, coordinate, learn, integrate and reconfigure their resources to address changing business environments. Sensing includes researching, investigating customer requirements and assessing supplier and competitor response (Roberts and Grover, 2012). In other words, it encompasses gathering, transmitting and acting on market signals (Pavlou and El Sawy, 2011). Coordinating refers to the firm's capacity to coordinate the deployment of tasks and resources and the synchronisation of operations with relevant stakeholders; hence encompassing resource allocation, task assignment and synchronisation (Pavlou and El Sawy, 2011; Mikalef and Pateli, 2017). The firm's inter-functional and channel coordination mechanisms enable it to respond quickly to market opportunities. Learning is described as the capacity to acquire, integrate, transform and exploit new knowledge to make informed decisions; hence knowledge acquisition, assimilation, transformation and use are all included (Mikalef and Pateli, 2017). Integrating capability entails assessing the firm's and partners' resources and capabilities, as well as their ability to incorporate and utilise them in new or restored operational capacities (Mikalef and Pateli, 2017). It encapsulates each input's contribution, representation and interrelationship with the overall business unit (Pavlou and El Sawy, 2011). Lastly, reconfiguration refers to the capacity to recombine and reorganise company assets and structures as the company expands and in response to markets and technology dynamics; as a result, the company gains consistent profitable growth (Ilmudeen, 2021). In the reconfiguration, the firm's ability to execute strategic changes is enhanced, allowing it to adapt to the changing business climate (Mikalef and Pateli, 2017).

2.4. *Ambidextrous innovation – exploratory and exploitative*

In management and theoretical discourses, innovation is portrayed as a critical source of organisational performance, competitiveness and survival (Berraies and Bchini, 2019; Zuraik and Kelly, 2019; Heij et al., 2020). To differentiate itself from the competition, a company generates new ideas and translates these concepts into new processes, products or services that are upgraded or new, in an iterative and multi-stage process (Wong et al., 2017; Berraies and Zine El Abidine, 2019). In this context, innovation is classed according to its intensity, which is determined by whether the firm uses current knowledge or seeks out new ones. Indeed, innovation ambidexterity is a fundamental DC that enables the pursuit of both short- and long-term innovative capabilities, leading to optimal performance (Wong et al., 2017; Ben Rejeb et al., 2020). Exploitative innovation is a type of incremental innovation that involves enhancing existing knowledge and competences to fulfil the demands of clients and markets (Berraies and Hamouda, 2018); while exploratory innovation allude to significant changes in processes, goods or services that need new knowledge or a departure from current knowledge (Jansen et al., 2006) in order to suit the needs of consumers and markets (Ben Rejeb et al., 2020). Exploration at the cost of exploitation and *vice versa*, might have a negative impact on business performance. Companies must confront the ambidexterity dilemma by presenting innovative methods that aim to leverage existing knowledge and abilities while also researching new performance improvement methods, both short and long term (Voss and Voss, 2013). Hence, the balancing exploitative and exploratory must not be overlooked (Gong et al., 2021). Scholars have either viewed ambidextrous innovation as a combination of exploitative and exploratory innovation (Wang et al., 2018); or separates them as distinct types of innovation (Ko and Liu, 2019). Following the latter stream, this study differentiates the interactive effects of ITDC on exploitative and exploratory innovation, respectively (Wang et al., 2021), to improve business sustainability.

2.5. *Sustainability*

Sustainability has garnered more attention from business leaders and has taken centre stage in many organisations' strategic goals. It is frequently associated with Elkington (1994)'s sustainability-related framework of economic, environmental and social components, the triple bottom line (TBL) principle. Typically, the terms 'TBL' and 'sustainability' are used interchangeably (Yusoff et al., 2019). Economic sustainability relates to the organisation's ability to meet its demands today and in the future (Fernando et al., 2019). While social sustainability represents the humanitarian context of business and focuses on the growth and fulfilment of people's needs as well as the maintenance of long-term social ties (Fernando et al., 2019). Lastly, environmental sustainability, considers the preservation and rejuvenation of the biosphere for current and future generations (Fernando et al., 2019). Scholars contend that all three are equally crucial for a business (Fernando et al., 2019; Yong et al., 2020).

3. Hypotheses development

3.1. *ITC*

From a firm's RBV and DC perspective, this study posits that enterprises require a combination of people, infrastructure and partnership resources to grow IT capability. As such, ITC is conceptualised as a higher-order notion, consisting of IT human capital, IT infrastructure flexibility and IT partnership quality, in accordance with the classification of IT capabilities used by Guo et al. (2021). The classification of resources into these three categories has long been utilised in the literature of ITC (Lu and Ramamurthy, 2011). To establish a strong ITC, the firm must invest in all three types of the aforementioned resources. The study argues that the value of ITC lies in its DC boosting potential whereby an ITC increases a firm's capability to sense, seize and transform identified opportunities or threats, leading to stronger innovative capabilities, and eventually assisting a firm in achieving business sustainability. Parida et al. (2016) backed this viewpoint by demonstrating how ICT capabilities can influence small enterprises' DC in order to function in a turbulent and dynamic environment. Mikalef et al. (2021) also share this viewpoint, arguing that the complementary effects of a flexible IT architecture and decentralised IT governance can promote the formation of ITDC, thereby sustaining competitive performance. The basic argument is that by enhancing ITC, businesses improve their capacity to detect new opportunities and threats, capitalise on opportunities ahead of rivals, and reconfigure organisational resources effectively. To remain competitive in today's market, businesses must continually reconfigure and upgrade their business processes (Guo et al., 2021). Therefore, firms must be proficient at detecting emerging threats and opportunities, seize possibilities for growth and survival, and alter current methods of operations to better meet market demands (i.e. dynamic capabilities). Based on these, we anticipate that:

H1 ITC will have a positive influence on ITDC.

3.2. ITDC

While DC may create competitive performance benefits in and of themselves, they may also enable or strengthen innovative capabilities (Drnevich and Kriauciunas, 2011). Eisenhardt and Martin (2000) argued that although DC are required, they may not suffice for competitive advantage. According to them, maintaining a competitive advantage is not dependent on DC in and of themselves, but rather on the resource configurations provided by DC (Pavlou and El Sawy, 2006). In this view, ITDC is described as the ability to systematically address problems by perceiving opportunities and threats, making timely judgements and efficiently implementing strategic choices and adjustments, thus assuring the right direction (Ferreira et al., 2020). This view was backed by Ferreira et al. (2020) who proposed that DC influence competitive advantage by facilitating creativity and innovation capability changes. Mikalef et al. (2019) take a similar stance, indicating that DC have a favourable influence on incremental and radical innovation capabilities. Similarly, organisations that cultivate strong DC are better positioned to recognise new technological advancements early (Pavlou and El Sawy, 2011; Mikalef et al., 2020). The ability to do so is also proposed to provide an edge in capitalising on such breakthroughs ahead of competition, resulting in enhanced innovative capabilities. Thus, we can speculate that:

H2 ITDC will have a positive influence on exploitative innovation.

H3 ITDC will have a positive influence on exploratory innovation.

3.3. Ambidextrous innovation and business sustainability

Organisations can benefit from innovation by gaining new perspectives and ideas, gaining a competitive edge, improving organisational performance and facilitating organisational development (Gong et al., 2021). Exploitative innovation promotes the use of available knowledge or technology to enhance and perfect goods or services, which typically results in incremental innovation and advantages for the organisation (Jansen et al., 2009). Exploitative innovation, which is characterised by low risk and low profitability, decreases the possibility of making mistakes, resulting in dependable product advancements (Yang et al., 2019). As a result, exploitative innovation can provide the firm with relatively steady rewards and advantages. Exploratory innovation, as opposed to exploitative innovation, encourages departing from current knowledge and moving towards new knowledge for breakthrough innovations in areas such as product design, business expansion and distribution network development (Benner and Tushman, 2003), thereby creating differentiation to occupy emerging markets. In contrast, exploratory innovation, frequently involves large uncertainties and high risks, but it can help businesses close the gap with current rivals and obtain distinct competitive advantages. Exploratory innovation enables businesses to leap from one technology curve to another, which can result in significant performance improvements. Exploratory innovation is concerned with a firm's long-term development goals, in which its impact to firm's performance may not be seen early on. Nevertheless, if exploratory innovation is effective, it will result in large returns and enormous advantages for the firm (Jansen et al., 2006). Existing research confirms that both innovations have significant positive effects on business performance (Berraies and Bchini, 2019; Gong et al., 2021; Wang et al., 2021), which eventually enhances sustainability performance. Accordingly, this study contends that both innovations positively affects a firm's sustainability performance, and the following assumptions are advanced:

H4 Exploitative innovation will have a positive influence on sustainability performance.

H5 Exploratory innovation will have a positive influence on sustainability performance.

3.4. Data-driven culture

Organisational culture is a difficult concept to define and comprehend. While some argue that organisational culture encompasses practically every aspect of a company, others refer to it as the 'glue' that holds it together (Iivari and Huisman, 2007). Organisational culture has been highlighted as a source of long-term company performance in previous management strategy study (Barney, 1986, 1995). Similarly, current research in IT/IS/big data suggests that a company's IT/big data initiatives are dependent on its organisational culture. For example, LaValle et al. (2011) argue that corporate culture, rather than data characteristics or a lack of technology, is to be blamed for the failure of big data efforts. According to Ross et al. (2013), culture can either hamper or aid an organisation's profitability potential from big data. It is crucial for organisations to build a DDC, which is defined in this study as the extent to which organisational members (including top-level executives, middle managers and lower-level employees) make insightful decisions based on data (McAfee and Brynjolfsson, 2012; Ross et al., 2013). Furthermore, as all employees of an organisation must make decisions, it is critical that a culture of DDC be cultivated at all levels to facilitate good judgements (Gupta and George, 2016). Organisational culture has been identified in several studies as a moderating element that leads to increased overall performance and innovation in particular (Ghasemzadeh et al., 2019; Jin et al., 2019; Lin and Kunnathur, 2019; Xie et al., 2019; Iranmanesh et al., 2021). A data-driven cultural value encourages its members to utilise the extracted data to make decisions, motivating businesses to take risks and developing continual creativity in problem-solving (Lin and Kunnathur, 2019; Iranmanesh et al., 2021). If a DDC strengthens a company's capacity to generate innovation, the impact of ITC on ambidextrous innovation could be greater in firms with higher degrees of DDC. The fundamental reason for this is that a DDC may inspire innovative behaviour among the organisational members, as such intangible resource is critical in extending decision-makers' horizon and increasing their knowledge for informed judgements (Maroufkhani et al., 2020). Therefore, it is envisaged that the linkage between ITDC and the level of ambidextrous innovation might be moderated by DDC, which has not been explored in the literature. The study hypothesises the following based on the above argument:

H6 DDC moderates the relationship between ITDC and exploitative innovation.

