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Big data in relation with business intelligence capabilities and e-commerce during COVID-19 pandemic in accountant's perspective

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Abstract

This research aims at producing a thorough and accurate analysis on how big data as a service and business intelligence capabilities provide a series of opportunities for small and medium enterprises to succeed in E-commerce. The statistical data were drawn from samples of accountants within small and medium enterprises, spanning two periods, the period of COVID-19 pandemic and the period of new normal. The structural equation modeling was applied in this study. The value of fine-grained insights in this work could guide policy-makers and practitioners to sense and seize how to implement E-commerce in an efficient and effective manner.

Keywords Big data, E-commerce, Business intelligence, Service, Small and medium enterprises

Introduction

Small- and medium-sized enterprises (SMEs) operating in the manufacturing sectors have been particularly negatively impacted by the COVID-19 due to the increased risk associated with the market contraction associated with the reorganization of global supply chains [1–3]; the increased cost associated with the reorganization of global supply chains as well as to the fresh difficulties brought on by the emergence of fresh market opportunities [4]. This is because SMEs are characterized by a lack of organizational resources, which forces them to rely on the stock of resources at hand [5]. Given their size and the individual-level components of such behavior, SMEs are under unprecedented pressure from the pandemic, which raises questions about their ability to eventually adjust or adapt their strategy [6]. The epidemic has put strain on how economic activity is organized, raising concerns about how businesses would respond to a worldwide disaster like COVID-19 and drawing attention to E-commerce (EC). Purchasing and selling products and services online is known as EC [7]. Since the COVID-19 coronavirus disease first appeared, EC has been increasingly popular [8]. The spread of COVID-19 improved EC as a medium for trade between businesses [9] and consumers and merchants. People started purchasing online since they could not leave their homes due to limitations [10]. By delivering products at a low cost to new customer categories, EC can help grow markets [11, 12]. After the epidemic, EC grew astronomically [8]. Many businesses are now required to establish a digital presence and take advantage of the opportunities offered by the internet as a result of the advent of EC [13]. According to Kumar and Ayedee [14], SMEs' use of technology to address COVID-19 issues may be prerequisite. Researchers and academicians have been debating the deployment of various types of technologies for a long time, not just during the COVID-19 epidemic. Given that almost all businesses now have limited knowledge of their clients, business

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intelligence (BI) will help these businesses better comprehend the strategies and tools utilized for data analysis by providing historical, current, and forecast views of business data [15]. Over the past two decades, BI has attracted a lot of attention in academia, EC, and business [16]. BI has emerged as a key technology for enhancing enterprise business performance as well as a driving force behind the development of EC and e-services [17]. Building on the viewpoints of Ransbotham and Kiron [18] and Shiau et al. [19], the majority of recent business information technology investments have gone toward the development of BI. According to the general consensus, BI is a brand-new decision support system built on cutting-edge information technology and methodologies [20]. In order to deliver smart solutions for corporate operations, it has a highly developed systematic capacity to gather and analyze data and turn it into knowledge or information about opportunities and dangers [21, 22]. Unfortunately, according to Marn-Ortega et al. [23], BI primarily concentrates on structured and internal corporate data while ignoring the useful information hidden in unstructured and external data. Due to this, a business may make decisions that are prejudiced and have an incomplete picture of the world [24, 25]. However, due to the rapid development of big data (BD) and BD technology, BI is now confronting new difficulties and opportunities [26].

The ability to develop and use additional analytics capabilities, such as prescriptive and diagnostic analysis, is provided by BD will primarily result in development of BI systems [27]. Businesses need cutting-edge solutions to properly use data science due to the continually expanding volume of data [28]. Prior studies have shown that BD is an essential long-term tool for EC businesses since these businesses need new technology to control and analyze large amounts of information and data [29]. Many EC companies have made significant investments in BD with the hope of gaining crucial insights and long-term competitive advantages [30]. The importance of BD services for business applications is primarily due to the enormous potential or impact of the data, not merely because it is large [31]. Despite the benefits, dealing with BD applications presents a significant difficulty because it calls for more cutting-edge technological solutions that swap out conventional databases for more scalable systems. This is where big data as a service (BAAS) for commercial applications can make a difference [32].

The idea of offering everything as a service encourages the creation and deployment of software applications as services in a world where service-oriented architecture and its design are supported [33]. In order to help enterprises to develop creative business strategies and derive intrinsic value from their BD, the BAAS model is a positive move [34]. Adopting BAAS has benefits for SMEs since it is more cost-effective and makes maintaining BD infrastructure simpler because it functions in the cloud. This applies to SMEs specifically because they have less financial and infrastructure resources at their disposal [31]. Several attempts have been conducted to capture insights into the structure of BAAS [28, 34–37] and the determinants of its adoption [31]. Regardless of this significant shift in research on BAAS, there is currently very little focus on demonstrating how BAAS supports EC and BI. In other words, it is reasonable to draw the conclusion that there is much to learn about the benefits and impacts brought on by this important information technology domain.

This incites the demand to rethink and formulate a new and in-depth insight on the role of BAAS implementation, to tap higher potential of BI and EC. Starting from these considerations on the lack of an established academic background on this specific subject pertaining to the potential role of BAAS in driving EC and BI, an analysis on how BAAS can foster the EC and business intelligence capabilities (BIC) in SMEs represented the main motivations in this research and underscored chances for theoretical and practical contributions. These theoretical gaps inspired the intriguing research questions as follows.

RQ1. What is the impact of BAAS on EC during COVID-19 pandemic and new normal?

RQ2. Does BIC mediate the interconnection between BAAS and EC during COVID-19 pandemic and new normal?

The implementation of EC is pondered as a rational and innovative step for the process of enhancing competition and encouraging organizational progress [38]. Based on the perspectives to Biagi and Falk [39] as well as Lee et al. [40], EC can help both developed and developing nations. Admittedly, EC can assist businesses in producing significant benefits that could reduce costs and time while boosting competitiveness [39, 41, 42]. EC can aid SMEs in expanding their markets and gaining financial advantages [43]. Nevertheless, emerging economies do not effectively use the advantages of EC. The present study is novel in the setting of a developing country since it expanded existing understandings of the EC among SMEs in developing countries in both the COVID-19 pandemic and new normal. By doing this, the findings of this research will enrich the growing body of literature focusing on the EC application in the COVID-19 pandemic [8, 44–49]. Alternatively, it can fill in the gaps that many earlier works with a strong cross-sectional design have inherently. This is due to the fact that one-time data acquisition only depicts a snapshot of how customers feel at a given point in time [50] and cross-sectional design is unable to show the intricate and dynamic elements of

a market. Surprisingly, the pandemic's social and organizational effects have been difficult to assess, long-lasting, and time-sensitive [51]. As a result, it is crucial to monitor and manage these effects quickly, effectively, and at the right time to ensure that efforts toward sustainable development are successful [52]. Through concentrating on the perspectives of accountants in SME on the role of BAAS toward EC and BIC, this research contributes to reaffirm and clarify the changing role of accountants in this type of enterprise, that is, advisors to generate competitive advantage for SMEs. Admittedly, because of their special ability to combine general human capital with digital human capital and social capital resources, accountants as consultants are expected to be a useful strategic resource [53].

Both business executives and academics have recently shown a great deal of interest in the development and application of BD [29]. In order to gather significant insights and maintain competitive advantages, many EC companies have made significant investments in BD [30]. The current study is a trailblazer in the field of research since it provides vital new information about the extraordinary effects of BAAS on EC in SMEs in developing nations. Both large and small and medium-sized enterprises are using BI systems as their utilization is on the rise [54]. BI can improve capacities, incorporate developing technologies, and interact with the external environment of firms to help shape how knowledge is developed [55, 56]. The results of this study's observations will broaden academics' perspectives on how BIC affects EC. Besides, the uniqueness of this research is in determining and assessing the function of BAAS that leads to BIC. Even while BI has been successfully applied by many organizations to assist decision-making and organizational performance, not all firms can claim to have achieved the same level of success [57]. Building on the argument of Sirin and Karacan [58], BI and BD share many similarities; however, there have not been many research discussing how BI is affected by BD. Outstandingly, in contrast to earlier studies that only looked at specific relationships, such as the relationship between BD and EC, the relationship between BD and BI, and the relationship between BI and EC, the goal of the current research is to expand the frontier of knowledge by delving into at the mediating effect of BIC on the relationship between BAAS and EC.

On the practical points of view, the value of more fine-grained insights in this work will guide policy-makers and SMEs' managements to sense and seize how to leverage BAAS and BIC in an efficient and effective manner. This is because a solution-based system called BAAS is intended to give enterprises a wide range of capabilities for deriving insights from data. Based on the observations of Sirin and Karacan [58], BI has been rare to come across successful BI application even though its value to the business has been widely acknowledged. Additionally, according to Rahayu and Day [59] and Dahbi and Benmoussa [60], information technology providers play a role in EC applications. As such, the findings of this research are likely to open up new business opportunities for new entrants, namely for merchants or hardware and software developers.

With the exception of the introduction, the portions of the current manuscript are structured in the following order. Theoretical understanding and foundation that focus on clarifying the adoption model and identifying the primary constructs are comprised in "Theoretical understanding and foundation" section. "Research hypotheses corroboration and model formulation" section considers the research model and the creation of hypotheses. The technique, which stresses on the development and application of empirical research, is then depicted in "Material and methods" section in more detail. The following section of this manuscript covered with a result analysis and discussion that are presented. The managerial repercussions are outlined in the penultimate section, along with a few hints for the creation of further works.

Theoretical understanding and foundation

Contingency theory (CT)

Based on the perspectives of Feidler [61], a management theory or model about leadership effectiveness that has its roots in organizational theory is called CT. It has gained popularity because it challenges the tenet of conventional management philosophy that there is just one right way to accomplish things [62]. The literature on information systems and information technology management has extensively employed CT. Although it was initially utilized to research systems design and implementation in the information system literature, it was later used to research how the environment and other factors affect task-performance fitness [63]. According to CT, there is no one optimum way to use an information system in every circumstance, rather, users and other stakeholders' perspectives must be taken into account while designing and utilizing information systems [64]. Scholars have proposed a contingent dynamic capability perspective to overcome some of the dynamic capability view's drawbacks [65]. According to Sirmon and Hitt [66], the bundling of resources and competencies can create a competitive advantage by taking advantage of contingencies. The creation of this theory is helpful in explaining how the dynamic capacities of the organization may be valuable [67]. Therefore, multiple fit concepts can be used and should be expressly taken into account

while doing research while taking CT into account [68]. In order to help companies and decision makers manage BAAS and BIC to thrive in EC, the CT was employed in this research as a theoretical lens.

E-commerce

EC, as a general term, refers to internet technology, based on browser or server applications, through which buyers and sellers engage in a variety of trade activities to facilitate consumer online shopping, online payment, as well as new business activities involving a number of different business activities and other models [69]. EC differs from traditional trade in four ways. As such, EC is global, direct, convenient, and equitable. In EC, businesses can sell their goods directly to customers after showing them their products online. They can even let buyers get involved in the product's creation and customization. The network offers businesses a lot of convenience. Businesses can use the network to release information, search for trading opportunities, exchange electronic documents, track goods, transfer funds, and use other methods to complete the transaction process. This helps businesses increase efficiency and cut costs. Businesses can quickly react to their project decisions and business strategies by gaining timely access to all types of market information through the network, conducting thorough, thorough, accurate, and quick analyses, making predictions, and making judgments about many factors related to production, sales, and procurement.

It is crucial and advantageous to understand the many sorts of EC that exist while building a business. The EC can be split into many types of business model platforms based on the negotiating factor, specifically the type of market and the economic connection between the parties involved. There are seven different types of EC platforms, according to Turban et al. [70], including business-to-business, business-to-consumer, consumer-to-business, and consumer-to-consumer. Each type of EC is also investigated in several studies [71–75].

When compared to the conventional buying procedure, the usage of EC offers many advantages and benefits, but it also has some risks and restrictions that required to be noted. It also provides several opportunities to be present in a global market. Consumers, organizations, and society can all gain from EC, according to Niranjanaurth et al. [76] and Turban et al. [70]. These benefits are growing gradually and can be categorized into three levels. The main non-technological constraints, according to Niranjanaurth et al. [76], Turban et al. [70] as well as Miyazaki and Fernandez [77], are the absence of physical contact with the product, resistance to change, a lack of collaboration in the value chain, and the fact that a significant amount of money is invested in security and privacy of the information transmitted by customers in EC, viruses, password spying, and phony stores. As such, the EC security management is emphasized in several studies [78–82].

Organizations can discover a collection of characteristics that emerge as explanatory variables of the online purchase process according to EC research already in existence. While Lin et al. [83] argued that system stability, system reliability, sales dynamics, and product line availability are the top four critical success factors, Vieira et al. [84] identified a list of ten determinants of online shopping behavior, including the availability of products and services online, website quality, confidence, convenience, price, online experience, and so on. Additionally, a variety of critical success factors are also determined in numerous studies [83, 85–88].