H7 DDC moderates the relationship between ITDC and exploratory innovation.

Figure 1 illustrates the conceptual framework for this research which represents the relations between ITC (i.e. IT human capital, IT infrastructure flexibility, IT partnership quality), ITDC (i.e. sensing, coordinating, learning, integrating, reconfiguring), ambidextrous innovations, sustainability (i.e. environmental, economic, social performance) and the moderating variable of DDC.

4. Methodology

4.1. Research design and data collection

Due to its rapid economic expansion, large population density and status as the state with the highest GDP contribution, Klang Valley Malaysia was selected as the sample location (Department of Statistics Malaysia, 2021). The firms were chosen from the Federation of Malaysian Manufacturers (FMM) Directory, which served as a sampling frame for this study. The FMM directory was chosen since it provides access to 3300 manufacturing and industrial service firms of all sizes (Lim et al., 2021). Thus, the sample chosen can be regarded as a valid representative of the entire population. The online questionnaires were administered to IT staff at the executive level and above from Malaysian manufacturing firms by a team of experienced data collectors. These individuals were chosen as the study's unit of analysis for their knowledge of their firm's IT capabilities and a clear understanding of their firms' innovative capability

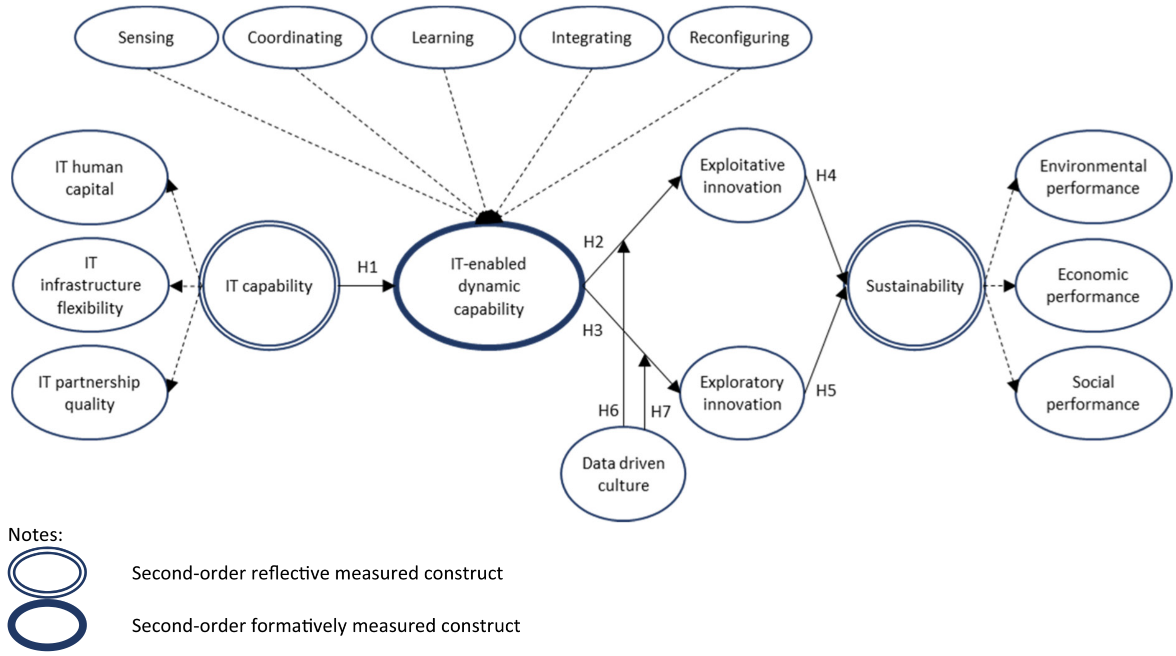


Figure 1. Research model.

and sustainability performance. Prior to the distribution of the questionnaire, a pre-test of the questionnaire was conducted among three academicians in the fields of IT and operations management to verify and ascertain that the questions were easily understood, relevant and meaningful. Regarding the actual data collection, a total of 254 completed responses were received. The study needed a minimum of 103 respondents using the G*power tool, and when 254 completed questionnaires were acquired, the sample size is considered sufficient, adequate and acceptable (Faul et al., 2007).

4.2. *Constructs and measurement development*

The ITC contains three first-order reflective constructs, namely IT human capital, IT infrastructure flexibility and IT partnership quality (Tippins and Sohi, 2003; Guo et al., 2021), of which each has a five-item measure, respectively. Meanwhile, the ITDC has five dynamic capabilities, each with four items (Ilmudeen, 2021) that are first-order reflective of their respective capability. The ITDC construct is a second-order formative construct. Ambidextrous innovation has a total of 14 items adapted and modified from Wang and Tsai (2017) and Jansen et al. (2006). Meanwhile, a 15-item scale derived from Yong et al. (2020) and Zhu et al. (2008) was used to measure business sustainability. Additionally, this study includes DDC as a moderator, with three items adapted from Jeble et al. (2018). All items in the questionnaire were validated on a seven-point Likert scale from ‘Strongly Disagree’ to ‘Strongly Agree’, except for ITDC (i.e. ranging from 1 = ‘Not Effective’ to 7 = ‘Most Effective’) and sustainability (i.e. from 1 = ‘Not at All’ to 7 = ‘To a very great extent’).

5. Data analysis

5.1. *Statistical analysis*

The partial Least Squares Structural-Equation Modelling approach (PLS-SEM) was applied to check the conceptual model. SmartPLS software version 3.2.6 was used to perform the PLS-SEM analysis as it allows for the testing of both reflective and formative indicators with a higher-order construct (Kim et al., 2020). Additionally, normality assessment found that the data deviated from the norm based on Mardia’s multivariate skewness (β=6.526, P<.001) and kurtosis (β=65.199, P<.001), respectively. Based on both reasons, PLS-SEM is therefore suitable for this study.

5.2. *Common method bias*

Since cross-sectional, self-administered surveys are susceptible to common method bias (CMB), the study employed a two-approach method as suggested by Podsakoff et al. (2003) to control for CMB. Procedurally, the study assured the respondents' anonymity and confidentiality that their responses would be strictly preserved. In addition, separate exogenous and endogenous variables, clear definitions of terminology and directions were employed in the questionnaire to avoid confusion (Li et al., 2017). The study then adopted the statistical method proposed by Liang et al. (2007) to detect CMV. As shown in Table 1, all substantive factor loading (Ra) values are significant at $P < .001$. In addition, the majority of the method factor loadings (Rb) were not significant with negative values. Finally, the average Ra (0.805) was greater than the average Rb (0.017) indicating that CMB was not a significant factor in this study.

5.3. Outer measurement model evaluation

Since the conceptual model includes reflectively and formatively measured constructs, the study first examined the reliability and both convergent validity (CV) and discriminant validity (DV) of first-order constructs. All first-order constructs achieved reliability as the values of Dijkstra-Henseler's rho (rhoA) and composite reliability (CR) in Table 2 were higher than the required 0.70 thresholds (Loh et al., 2019; Antonetti et al., 2020; Tuncdogan and Volberda, 2020). Additionally, average variance extracted (AVE) and factor loadings (FL) were adopted to check for CV. All the AVE values in Table 2 ranged between 0.539 and 0.725 and exceeded the recommended minimum of 0.50. Additionally, FLs should have at least 0.708 and should only be considered for removal if the values are below 0.40. Tan and Ooi (2018) stressed that the FLs between 0.40 and 0.70 should be retained in the event that AVE can explain about 50% of the construct variance. Table 2 shows that all FL values are significant at the 0.001 level, with the exception of ENP5, which was removed due to poor FL. Based on both results, CV has been established. As shown in Table 3, the DV for all the first-order constructs has also been established as all items are correlated most strongly with their intended constructs than with any other constructs as recommended by Wong et al. (2020). This shows that DV has been identified as every sample construct is statistically distinct. Table 2 also indicated that reliability, apart from CV, have been achieved. Finally, DV for the second order has been assessed with a Hetero-Trait-Mono-Trait (HTMT) ratio. As the values in Table 4 are below 0.85, DV has also been established (Henseler et al., 2015).

The first-order formative constructs were assessed as per Hair et al.'s (2017) recommendation. Table 5 shows that the variance inflation factor (VIF) was below 3.3, suggesting that multicollinearity is not present in this study. While the outer weights for CRD and RCF were not significant, the outer loading was significant with P-values < .001, which supports the retaining of the construct in the formative measurement model (Ghazali et al., 2020). Thus, the study confirmed that this formative measurement model is valid.

5.4. Inner structural model evaluation

Table 6 and Figure 2 show the outcomes of path coefficient assessment using the 5000 bootstrapping procedure for all the hypothesised relationships in the conceptual model. All the proposed direct relationships in this study are statistically significant with a positive relationship. Hence, H1, H2, H3, H4 and H5 were supported. On the moderating effect of DDC, H7 was not supported as DDC did not moderate the path between ITDC and EXP ($\beta = -0.057$, $P > .05$). The moderating effect of DDC between ITDC and EXT was significant, thus supporting H6. The coefficient of determination (R^2) in Table 7 for BUS, EXP, EXT and ITDC is 0.642, 0.299 0.449 and 0.571, respectively. Additionally, all the Stone-Geisser Q^2 values are greater than zero, as shown in Table 7, suggesting that all the paths exhibit predictive relevance. Lastly, to assess the effect size of the constructs, Cohen's (f^2) was employed and the results in Table 7 show that the f^2 values range from weak to strong, respectively (Cohen, 1988).

5.5. Artificial neural network (ANN) analysis

While PLS-SEM can detect linear relationships between exogenous and endogenous constructs, it cannot detect non-linear relationships and thus cannot explain the complexity of the human decision-making process (Hew et al., 2018). To overcome this, an artificial intelligence approach known as Artificial Neural Network (ANN) analysis was conducted to capture linear and non-linear relationships within a non-compensatory model (Wong et al., 2020). Four ANN models were constructed for ITDC, EXT, EXP and BUS, as shown in Figures 3–6. In order to avoid over-fitting, Ooi and Tan (2016) suggested engaging a tenfold cross-validating procedure to obtain the root mean square of errors (RMSE) by allocating 90% of the data for the training process and the remaining 10% for testing purposes. The RMSE values for training and testing procedures for ANN models A, B, C and D ranged from 0.068 to 0.145, which is relatively small. The

Table 1. Common method bias

Latent construct	Indicators	Substantive factor loading (Ra)	Ra^2	Method factor loading (Rb)	Rb^2
CRD	CRD1	0.705***	0.497	0.143*	0.020
	CRD2	0.869***	0.755	−0.038NS	0.001
	CRD3	0.890***	0.792	−0.074NS	0.005
	CRD4	0.759***	0.576	−0.040NS	0.002
DDC	DDC1	0.679***	0.461	0.183*	0.033
	DDC2	0.758***	0.575	0.103NS	0.011
	DDC3	1.058***	1.119	−0.410***	0.168
	DDC4	0.805***	0.648	0.018NS	0.000
	DDC5	0.787***	0.619	0.004NS	0.000
ECP	ECP1	0.633***	0.401	0.282***	0.080
	ECP2	0.824***	0.679	−0.040NS	0.002
	ECP3	0.900***	0.810	−0.101NS	0.010
	ECP4	0.865***	0.748	−0.081NS	0.007
	ECP5	0.821***	0.674	−0.072NS	0.005
ENP	ENP1	0.826***	0.682	0.002NS	0.000
	ENP2	0.911***	0.830	−0.069NS	0.005
	ENP3	0.863***	0.745	−0.010NS	0.000
	ENP4	0.805***	0.648	0.077NS	0.006
EXP	EXP1	0.640***	0.410	0.173*	0.030
	EXP2	0.846***	0.716	−0.094NS	0.009
	EXP3	0.858***	0.736	−0.130*	0.017
	EXP4	0.912***	0.832	−0.114*	0.013
	EXP5	0.892***	0.796	−0.072NS	0.005
	EXP6	0.733***	0.537	0.138*	0.019
	EXP7	0.786***	0.618	0.083NS	0.007
EXT	EXT1	0.846***	0.716	−0.018NS	0.000
	EXT2	0.884***	0.781	−0.037NS	0.001
	EXT3	0.936***	0.876	−0.141*	0.020
	EXT4	0.924***	0.854	−0.065NS	0.004
	EXT5	0.877***	0.769	−0.011NS	0.000
	EXT6	0.875***	0.766	−0.017NS	0.000
	EXT7	0.389***	0.151	0.356***	0.127
INT	INT1	0.755***	0.570	0.083NS	0.007
	INT2	0.844***	0.712	−0.099NS	0.010
	INT3	0.844***	0.712	0.026NS	0.001
	INT4	0.812***	0.659	−0.024NS	0.001
ITHC	ITHC1	0.662***	0.438	0.153**	0.023
	ITHC2	0.803***	0.645	−0.020NS	0.000
	ITHC3	0.833***	0.694	−0.085NS	0.007
	ITHC4	0.833***	0.694	−0.035NS	0.001
	ITHC5	0.885***	0.783	−0.112NS	0.013
	ITHC6	0.777***	0.604	0.086NS	0.007
ITIF	ITIF1	0.849***	0.721	−0.103NS	0.011
	ITIF2	0.893***	0.797	−0.164*	0.027
	ITIF3	0.880***	0.774	−0.127NS	0.016
	ITIF4	0.597***	0.356	0.271***	0.073
	ITIF5	0.620***	0.384	0.096NS	0.009

(Continues)

Table 1. (Continued)

Latent construct	Indicators	Substantive factor loading (Ra)	Ra^2	Method factor loading (Rb)	Rb^2
ITPQ	ITPQ1	0.738***	0.545	0.042NS	0.002
	ITPQ2	0.896***	0.803	−0.020NS	0.000
	ITPQ3	0.844***	0.712	0.016NS	0.000
	ITPQ4	0.866***	0.750	−0.025NS	0.001
	ITPQ5	0.844***	0.712	−0.009NS	0.000
LRN	LRN1	0.612***	0.375	0.041NS	0.002
	LRN2	0.897***	0.805	−0.027NS	0.001
	LRN3	0.901***	0.812	−0.055NS	0.003
	LRN4	0.822***	0.676	0.052NS	0.003
RCF	RCF1	0.864***	0.746	−0.138*	0.019
	RCF2	1.020***	1.040	−0.258***	0.067
	RCF3	0.683***	0.466	0.156**	0.024
	RCF4	0.675***	0.456	0.201***	0.040
SCP	SCP1	0.683***	0.466	0.091NS	0.008
	SCP2	0.676***	0.457	0.118NS	0.014
	SCP3	0.894***	0.799	−0.118*	0.014
	SCP4	0.791***	0.626	−0.020NS	0.000
	SCP5	0.756***	0.572	−0.061NS	0.004
SNS	SNS1	0.540***	0.292	0.282**	0.080
	SNS2	0.828***	0.686	−0.044NS	0.002
	SNS3	0.935***	0.874	−0.315***	0.099
	SNS4	0.762***	0.581	0.012NS	0.000
Average		0.805	0.661	−0.003	0.017

*$P < .05$. **$P < .01$. ***$P < .001$
NSInsignificant

lower RMSE value in Table 8 implies higher predictive accuracy and represents an excellent model fit of the data (Ng et al., 2022). Additionally, the R^2 of the ANN model shows that the ANN model predicts BUS with an accuracy of 71.815% (Leong et al., 2020). To determine the normalised relative importance of these neurons, a sensitivity analysis was performed (Wan et al., 2022). As per the sensitivity analysis results presented in Table 9, the single-neuron ANN models of A, B and C show a 100% normalised importance. In ANN model D, EXT (100%) is of primary importance to BUS, whereas EXP (23.574%) is the second most important predictor. In addition, all the ANN models in this study have adequate predictive relevance as the non-zero synaptic weights are connected to at least one hidden neuron in Table 10. Finally, in order to compare the results generated in PLS-SEM and ANN, a ranking comparison was performed by comparing the path coefficients in PLS-SEM with the normalised relative importance in ANN. Table 11 shows that ANN models A, B, C and D are consistent for both analyses.

6. Discussion

This study investigates how ITC promotes the emergence of ITDC, which leads to increased ambidextrous innovation, and subsequently, business sustainability. Building on a sample of 254 IT managerial personnel and employing PLS-SEM analysis, we discovered the following conclusions.

First, we provide empirical evidence that ITC promotes the emergence of ITDC, hence verifying H1. This finding effectively suggests that firms can build ITDC that are vital for competitive survival by investing in IT infrastructure flexibility, IT human capital and IT partnership quality. This finding is significant since an increasing number of businesses are adopting IT to support some of their key activities (Parida et al., 2016; Guo et al., 2021; Mikalef et al., 2021). For example, big data analytics and business analytics have allowed organisations to harness their data and gain valuable insights from it. Externally, firms can leverage on these IT solutions to detect emerging trends, analyse individual opinions and understand changing

Table 2. Factor loading, Rho (pA), composite reliability and average variance extracted

Constructs	Items	Factor loadings (FL) (***P***-levels)	Rho (pA)	Composite reliability (CR)	Average variance extracted (AVE)
First-order					
CRD	CRD1	0.800***	0.82	0.881	0.649
	CRD2	0.829***			
	CRD3	0.841***			
	CRD4	0.748***			
DDC	DDC1	0.850***	0.887	0.896	0.635
	DDC2	0.857***			
	DDC3	0.636***			
	DDC4	0.826***			
	DDC5	0.796***			
ECP	ECP1	0.821***	0.868	0.903	0.652
	ECP2	0.795***			
	ECP3	0.830***			
	ECP4	0.813***			
	ECP5	0.776***			
ENP	ENP1	0.831***	0.873	0.913	0.725
	ENP2	0.865***			
	ENP3	0.855***			
	ENP4	0.854***			
EXP	EXP1	0.775***	0.915	0.929	0.653
	EXP2	0.775***			
	EXP3	0.756***			
	EXP4	0.821***			
	EXP5	0.836***			
	EXP6	0.839***			
	EXP7	0.850***			
EXT	EXT1	0.831***	0.927	0.939	0.687
	EXT2	0.852***			
	EXT3	0.817***			
	EXT4	0.870***			
	EXT5	0.868***			
	EXT6	0.863***			
	EXT7	0.688***			
INT	INT1	0.815***	0.829	0.885	0.659
	INT2	0.786***			
	INT3	0.859***			
	INT4	0.785***			
ITHC	ITHC1	0.774***	0.886	0.913	0.636
	ITHC2	0.785***			
	ITHC3	0.772***			
	ITHC4	0.810***			
	ITHC5	0.804***			
	ITHC6	0.837***			
ITIF	ITIF1	0.783***	0.825	0.875	0.585
	ITIF2	0.783***			
	ITIF3	0.776***			
	ITIF4	0.791***			
	ITIF5	0.686***			

(Continues)

Table 2. (Continued)

Constructs	Items	Factor loadings (FL) (***P***-levels)	Rho (pA)	Composite reliability (CR)	Average variance extracted (AVE)
ITPQ	ITPQ1	0.780***	0.895	0.922	0.704
	ITPQ2	0.880***			
	ITPQ3	0.855***			
	ITPQ4	0.842***			
	ITPQ5	0.835***			
LRN	LRN1	0.688***	0.829	0.887	0.664
	LRN2	0.865***			
	LRN3	0.849***			
	LRN4	0.846***			
RCF	RCF1	0.772***	0.818	0.879	0.646
	RCF2	0.829***			
	RCF3	0.794***			
	RCF4	0.819***			
SCP	SCP1	0.848***	0.957	0.85	0.539
	SCP2	0.884***			
	SCP3	0.712***			
	SCP4	0.621***			
	SCP5	0.549***			
SNS	SNS1	0.755***	0.755	0.841	0.570
	SNS2	0.787***			
	SNS3	0.697***			
	SNS4	0.777***			
Second-order					
ITC			0.894	0.934	0.824
BUS			0.838	0.823	0.630

***$P < .001$.

customer preferences. Internally, these capabilities can assist firms to analyse the likelihood of future outcomes based on past data. In this manner, organisations can be more confident that they are making the most viable and optimal decision possible. Therefore, the ITC on which these solutions are based is critical for launching digital solutions to support vital operations.

Second, our findings indicate ITDC positively and significantly impacts on ambidextrous innovation, confirming H2 and H3. This is consistent with the DC theory, in that a firm's ITDCs hinge on its capacity to simultaneously sense, coordinate, learn, integrate and reconfigure its IT capability to build innovative capacity to gain competitive edge (Pavlou and El Sawy, 2011; Mikalef et al., 2019; Ferreira et al., 2020; Mikalef et al., 2020). Businesses are increasingly relying on technology and integrating IT resources with firm-level resources and management processes to remain competitive and respond quickly to market developments thereby necessitating the development of dynamic skills.

Third, our findings indicate that manufacturing firms' sustainability performance largely depends on ambidextrous innovation. This highlights the importance of innovation, which a manufacturing firm requires to compete in today's market. Accordingly, such a finding is consistent with the prior studies that have demonstrated the positive effects of innovative capability on enhanced corporate success (Ilmudeen, 2021; Iranmanesh et al., 2021; Wang et al., 2021).