The success of the Internet depends on interaction rather than just being a new conduit for communication [89]. Internet offers a variety of tools and technology that support EC. Many academic publications have focused on the impact of internet of things on EC [90–95]. In wealthy nations, commercial 5G cellular services are anticipated, according to Kumar [96]. The creation of 5G networks, platforms, and gadgets undoubtedly calls for significant financial outlays. However, 5G has significant psychological and emotional benefits in addition to its economic advantages.

While Ahi et al. [97] focused on the EC policy and global economy to pave the route for inclusive development, current literature has also started to discuss the COVID-19 pandemic and EC [8, 44–49]. In addition, customers have advanced a notch, and now always want green or sustainable EC purchasing due to the increasing number of individuals taking benefit of modern EC enterprises, the variety of products accessible, and the ability to compare costs [98]. Numerous studies have been conducted to delve into more about the sustainability and EC [99–107].

Given that almost all of enterprises currently know little about their customers, BI will enable those enterprises to understand the tactics and technologies used for data analysis, offering historical, current, and forecast views of business information [15].

Business intelligence capabilities

BI is a framework made up of a selection of ideas, theories, and techniques for enhancing business decision making through the use of fact-based support systems [16]. In order to enhance business decision making, it refers to decision support systems that are based on the integration and analysis of organizational data resources [108]. Additionally, it is used to track and take in data from a dynamic environment to identify new

opportunities while reducing the risks brought on by uncertainty [109]. BI uses various data sources, as well as organized and unstructured information, to supply decision makers with useful information and expertise [110]. Strategic capabilities, operational capabilities, and data integration capabilities are the three different forms of BIC [111]. Utilizing BI systems to support strategic organizational operations, such as identifying opportunities, threats, risk assessments, and trends in the business environment, is referred to as having strategic BI capabilities. These capabilities can be vital for creating new corporate strategies [111]. The use of BI systems to support operational organizational operations, however, includes operational BI capabilities. Operational BI capabilities include exchanging information across business units, modeling, and process optimization for service and production [108]. Last but not least, data integration capabilities entail the fusion of observable data from diverse sources to generate descriptive data about who, what, when, and how much the combined dataset influences [112].

Most previous academic works put accent on the BI advantages, success and growth of BI [113–115]. Many academic publications have focused on information technology acceptance and measurement [116–120]. Building on the perspective of Naznen and Lim [121], BI is considered as a cutting-edge method of generating highly intelligent data to facilitate decision making, which supports revenue growth and makes it possible to gain a competitive advantage. Several academic notes delve into the impact of BI on organizations [54, 122–125]. More recently, a few research investigate BI under the perspective of information and business analytics [126–129] as well as and social media text analytics [130–134]. On the other hand, it is yet unclear whether BI solutions focused on data analytics will add value and benefits to organizations [135]. In this regard, the interconnection between BI and big data analytics also highlighted in several studies [26, 135–137]. Remarkably, on account of its immense potential to have a positive impact on business, BD and its use in BI have received a significant deal of attention recently [22].

Big data as a service

A number of developing technology developments influenced by BD and cloud computing can be recognized by various "as-a-Service" models as a result of the shift in the information technology paradigm [138]. The idea of "everything as a service" encourages the creation and deployment of software applications as services in a world where service-oriented architecture and its design are supported [33]. To help enterprises implement cutting-edge business strategies and derive intrinsic value from their BD, the BAAS model is a positive move [34]. While Zheng et al. [37] argued that it typically comprised of three layers, including BD analytics, BD platform, and BD infrastructure, each of which offers consumers a distinct level of abstraction. The most fundamental services are specifically provided by BD infrastructure, while more sophisticated services are provided by higher levels. However, this proposal was unable to highlight a methodical approach to service delivery, particularly with the type of data processing method to be employed [36]. As a result, Wang et al. [36] suggested a novel BAAS structure with three planes such as the sensing plane, the cloud plane, and the application plane. More concretely, sensing plane's role in the cyber–physical–social systems is to more specifically organize data produced by diverse sources. While the cloud plane enables all of these tensor network operations to be carried out effectively in the cloud using the benefits of tensor networks and cloud computing in terms of storage and computation, the purpose of the application plane is to offer necessary proactive services in a variety of application domains after obtaining the mapped tensor network models. The integration of BD based on tensor networks necessitates a rethink of BD analytics techniques including learning, mining, and recommendation [36].

Research hypotheses corroboration and model formulation

Hypothesis corroboration

The collaboration with a large number of enterprises will make it difficult to manage EC activities, to unify the corporate image, and to maintain consistent service levels [139]. In this regard, BD will not only give businesses unprecedented insights into their customer's buying habits and their own internal processes, it is also claimed that it will herald a management revolution where technology replaces human judgment, enabling businesses to take better decisions, more quickly, and provide value for their customers in new and unimagined ways [140]. Organizations and employees see these BD databases as a real opportunity and use it for targeted advertising, for optimizing their offers, or even compare the rest of the market [141]. The vast volumes of data that are available can be processed by BAAS to help EC enterprises identify market trends, forecast consumer demands, and assess consumer purchasing behavior. Drawing on the analyses described above, the second hypothesis was rationally conjectured as follows.

Hypothesis 1 (H1) BAAS exerts an influence on EC in a substantial and positive manner.

In order to take any particular decision BI, BIC plays a vital role. To analyze, process, and predict BD takes a crucial role in BIC. BD helps the BI to make decision-driven decisions and to identify the unknown facts which indeed contributes to taking a step in the process of making a statement in profits aspects of the organization [142]. BD have also started to be a significant source for BI activities aimed at creating, delivering, and capturing customer value [143]. BD can make a difference for the BI of enterprises, help them make better strategic and tactical decisions as well as create value [143]. By attempting to extract value from semi-structured and unstructured data coming from external data sources like the web, mobile devices, and sensor networks, BAAS, in this viewpoint, enhances the capabilities of BI in integrating and reporting structured data located in enterprise-internal databases. Drawing on the analyses described above, the first hypothesis was rationally speculated as follows.

Hypothesis 2 (H2) BAAS exerts an influence on BIC in a substantial and positive manner.

In accordance with Balachandran and Prasad's [144] suggestion, BI refers to technology, tools, and techniques for gathering, integrating, analyzing, and displaying business information to uphold better and quicker business decisions. BI is the set of technology methods and instruments that help turn data into knowledge and information. Particularly, BI is taken advantage by businesses to extract useful patterns through outlier detection, process mining, and clustering, such as increasing combustion efficiency, in addition to being used as a tool to transform raw data into useful information for better decision making for administrative purposes [145]. As such, BI has grown to be a key tool for enhancing business performance of organizations as well as a driving force behind the development of EC and e-services [146]. Taken together, the higher BIC can enable enterprises to extract valuable market information of all competitors and determine potential business opportunities in EC. Drawing on the analyses described above, the third hypothesis was rationally postulated as follows.

Hypothesis 3 (H3) BIC exerts an influence on EC in a substantial and positive manner.

Research model formulation

Building on the above analyses, the research model is depicted in Fig. 1, which maps the hypothesized interrelationships among the BAAS and EC with BIC as a mediator.

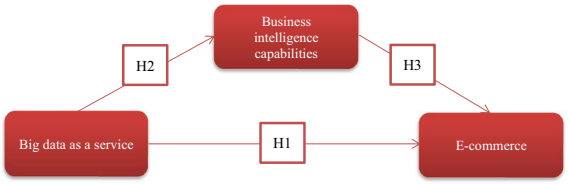

Fig. 1 Hypothesized model

Material and methods

Measurement of the model's constructs

In order to identify causal links between dimensions and make generalizable claims about the research environment, this study employed the questionnaire-based survey approach. Firstly, the questionnaire was purposefully constructed and structured based on a thorough evaluation of the literature to address the study's goals. Secondly, 6 experts with sufficient, in-depth expertise of the subject matter of this study were consulted in order to increase the questionnaire's thoroughness. A five-point Likert scale was used to quantify the responses. Higher point scales might have made it harder and more complex for respondents to select an appropriate alternative from the available possibilities because the present study is unique. A small-scale pilot test was carried out using a sample size of 30 respondents in order to verify the reliability of the scales. The respondents for the main survey and the pilot test were not the same respondents. The reliability of the developed constructs was demonstrated by the fact that all Cronbach's alpha values obtained in the pilot test were higher than 0.7 [147].

E-commerce

In order to obtain the theoretical and empirical meaning, the measures of EC in this research were developed from the contribution of Susanty et al. [38] which was corroborated from the current literature and testified by small-scale pilot test.

Big data as a service

The high-order and composite construct was used as the measure of BAAS in this study in order to gain the theoretical and empirical meaning. As such, BAAS constructs comprised of Sensing Plane, Cloud Plane, and Application Plane following the recommendation of Wang et al. [36]. The criteria applied to assess first-order constructs were then formulated employing the outcomes of Wang et al. [36] and were testified by small-scale pilot test.

Business intelligence capabilities

In this study, high-order and composite constructs that were supported by recent literature were used as the BIC measures in order to acquire theoretical and empirical

meaning. As such, the BIC consisted of three pillars such as data integration capability, operational BI capabilities, and strategic BI capabilities. The criteria applied to evaluate data integration capability were stemmed from the findings of Cheng et al. [112]. The criteria applied to evaluate operational BI capabilities and strategic BI capabilities were arisen from the work of Fink et al. [108]. All of these scales were testified by small-scale pilot test.

Sampling procedure and data collection

The unit of analysis was SMEs and the accountants in SMEs were selected as the target participants of this study. In two waves of data collecting for this investigation, a convenience sampling was used. When the most stringent lockout and limiting limitations were in place, the first wave of data collection took place from April through November of 2021. Because paper-based questionnaires would be difficult to provide during the lockdown periods, telephone interviews were proposed as a replacement. One of the ongoing restrictions in this round of data collection was the suspension of public transit as well as the closure of schools and non-imperative service operations. The second wave, which took place in 2022 between April and November, was brought on by a minor decrease in viral transmission, additional relaxation of restrictions, and a complete reopening of society. Surveys on paper that were sent directly saw a rise in response rates and a decline in sampling error. After deleting useless responses, the number of valid responses for the first wave and second wave of the database collection periods was 812 and 683, respectively. The sociodemographic profile of the respondents is demonstrated in Table 1.

Table 1 Demographic information

Demographic profile	Model 1 COVID-19 PANDEMIC (sample size = 812)		Model 2 NEW NORMAL (sample size = 623)	
	Usable responses	Weight (%)	Usable responses	Weight (%)
Gender				
Male	333	41.01	255	40.93
Female	479	58.99	368	59.07
Age				
Below 30	47	5.79	63	10.12
31–40	477	58.74	379	60.83
41–50	288	35.47	181	29.05
Experience (years)				
Below 10	47	5.79	63	10.11
10–Below 20	573	70.57	439	70.47
20–Below 30	192	23.64	121	19.42
Education				
Undergraduate	793	97.66	611	98.07
Postgraduate	19	2.34	12	1.93

Result and interpretation analytical observations

Common method variance

As there are no multicollinearity problems when the values of the variance inflation factor (VIF) are less than 3.3., the VIF assessment was performed. The statistical outcomes highlighted that the VIF values in the current study varied from 1.801 to 3.205 during the period of COVID-19 while the VIF values in the current study varied from 1.497 to 2.355 during the period of new normal. To this end, statistical tools showed that common method variance did not pose a serious threat to the interconnections in the measurement model.

Measurement characteristics and discriminant validity test

Cross-loading was used to evaluate the content validity, which showed that the questionnaire items conveyed similar meanings to those incorporated into specific concepts. So, a construct being evaluated has to have a higher value than other constructs in the same rows and columns. It is possible to conclude that the measurement scale used in the period of COVID-19 pandemic and new normal achieved full content validity based on the values of all tested constructs shown in Table 2.

Item-loadings were used to evaluate item reliability and check for irregularities across all concept scales in terms of convergent validity [147]. Items should load over the advised level of 0.70, providing strong evidence for the reliability of the items [147]. In order to assess the construct reliability's internal consistency, the values for composite reliability and Cronbach's alpha were also confirmed. According to Hair et al. [147], for all values to be considered admissible, the construct dependability must be greater than the cutoff of 0.70. Utilizing average variance extracted (AVE) from the data, the model's convergence validity has been assessed. According to Hair et al. [147], this size should be 0.5 larger than the minimum standard.

As shown by the proper detail of reliability and convergent validity listed in Table 3, both **Models 1** and **Model 2** attain the reliability and robustness of the measurement model. Simply put, these results supported an appropriate measuring methodology for both the COVID-19 pandemic and the new normal periods.