Fourth, we provide empirical support for the hypotheses that DDC moderates the link between ITDC and exploitative innovation but not for exploratory innovation, verifying H6, but not H7. Contradicting many prior studies that emphasised the significance of such a culture (Lin and Kunnathur, 2019; Maroufkhani et al., 2020; Iranmanesh et al., 2021), DDC in our study was found to weaken the linkage between ITDC and exploitative innovation. This is mostly owing to the fact that, while Malaysian businesses have recognised the need for a modern data culture, many of these enterprises have a limited digital strategy in

Table 3. Loading and cross-loading value for first-order constructs

	CRD	DDC	ECP	ENP	EXP	EXT	INT	ITHC	ITIF	ITPQ	LRN	RCF	SCP	SNS
CRD1	0.800	0.624	0.431	0.365	0.430	0.544	0.471	0.434	0.473	0.590	0.497	0.506	0.332	0.587
CRD2	0.829	0.550	0.283	0.305	0.338	0.455	0.523	0.432	0.459	0.527	0.430	0.486	0.408	0.582
CRD3	0.841	0.528	0.155	0.142	0.225	0.321	0.487	0.513	0.580	0.504	0.560	0.569	0.498	0.655
CRD4	0.748	0.521	0.130	0.149	0.094	0.161	0.484	0.482	0.550	0.526	0.537	0.564	0.467	0.561
DDC1	0.601	0.850	0.440	0.455	0.506	0.568	0.570	0.542	0.587	0.717	0.495	0.568	0.406	0.560
DDC2	0.546	0.857	0.367	0.457	0.475	0.596	0.583	0.548	0.569	0.666	0.555	0.572	0.424	0.481
DDC3	0.504	0.636	0.065	0.093	0.055	0.192	0.410	0.477	0.511	0.526	0.418	0.539	0.378	0.413
DDC4	0.530	0.826	0.400	0.405	0.427	0.520	0.504	0.562	0.530	0.632	0.507	0.522	0.402	0.494
DDC5	0.611	0.796	0.293	0.322	0.392	0.475	0.445	0.556	0.560	0.583	0.464	0.561	0.412	0.544
ECP1	0.392	0.513	0.821	0.713	0.687	0.732	0.418	0.323	0.306	0.537	0.448	0.355	0.295	0.429
ECP2	0.201	0.345	0.795	0.553	0.569	0.542	0.237	0.198	0.155	0.367	0.357	0.166	0.176	0.248
ECP3	0.226	0.322	0.830	0.569	0.564	0.546	0.261	0.159	0.109	0.348	0.231	0.217	0.153	0.299
ECP4	0.230	0.297	0.813	0.633	0.575	0.563	0.258	0.154	0.091	0.327	0.259	0.207	0.117	0.267
ECP5	0.181	0.267	0.776	0.641	0.578	0.561	0.221	0.161	0.116	0.340	0.255	0.150	0.070	0.203
ENP1	0.259	0.372	0.684	0.831	0.613	0.574	0.259	0.165	0.193	0.380	0.287	0.246	0.213	0.270
ENP2	0.220	0.405	0.668	0.865	0.622	0.613	0.200	0.180	0.163	0.376	0.251	0.175	0.171	0.164
ENP3	0.275	0.410	0.635	0.855	0.585	0.592	0.257	0.188	0.207	0.377	0.364	0.240	0.214	0.274
ENP4	0.259	0.445	0.647	0.854	0.632	0.650	0.324	0.278	0.276	0.392	0.419	0.275	0.285	0.237
EXP1	0.327	0.450	0.599	0.629	0.775	0.677	0.433	0.354	0.372	0.466	0.425	0.303	0.269	0.339
EXP2	0.234	0.369	0.541	0.546	0.775	0.633	0.290	0.157	0.213	0.350	0.368	0.238	0.125	0.321
EXP3	0.170	0.372	0.587	0.538	0.756	0.617	0.291	0.175	0.181	0.345	0.304	0.198	0.097	0.227
EXP4	0.248	0.383	0.583	0.524	0.821	0.676	0.342	0.212	0.255	0.396	0.285	0.256	0.067	0.323
EXP5	0.242	0.400	0.572	0.606	0.836	0.725	0.327	0.213	0.245	0.420	0.324	0.304	0.171	0.277
EXP6	0.351	0.486	0.621	0.624	0.839	0.762	0.411	0.353	0.327	0.513	0.394	0.404	0.223	0.370
EXP7	0.310	0.469	0.667	0.590	0.850	0.785	0.360	0.283	0.320	0.521	0.382	0.375	0.191	0.355
EXT1	0.356	0.509	0.649	0.622	0.767	0.831	0.368	0.308	0.306	0.526	0.479	0.387	0.179	0.382

Table 3. (Continued)

	CRD	DDC	ECP	ENP	EXP	EXT	INT	ITHC	ITIF	ITPQ	LRN	RCF	SCP	SNS
EXT2	0.346	0.505	0.653	0.673	0.786	0.852	0.367	0.296	0.306	0.518	0.518	0.390	0.216	0.382
EXT3	0.347	0.503	0.536	0.596	0.674	0.817	0.286	0.259	0.308	0.464	0.427	0.337	0.267	0.417
EXT4	0.382	0.547	0.633	0.671	0.736	0.870	0.367	0.261	0.342	0.504	0.473	0.404	0.333	0.391
EXT5	0.371	0.533	0.664	0.599	0.739	0.868	0.426	0.349	0.361	0.550	0.446	0.405	0.332	0.398
EXT6	0.408	0.532	0.659	0.603	0.763	0.863	0.459	0.301	0.319	0.514	0.423	0.449	0.264	0.404
EXT7	0.481	0.565	0.439	0.344	0.535	0.688	0.526	0.476	0.483	0.567	0.412	0.526	0.321	0.469
INT1	0.479	0.498	0.366	0.341	0.419	0.456	0.815	0.460	0.416	0.544	0.539	0.517	0.442	0.471
INT2	0.552	0.496	0.108	0.088	0.169	0.225	0.786	0.420	0.448	0.463	0.494	0.594	0.478	0.456
INT3	0.517	0.559	0.351	0.296	0.438	0.456	0.859	0.464	0.440	0.530	0.517	0.547	0.362	0.485
INT4	0.429	0.511	0.309	0.264	0.395	0.421	0.785	0.427	0.410	0.447	0.357	0.575	0.228	0.465
ITHC1	0.460	0.571	0.258	0.293	0.362	0.386	0.483	0.774	0.675	0.576	0.426	0.463	0.349	0.493
ITHC2	0.511	0.540	0.160	0.118	0.184	0.276	0.467	0.785	0.576	0.557	0.451	0.458	0.443	0.401
ITHC3	0.413	0.465	0.141	0.116	0.188	0.240	0.392	0.772	0.645	0.517	0.397	0.400	0.390	0.377
ITHC4	0.458	0.504	0.179	0.171	0.235	0.310	0.408	0.810	0.664	0.560	0.405	0.444	0.353	0.449
ITHC5	0.386	0.480	0.176	0.184	0.248	0.286	0.366	0.804	0.620	0.509	0.387	0.384	0.311	0.371
ITHC6	0.536	0.615	0.275	0.248	0.286	0.330	0.490	0.837	0.682	0.597	0.481	0.513	0.403	0.536
ITIF1	0.494	0.488	0.098	0.172	0.180	0.241	0.350	0.719	0.783	0.485	0.428	0.371	0.365	0.428
ITIF2	0.406	0.452	0.074	0.107	0.205	0.258	0.307	0.708	0.783	0.484	0.361	0.395	0.254	0.428
ITIF3	0.486	0.484	0.094	0.119	0.246	0.290	0.419	0.560	0.776	0.484	0.403	0.409	0.355	0.449
ITIF4	0.574	0.615	0.310	0.353	0.444	0.503	0.513	0.594	0.791	0.664	0.495	0.520	0.487	0.591
ITIF5	0.489	0.562	0.168	0.181	0.229	0.281	0.433	0.493	0.686	0.581	0.419	0.501	0.450	0.418
ITPQ1	0.460	0.595	0.332	0.340	0.458	0.520	0.493	0.563	0.598	0.780	0.463	0.476	0.427	0.413
ITPQ2	0.571	0.657	0.431	0.397	0.502	0.560	0.516	0.622	0.603	0.880	0.513	0.521	0.439	0.479
ITPQ3	0.593	0.713	0.386	0.381	0.432	0.546	0.548	0.585	0.573	0.855	0.498	0.570	0.452	0.531
ITPQ4	0.589	0.633	0.423	0.382	0.426	0.496	0.504	0.558	0.610	0.842	0.521	0.455	0.463	0.580
ITPQ5	0.577	0.695	0.439	0.376	0.440	0.502	0.507	0.581	0.578	0.835	0.439	0.420	0.456	0.556
LRN1	0.577	0.472	0.062	0.008	0.097	0.200	0.499	0.491	0.515	0.439	0.688	0.477	0.454	0.572
LRN2	0.518	0.515	0.405	0.420	0.404	0.508	0.459	0.415	0.417	0.510	0.865	0.448	0.443	0.467
LRN3	0.470	0.485	0.355	0.340	0.449	0.517	0.446	0.411	0.435	0.452	0.849	0.490	0.350	0.443
LRN4	0.483	0.511	0.429	0.480	0.479	0.548	0.515	0.418	0.429	0.486	0.846	0.495	0.419	0.473
RCF1	0.531	0.462	0.106	0.058	0.187	0.255	0.602	0.411	0.408	0.370	0.397	0.772	0.391	0.533
RCF2	0.540	0.459	0.065	0.066	0.138	0.241	0.537	0.421	0.486	0.401	0.384	0.829	0.355	0.516

Table 3. (Continued)

	CRD	DDC	ECP	ENP	EXP	EXT	INT	ITHC	ITIF	ITPQ	LRN	RCF	SCP	SNS
RCF3	0.480	0.588	0.335	0.381	0.464	0.543	0.531	0.413	0.451	0.491	0.579	0.794	0.339	0.452
RCF4	0.570	0.650	0.361	0.357	0.392	0.535	0.538	0.540	0.495	0.598	0.516	0.819	0.364	0.531
SCP1	0.382	0.372	0.180	0.254	0.197	0.312	0.377	0.381	0.394	0.451	0.416	0.338	0.848	0.395
SCP2	0.413	0.431	0.275	0.317	0.254	0.337	0.363	0.359	0.378	0.447	0.365	0.313	0.884	0.382
SCP3	0.450	0.371	−0.048	0.026	0.007	0.100	0.418	0.363	0.421	0.381	0.427	0.405	0.712	0.350
SCP4	0.510	0.404	0.036	0.027	0.045	0.155	0.372	0.401	0.428	0.395	0.453	0.450	0.621	0.416
SCP5	0.424	0.330	0.027	0.014	0.020	0.084	0.334	0.368	0.399	0.308	0.451	0.422	0.549	0.371
SNS1	0.601	0.531	0.400	0.386	0.466	0.542	0.490	0.460	0.490	0.578	0.505	0.515	0.415	0.755
SNS2	0.519	0.480	0.323	0.249	0.339	0.380	0.438	0.388	0.434	0.454	0.462	0.465	0.368	0.787
SNS3	0.504	0.336	0.042	−0.048	0.033	0.106	0.330	0.384	0.431	0.294	0.390	0.400	0.397	0.697
SNS4	0.605	0.510	0.281	0.192	0.294	0.384	0.468	0.426	0.475	0.480	0.445	0.514	0.299	0.777

place, capable of driving businesses to achieve more (Paramasivam, 2016).

7. Implications

7.1. Theoretical implications

Drawing on the RBV and the DC perspective, this study provided a singular and distinctive model through which ITC's effect on ITDC can be evaluated. ITDC's impact on ambidextrous innovation and the subsequent sustainability performance of Malaysian manufacturing firms is also examined. Further, the moderating effect of DDC on the relationship between ITDC and ambidextrous innovation is also empirically examined. First, we conceptualise ITC as a latent construct with three elements (i.e. IT infrastructure flexibility, IT human capital and IT partnership quality) (Guo et al., 2021), and we investigate the influence of ITC at an aggregated level. This idea is based on the well-known RBV, and we underline that ITC is more than a technology endeavour; it also requires the development and coordination of numerous additional non-technical resources. Secondly, the conceptualization of ITDC illustrates how IT is entrenched in firm processes that aid the realisation of improved business performance (Mikalef and Pateli, 2017; Ilmudeen, 2021). As prior research claimed that dynamic capabilities are inimitable because they are built on the distinctive characteristics of innovation, this paper draws on DC theory to explicate the importance and uniqueness of ITDC. Third, based on a DC perspective, this study identifies the impacts of ITDC on ambidextrous innovation for business sustainability. This paper contends that ITDC encourages exploitative and exploratory innovation, which consequently improves business sustainability, an area where attention has been scant in the past. Lastly, this study contributes to the body of literature on the moderating role of DDC in the ITDC-innovation relationship in the context of Malaysia, where prior research has fallen short.

7.2. Practical implications

This study has significant practical and managerial implications for practitioners and industry leaders. First, this study validates the significance of ITC in promoting ITDC. Therefore, enterprises must develop and maintain ITC, as well as efficiently leverage such skills to support and promote ITDC in order to attain better levels of innovation and business sustainability. Firms must also be aware that ITC requires a flexible IT infrastructure, trained and competent IT

Table 4. Hetero-Trait-Mono-Trait (HTMT) for second-order constructs

Constructs	BUS	DDC	EXP	EXT	ITC	ITDC
BUS						
DDC	0.545					
EXP	0.768	0.522				
EXT	0.783	0.635	0.866			
ITC	0.442	0.783	0.44	0.523		
ITDC	0.511	0.777	0.498	0.613	0.762	

Table 5. Assessing the formative construct

Formative indicators	Variance inflation factor (VIF)	Outer weight	Outer loading
CRD	2.785	0.128[NS]	0.826***
INT	2.192	0.271**	0.830***
LRN	1.970	0.369***	0.862***
RCF	2.429	0.170[NS]	0.818***
SNS	2.520	0.255*	0.835***

*$P < .05$.
**$P < .01$.
***$P < .001$
[NS]Insignificant

people, and effective internal and external IT collaboration. Second, our findings imply that, albeit indirectly, firm-wide ITC is vital for the generation of genuine economic yields. This emphasises the need of investing in the creation of a superior ITC for the entire company. Firms could, for example, replace less-skilled workers with trained and competent personnel who must also obtain an acceptable degree of ITC to achieve outstanding innovative performance. Firms can invest in trainings and seminars for their professional employees in order to enhance their IT proficiency, which will eventually lead to increased business sustainability. Third, according to Microsoft Asia's Data Culture study (Paramasivam, 2016), 85% of Malaysian Business Decision Makers agree that having an agile, data-driven business is vital; yet only 44% have started or have a limited digital strategy in place. Exorbitant costs, a digital skills shortage, resistance to change and limited funding have been cited as the main inhibitors of a successful digital transformation for many Malaysian firms. Therefore, policymakers should take additional steps to make it easier for businesses to employ IT capability. As this study demonstrates, ITC fundamentally influences firms' operations and performance,

Table 6. Hypothesis testing

PLS path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	***P*** **values**	Bias-corrected confidence interval		Remarks
EXP → BUS***	0.351	0.349	0.094	3.734	.000	0.165	0.533	Supported
EXT → BUS***	0.478	0.48	0.096	4.982	.000	0.283	0.657	Supported
ITC → ITDC***	0.756	0.76	0.036	20.729	.000	0.662	0.814	Supported
ITDC → EXP**	0.265	0.285	0.102	2.612	.009	0.018	0.430	Supported
ITDC → EXT***	0.343	0.359	0.090	3.829	.000	0.127	0.493	Supported
ITDCxDDC → EXT**	−0.080	−0.082	0.026	3.054	.002	−0.131	−0.028	Supported
ITDCxDDC → EXP	−0.057	−0.059	0.034	1.665	.096	−0.120	0.019	Not significant

**$P < .01$.
***$P < .001$.

Table 7. Quality of the structural model

Endogenous variables	Coefficient of determination (R^2)	Stone-Geisser (Q^2)	Exogenous variables	Effect size (f^2)
BUS	0.642	0.393	EXP	0.087
			EXT	0.160
EXP	0.299	0.283	DDC	0.074
			ITDC	0.037
EXT	0.449	0.431	DDC	0.134
			ITDC	0.080
ITDC	0.571	0.404	ITC	1.332

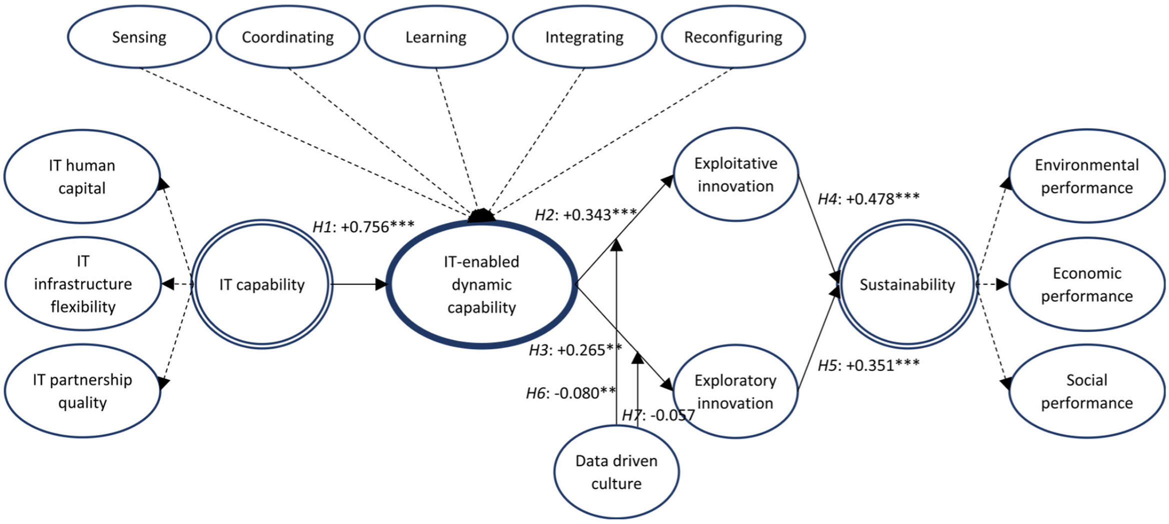


Figure 2. Hypotheses testing.

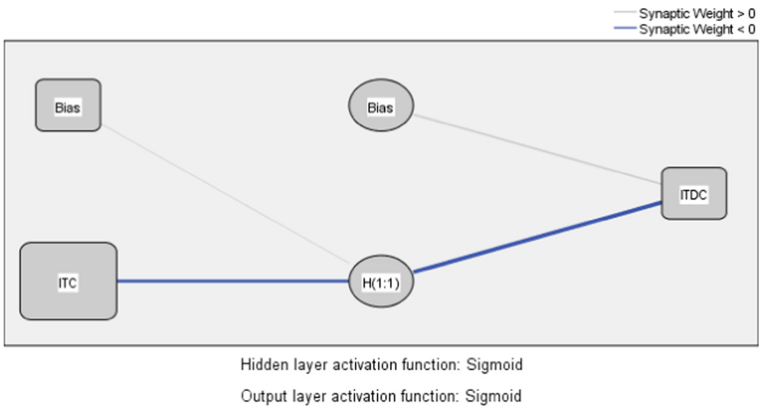


Figure 3. ANN model A for ITDC.

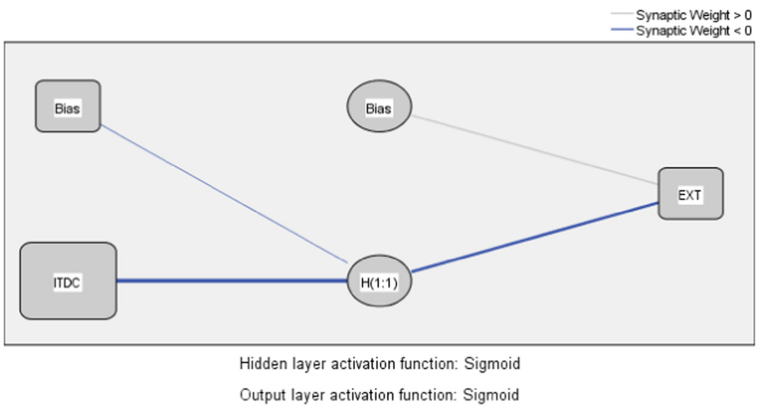


Figure 4. ANN model B for EXT.

including dynamic capability, innovation and overall business sustainability. The government can reduce the cost of IT infrastructure/expenditure to encourage enterprises to use IT. For example, the Malaysian government has offered grants and loans to qualifying firms through initiatives such as the SME Digitalisation Matching Grant, the SME Technology Transformation Fund, and the Smart Automation

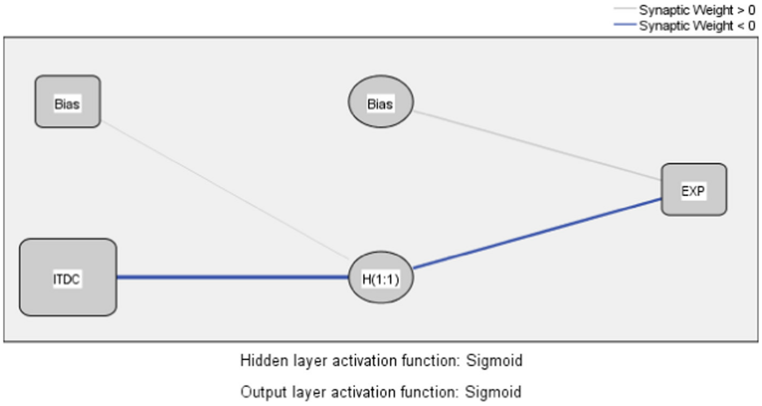


Figure 5. ANN model C for EXP.