Concerning to discriminant validity, it demonstrates how differently each measuring item in the suggested model represents its factor from every other item. The heterotrait–monotrait (HTMT) ratio method and the Fornell and Larcker [148] correlation method can both be used to evaluate the discriminant validity in the

Table 2 Results summary for the content validity

	Model 1 COVID-19 pandemic (sample size = 812)							Model 2 New normal (sample size = 623)						
	AP	CP	DIC	EC	OBIC	SBIC	SP	AP	CP	DIC	EC	OBIC	SBIC	SP
AP1	0.779	0.013	0.023	0.012	0.009	0.103	0.064	0.823	−0.039	0.005	0.201	0.045	−0.006	0.145
AP2	0.774	0.055	0.020	−0.062	0.015	0.099	0.056	0.876	−0.041	0.007	0.193	0.008	0.025	0.072
AP3	0.820	0.043	0.043	0.009	0.053	0.108	0.090	0.853	0.011	0.028	0.154	0.022	0.018	0.154
AP4	0.796	−0.006	0.026	0.046	0.004	0.174	0.139	0.859	−0.048	−0.043	0.181	0.011	0.044	0.120
CP1	0.047	0.790	0.027	0.083	0.283	0.077	0.159	−0.030	0.809	0.032	0.073	0.037	0.123	0.071
CP2	0.104	0.828	0.045	0.070	0.308	0.094	0.113	−0.033	0.810	−0.023	−0.030	0.122	0.103	0.000
CP3	0.029	0.793	0.046	0.127	0.308	0.122	0.149	−0.031	0.835	−0.048	−0.067	0.129	0.040	0.072
CP4	−0.022	0.757	0.051	0.058	0.212	0.030	0.082	0.006	0.834	−0.016	−0.021	0.083	0.073	0.007
CP5	−0.074	0.738	−0.031	0.015	0.213	−0.051	0.004	−0.048	0.788	0.008	0.066	0.046	0.090	0.034
DIC1	−0.010	0.049	0.826	0.069	−0.013	0.056	0.083	0.028	−0.014	0.877	0.289	0.034	0.009	0.033
DIC2	0.006	0.018	0.796	0.157	−0.033	0.041	0.070	0.001	−0.011	0.868	0.294	0.031	0.017	0.032
DIC3	0.060	0.004	0.762	0.104	−0.052	0.063	0.067	0.001	−0.004	0.837	0.320	0.034	0.034	0.058
DIC4	0.061	0.052	0.788	0.145	−0.018	0.042	0.050	−0.031	−0.009	0.849	0.254	0.058	0.026	0.039
EC1	0.006	0.119	0.133	0.900	0.103	0.311	0.263	0.192	0.025	0.338	0.918	0.074	0.030	0.127
EC2	−0.047	0.032	0.132	0.845	0.105	0.235	0.225	0.172	−0.009	0.304	0.879	0.096	−0.023	0.125
EC3	0.044	0.092	0.124	0.887	0.069	0.271	0.248	0.210	−0.003	0.265	0.900	0.078	0.025	0.154
OBIC1	0.040	0.303	−0.013	0.127	0.814	0.085	0.053	0.053	0.048	0.019	0.102	0.793	−0.025	0.073
OBIC2	0.018	0.253	−0.039	0.091	0.821	0.006	−0.002	0.013	0.070	0.035	0.056	0.852	−0.031	0.016
OBIC3	−0.019	0.297	−0.100	0.090	0.742	0.007	0.042	−0.002	0.087	0.057	0.079	0.900	−0.016	0.032
OBIC4	0.017	0.272	0.015	0.061	0.800	0.023	0.038	−0.003	0.119	0.044	0.077	0.810	0.044	0.048
OBIC5	0.037	0.237	−0.019	0.042	0.766	0.059	0.054	0.051	0.096	0.034	0.070	0.808	−0.020	0.025
SBIC1	0.121	0.047	0.082	0.298	0.038	0.856	0.445	0.030	0.102	0.055	0.012	−0.010	0.888	0.115
SBIC2	0.134	0.098	0.038	0.258	−0.023	0.782	0.433	0.003	0.072	0.033	0.020	−0.020	0.828	0.150
SBIC3	0.122	0.041	0.028	0.232	0.051	0.805	0.441	0.036	0.121	0.008	0.026	−0.042	0.859	0.092
SBIC4	0.141	0.092	0.038	0.206	0.111	0.792	0.435	0.039	0.051	0.002	0.007	0.045	0.845	0.112
SBIC5	0.102	0.046	0.068	0.263	0.013	0.773	0.395	−0.024	0.102	−0.004	−0.019	−0.041	0.755	0.080
SP1	0.076	0.136	0.093	0.234	0.061	0.419	0.763	0.158	0.093	0.002	0.153	0.055	0.119	0.851
SP2	0.090	0.093	0.054	0.229	0.005	0.462	0.763	0.127	0.031	0.049	0.158	0.042	0.089	0.827
SP3	0.064	0.120	0.063	0.207	0.068	0.396	0.791	0.089	0.031	0.048	0.077	0.041	0.114	0.821
SP4	0.106	0.087	0.088	0.261	0.031	0.429	0.801	0.094	0.045	0.039	0.124	0.006	0.124	0.822
SP5	0.103	0.109	0.035	0.166	0.022	0.389	0.784	0.132	0.009	0.060	0.112	0.046	0.109	0.839

current study. The first method is an alternate approach, as suggested by Henseler et al. [149], to evaluating discriminant validity in partial least squares structural equation modeling (PLS-SEM). Based on the multitrait and multimethod matrix, or HTMT of correlations, discriminant validity can be assessed. The discriminant validity is insufficient when the HTMT value is close to 1. As a result, Table 4 shows the HTMT criterion values during the COVID-19 pandemic and the new normal, which satisfy the lowest HTMT value and fall within the recommended range.

The second way is to evaluate discriminant validity based on the Fornell–Larcker correlation matrix. In this way, discriminant validity is well established when the AVE of a single factor is greater than the squared multiple correlations of that factor with other factors. Given that the correlation matrix illustrated in Table 5 satisfied the Fornell–Larcker criterion, all the constructs in the proposed model during the COVID-19 pandemic and the new normal illustrated discriminant validity for the empirical data.

Analyzing the hypothesized model

The evaluation of the structural or inner model to examine the hypothesized interconnections relationships was the start of the second step [147]. Based on the advice of Hair et al. [150], the bootstrapping method with 5,000 subsamples was used to calculate path coefficients (β).

Table 3 Results summary for the measurement model

Constructs and operationalization		Model 1 COVID-19 pandemic (sample size = 812)					Model 2 New normal (sample size = 623)					Discriminant validity
		Convergent validity		Construct reliability			Convergent validity		Construct reliability			
		Factor loadings range	AVE	Cronbach's alpha	Composite reliability	PA	Factor loadings Range	AVE	Cronbach's alpha	Composite reliability	PA	
Sensing plane	**SP**	0.821–0.851	0.692	0.889	0.918	0.890	0.763–0.801	0.609	0.840	0.886	0.840	Yes
Cloud plane	**CP**	0.788–0.835	0.665	0.875	0.908	0.888	0.738–0.828	0.611	0.842	0.887	0.852	Yes
Application plane	**AP**	0.823–0.876	0.727	0.875	0.914	0.875	0.774–0.820	0.628	0.803	0.871	0.807	Yes
E-commerce	**EC**	0.879–0.918	0.808	0.881	0.927	0.883	0.845–0.900	0.770	0.852	0.910	0.865	Yes
Data integration capability	**DIC**	0.837–0.877	0.736	0.880	0.918	0.881	0.762–0.826	0.629	0.803	0.872	0.806	Yes
Operational BI capabilities	**OBIC**	0.793–0.900	0.695	0.890	0.919	0.893	0.742–0.821	0.623	0.849	0.892	0.855	Yes
Strategic BI capabilities	**SBIC**	0.755–0.888	0.699	0.893	0.921	0.910	0.773–0.856	0.643	0.861	0.900	0.863	Yes

Table 4 Results summary for discriminant validity—heterotrait–monotrait ratio

	Model 1 COVID-19 pandemic (sample size = 812)							Model 2 New normal (sample size = 623)						
	AP	**CP**	**DIC**	**EC**	**OBIC**	**SBIC**	**SP**	**AP**	**CP**	**DIC**	**EC**	**OBIC**	**SBIC**	**SP**
AP								AP						
CP	0.054							CP	0.089					
DIC	0.041	0.037						DIC	0.056	0.070				
EC	0.243	0.072	0.382					EC	0.079	0.109	0.181			
OBIC	0.045	0.117	0.051	0.105				OBIC	0.054	0.401	0.062	0.123		
SBIC	0.042	0.123	0.033	0.037	0.062			SBIC	0.184	0.120	0.079	0.362	0.087	
SP	0.162	0.065	0.056	0.169	0.056	0.147		SP	0.134	0.161	0.104	0.331	0.066	0.631

Table 5 Results summary for discriminant validity—Fornell–Larker Scale

	Model 1 COVID-19 PANDEMIC (sample size = 812)							Model 2 NEW NORMAL (sample size = 623)						
	AP	**CP**	**DIC**	**EC**	**OBIC**	**SBIC**	**SP**	**AP**	**CP**	**DIC**	**EC**	**OBIC**	**SBIC**	**SP**
AP	0.853							AP	0.792					
CP	−0.033	0.815						CP	0.032	0.782				
DIC	0.000	−0.011	0.858					DIC	0.036	0.039	0.793			
EC	0.213	0.005	0.337	0.899				EC	0.004	0.096	0.148	0.878		
OBIC	0.026	0.101	0.046	0.092	0.834			OBIC	0.026	0.345	−0.036	0.105	0.789	
SBIC	0.024	0.104	0.025	0.012	−0.011	0.836		SBIC	0.155	0.081	0.064	0.313	0.049	0.802
SP	0.145	0.051	0.047	0.150	0.046	0.133	0.832	SP	0.112	0.140	0.086	0.281	0.048	0.536	0.781

Table 6 Results of hypotheses testing for Model 1

Relevant path	Path coefficient	SE	95% Confidence interval	*t* value	*p* value	VIF	Result
Direct effect							
BAAS → EC	0.202	0.043	[0.113–0.284]	4.703	0.000	1.010	Undergirded
BAAS → BIC	0.100	0.071	[−0.066–0.207]	1.401	0.161	1.000	Rejected
BIC → EC	0.246	0.088	[−0.034–0.319]	2.812	0.005	1.010	Undergirded
Indirect effect							
BAAS → BIC→ EC	0.025	0.016	[−0.014–0.048]	1.503	0.133	–	Rejected
R^2	$R^2_{BIC} = 0.010$; $R^2_{EC} = 0.112$						
f^2	$f^2_{BAAS => BIC} = 0.010$; $f^2_{BAAS => EC} = 0.046$; $f^2_{BIC => EC} = 0.068$						
Q^2	$Q^2_{BIC} = 0.002$; $Q^2_{EC} = 0.088$						

Concerning to **Model 1**, the statistical outcomes in Table 6 highlighted that BAAS illustrated an insignificant association with BIC (H2: $\beta = 0.100$, t value = 1.401; p value = 0.161). Similarly, the effect of BAAS (H1: $\beta = 0.202$, t value = 4.703; p value = 0.000) underlined a strictly positive interconnection with EC. The interconnection between BIC and EC (H3: $\beta = 0.246$, t value = 2.812; p value = 0.005) was supported. To this end, the H1 and H3 were accepted while H2 was rejected. On the other hand, the statistical outcomes on the mediating impact of BIC on the interlink between BAAS and EC reveal that BIC did not act as a mediator of this interlink.

Regarding to **Model 2**, the statistical outcomes in Table 7 emphasized that the BAAS had significantly positive association with BIC (H2: $\beta = 0.516$, t value = 14.499; p value = 0.000). Besides, the BAAS was substantiated to be related to EC (H1: $\beta = 0.107$, t value = 2.219; p value = 0.027) in a significantly positive manner. As

Table 7 Results of hypotheses testing for Model 2

Relevant path	Path coefficient	SE	95% Confidence interval	*t* value	*p* value	VIF	Result
Direct effect							
BAAS → EC	0.107	0.048	[0.020–0.206]	2.219	0.027	1.363	Undergirded
BAAS → BIC	0.516	0.036	[0.440–0.578]	14.499	0.000	1.000	Undergirded
BIC → EC	0.289	0.050	[0.181–0.380]	5.732	0.000	1.363	Undergirded
Indirect effect							
BAAS → BIC → EC	0.149	0.028	[0.092–0.201]	5.373	0.000	–	Undergirded
R^2	$R^2_{BIC}=0.266$; $R^2_{EC}=0.127$						
f^2	$f^2_{BAAS=>BIC}=0.363$; $f^2_{BAAS=>EC}=0.020$; $f^2_{BIC=>EC}=0.070$						
Q^2	$Q^2_{BIC}=0.062$; $Q^2_{EC}=0.093$						