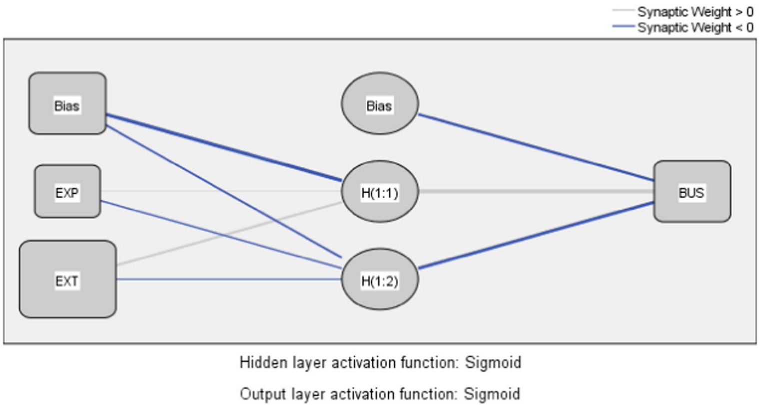


Figure 6. ANN model D for BUS.

Table 8. RMSE values for ITDC, EXT, EXP and BUS

	Model A		Model B		Model C		Model D	
	Input: ITC		Input: ITDC		Input: ITDC		Input: EXP, EXT	
	Output: ITDC		Output: EXT		Output: EXP		Output: BUS	
Neural network	Training RMSE	Testing RMSE	Training RMSE	Testing RMSE	Training RMSE	Testing RMSE	Training RMSE	Testing RMSE
ANN1	0.075	0.047	0.133	0.126	0.145	0.092	0.080	0.075
ANN2	0.073	0.080	0.129	0.104	0.145	0.123	0.071	0.089
ANN3	0.073	0.058	0.129	0.141	0.143	0.133	0.075	0.064
ANN4	0.072	0.064	0.126	0.137	0.157	0.141	0.073	0.079
ANN5	0.075	0.079	0.128	0.114	0.142	0.134	0.079	0.092
ANN6	0.072	0.074	0.126	0.137	0.145	0.112	0.078	0.084
ANN7	0.078	0.079	0.133	0.125	0.144	0.122	0.074	0.070
ANN8	0.074	0.070	0.127	0.126	0.137	0.176	0.079	0.069
ANN9	0.076	0.055	0.133	0.115	0.141	0.136	0.075	0.066
ANN10	0.074	0.078	0.132	0.094	0.147	0.139	0.074	0.235
Mean	0.074	0.068	0.130	0.122	0.145	0.131	0.076	0.092
SD	0.002	0.012	0.003	0.015	0.005	0.022	0.003	0.051

Table 9. Sensitivity analysis

Neural network	Model A (output: ITDC) ITC	Model B (output: EXT) ITDC	Model C (output: EXP) ITDC	Model D (output: BUS) EXP	Model D (output: BUS) EXT
ANN1	1.000	1.000	1.000	0.184	0.816
ANN2	1.000	1.000	1.000	0.102	0.898
ANN3	1.000	1.000	1.000	0.221	0.779
ANN4	1.000	1.000	1.000	0.186	0.814
ANN5	1.000	1.000	1.000	0.068	0.932
ANN6	1.000	1.000	1.000	0.180	0.820
ANN7	1.000	1.000	1.000	0.211	0.789
ANN8	1.000	1.000	1.000	0.159	0.481
ANN9	1.000	1.000	1.000	0.197	0.803
ANN10	1.000	1.000	1.000	0.331	0.669
Average relative importance	1.000	1.000	1.000	0.184	0.780
Normalised relative importance (%)	100.000	100.000	100.000	23.574	100.000

Table 10. Relevance of variables based on non-zero synaptic weight with hidden neurons

Neural network	Model A ITC	Model B ITDC	Model C ITDC	Model D EXP	Model D EXT
ANN1	1	1	1	2	2
ANN2	1	1	1	2	2
ANN3	1	1	1	2	2
ANN4	1	1	1	2	2
ANN5	1	1	1	2	2
ANN6	1	1	1	2	2
ANN7	1	1	1	2	2
ANN8	1	1	1	2	2
ANN9	1	1	1	2	2
ANN10	1	1	1	2	2

Grant, to help firms with technological growth and adoption. This is in line with the government's efforts to drive digitalization of the economy through the Industry 4.0 National Policy aimed to boost connectivity and technological innovation. Such government assistance would benefit Malaysian firms' productivity and innovation. Additionally, the government can also help enterprises with IT infrastructure training, after which firms can fully utilise their ITC to boost their competitiveness.

8. Limitations and future research

The current study has a number of limitations that could be addressed in future research. First, this study examines the impact of ITC on sustainability performance based on the Malaysian experience. Although the findings might be applicable in Malaysia, its applicability in other countries, such as developed countries, is debatable. Future research should consider examining the proposed relationships in a larger cross-industry sample. Secondly, this research employs self-reported data gathered from managerial personnel to examine hypotheses and propositions. Although extensive efforts are made to assure the validity and reliability of all variables through data analysis, the possibility of biases cannot be ruled out (Montani and Staglianò, 2021). Therefore, future research should consider sampling multiple respondents inside a single organisation in order to assess inter-rater validity and increase internal validity. Thirdly, the moderating role of DDC is considered in this study. Other factors, such as firm size (Parida et al., 2016), entrepreneurial

Table 11. Comparison between PLS-SEM and ANN results

PLS path	Original sample (O)/path coefficient	ANN results: Normalised relative importance (%)	Ranking (PLS-SEM) [based on path coefficient]	Ranking (ANN) [based on normalised relative importance]	Remark
Model A (Output: ITDC)					
ITC → ITDC	0.756	100.000	1	1	Match
Model B (Output: EXT)					
ITDC → EXT	0.343	100.000	1	1	Match
Model C (Output: EXP)					
ITDC → EXP	0.265	100.000	1	1	Match
Model D (Output: BUS)					
EXP → BUS	0.351	23.574	2	2	Match
EXT → BUS	0.478	100.000	1	1	Match

orientation (Ferreira et al., 2020), and other forms of environmental factors (Chen et al., 2014) could potentially affect the outcome of the proposed relationships. Moreover, the relationship of ITC with sustainability performance may be mediated by business agility (Chen et al., 2014; Ilmudeen, 2021), knowledge management capability (Akram et al., 2018; Wu and Ding, 2020), or other forms of organisational factors (Mikalef et al., 2020; AlNuaimi et al., 2021). When testing for the effect of ITC, future studies should include moderators and mediators in their research models.

Acknowledgement

None.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

Akram, M.S., Goraya, A.S., Malik, A., and Aljarallah, A.M. (2018) Organizational performance and sustainability: exploring the roles of IT capabilities and knowledge management capabilities. *Sustainability (Switzerland)*, **10**, 10, 3816. https://doi.org/10.3390/su10103816.

AlNuaimi, B.K., Khan, M., and Ajmal, M.M. (2021) The role of big data analytics capabilities in greening e-procurement: a higher order PLS-SEM analysis. *Technological Forecasting and Social Change*, **169**, November 2020, 120808. https://doi.org/10.1016/j.techfore.2021.120808.

Antonetti, P., Crisafulli, B., and Tuncdogan, A. (2020) Just look the other way: job seekers' reactions to the irresponsibility of market-dominant employers. *Journal of Business Ethics*, **174**, 4, 1–20. https://doi.org/10.1007/s10551-020-04623-0.

Barney, J.B. (1986) Organizational culture: can it be a source of sustained competitive advantage? *The Academy of Management Review*, **11**, 656–665. https://doi.org/10.2307/258317.

Barney, J.B. (1991) Firm resources and sustained competitive advantage. *Journal of Management*, **17**, 99–120. https://doi.org/10.1016/S0742-3322(00)17018-4.

Barney, J.B. (1995) Looking inside for competitive advantage. *Academy of Management Perspectives*, **9**, 49–61. https://doi.org/10.5465/ame.1995.9512032192.

Ben Rejeb, W., Berraies, S., and Talbi, D. (2020) The contribution of board of directors' roles to ambidextrous innovation: do board's gender diversity and independence matter? *European Journal of Innovation Management*, **23**, 1, 40–66. https://doi.org/10.1108/EJIM-06-2018-0110.

Benner, M.J. and Tushman, M.L. (2003) Exploitation, exploration, and process management: the productivity dilemma revisited. *Academy of Management Review*, **28**, 2, 238–256. https://doi.org/10.5465/AMR.2003.9416096.

Berraies, S. and Bchini, B. (2019) Effect of leadership styles on financial performance: mediating roles of exploitative and exploratory innovations case of knowledge-intensive firms. *International Journal of Innovation Management*, **23**, 3, 1–33. https://doi.org/10.1142/S1363919619500208.

Berraies, S. and Hamouda, M. (2018) Customer empowerment and firms' performance: the mediating effects of innovation and customer satisfaction. *International Journal of Bank Marketing*, **36**, 2, 336–356. https://doi.org/10.1108/IJBM-10-2016-0150.

Berraies, S. and Zine El Abidine, S. (2019) Do leadership styles promote ambidextrous innovation? Case of knowledge-intensive firms. *Journal of Knowledge Management*, **23**, 5, 836–859. https://doi.org/10.1108/JKM-09-2018-0566.

Byrd, T.A. and Turner, D.E. (2000) Measuring the flexibility of information technology infrastructure:

exploratory analysis of a construct. *Journal of Management Information Systems*, **17**, 1, 167–208. https://doi.org/10.1080/07421222.2000.11045632.

Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L., and Chow, W.S. (2014) IT capability and organizational performance: the roles of business process agility and environmental factors. *European Journal of Information Systems*, **23**, 3, 326–342.

Cohen, J. (1988) The concepts of power analysis. In: *Statistical Power Analysis for the Behavioral Sciences*. Hillsdale: Lawrence Erlbaum Associates, Inc.

Department of Statistics Malaysia. (2021) *Department of Statistics Malaysia*. Available at: https://www.dosm.gov.my/v1/index.php?r=column/cthemeByCat&cat=102&bul_id=anVob1dYUFZLNE5WV1RVRExkSWEyZz09&menu_id=TE5CRUZCblh4ZTZMODZIbmk2aWRRQT09 (Accessed: 28 December 2021).

Drnevich, P.L. and Kriauciunas, A.P. (2011) Clarifying the conditions and limits of the contributions of ordinary and dynamic capabilities to relative firm performance. *Strategic Management Journal*, **32**, 3, 254–279.