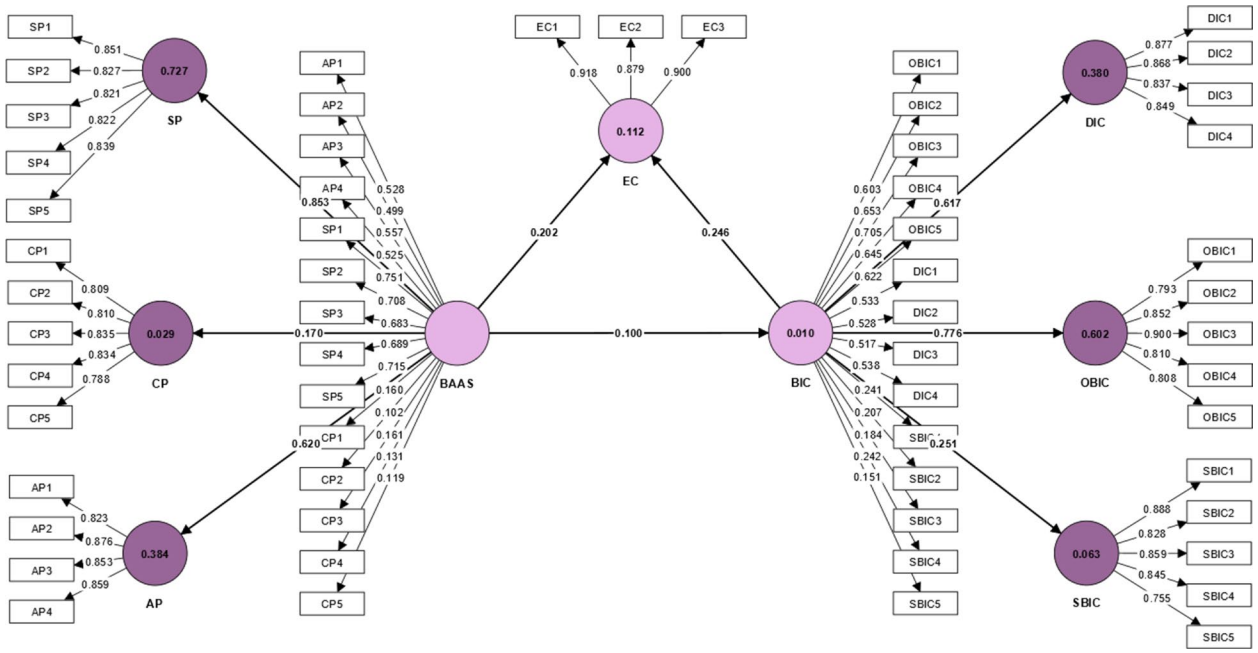

Fig. 2 Diagram of structural model; this figure was extracted from SmartPLS version 4.0.8.5 and illustrates the path directions for H1–H3 based on the empirical data collection in COVID-19 pandemic

expected, the paths linking BIC and EC (H3: $\beta=0.289$, t value = 5.732; p value = 0.000) were significantly positive. To this end, the H1, H2, and H3 were accepted. Remarkably, the statistical outcomes on the mediating impact of BIC on the interlink between BAAS and EC reveal that BIC acts as a mediator of this interlink.

The test of effect size (f^2) enables assessing the contribution of an exogenous variable to an endogenous variable [147]. Examining Cohen's f-square formula and comparing to the suggested threshold values of 0.35 (large), 0.15 (medium), and 0.02 (small) were the recommended methods for calculating the effect size of each component. Building on the outcomes in Tables 6 and 7, the values of f^2 of all components were reported to be small.

The other critical scale was the determination coefficient (R^2), which referred to the extent of variance between endogenous and exogenous latent variables. The values of R^2 could be deemed substantial (0.75), medium (0.50), or weak (0.25) [147]. As seen in Fig. 2, the hypothesized model in the COVID-19 pandemic accounts for 1 percent of the variance in BIC; 11.2 percent of the variance in EC. While in Fig. 3, the hypothesized model in

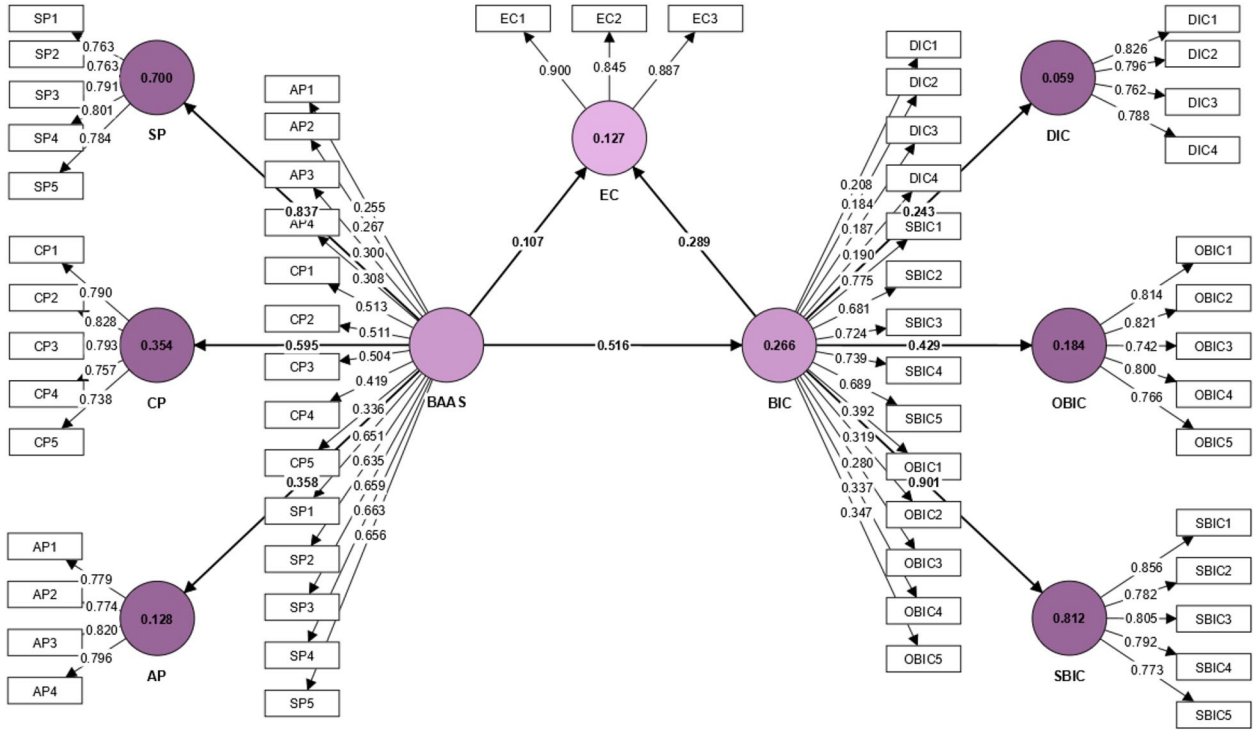

Fig. 3 Diagram of structural model; this figure was extracted from SmartPLS version 4.0.8.5 and illustrates the path directions for H1–H3 based on the empirical data collection in new normal

the new normal accounts for 26.6 percent of the variance in BIC; 12.7 percent of the variance in EC.

The assessment test predictive relevance (Q^2) stood for a hypothesized model's predictive power [147]. The hypothesized model could be pondered to have adequate predictive relevance when endogenous variable values were greater than Zero [147].

As indicated in Table 6, during the COVID-19 pandemic the score for Q^2 was 0.002 for BIC and 0.088 for EC. In the meanwhile, in Table 7, in the new normal, the score for Q^2 was 0.062 for BIC and 0.093 for EC.

Discussion

Broadly speaking, the current research was performed to produce a holistic picture on how to succeed in EC in both pandemic and the post-pandemic through provide precise and meticulous analysis on the perspectives of accountants in SMEs on BAAS implementation and BIC enhancement in these two periods of time.

The statistical outcomes of the hypothesized models drawing on the two wave of data collection revealed several differences in the significance and the effect size of the constructs. From an overall perspective, the effect size of BAAS and BIC on EC in the COVID-19 pandemic seemed to be less than those in the new normal and the BAAS is even verified to induce insignificant influence on BIC. The statistical findings of the current study cast light on the crucial part that BAAS plays in improving EC. BD does in fact become a crucial instrument as the EC market grows [151]. This discovery echoes and broadens the conclusions of a number of academic studies that examine how BD affects EC [29, 151–154]. BD opens up a lot of opportunities for EC, allowing a virtual business to thoroughly engage and investigate its online customers [155]. In addition, BIC is found to have a noticeable impact on EC, as predicted by the researchers. These data support and extend the conclusions reached by earlier researchers, including Ferreira et al. [156], Azhagan and Thamizharasi [157], Bhuvaneswari and Natarajan [158], and Pan et al. [159]. In other words, the effective use of BIC will increase the EC in the cutthroat corporate environment.

The plausible for the differences in effect size of all the components in the proposed model in the COVID-19 pandemic and new normal as well as the insignificant interconnection between BAAS and BIC can be illuminated at the organizational degree and individual degree. Concerning to the organizational degree, the manufacturing industry's supply chains were severely impacted by the COVID-19 epidemic. SMEs were hardest hit because of the lack of materials and parts, problems with the logistics process, and changes in demand [160].

Manufacturing SMEs are firmly ingrained in an industrial system that is influenced by the market as suppliers and partners [161]. For SMEs to reorient and adapt in the face of uncertainty, creativity and innovation are essential skills [162]. To maintain resilience, there must be close communication among the various supply chain participants [163]. Manufacturing SMEs typically concentrate on differentiation methods such diversified product offers and adaptable customer responses, in contrast to large enterprises that obtain a competitive advantage through cost savings [164]. Inadequate financial resources, a lack of managerial experience, and a lack of technical knowledge are some of the challenges that SMEs face when trying to innovate [163]. SMEs rarely innovate on their own because of their strategic direction and capability limitations, instead, they rely on outside sources to support their internal innovation [165]. Although the recent pandemic's instability hastened SMEs' transition to automated, autonomous, and intelligent manufacturing systems [160].

The development brought about by digital transformation improves connectivity and facilitates effective communication among supply chain partners [161]. However, SMEs are unable to achieve the best results in digital transformation due to their limitations in the implementation of multi-tasking roles, a lack of resources, risk management, data-driven decision-making processes, ineffective communications, and a lack of strategic planning [166]. The interaction between technologies and the people who use them must be taken into account while evaluating them. It is possible to make the case that technological transformation includes both the introduction of new technologies and a cultural revolution that makes it possible for a new perspective on and manner of thinking about technologies.

On the one side, space–time flexibility has made it possible to work in more equitable and healthy daily working conditions, which has helped to solve the issue of excessive levels of stress [167, 168]. On the other side, numerous researchers (i.e., Adisa et al. [169], Möhring et al. [170]) have emphasized how some employees exhibit resistance related to the effective use of technology that has a crucial impact on well-being because of an increased level of technostress [171]. The topic of relationships in the setting of the family is closely tied to the question of well-being. The adoption of remote and flexible working has an impact on the routines and behavioral patterns that govern family connections. Building on the findings of Eddleston and Mulik [172] as well as Allen et al. [173], the integration of work activities at home and family activities, which is characterized by increased flexibility, increases work–family conflict because people find it difficult to withdraw from work. The amount of work completed would grow as a result of remote working, but family problems would worsen. More specifically, these accountants, who had previously worked primarily inside the organizational walls, had to quickly adjust to remote work environments. Parental requirements for accountants have increased due to the closure of schools and daycare facilities. Although these work–family relationships appeared to be more difficult for accountants who had children, single and childless personnel were nonetheless susceptible to the negative consequences of such altered work settings, posing a serious risk to their productivity and mental health. These matters resulted in their ignorance on the role of advanced technologies implementation. Remarkably, SMEs also have restrained oxygen pertaining to money and other resources. Additionally, unprecedented difficulties are faced by the brick-and-mortar retail sector, particularly during the COVID-19 epidemic. As a result, it is difficult for SME employees to fully assist their company in utilizing the benefits of the digital transformation.

Nevertheless, in the new normal which is a period of moderately lessened virus transmission and in which more restrictions were eased and society fully reopened, the advantages of BAAS and BIC have been gradually recognized and accepted by numerous accountants in SMEs. The evolution of work activities, as well as the enhancement of production processes and organizational structures, are all influenced by technological transformation [174–176]. This relationship between technological transformation and increased organizational flexibility is also evident. Better connectivity and efficient communication among supply chain partners are results of the improvements brought about by digital transformation [161]. According to Brem et al. [11] as well as Harker Martin and MacDonnell [12], EC can aid in market expansion by reaching new consumer segments through affordable ways of product distribution. With the quick advancement of information technology, EC has emerged as a brand-new, extensively used method of transaction. This has just raised an urgent claim on implementation of BAAS and BIC. These outcomes not only reaffirm but also widen the findings on the potential of implementing BD and its applications on BI in generating business impacts of several previous studies [26, 177, 178].

Implication and avenues for future research

The current study is concluded in this section by outlining the implications for practice and summarizing a number of inherent flaws that warrant further investigation.

Theory implication

As COVID-19 can cause illnesses ranging from the common cold to more serious conditions (Yang et al. [179]),

maintaining social distance was advised in order to combat this pandemic, which resulted in severe lockdowns everywhere. Companies who relied on physical storefronts to stay afloat before the COVID-19 epidemic broke out were forced to diversify into the online market. EC still has a promising future despite the drawbacks. The findings of Hoang et al. [180] on how SMEs used EC to guide national economic recovery after COVID-19 highlighted how several technologies were used, despite the pandemic's short length, to assure organizational survivability and revival in the cutthroat market climate. The results show that during COVID-19, technological compatibility had the biggest impact on the uptake of EC. EC needs the support of digital platforms to survive and develop in the post-pandemic period. Due to the fact that almost all businesses now know little about their clients, BI will help these businesses better comprehend the strategies and tools utilized for data analysis while providing historical, present-day, and future perspectives of business information [15]. Therefore, when developing EC, BIC should be taken into account. However, Marn-Ortega et al. [23] claim that BI predominantly focuses on structured and internal business data while ignoring the important information buried in unstructured and external data. As a result, a corporation may come to decisions with preconceived notions and an imperfect understanding of the world [24, 25]. The rapid advancement of BD and BD technology has presented BI with both new challenges and opportunities [26]. The capacity to create and employ extra analytics capabilities, such prescriptive and diagnostic analysis, is provided by BD will primarily lead to the development of BI systems [27]. On the other hand, according to Alsaig et al. [181], BD is a crucial tool for the expansion of the EC network. BD offers a brand-new, very effective method of organizing, carrying out, disseminating, and evaluating study, revolutionizing the growth of information both within and outside of science [155]. The BAAS model is a wise choice since it can assist businesses in creating innovative business plans and extracting intrinsic value from their large data [34]. SMEs can benefit from adopting BAAS because it is more cost-effective and because it makes managing BD infrastructure easier because it works in the cloud. Because they have fewer financial and infrastructure resources available, SMEs are particularly affected by this [31]. Taken together, BAAS form a sizable key that unlocks enhancement of BIC and the future expansion of the EC industry.

Policy and practical implication

The obtained observations in this study provided a variety of practical takeaways based on the managerial outlooks. According to the statistical results of the current study, BAAS would be the main factor in driving BIC improvement and EC success. As such, all managers of SMEs should develop their managerial cognitive abilities and give this issue more attention on BAAS. To do so, all managers in SMEs should assure that the BAAS implementation has been more than a technical project and has been linked to organizational transformation initiative requesting analytics strategies, management support, and proactive and careful painstaking management to seize the entire potential of BAAS. The leaders of SMEs should become knowledgeable of BAAS formulation and implementation in order to guarantee the smooth evolution of BAAS. As a consequence, it has been urged for key resources, such as infrastructure and digital platforms, to be consolidated. Instrumentally, in order to keep their staff up to date with cutting-edge programming systems, all managers in SMEs should focus on enhancing the organizational workforce's expertise through appropriate training programs. In particular, emphasis should be placed on enhancing professional education, developing professional knowledge, and honing essential professional judgment skills. In addition to internal training initiatives, SMEs were encouraged to set up specialized outside training initiatives to capitalize on market conditions and gain knowledge of cutting-edge digital information.

The findings of this study also showed how important BIC is, since it was found to considerably and favorably improve the influence of EC. Therefore, managers must see investing in BI systems as a crucial strategic choice that will affect their company's ability to successfully launch new products/services. We advise managers evaluating BI investments to take into account BI's potential to facilitate and improve EC in addition to its ultimate goals. Additionally, it is recommended to all managers in SMEs to implement extraordinary tactics that are in line with organizational quirks and to set up internal procedures to achieve BIC.

In every developing economy, the government plays an important role in facilitating the essential requirements for the development of EC through supplying robust and secure online payment options, warranting a stable information technology infrastructure, offering sufficient programs, building up awareness of using different means of media and education institutions [182]. As such, supporting policies positively influence EC applications of the SMEs [59, 60]. Government's supports via its policies and regulations are priceless for SMEs engaging to EC [59]. At the same time, policy-makers and governmental influencers should establish and promulgate policies as well as guidelines in relation to the adoption of advanced information technologies in order to revamp the efficiency and effectiveness of deployment across all organizations.

In order to produce more cutting-edge systems that are suitable for the quirks of SMEs, hardware and software makers and merchants have also demanded that efforts be made to understand much more explicitly the advantages and limitations of contemporary information technologies.

Research limitations

There were a number of shortcomings, which allowed for the creation of new relevant foundation development starting points in the future. First, given the importance placed on geographic provenance by individual nations, the sample collected for the current study, which originated in Vietnam, might not be immediately convertible to the other contexts. Alternately, despite the fact that the current data were taken from a single developing country that was meant to have many things in common, other emerging economies nonetheless have peculiarities [183]. This constraint would be overcome by conducting replications and extensions in more extensive geographic areas to demonstrate the reliability and generalizability of the findings, as meaningful disparities may also become apparent in a number of cases. The second limitation was the relatively small size of the data set obtained via an anonymous survey-based methodology using a convenient selection of informants. This study also used a convenience and snowball sample, which could have skewed the results in favor of particular participant categories. To that purpose, more target group circulation should be used to support the current observations. In parallel, random sample collection should be taken into account in follow-up research to support the findings when the necessary facilitations can be attained. Last but not least, despite the fact that this study could be regarded as a trailblazing effort to examine the connections between SMEs and BAAS, BIC, and EC in the context of the COVID-19 crisis over two remarkable periods of time, the interlinks formed in the structural model seemed to be treated in a static manner. The COVID-19 pandemic was predicted to continue spreading; hence, it led to the discovery of a future route to seek empirical validation of these results in the future.

Conclusion

As EC model has been considered as a model with numerous beneficial features, namely low-cost and boundless model, easier formulation and operationalization, effective marketing opportunities generation, it will allow SMEs to carry on with their operations and continue to profit even during the COVID-19 pandemic. According to Kumar and Ayedee [14], SMEs' utilization of technology to address COVID-19 issues may be prerequisite. In this regard, the deployment of BAAS will improve SMEs' capacity to successfully handle any problems that may arise as a result of the quickly altering business environment. In the meanwhile, BI has emerged as a key technology for enhancing enterprise business performance as well as a driving force behind the development of EC and e-services [17]. In order to formulate a new and in-depth insight on the role of BAAS implementation, to tap higher potential of BI and EC, an analysis on how BAAS can foster the EC and BIC in SMEs represented the main motivations in this research. The current research enriches the growing body of literature on the potential of BAAS and BIC in EC within SMEs in developing country in both the period of COVID-19 pandemic and the period of new normal through provide precise and meticulous analysis on the perspectives of accountants in SMEs on BAAS application, BIC enhancement and the effectiveness of EC, in these two periods of time. In doing so, this will enable the researchers to produce more robust empirical results and minimize potential sample biases, reflecting the complex and dynamic characteristics of the market [184].

Appendix A: Questionnaire survey items

Construct	Questions/indicators
Big data as a service (BAAS)	
Sensing plane (SP)	**SP1:** Sensing plane efficiently carries out the big data cleansing and reduction for corporate predictive analytics
	SP2: Sensing plane effectively accomplishes the big data cleaning and reduction for descriptive analysis of a company's status among its competitors
	SP3: Sensing plane successfully implements big data cleansing and reduction for prescriptive analytics to evaluate how reviews and behavioral adjustments might be enhanced
	SP4: Sensing plane effectively carries out the big data cleansing and reduction for prescriptive analytics to conduct dynamic pricing for customers
	SP5: Sensing plane successfully executes big data cleaning and reduction for forecasting for improved planning to continuously update E-commerce strategies

Construct	Questions/indicators
Cloud plane (CP)	**CP1**: Using a cloud plane, businesses can implement precise marketing in E-commerce
	CP2: Cloud plane enables organizations to choose the best E-Commerce logistics route
	CP3: Organizations can offer information security assessments in a cloud computing environment due to cloud plane
	CP4: In a cloud computing context, cloud plane enables organizations to provide information privacy assessment
Application plane (AP)	**AP1**: Application plane allows the organization to conduct personalization of products for consumers
	AP2: Application plane allows the organization to conduct supply chain management
	AP3: Application plane allows the organization to conduct automated sourcing of product
	AP4: Application plane allows the organization to conduct better vendor management
	AP5: Application plane allows the organization to conduct managing fraud and risk
E-commerce (EC)	**EC1**: E-commerce enables businesses to cut expenses and save time
	EC2: E-commerce enables businesses to reach out to more clients
	EC3: E-commerce enables businesses to broaden their market reach, boost sales, and boost profits
Business intelligence capabilities (BIC)	
Data integration capability (DIC)	**DIC1**: We are able to better integrate the variety of available data than our rivals
	DIC2: Compared to rivals, our organizations' data sources have more consistent data across them
	DIC3: Unlike rivals, our businesses have good synchronization with other organizational databases in the targeted markets
	DIC4: When compared to rivals, staff from many divisions at our companies collaborate and exchange information
Operational BI capabilities (OBIC)	**OBIC1**: On a regular basis, the organization thoroughly evaluates operational and administrative data
	OBIC2: The company incorporates information from the BI system into its ongoing operations
	OBIC3: The organization's departments frequently share data and insights obtained from the BI system
	OBIC4: The business incorporates BI tools into its continuous operations
	OBIC5: The BI system considerably aids mid-level managers in making decisions
Strategic BI capabilities (SBIC)	**SBIC1**: The BI system greatly facilitates decision making for senior executives
	SBIC2: The BI system makes it possible to convey the organization's position in a thorough and comprehensive manner
	SBIC3: The BI system offers comprehensive analytical tools for the organization's status
	SBIC4: The BI system is employed to spot trends, chances, and risks in the corporate environment
	SBIC5: The BI system's information is a great help in developing the organizational strategy

Abbreviations

AP	Application plane
BD	Big data
BAAS	Big data as a service
BI	Business intelligence
BIC	Business intelligence capabilities
CP	Cloud plane
CT	Contingency theory
COVID-19	Coronavirus disease 2019
DIC	Data integration capability
EC	E-commerce
HTMT	Heterotrait–monotrait
OBIC	Operational business intelligence capabilities
PLS-SEM	Partial least squares structural equation modeling
SP	Sensing plane
SMEs	Small and medium enterprises
SBIC	Strategic business intelligence capabilities
VIF	Variance inflation factor