Eisenhardt, K.M. and Martin, J.A. (2000) Dynamic capabilities: what are they? *Strategic Management Journal*, **21**, 10–11, 1105–1121.

Elkington, J. (1994) Towards the sustainable corporation: win-win-win business strategies for sustainable development. *California Management Review*, **36**, 2, 90–100. https://doi.org/10.2307/41165746.

Faul, F., Erdfelder, E., Lang, A.G., and Buchner, A. (2007) G* power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, **39**, 2, 175–191.

Fernando, Y., Chiappetta Jabbour, C.J., and Wah, W.X. (2019) Pursuing green growth in technology firms through the connections between environmental innovation and sustainable business performance: does service capability matter? *Resources, Conservation and Recycling*, **141**, July 2018, 8–20. https://doi.org/10.1016/j.resconrec.2018.09.031.

Ferreira, J., Coelho, A., and Moutinho, L. (2020) Dynamic capabilities, creativity and innovation capability and their impact on competitive advantage and firm performance: the moderating role of entrepreneurial orientation. *Technovation*, **92–93**, July, 102061. https://doi.org/10.1016/j.technovation.2018.11.004.

Ghasemzadeh, P., Nazari, J.A., Farzaneh, M., and Mehralian, G. (2019) Moderating role of innovation culture in the relationship between organizational learning and innovation performance. *The Learning Organization*, **26**, 3, 289–303. https://doi.org/10.1108/TLO-08-2018-0139.

Ghazali, E.M., Ngiam, E.Y.L., and Mutum, D.S. (2020) Elucidating the drivers of residential mobility and housing choice behaviour in a suburban township via push–pull–mooring framework. *Journal of Housing and the Built Environment*, **35**, 2, 633–659.

Gong, L., Liu, Z., Rong, Y., and Fu, L. (2021) Inclusive leadership, ambidextrous innovation and organizational performance: the moderating role of environment uncertainty. *Leadership and Organization Development Journal*, **42**, 5, 783–801. https://doi.org/10.1108/LODJ-06-2020-0253.

Guo, J., Zhou, S., Chen, J., and Chen, Q. (2021) How information technology capability and knowledge integration capability interact to affect business model design: a polynomial regression with response surface analysis. *Technological Forecasting and Social Change*, **170**, May, 120935. https://doi.org/10.1016/j.techfore.2021.120935.

Gupta, M. and George, J.F. (2016) Toward the development of a big data analytics capability. *Information and Management*, **53**, 8, 1049–1064. https://doi.org/10.1016/j.im.2016.07.004.

Hair, J.F., Hult, G.T.M., Ringle, C.M., and Sarstedt, M. (2017) *A primer on partial least squares structural equation modeling (PLS-SEM)*, 2nd edn. Thousand Oaks: SAGE Publications Inc.

Heij, C.V., Volberda, H.W., Van den Bosch, F.A., and Hollen, R.M. (2020) How to leverage the impact of R&D on product innovation? The moderating effect of management innovation. *R&D Management*, **50**, 2, 277–294.

Henseler, J., Ringle, C.M., and Sarstedt, M. (2015) A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, **43**, 1, 115–135. https://doi.org/10.1007/s11747-014-0403-8.

Hew, J.J., Leong, L.Y., Tan, G.W.H., Lee, V.H., and Ooi, K.B. (2018) Mobile social tourism shopping: a dual-stage analysis of a multi-mediation model. *Tourism Management*, **66**, 121–139.

Iivari, J. and Huisman, M. (2007) The relationship between organizational culture and the deployment of systems development methodologies. *MIS Quarterly: Management Information Systems*, **31**, 1, 35–58. https://doi.org/10.2307/25148780.

Ilmudeen, A. (2021) Information technology (IT) governance and IT capability to realize firm performance: enabling role of agility and innovative capability. *Benchmarking: An International Journal*, **29**, 1137–1161. https://doi.org/10.1108/BIJ-02-2021-0069.

Iranmanesh, M., Kumar, K.M., Foroughi, B., Mavi, R.K., and Min, N.H. (2021) The impacts of organizational structure on operational performance through innovation capability: innovative culture as moderator. *Review of Managerial Science*, **15**, 7, 1885–1911. https://doi.org/10.1007/s11846-020-00407-y.

Jansen, J.J.P., Van Den Bosch, F.A.J., and Volberda, H.W. (2006) Exploratory innovation, exploitative innovation, and performance: effects of organizational antecedents and environmental moderators. *Management Science*, **52**, 11, 1661–1674. https://doi.org/10.1287/mnsc.1060.0576.

Jansen, J.J.P., Vera, D., and Crossan, M. (2009) Strategic leadership for exploration and exploitation: the moderating role of environmental dynamism. *Leadership Quarterly*, **20**, 1, 5–18. https://doi.org/10.1016/j.leaqua.2008.11.008.

Jeble, S., Dubey, R., Childe, S.J., Papadopoulos, T., Roubaud, D., and Prakash, A. (2018) Impact of big data and predictive analytics capability on supply chain sustainability. *The International Journal of Logistics Management*, **29**, 513–538. https://doi.org/10.1108/IJLM-05-2017-0134.

Jin, Z., Navare, J., and Lynch, R. (2019) The relationship between innovation culture and innovation outcomes: exploring the effects of sustainability orientation and firm size. *R&D Management*, **49**, 4, 607–623.

Kim, M.J., Lee, C.K., and Jung, T. (2020) Exploring consumer behavior in virtual reality tourism using an extended stimulus-organism-response model. *Journal of Travel Research*, **59**, 1, 69–89.

Ko, W.W. and Liu, G. (2019) How information technology assimilation promotes exploratory and exploitative innovation in the small- and medium-sized firm context: the role of contextual ambidexterity and Knowledge Base. *Journal of Product Innovation Management*, **36**, 4, 442–466. https://doi.org/10.1111/jpim.12486.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M.S., and Kruschwitz, N. (2011) Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, **52**, 2, 21–32.

Leong, L.Y., Hew, T.S., Ooi, K.B., and Wei, J. (2020) Predicting mobile wallet resistance: a two-staged structural equation modeling-artificial neural network approach. *International Journal of Information Management*, **51**, 102047.

Li, X., Zhang, J., Zhang, S., and Zhou, M. (2017) A multi-level analysis of the role of interactional justice in promoting knowledge-sharing behavior: the mediated role of organizational commitment. *Industrial Marketing Management*, **62**, 226–233.

Liang, H., Saraf, N., Hu, Q., and Xue, Y. (2007) Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management. *MIS Quarterly*, **31**, 1, 59–87. https://doi.org/10.2307/25148781.

Lim, A.F., Lee, V.H., Foo, P.Y., Ooi, K.B., and Wei–Han Tan, G. (2021) Unfolding the impact of supply chain quality management practices on sustainability performance: an artificial neural network approach. *Supply Chain Management*, **27**, 611–624. https://doi.org/10.1108/SCM-03-2021-0129.

Lin, C. and Kunnathur, A. (2019) Strategic orientations, developmental culture, and big data capability. *Journal of Business Research*, **105**, July, 49–60. https://doi.org/10.1016/j.jbusres.2019.07.016.

Liu, X., Huang, Q., Dou, J., and Zhao, X. (2017) The impact of informal social interaction on innovation capability in the context of buyer-supplier dyads. *Journal of Business Research*, **78**, 314–322. https://doi.org/10.1016/j.jbusres.2016.12.027.

Loh, X.M., Lee, V.H., Tan, G.W.H., Hew, J.J., and Ooi, K.B. (2019) Towards a cashless society: the imminent role of wearable technology. *Journal of Computer Information Systems*, **62**, 1, 39–49. https://doi.org/10.1080/08874417.2019.1688733.

Lowry, P.B. and Wilson, D. (2016) Creating agile organizations through IT: the influence of internal IT service perceptions on IT service quality and IT agility. *Journal of Strategic Information Systems*, **25**, 3, 211–226. https://doi.org/10.1016/j.jsis.2016.05.002.

Lu, Y. and Ramamurthy, K. (2011) Understanding the link between information technology capability and organizational agility: an empirical examination. *MIS Quarterly*, **35**, 4, 931–954.

Maroufkhani, P., Tseng, M.L., Iranmanesh, M., Ismail, W.K.W., and Khalid, H. (2020) Big data analytics adoption: determinants and performances among small to medium-sized enterprises. *International Journal of Information Management*, **54**, 102190. https://doi.org/10.1016/j.ijinfomgt.2020.102190.

McAfee, A. and Brynjolfsson, E. (2012) Big data: the management revolution. *Harvard Business Review*, **90**, 10, 60–68. Available at: https://promdevelop.ru/big-data/.

Mikalef, P., Boura, M., Lekakos, G., and Krogstie, J. (2019) Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management*, **30**, 2, 272–298. https://doi.org/10.1111/1467-8551.12343.

Mikalef, P., Krogstie, J., Pappas, I.O., and Pavlou, P. (2020) Exploring the relationship between big data analytics capability and competitive performance: the mediating roles of dynamic and operational capabilities. *Information & Management*, **57**, 2, 103169. https://doi.org/10.1016/j.im.2019.05.004.

Mikalef, P. and Pateli, A. (2017) Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: findings from PLS-SEM and fsQCA. *Journal of Business Research*, **70**, 1–16. https://doi.org/10.1016/j.jbusres.2016.09.004.

Mikalef, P., Pateli, A., and van de Wetering, R. (2021) IT architecture flexibility and IT governance decentralisation as drivers of IT-enabled dynamic capabilities and competitive performance: the moderating effect of the external environment. *European Journal of Information Systems*, **30**, 5, 512–540. https://doi.org/10.1080/0960085X.2020.1808541.

Montani, F. and Staglianò, R. (2021) Innovation in times of pandemic: the moderating effect of knowledge sharing on the relationship between COVID-19-induced job stress and employee innovation. *R&D Management*, **52**, 2, 193–205. https://doi.org/10.1111/radm.12457.

Nejatian, M., Zarei, M.H., Nejati, M., and Zanjirchi, S.M. (2018) A hybrid approach to achieve organizational agility: an empirical study of a food company. *Benchmarking: An International Journal*, **25**, 1, 201–234. https://doi.org/10.1108/bij-09-2016-0147.

Ng, F.Z.X., Yap, H.Y., Tan, G.W.H., Lo, P.S., and Ooi, K.B. (2022) Fashion shopping on the go: a dual-stage predictive-analytics SEM-ANN analysis on usage behaviour, experience response and cross-category usage. *Journal of Retailing and Consumer Services*, **65**, 102851. https://doi.org/10.1016/j.jretconser.2021.102851.

Ooi, K.B. and Tan, G.W.H. (2016) Mobile technology acceptance model: an investigation using mobile users to explore smartphone credit card. *Expert Systems with Applications*, **59**, 33–46.