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References

1. Dohale V, Ambilkar P, Gunasekaran A, Verma P (2022) Supply chain risk mitigation strategies during COVID-19: exploratory cases of "make-to-order" handloom saree apparel industries. Int J Phys Distrib Logist Manag 52(2):109–129. https://doi.org/10.1108/IJPDLM-12-2020-0450
2. Kano L, Oh CH (2020) Global value chains in the post-COVID world: governance for reliability. J Manag Stud 57(8):1773–1777. https://doi.org/10.1111/joms.12626
3. Mouzas S, Florian B (2022) Rethinking business performance in global value chains. J Bus Res 144:679–689. https://doi.org/10.1016/j.jbusres.2022.02.012
4. Campbell MC, Inman JJ, Kirmani A, Price LL (2020) In times of trouble: a framework for understanding consumers' responses to threats. J Consum Res 47(3):311–326. https://doi.org/10.1093/jcr/ucaa036
5. Nofiani D, Indarti N, Lukito-Budi AS, Manik HFGG (2021) The dynamics between balanced and combined ambidextrous strategies: a paradoxical affair about the effect of entrepreneurial orientation on SMEs' performance. J Entrep Emerg Econ 13(5):1262–1286
6. Bressan A, Duarte Alonso A, Kok SK (2021) Confronting the unprecedented: micro and small businesses in the age of COVID-19. Int J Entrep Behav Res 27(3):799–820. https://doi.org/10.1108/IJEBR-09-2020-0602
7. Kitukutha NM, Vasa L, Oláh J (2021) The impact of COVID-19 on the economy and sustainable e-commerce. Forum Scientiae Oeconomia 9(2):47–72
8. Alwan SY, Hu Y, Al Asbahi AAMH, Al Harazi YK, Al Harazi AK (2023) Sustainable and resilient e-commerce under COVID-19 pandemic: a hybrid grey decision-making approach. Environ Sci Pollut Res 30:47328–47348. https://doi.org/10.1007/s11356-023-25456-0
9. Myovella G, Karacuka M, Haucap J (2020) Digitalization and economic growth: a comparative analysis of Sub-Saharan Africa and OECD economies. Telecommun Policy 44:1–12. https://doi.org/10.1016/j.telpol.2019.101856
10. Yuan J, Zou H, Xie K, Dulebenets MA (2021) An assessment of social distancing obedience behavior during the COVID-19 post-epidemic period in China: a cross-sectional survey. Sustainability 13(14):1–16. https://doi.org/10.3390/su13148091
11. Brem A, Viardot E, Nylund PA (2021) Implications of the coronavirus (COVID-19) outbreak for innovation: which technologies will improve our lives? Technol Forecast Soc Chang 163:1–20. https://doi.org/10.1016/j.techfore.2020.120451
12. Harker Martin B, MacDonnell R (2012) Is telework effective for organizations? Manag Res Rev 35(7):602–616. https://doi.org/10.1108/01409171211238820
13. Abebe M (2014) Electronic commerce adoption, entrepreneurial orientation and small- and medium-sized enterprise (SME) performance. J Small Bus Enterp Dev 21(1):100–116. https://doi.org/10.1108/jsbed-10-2013-0145
14. Kumar A, Ayedee N (2021) Technology adoption: a solution for SMEs to overcome problems during COVID-19. Acad Mark Stud J 25(1):1–16
15. Ferreira T, Pedrosa I, Bernardino J (2019) Integration of business intelligence with e-commerce. In: 2019 14th Iberian conference on information systems and technologies (CISTI), pp 1–7. https://doi.org/10.23919/cisti.2019.8760992
16. Lim E-P, Chen H, Chen G (2013) Business intelligence and analytics. ACM Trans Manag Inf Syst 3(4):1–10. https://doi.org/10.1145/2407740.2407741
17. Turban E, Volonino L (2011) Information technology for management: improving strategic and operational performance, 8th edn. Wiley, Danvers
18. Ransbotham BS, Kiron D (2017) Analytics as a source of business innovation. MIT Sloan Manag Rev 58(3):1–21
19. Shiau W-L, Chen H, Wang Z, Dwivedi YK (2022) Exploring core knowledge in business intelligence research. Internet Res. https://doi.org/10.1108/INTR-04-2021-0231
20. Liang TP, Liu YH (2018) Research landscape of business intelligence and big data analytics: a bibliometrics study. Expert Syst Appl 111(128):2–10. https://doi.org/10.1016/j.eswa.2018.05.018
21. Božič K, Dimovski V (2019) Business intelligence and analytics for value creation: the role of absorptive capacity. Int J Inf Manage 46:93–103. https://doi.org/10.1016/j.ijinfomgt.2018.11.020
22. Chen H, Chiang RH, Storey VC (2012) Business intelligence and analytics: from big data to big impact. MIS Q 36(4):1165–1188. https://doi.org/10.2307/41703503
23. Marín-Ortega PM, Dmitriyev V, Abilov M, Gómez JM (2014) ELTA: new approach in designing business intelligence solutions in era of big data. Procedia Technol 16:667–674. https://doi.org/10.1016/j.protcy.2014.10.015
24. Llave MR (2018) Data lakes in business intelligence: reporting from the trenches. Procedia Comput Sci 138:516–524. https://doi.org/10.1016/j.procs.2018.10.071
25. Ram J, Zhang C, Koronios A (2016) The implications of big data analytics on business intelligence: a qualitative study in China. Procedia Comput Sci 87:221–226. https://doi.org/10.1016/j.procs.2016.05.152
26. Fan S, Lau RYK, Zhao JL (2015) Demystifying big data analytics for business intelligence through the lens of marketing mix. Big Data Res 2(1):28–32. https://doi.org/10.1016/j.bdr.2015.02.006
27. Faroukhi AZ, El Alaoui I, Gahi Y, Amine A (2020) A multi-layer big data value chain approach for security issues. Procedia Comput Sci 175:737–744. https://doi.org/10.1016/j.procs.2020.07.109
28. Al-Hakeem MS (2016) A proposed big data as a service (BDaaS) model. International Journal of Computer Sciences and Engineering 4(11):15–21
29. Sazu MH (2022) Does big data drive innovation in E-commerce: A global perspective? SEISENSE Bus Rev 2(1):55–66. https://doi.org/10.33215/sbr.v2i1.797
30. Bresciani S, Ciampi F, Meli F, Ferraris A (2021) Using big data for co-innovation processes: mapping the field of data-driven innovation, proposing theoretical developments and providing a research agenda. Int J Inf Manag 60:1–15. https://doi.org/10.1016/j.ijinfomgt.2021.102347
31. Wessels T, Jokonya O (2022) Factors affecting the adoption of big data as a service in SMEs. Procedia Comput Sci 196:332–339. https://doi.org/10.1016/j.procs.2021.12.021
32. Ardagna CA, Bellandi V, Bezzi M, Ceravolo P, Damiani E, Hebert C (2021) Model-based big data analytics-as-a-service: take big data to the next level. IEEE Trans Serv Comput 14(2):516–529
33. An K, Pradhan S, Caglar F, Gokhale A (2012) A publish/subscribe middleware for dependable and real-time resource monitoring in the cloud. In Proceedings of the Workshop on Secure and Dependable Middleware for Cloud Monitoring and Management 3:1–6. https://doi.org/10.1145/2405186.2405189
34. Xinhua E, Han J, Wang Y, Liu L (2013) Big Data-as-a-Service: definition and architecture. In: 2013 15th IEEE international conference on communication technology, pp 738–742. https://doi.org/10.1109/icct.2013.6820472

35. Vu QH, Asal R (2015) A framework for big data as a service. In: 2015 IEEE international conference on digital signal processing (DSP), pp 1–5. https://doi.org/10.1109/icdsp.2015.7251921
36. Wang X, Yang LT, Liu H, Deen MJ (2017) A Big Data-as-a-service framework: state-of-the-art and perspectives. IEEE Trans Big Data. https://doi.org/10.1109/tbdata.2017.2757942
37. Zheng Z, Zhu J, Lyu MR (2013) Service-generated big data and big data-as-a-service: an overview. In: 2013 IEEE international congress on Big Data, pp 1–8. https://doi.org/10.1109/bigdata.congress.2013.60
38. Susanty A, Handoko A, Puspitasari N (2020) Push-pull-mooring framework for e-commerce adoption in small and medium enterprises. J Enterp Inf Manag 33(2):381–406
39. Biagi F, Falk M (2017) The impact of ICT and e-commerce on employment in Europe. J Policy Model 39(1):1–18. https://doi.org/10.1016/j.jpolmod.2016.12.004
40. Lee YJ, Ha S, Johnson Z (2019) Antecedents and consequences of flow state in e-commerce. J Consum Mark 36(2):264–275. https://doi.org/10.1108/JCM-10-2015-1579
41. Qi X, Chan JH, Hu J, Li Y (2020) Motivations for selecting cross-border e-commerce as a foreign market entry mode. Ind Mark Manag 89:50–60. https://doi.org/10.1016/j.indmarman.2020.01.009
42. Saridakis G, Lai Y, Mohammed A, Hansen JM (2018) Industry Characteristics, stages of E-commerce communications, and entrepreneurs and SMEs revenue growth. Technol Forecast Soc Chang 128:56–66. https://doi.org/10.1016/j.techfore.2017.10.017
43. Ha VD (2020) Enhancing the e-commerce application in SMEs. Manag Sci Lett 10:2821–2828. https://doi.org/10.5267/j.msl.2020.4.027
44. Aslan C, Derindag OF, Parmaksiz S (2023) Effects of cross-border E-commerce customs declaration ceiling increase on export performance under COVID-19 conditions. Kybernetes, 1–22. https://doi.org/10.1108/K-02-2023-0182
45. Din AU, Han H, Ariza-Montes A, Vega-Muñoz A, Raposo A, Mohapatra S (2022) The impact of COVID-19 on the food supply chain and the role of E-commerce for food purchasing. Sustainability 14:1–14. https://doi.org/10.3390/su14053074
46. Hamid S, Azhar M (2023) Behavioral intention to order food and beverage items using e-commerce during COVID-19: an integration of theory of planned behavior (TPB) with trust. Br Food J 125(1):112–131. https://doi.org/10.1108/BFJ-03-2021-0338
47. Jílková P, Králová P (2021) Digital consumer behaviour and ecommerce trends during the COVID-19 crisis. Int Adv Econ Res 27(1):83–85. https://doi.org/10.1007/s11294-021-09817-4
48. Lee JY, Yang YS, Ghauri PN (2023) E-commerce policy environment, digital platform, and internationalization of Chinese new ventures: the moderating effects of Covid-19 pandemic. Manag Int Rev 63:57–90. https://doi.org/10.1007/s11575-022-00491-0
49. Ramadan Z, Farah M, Abosag I, Sleiman A (2023) Typology of e-commerce shoppers: the case of COVID-19. Quale Mark Res. https://doi.org/10.1108/QMR-12-2021-0154
50. Huy PQ, Phuc VK (2022) Insight into the critical success factors of performance-based budgeting implementation in the public sector for sustainable development in the COVID-19 pandemic. Sustainability 14(20):1–37. https://doi.org/10.3390/su142013198
51. Shulla K, Voigt B-F, Cibian S, Scandone G, Martinez E, Nelkovski F, Salehi P (2021) Effects of COVID-19 on the sustainable development goals (SDGs). Discov Sustain 2(1):1–19. https://doi.org/10.1007/s43621-021-00026-x
52. Ranjbari M, Shams Esfandabadi Z, Zanetti MC, Scagnelli SD, Siebers P-O, Aghbashlo M, Peng W, Quatraro F, Tabatabaei M (2021) Three pillars of sustainability in the wake of COVID-19: A systematic review and future research agenda for sustainable development. J Clean Prod 297:1–23. https://doi.org/10.1016/j.jclepro.2021.126660
53. Yigitbasioglu O, Green P, Cheung M-YD (2022) Digital transformation and accountants as advisors. Acc Audit Account J. https://doi.org/10.1108/AAAJ-02-2019-3894
54. Ragazou K, Passas I, Garefalakis A, Zopounidis C (2023) Business intelligence model empowering SMEs to make better decisions and enhance their competitive advantage. Discov Anal 1(2):1–15. https://doi.org/10.1007/s44257-022-00002-3
55. Antoniadis I, Tsiakiris T, Tsopogloy S (2015) Business intelligence during times of crisis: adoption and usage of ERP systems by SMEs. Procedia Soc Behav Sci 175:299–307. https://doi.org/10.1016/j.sbspro.2015.01.1204
56. Tutunea MF, Rus RV (2012) Business intelligence solutions for SME's. Procedia Econ Finance 3:865–870. https://doi.org/10.1016/s2212-5671(12)00242-0
57. Ramakrishnan T, Jones MC, Sidorova A (2012) Factors influencing business intelligence (BI) data collection strategies: an empirical investigation. Decis Support Syst 52(2):486–496. https://doi.org/10.1016/j.dss.2011.10.009
58. Sirin E, Karacan H (2017) A review on business intelligence and big data. Int J Intell Syst Appl Eng 5(4):206–215
59. Rahayu R, Day J (2015) Determinant factors of E-commerce adoption by SMEs in developing country: evidence from Indonesia. Procedia Soc Behav Sci 195:142–150. https://doi.org/10.1016/j.sbspro.2015.06.423
60. Dahbi S, Benmoussa C (2019) What hinder SMEs from adopting E-commerce? A multiple case analysis. Procedia Comput Sci 158:811–818. https://doi.org/10.1016/j.procs.2019.09.118
61. Feidler F (1964) Advances in experimental social psychology, contingency model of leadership effectiveness. Academic Press, New York
62. Csaszar FA, Ostler J (2020) A contingency theory of representational complexity in organizations. Organ Sci 31(5):1053–1312. https://doi.org/10.1287/orsc.2019.1346
63. Reinking J (2012) Contingency theory in information systems research. Integr Ser Inf Syst 28:247–263. https://doi.org/10.1007/978-1-4419-6108-2_13
64. Shao Z, Feng Y, Hu Q (2016) Effectiveness of top management support in enterprise systems success: a contingency perspective of fit between leadership style and system life-cycle. Eur J Inf Syst 25(2):131–153. https://doi.org/10.1057/ejis.2015.6
65. Eckstein D, Goellner M, Blome C, Henke M (2015) The performance impact of supply chain agility and supply chain adaptability: the moderating effect of product complexity. Int J Prod Res 53(10):3028–3046. https://doi.org/10.1080/00207543.2014.970707
66. Sirmon DG, Hitt MA (2009) Contingencies within dynamic managerial capabilities: interdependent effects of resource investment and deployment on firm performance. Strateg Manag J 30(13):1375–1394. https://doi.org/10.1002/smj.791
67. Schilke O (2014) On the contingent value of dynamic capabilities for competitive advantage: the nonlinear moderating effect of environmental dynamism. Strateg Manag J 35(2):179–203. https://doi.org/10.1002/smj.2099
68. Sousa R, Voss C (2008) Contingency research in operations management practices. J Oper Manag 26(6):697–713. https://doi.org/10.1016/j.jom.2008.06.001
69. Yue H (2022) Research on E-commerce data standard system in the era of digital economy from the perspective of organizational psychology. Front Psychol 13:1–10. https://doi.org/10.3389/fpsyg.2022.900698
70. Turban E, King D, Lee JK, Liang T-P, Turban DC (2015) Electronic commerce: a managerial and social networks perspective, 8th edn. Springer, Cham
71. Alryalat MAA, Alryalat H, Alhamzi KHM, Sharma A (2023) Perceived barriers to business-to-government (B2G) E-commerce adoption: the case of government E-marketplace (GeM) portal in India. Int J Electron Gov Res 19(1):1–19. https://doi.org/10.4018/IJEGR.323571
72. Li X, Ma J, Zhou X, Yuan R (2023) Research on consumer trust mechanism in China's B2C E-commerce platform for second-hand cars. Sustainability 15:1–15. https://doi.org/10.3390/su15054244
73. Skare M, Gavurova B, Rigelsky M (2023) Innovation activity and the outcomes of B2C, B2B, and B2G E-Commerce in EU countries. J Bus Res 163:1–12. https://doi.org/10.1016/j.jbusres.2023.113874
74. Timotius E, Sunardi O, Soenandi IA, Ginting M, Sabini B, Sutikno Y (2023) Buyers-sellers' value of courier services: assessment in the Indonesian C2C e-commerce. Int J Retail Distrib Manag 51(4):503–522. https://doi.org/10.1108/IJRDM-09-2021-0414
75. Wei J, Wei X, Zhang DD, Liu J (2023) First-party content and market concentration on a B2B E-commerce platform—theory and empirical evidence. Decis Support Syst 170:1–11. https://doi.org/10.1016/j.dss.2023.113958
76. Niranjanaurth M, Kavyashree N, Jagannath S, Chahar D (2013) Analysis of e-commerce and m-commerce: advantages, limitations and security issues. Int J Adv Res Comput Commun Eng 2(6):2360–2370

77. Miyazaki AD, Fernandez A (2018) Internet privacy and security: an examination of online retailer disclosures. J Public Policy Mark 19(1):54–61. https://doi.org/10.1509/jppm.19.1.54.16942
78. D'Adamo I, González-Sánchez R, Medina-Salgado MS, Settembre-Blundo D (2021) E-commerce calls for cyber-security and sustainability: how European citizens look for a trusted online environment. Sustainability 13(12):1–17. https://doi.org/10.3390/su13126752
79. Miao M, Jalees T, Zaman SI, Khan S, Hanif N-U, Javed MK (2022) The influence of e-customer satisfaction, e-trust and perceived value on consumer's repurchase intention in B2C e-commerce segment. Asia Pac J Mark Logist 34(10):2184–2206. https://doi.org/10.1108/APJML-03-2021-0221
80. Zhang R, Fang L, He X, Wei C (2023) E-commerce security management resources and organization. In: Zhang R, Fang L, He X, Wei C (eds) The whole process of e-commerce security management system, advanced studies in e-commerce. Springer, Singapore, pp 37–60. https://doi.org/10.1007/978-981-19-9458-6_3
81. Zhang R, Fang L, He X, Wei C (2023) E-commerce security management plan. In: Zhang R, Fang L, He X, Wei C (eds) The whole process of e-commerce security management system. Advanced studies in e-commerce. Springer, Singapore, pp 15–36. https://doi.org/10.1007/978-981-19-9458-6_2
82. Zhang R, Fang L, He X, Wei C (2023) Supervision and optimization mechanism of e-commerce security management. In: Zhang R, Fang L, He X, Wei C (eds) The whole process of e-commerce security management system. Advanced studies in e-commerce. Springer, Singapore, pp 281–295. https://doi.org/10.1007/978-981-19-9458-6_9
83. Lin S-W, Fu H-P, Lin AJ (2023) Critical success factors and implementation strategies for B2B electronic procurement systems in the travel industry. J Hosp Tour Technol. https://doi.org/10.1108/JHTT-08-2021-0230
84. Vieira J, Frade R, Ascenso R, Prates I, Martinho F (2020) Generation Z and key-factors on e-commerce: a study on the Portuguese tourism sector. Admin Sci 10(4):1–17. https://doi.org/10.3390/admsci10040103
85. Bao Z, Zhu Y (2023) Understanding customers' stickiness of live streaming commerce platforms: an empirical study based on modified e-commerce system success model. Asia Pac J Mark Logist 35(3):775–793. https://doi.org/10.1108/APJML-09-2021-0707
86. Colla E, Lapoule P (2012) E-commerce: exploring the critical success factors. Int J Retail Distrib Manag 40(11):842–864. https://doi.org/10.1108/09590551211267601
87. Jian J, Lv L, Wan L (2023) Exploring consumer purchase intention in cross-border e-commerce: evidence from 'belt and road' countries. Asia Pac J Mark Logist 35(3):625–644. https://doi.org/10.1108/APJML-12-2021-0934
88. Sharma H, Aggarwal AG (2019) Finding determinants of e-commerce success: a PLS-SEM approach. J Adv Manag Res 16(4):453–471. https://doi.org/10.1108/JAMR-08-2018-0074
89. Boas VV, Sousa BB (2022) The role of technical and relational factors in trust and predisposition for online commerce: digital markets and consumer perspective. Int J Electron Custom Relatsh Manag 13(2):166–185. https://doi.org/10.1504/IJECRM.2021.120353
90. Fan Z, Zhai X (2023) The performance improvement mechanism of cross-border E-commerce grassroots entrepreneurship empowered by the internet platform. Sustainability 15:1–14. https://doi.org/10.3390/su15021178
91. Khan SA (2023) E-marketing, e-commerce, e-business, and internet of things: an overview of terms in the context of small and medium enterprises (SMEs). In: Naim A, Devi AV (eds) Global applications of the internet of things in digital marketing, pp 332–348. https://doi.org/10.4018/978-1-6684-8166-0
92. Picoto WN, Abreu JC, Martins P (2023) Integrating the internet of things into E-commerce: the role of trust, privacy, and data confidentiality concerns in consumer adoption. Int J E-Bus Res 19(1):1–18. https://doi.org/10.4018/IJEBR.321647
93. Shanmugalingam P, Shanmuganeshan A, Manorajan A, Kugathasan M, Pathirana GY (2023) Does e-commerce really matter on international trade of Asian countries: evidence from panel data. PLoS ONE 18(4):1–16. https://doi.org/10.1371/journal.pone.0284503
94. Sulthana AN, Vasantha S (2022) Effect of Internet of Things (IoT) and social media on e-commerce. In: Srivastava P, Thivagar ML, Oros GI, Tan CC (eds) Mathematical and computational intelligence to socio-scientific analytics and applications. Lecture notes in networks and systems, vol 518. Springer, Singapore, pp 223–230. https://doi.org/10.1007/978-981-19-5181-7_17
95. Wang G, Zhang X, Gao Y, Yee AL, Wang X (2023) The use of an internet of things data management system using data mining association algorithm in an e-commerce platform. J Organ End User Comput 35(3):1–19. https://doi.org/10.4018/JOEUC.322553
96. Kumar N (2018) E-commerce in India: an analysis of present status, challenges and opportunities. Int J Manag Stud 5(2):1–14. https://doi.org/10.18843/ijms/v5i2(3)/11
97. Ahi AA, Sinkovics N, Sinkovics RR (2023) E-commerce Policy and the Global Economy: A Path to More Inclusive Development? Manag Int Rev 63:27–56. https://doi.org/10.1007/s11575-022-00490-1
98. Aras G, Crowther D (2009) Making sustainable development sustainable. Manag Decis 47(6):975–988. https://doi.org/10.1108/00251740910966686
99. Escursell S, Llorach-Massana P, Roncero MB (2021) Sustainability in e-commerce packaging: a review. J Clean Prod 280:1–17. https://doi.org/10.1016/j.jclepro.2020.124314
100. Faccia A, Le Roux CL, Pandey V (2023) Innovation and E-commerce models, the technology catalysts for sustainable development: the Emirate of Dubai case study. Sustainability 15:1–29. https://doi.org/10.3390/su15043419
101. Gao J, Siddik AB, Khawar Abbas S, Hamayun M, Masukujjaman M, Alam SS (2023) Impact of E-commerce and digital marketing adoption on the financial and sustainability performance of MSMEs during the COVID-19 pandemic: an empirical study. Sustainability 15:1–21. https://doi.org/10.3390/su15021594
102. Haryanti T, Subriadi AP (2022) E-commerce acceptance in the dimension of sustainability. J Model Manag 17(2):715–745. https://doi.org/10.1108/JM2-05-2020-0141
103. Hayakawa K, Mukunoki H, Urata S (2023) Can e-commerce mitigate the negative impact of COVID-19 on international trade? Jpn Econ Rev 74:215–232. https://doi.org/10.1007/s42973-021-00099-3
104. Islam MS, Proma AM, Wohn C, Berger K, Uong S, Kumar V, Korfmacher KS, Hoque E (2023) SEER: sustainable E-commerce with environmental-impact rating. Clean Environ Syst 8:1–10. https://doi.org/10.1016/j.cesys.2022.100104
105. Oláh J, Kitukutha N, Haddad H, Pakurár M, Máté D, Popp J (2018) Achieving sustainable E-commerce in environmental, social and economic dimensions by taking possible trade-offs. Sustainability 11(1):1–22. https://doi.org/10.3390/su11010089
106. Pratap S, Jauhar SKJ, Daultani Y, Paul SK (2022) Benchmarking sustainable E-commerce enterprises based on evolving customer expectations amidst COVID-19 pandemic. Bus Strateg Environ 32(1):736–752. https://doi.org/10.1002/bse.3172
107. Zhang M (2023) Sustainability transitions in e-commerce research—academic achievements and impediments. Circul Econ Sustain. https://doi.org/10.1007/s43615-023-00252-7
108. Fink L, Yogev N, Even A (2017) Business intelligence and organizational learning: an empirical investigation of value creation processes. Inf Manag 54(1):38–56. https://doi.org/10.1016/j.im.2016.03.009
109. Tarek BH, Adel G, Sami A (2016) The relationship between 'competitive intelligence' and the internationalization of North African SMEs. Compet Chang 20(5):326–336. https://doi.org/10.1177/1024529416657494
110. Sabherwal R, Becerra-Fernandez I (2011) Business intelligence: practices, technologies, and management. Wiley, Hoboken
111. Alsaad A, Selem KM, Alam MM, Melhim LKB (2022) Linking business intelligence with the performance of new service products: insight from a dynamic capabilities perspective. J Innov Knowl 7(4):1–11. https://doi.org/10.1016/j.jik.2022.100262
112. Cheng C, Zhong H, Cao L (2020) Facilitating speed of internationalization: the roles of business intelligence and organizational agility. J Bus Res 110:95–103. https://doi.org/10.1016/j.jbusres.2020.01.003
113. Novo E, Ribeiro HNR, Martins CAD (2023) The importance of business intelligence tools in the digital transition era: the Printria case. In: Economic and social development: book of proceedings, Varazdin: Varazdin Development and Entrepreneurship Agency, pp 357–365