Paramasivam, S. (2016) 85% of Malaysian businesses feel the need for a modern data culture – Yet 44% have a limited digital strategy in place. [online]. *Microsoft Malaysia News Center*. Available at: <https://news.microsoft.com/en-my/2016/05/11/85-malaysian-businesses-feel-need-modern-data-culture-yet-44-limited-digital-strategy-place/> [Accessed 17 January 2022].

Parida, V., Oghazi, P., and Cedergren, S. (2016) A study of how ICT capabilities can influence dynamic capabilities. *Journal of Enterprise Information Management*, **29**, 2, 179–201. https://doi.org/10.1108/JEIM-07-2012-0039.

Pavlou, P.A. and El Sawy, O.A. (2006) From IT leveraging competence to competitive advantage in turbulent environments: the case of new product development. *Information Systems Research*, **17**, 3, 198–227.

Pavlou, P.A. and El Sawy, O.A. (2011) Understanding the elusive black box of dynamic capabilities. *Decision Sciences*, **42**, 1, 239–273.

Pavlou, P.A. and Sawy, O.A.E. (2010) The third hand: IT-enabled competitive advantage in turbulence through improvisational capabilities. *Information Systems Research*, **21**, 3, 443–471. https://doi.org/10.1287/isre.1100.0280.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., and 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, 879–903.

Ravichandran, T. and Lertwongsatien, C. (2005) Effect of information systems resources and capabilities on firm performance: a resource-based perspective. *Journal of Management Information Systems*, **21**, 4, 237–276. https://doi.org/10.1080/07421222.2005.11045820.

Roberts, N. and Grover, V. (2012) Leveraging information technology infrastructure to facilitate a firm's customer agility and competitive activity: an empirical investigation. *Journal of Management Information Systems*, **28**, 4, 231–270. https://doi.org/10.2753/MIS0742-1222280409.

Ross, J.W., Beath, C.M., and Quaadgras, A. (2013) You may not need big data after all. *Harvard Business Review*, **91**, 90–98.

Senaratne, C., Wang, C.L., and Sarma, M. (2021) Commonalities and specificities of dynamic capabilities: a mixed methods study of UK high-tech SMEs. *R&D Management*, **52**, 4, 735–754. https://doi.org/10.1111/radm.12518.

Tan, G.W.H. and Ooi, K.B. (2018) Gender and age: do they really moderate mobile tourism shopping behavior? *Telematics and Informatics*, **35**, 6, 1617–1642. https://doi.org/10.1016/j.tele.2018.04.009.

Teece, D.J., Pisano, G., and Shuen, A. (1997) Dynamic capabilities and strategic management. *Strategic Management Journal*, **18**, 7, 509–533.

Tippins, M.J. and Sohi, R.S. (2003) IT competency and firm performance: is organizational learning a missing link? *Strategic Management Journal*, **24**, 8, 745–761. https://doi.org/10.1002/smj.337.

Tuncdogan, A. and Volberda, H.W. (2020) The effects of perceived corporate brand personality on individuals' exploration and exploitation orientations: the moderating role of self-brand connection. *R&D Management*, **50**, 2, 188–197. https://doi.org/10.1111/radm.12388.

Voss, G.B. and Voss, Z.G. (2013) Strategic ambidexterity in small and medium-sized enterprises: implementing exploration and exploitation in product and market domains. *Organization Science*, **24**, 5, 1459–1477. https://doi.org/10.1287/orsc.1120.0790.

Wan, S.M., Cham, L.N., Tan, G.W.H., Lo, P.S., Ooi, K.B., and Chatterjee, R.S. (2022) What's stopping you from migrating to Mobile tourism shopping? *Journal of Computer Information Systems*, **62**, 6, 1223–1238. https://doi.org/10.1080/08874417.2021.2004564.

Wang, Y., Jia, T., Chen, J., and Sun, H. (2018) Recombine supplier-side search via innovation ambidexterity: an empirical study on Hong Kong manufacturing firms. *International Journal of Physical Distribution and Logistics Management*, **49**, 2, 178–199. https://doi.org/10.1108/IJPDLM-02-2018-0054.

Wang, Y., Sun, H., Jia, T., and Chen, J. (2021) The impact of buyer–supplier interaction on ambidextrous innovation and business performance: the moderating role of competitive environment. *The International Journal of Logistics Management*, **32**, 2, 673–695. https://doi.org/10.1108/IJLM-05-2019-0141.

Wang, C. and Tsai, M.C. (2017) Linking service innovation to firm performance: the roles of ambidextrous innovation and market orientation capability. *Chinese Management Studies*, **11**, 4, 730–750.

Wong, Y.J., Lee, C.Y., and Chang, S.C. (2017) CEO overconfidence and ambidextrous innovation. *Journal of Leadership and Organizational Studies*, **24**, 3, 414–430. https://doi.org/10.1177/1548051817692329.

Wong, L.W., Tan, G.W.H., Lee, V.H., Ooi, K.B., and Sohal, A. (2020) Unearthing the determinants of blockchain adoption in supply chain management. *International Journal of Production Research*, **58**, 7, 2100–2123.

Wu, L.Y. (2010) Applicability of the resource-based and dynamic-capability views under environmental volatility. *Journal of Business Research*, **63**, 1, 27–31. https://doi.org/10.1016/j.jbusres.2009.01.007.

Wu, S.M. and Ding, X.H. (2020) Unpacking the relationship between external IT capability and open innovation performance: evidence from China. *Business Process Management Journal*, **26**, 7, 1789–1805. https://doi.org/10.1108/BPMJ-06-2019-0242.

Xie, X., Wang, H., and Jiao, H. (2019) Non-R&D innovation and firms' new product performance: the joint moderating effect of R&D intensity and network embeddedness. *R&D Management*, **49**, 5, 748–761.

Yang, Y., Jia, F., and Xu, Z. (2019) Towards an integrated conceptual model of supply chain learning: an extended resource-based view. *Supply Chain Management*, **24**, 2, 189–214. https://doi.org/10.1108/SCM-11-2017-0359.

Yong, J.Y., Yusliza, M.Y., Ramayah, T., Chiappetta Jabbour, C.J., Sehnem, S., and Mani, V. (2020) Pathways towards sustainability in manufacturing organizations: empirical evidence on the role of green human resource management. *Business Strategy and the Environment*, **29**, 1, 212–228. https://doi.org/10.1002/bse.2359.

Yusoff, Y.M., Omar, M.K., Zaman, M.D.K., and Samad, S. (2019) Do all elements of green intellectual capital contribute toward business sustainability? Evidence from the Malaysian context using the partial least squares method. *Journal of Cleaner Production*, **234**, 626–637. https://doi.org/10.1016/j.jclepro.2019.06.153.

Zhang, P., Zhao, K., and Kumar, R.L. (2016) Impact of IT governance and IT capability on firm performance. *Information Systems Management*, **33**, 4, 357–373. https://doi.org/10.1080/10580530.2016.1220218.

Zhu, Q., Sarkis, J., and Lai, K. (2008) Confirmation of a measurement model for green supply chain management practices implementation. *International Journal of Production Economics*, **111**, 2, 261–273. https://doi.org/10.1016/j.ijpe.2006.11.029.

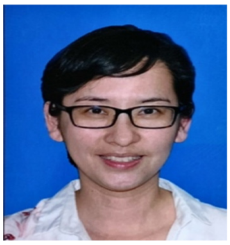
Zuraik, A. and Kelly, L. (2019) The role of CEO transformational leadership and innovation climate in exploration and exploitation. *European Journal of Innovation Management*, **22**, 1, 84–104. https://doi.org/10.1108/EJIM-10-2017-0142.

Voon-Hsien Lee is an Associate Professor at the Faculty of Business and Finance, University Tunku Abdul Rahman, Malaysia. She has been acknowledged as one of the most prolific authors, highly cited authors and influential authors in TQM research in the world from 2006–2015. Her research interests include Total quality management, supply chain management and mobile commerce. To date, her papers have been accepted and published in more than 50 international refereed journals and conference proceedings.

Yogesh K. Dwivedi is a Professor of Digital Marketing and Innovation and Founding Director of the Emerging Markets Research Centre (EMaRC) at the School of Management, Swansea University, Wales, UK. In addition, he holds a Distinguished Research Professorship at the Symbiosis Institute of Business Management (SIBM), Pune, India. Professor Dwivedi is also currently leading the *International Journal of Information Management* as its Editor-in-Chief. His research interests are at the interface of Information Systems (IS) and Marketing, focusing on issues related to consumer adoption and diffusion of emerging digital innovations, digital government and digital and social media marketing particularly in the context of emerging markets. Professor Dwivedi has published more than 400 articles in a range of leading academic journals and conferences that are widely cited (more than 33,000 times as per Google Scholar). He has been named on the annual Highly Cited Researchers™ 2020 and 2021 lists from Clarivate Analytics. Professor Dwivedi is an Associate Editor of the *Journal of Business Research*, *European Journal of Marketing, Government Information Quarterly* and *International Journal of Electronic Government Research*, and Senior Editor of the *Journal of Electronic Commerce Research*. More information about Professor Dwivedi can be found at: http://www.swansea.ac.uk/staff/som/academic-staff/y.k.dwivedi/.

Garry Wei-Han Tan has been acknowledged as the world 10 Most Productive and Influential Authors in Mobile Commerce and Applications in 2017, 2018, 2019 and 2020. He was the recipient of the Outstanding Reviewer Award (2019) by Internet Research, Emerald, Emerald Outstanding Contribution Award (2020) by Emerald, Top Reviewer Award (2020) by Sustainable Production and Consumption (Elsevier) and the recipient of the Hot and Highly Cited Paper (2021) by Clarivate Analytics. His work has appeared in *Expert Systems with Applications, Computers in Human Behavior, International Journal of Information Management, Tourism Management, Technological Forecasting and Social Change, Supply Chain Management: An International Journal and International Journal of Production Research*.

Keng-Boon Ooi is a Professor in Information Systems and Industrial Management. He is the Dean for Graduate Business School, UCSI University. He has authored and co-authored over 100 papers in international refereed journals. His works have been published in *Decision Support Systems*, *Computers in Human Behavior*, *Technological Forecasting & Social Change*, *Tourism Management*, *International Journal of Production Research*, *International Journal of Production Economics*, and *International Journal of Information Management*, etc.



Lai-Wan Wong is interested in human dynamics specifically in the digitization and transformation of society, both micro and macro levels. She is an Assistant Professor in the School of Electrical and Computer Engineering and the Deputy Registrar of Xiamen University Malaysia. She has published her works in a number of reputable journals, such as *International Journal of Information Managemen*t, *Telematics & Informatics*, *International Journal of Production Research*, *IEEE Transactions on Engineering Management*, and *Supply Chain Management: An International Journal*.