114. Sun Z, Zou H, Strang K (2015) Big Data analytics as a service for business intelligence. Lecture notes in computer science, 200–211. https://doi.org/10.1007/978-3-319-25013-7_16
115. Zhou J, San OT, Liu Y (2023) Design and implementation of enterprise financial decision support system based on business intelligence. Int J Profess Bus Rev 8(4):1–14. https://doi.org/10.26668/businessreview/2023.v8i4.873
116. Alsibhawi IAA, Yahaya JB, Mohamed HB (2023) Business intelligence adoption for small and medium enterprises: conceptual framework. Appl Sci 13:1–12. https://doi.org/10.3390/app13074121
117. Lateef M, Keikhosrokiani P (2022) Predicting critical success factors of business intelligence implementation for improving SMEs' performances: a case study of Lagos State, Nigeria. J Knowl Econ. https://doi.org/10.1007/s13132-022-00961-8
118. Popovič A, Puklavec B, Oliveira T (2019) Justifying business intelligence systems adoption in SMEs: impact of systems use on firm performance. Ind Manag Data Syst 119(1):210–228. https://doi.org/10.1108/IMDS-02-2018-0085
119. Wee M, Scheepers H, Tian X (2023) The role of leadership skills in the adoption of business intelligence and analytics by SMEs. Inf Technol People 36(4):1439–1458. https://doi.org/10.1108/ITP-09-2021-0669
120. Zoubi M, ALfaris Y, Fraihat B, Otoum A, Nawasreh M, ALfandi A (2023) An extension of the diffusion of innovation theory for business intelligence adoption: a maturity perspective on project management. Uncertain Supply Chain Manag 11(2):465–472
121. Naznen F, Lim WL (2023) Conceptualizing business intelligence (BI) adoption in SME to gain competitive advantage: effects of organizational mindfulness, inter-organizational relationship and technology orientation. In: Al-Sharafi MA, Al-Emran M, Al-Kabi MN, Shaalan K (eds) Proceedings of the 2nd international conference on emerging technologies and intelligent systems, ICETIS 2022. Lecture notes in networks and systems, vol 584. Springer, Cham, pp 90–100. https://doi.org/10.1007/978-3-031-25274-7_8
122. Aini Q, Harahap EP, Faradilla F (2019) The Effects of Sales Reports Business Intelligence on Employee Performance. APTISI Transactions on Management (ATM) 4(1):83–91. https://doi.org/10.33050/atm.v4i1.1205
123. Mbima D, Tetteh FK (2023) Effect of business intelligence on operational performance: the mediating role of supply chain ambidexterity. Modern Supply Chain Res Appl 5(1):28–49. https://doi.org/10.1108/MSCRA-08-2022-0020
124. Qaffas AA, Ilmudeen A, Almazmomi NK, Alharbi IM (2023) The impact of big data analytics talent capability on business intelligence infrastructure to achieve firm performance. Foresight 25(3):448–464. https://doi.org/10.1108/FS-01-2021-0002
125. Torres R, Sidorova A (2019) Reconceptualizing information quality as effective use in the context of business intelligence and analytics. Int J Inf Manag 49:316–329. https://doi.org/10.1016/j.ijinfomgt.2019.05.028
126. Almtiri Z, Miah SJ, Noman N (2023) Impact of business analytics and decision support systems on E-commerce in SMEs. In: Hsu CH, Xu M, Cao H, Baghban H, ShawkatAli ABM (eds) Big Data intelligence and computing. DataCom 2022. Lecture notes in computer science, vol 13864. Springer, Singapore, pp 344–361. https://doi.org/10.1007/978-981-99-2233-8_25
127. Daradkeh M (2023) The nexus between business analytics capabilities and knowledge orientation in driving business model innovation: the moderating role of industry type. Informatics 10:1–23. https://doi.org/10.3390/informatics10010019
128. Kabiraj S, Joghee S (2023) Improving marketing performance: how business analytics contribute to digital marketing. Int J Technol Innov Manag 3(1):9–18
129. Schuetz CG, Schrefl M (2023) Conceptualizing analytics: an overview of business intelligence and analytics from a conceptual-modeling perspective. In: Vogel-Heuser B, Wimmer M (eds) Digital transformation. Springer, Berlin, Heidelberg, pp 311–336. https://doi.org/10.1007/978-3-662-65004-2_13
130. Choi J, Yoon J, Chung J, Coh B-Y, Lee J-M (2020) Social media analytics and business intelligence research: a systematic review. Inf Process Manage 57(6):1–18. https://doi.org/10.1016/j.ipm.2020.102279
131. Hu Y, Xu A, Hong Y, Gal D, Sinha V, Akkiraju R (2019) Generating business intelligence through social media analytics: measuring brand personality with consumer-, employee-, and firm-generated content. J Manag Inf Syst 36(3):893–930. https://doi.org/10.1080/07421222.2019.1628908
132. Kanan T, Mughaid A, Al-Shalabi R, Al-Ayyoub M, Elbes M, Sadaqa O (2023) Business intelligence using deep learning techniques for social media contents. Clust Comput 26:1285–1296. https://doi.org/10.1007/s10586-022-03626-y
133. Kurnia PF (2018) Business intelligence model to analyze social media information. Procedia Comput Sci 135:5–14. https://doi.org/10.1016/j.procs.2018.08.144
134. Wittwer M, Reinhold O, Alt R, Jessen F, Stüber R (2017) Social media analytics using business intelligence and social media tools—differences and implications. In: Abramowicz W, Alt R, Franczyk B (eds) Business information systems workshops. BIS 2016. Lecture notes in business information processing, vol 263. Springer, Cham, pp 252–259. https://doi.org/10.1007/978-3-319-52464-1_23
135. Al-Okaily A, Teoh AP, Al-Okaily M (2023) Evaluation of data analytics-oriented business intelligence technology effectiveness: an enterprise-level analysis. Bus Process Manag J 29(3):777–800. https://doi.org/10.1108/BPMJ-10-2022-0546
136. Agarwal R, Gupta BK, Sharma R (2022) Big data analytics for business intelligence as a service. International Research Journal of Modernization in Engineering Technology and Science 4(6):66–72
137. Guru SK (2023) Influence of big data analytics on business intelligence. In: Sharma V, Maheshkar C, Poulose J (eds) Analytics enabled decision making. Palgrave Macmillan, Singapore, pp 45–58. https://doi.org/10.1007/978-981-19-9658-0_3
138. Duan Y, Fu G, Zhou N, Sun X, Narendra NC, Hu B (2015) Everything as a service (XaaS) on the cloud: origins, current and future trends. In: 2015 IEEE 8th international conference on cloud computing, pp 621–628. https://doi.org/10.1109/cloud.2015.88
139. Zheng Q, Chen J, Zhang R, Wang HH (2020) What factors affect Chinese consumers' online grocery shopping? Product attributes, e-vendor characteristics and consumer perceptions. China Agric Econ Rev 12(2):193–213. https://doi.org/10.1108/caer-09-2018-0201
140. McAfee A, Brynjolfsson E (2012) Big data: the management revolution. Harv Bus Rev 90:59–68
141. BoydCrawford DK (2012) Critical questions for big data. Inf Commun Soc 15(5):662–679. https://doi.org/10.1080/1369118x.2012.678878
142. Sivarajah U, Kamal MM, Irani Z, Weerakkody V (2017) Critical analysis of Big Data challenges and analytical methods. J Bus Res 70:263–286. https://doi.org/10.1016/j.jbusres.2016.08.001
143. Verhoef PC, Kooge E, Walk N (2016) Creating value with big data analytics: making smarter marketing decisions. Routledge, London
144. Balachandran BM, Prasad S (2017) Challenges and benefits of deploying big data analytics in the cloud for business intelligence. Procedia Comput Sci 112:1112–1122. https://doi.org/10.1016/j.procs.2017.08.138
145. Duan L, Xu LD (2012) Business intelligence for enterprise systems: a survey. IEEE Trans Ind Inf 8(3):679–687. https://doi.org/10.1109/tii.2012.2188804
146. Sun Z, Sun L, Strang K (2016) Big Data analytics services for enhancing business intelligence. J Comput Inf Syst 58(2):162–169. https://doi.org/10.1080/08874417.2016.1220239
147. Hair JF, Hult GTM, Ringle CM, Sarstedt M (2022) A primer on partial least squares structural equation modeling (PLS-SEM), 3rd edn. Sage, New York
148. Fornell C, Larcker DF (1981) Evaluating structural equation models with unobservable variables and measurement error. J Mark Res 18(1):39–50. https://doi.org/10.2307/3151312
149. Henseler J, Ringle CM, Sarstedt M (2015) A new criterion for assessing discriminant validity in variance-based structural equation modeling. J Acad Mark Sci 43(1):115–135. https://doi.org/10.1007/s11747-014-0403-8
150. Hair JF, Risher JJ, Sarstedt M, Ringle CM (2019) When to use and how to report the results of PLS-SEM. Eur Bus Rev 31(1):2–24. https://doi.org/10.1108/EBR-11-2018-0203
151. Painuly S, Sharma S, Matta P (2021) Big Data driven E-commerce application management system. 2021 6th international conference on communication and electronics systems (ICCES), pp 1–5. https://doi.org/10.1109/icces51350.2021.9489108
152. Ghandour A (2015) Big data driven e-commerce architecture. Int J Econ Commerce Manag 3(5):940–947

153. Yu R, Wu C, Yan B, Yu B, Zhou X, Yu Y, Chen N (2023) Analysis of the impact of Big Data on E-commerce in cloud computing environment. Complexity. https://doi.org/10.1155/2021/5613599
154. Zhao Y, Zhou Y, Deng W (2020) Innovation mode and optimization strategy of B2C E-commerce logistics distribution under Big Data. Sustainability 12(8):1–13. https://doi.org/10.3390/su12083381
155. Gao Y (2021) Big Data analysis on E-commerce platform. In: Proceedings of the 2021 international conference on economic development and business culture (ICEDBC 2021), pp 191–195
156. Ferreira T, Pedrosa I, Bernardino J (2017) Business intelligence for E-commerce: survey and research directions. Recent Adv Inf Syst Technol 10:215–225. https://doi.org/10.1007/978-3-319-56535-4_22
157. Azhagan CT, Thamizharasi S (2018) A study on the role of business intelligence in E-commerce solutions. Int J Res Eng IT Soc Sci 08(5):176–181
158. Bhuvaneswari R, Natarajan P (2018) Business intelligence-A tool for robust E-Commerce. ZENITH Int J Multidiscip Res 8(9):165–180
159. Pan C-L, Bai X, Li F, Zhang D, Chen H, Lai Q (2021) How business intelligence enables e-commerce: breaking the traditional e-commerce mode and driving the transformation of digital economy. In: 2021 2nd international conference on e-commerce and internet technology (ECIT), pp 1–5. https://doi.org/10.1109/ecit52743.2021.00013.
160. Cai M, Luo J (2020) Influence of COVID-19 on manufacturing industry and corresponding countermeasures from supply chain perspective. J Shanghai Jiaotong Univ (Science) 25(4):409–416. https://doi.org/10.1007/s12204-020-2206-z
161. Ahmed A, Bhatti SH, Gölgeci I, Arslan A (2022) Digital platform capability and organizational agility of emerging market manufacturing SMEs: the mediating role of intellectual capital and the moderating role of environmental dynamism. Technol Forecast Soc Chang 177:1–13. https://doi.org/10.1016/j.techfore.2022.121513
162. Ratten V (2020) Coronavirus and international business: an entrepreneurial ecosystem perspective. Thunderbird Int Bus Rev 62(5):629–634. https://doi.org/10.1002/tie.22161
163. Thukral E (2021) COVID-19: small and medium enterprises challenges and responses with creativity, innovation, and entrepreneurship. Strateg Chang 30(2):153–158. https://doi.org/10.1002/jsc.2399
164. Terziovski M (2010) Innovation practice and its performance implications in small and medium enterprises (SMEs) in the manufacturing sector: a resource-based view. Strateg Manag J 31(8):892–902. https://doi.org/10.1002/smj.841
165. Lin F-J, Lin Y-H (2016) The effect of network relationship on the performance of SMEs. J Bus Res 69(5):1780–1784. https://doi.org/10.1016/j.jbusres.2015.10.055
166. Walsh J, Nguyen TQ, Hoang T (2023) Digital transformation in Vietnamese SMEs: managerial implications. J Internet Digit Econ. https://doi.org/10.1108/JIDE-09-2022-0018
167. Grant CA, Wallace LM, Spurgeon PC (2013) An exploration of the psychological factors affecting remote e-worker's job effectiveness, well-being and work-life balance. Empl Relat 35(5):527–546. https://doi.org/10.1108/er-08-2012-0059
168. Xiao Y, Becerik-Gerber B, Lucas G, Roll SC (2021) Impacts of working from home during COVID-19 pandemic on physical and mental well-being of office workstation users. J Occup Environ Med 63(3):181–190. https://doi.org/10.1097/JOM.0000000000002097
169. Adisa TA, Aiyenitaju O, Adekoya OD (2021) The work–family balance of British working women during the COVID-19 pandemic. Journal of Work-Applied Management 13(2):241–260. https://doi.org/10.1108/JWAM-07-2020-0036
170. Möhring K, Naumann E, Reifenscheid M, Wenz A, Rettig T, Krieger U, Friedel S, Finkel M, Cornesse C, Blom AG (2021) The COVID-19 pandemic and subjective well-being: longitudinal evidence on satisfaction with work and family. Eur Soc 23(1):S601–S617. https://doi.org/10.1080/14616696.2020.1833066
171. Suh A, Lee J (2017) Understanding teleworkers' technostress and its influence on job satisfaction. Internet Res 27(1):140–159. https://doi.org/10.1108/intr-06-2015-0181
172. Eddleston KA, Mulki J (2015) Toward understanding remote workers' management of work-family boundaries: the complexity of workplace embeddedness. Group Org Manag 42(3):346–387. https://doi.org/10.1177/1059601115619548
173. Allen TD, Johnson RC, Kiburz KM, Shockley KM (2013) Work-Family Conflict and Flexible Work Arrangements: Deconstructing Flexibility. Pers Psychol 66(2):345–376. https://doi.org/10.1111/peps.12012
174. Hjelmar U (2019) The institutionalization of public sector innovation. Public Manag Rev 23(1):53–69. https://doi.org/10.1080/14719037.2019.1665702
175. Leonardi P, Treem JW (2020) Behavioral visibility: a new paradigm for organization studies in the age of digitization, digitalization, and datafication. Organ Stud 41(12):1601–1625. https://doi.org/10.1177/0170840620970728
176. Todisco L, Tomo A, Canonico P, Mangia G, Sarnacchiaro P (2021) Exploring social media usage in the public sector: Public employees' perceptions of ICT's usefulness in delivering value added. Socioecon Plann Sci 73:1–28. https://doi.org/10.1016/j.seps.2020.100858
177. Du X, Liu B, Zhang J (2019) Application of business intelligence based on big data in e-commerce data analysis. In: 2019 high performance computing and computational intelligence conference, pp 1–7
178. Padberg M (2015) Big Data and Business Intelligence: a data-driven strategy for e-commerce organizations in the hotel industry. Master in Business Administration and Business Information Management. University of Twente the Netherlands
179. Yang Y, Gong Y, Land LPW, Chesney T (2020) Understanding the effects of physical experience and information integration on consumer use of online to offline commerce. Int J Info Manag 51:1–18. https://doi.org/10.1016/j.ijinfomgt.2019.102046
180. Hoang TDL, Nguyen HK, Nguyen HT (2021) Towards an economic recovery after the COVID-19 pandemic: Empirical study on electronic commerce adoption of small and medium enterprises in Vietnam. Manag Mark 16(1):47–68. https://doi.org/10.2478/mmcks-2021-0004
181. Alsaig A, Alagar V, Ormandjieva O (2018) A critical analysis of the V-model of Big Data. In: 2018 17th IEEE international conference on trust, security and privacy in computing and communications/12th IEEE international conference on Big Data science and engineering (TrustCom/BigDataSE), pp 1809–1813. https://doi.org/10.1109/TrustCom/BigDataSE.2018.00273
182. Kabango CM, Asa AR (2015) Factors influencing e-commerce development: implications for the developing countries. Int J Innov Econ Dev 1(1):64–72. https://doi.org/10.18775/ijied.1849-7551-7020.2015.11.2006
183. Hoskisson RE, Eden L, Lau CM, Wright M (2000) Strategy in emerging economies. Acad Manag J 43(3):249–267. https://doi.org/10.2307/1556394
184. Davis DF, Golicic SL, Boerstler CN (2010) Benefits and challenges of conducting multiple methods research in marketing. J Acad Mark Sci 39(3):467–479. https://doi.org/10.1007/s11747-010-0204-7

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