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Business analytics competencies in stabilizing firms' agility and digital innovation amid COVID-19

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A B S T R A C T

Digital innovation is not a technology in itself but businesses' ability to exploit digital technology to resolve outmoded problems. Digital innovation is leveraging improvements or innovating technology to reimagine business practice. The Coronavirus disease 2019 exerted enormous effects on people's physical and psychological health. In addition, this pandemic adversely affected the global economy, from sole proprietors to multinational firms. However, such an effect did not hinder versatile products, services, and upgraded versions of technologies. Modern firms rely heavily on available data sets to make decisions through analytics. Manufacturing is one of the most dynamic industries due to market pressures and continually changing customer demands. This study examines the relationship between business analytics competencies and digital innovation and explores the mediating role of absorptive capacity and firm agility. Data are collected from 493 managers of manufacturing firms and analyzed by using structural equation modeling through smartPLS. Results reveal a positive relationship between business analytics competence and digital innovation mediated by absorptive capacity and firm agility. With its theoretical contributions, this study can initiate practical research outcomes in manufacturing firms.

Introduction

Digitalizing business across various industries empowered new digital technologies such as big data analytics, The Internet of Things (IoT), cloud computing, and artificial intelligence. Firms can flourish by integrating transformation through digital innovation to improve their performance. To digitalize their products or services, modern firms must integrate new digital solutions, such as market intelligence software that uses innovative technology to identify trends among target customers, which helps businesses customize their products and services accordingly. For example, in South Korea, Tesco adopted a virtual grocery mobile application to enable customers to purchase without visiting the store (Khin & Ho, 2019). Business analytic competence (BAC) denotes "the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand it's business and market and make timely business decisions" (Omar et al., 2019).

The concept of digital innovation has attained academic attention in recent decades. Innovation is beneficial for collaboration among professionals to eliminate social and technological boundaries. Innovation integrates diverse streams of knowledge and business analytics competencies, which is a prerequisite for developing and establishing product/service innovation. Firms with solid business analytics competencies, knowledge management, and agility can easily attain innovation. Knowledge management theories suggest that a firm's absorptive capacity can be a unique skill to achieve innovation (Khan & Tao, 2022). Although numerous innovation antecedents have been highlighted in the literature, minimal research shows the interplay between business analytics competencies and digital innovation through absorptive capacity and firm agility. Absorptive capacity can be a pertinent predictor of innovation, but this relationship can be more robust when bridged through firm agility. The current study investigates the effect of business analytic competence on innovation through core mediators such as absorptive capacity and firm agility, a less explored area in the current literature.

Since its origin, innovation has shown the invasive use of digital technologies and highly progressive endeavors at digitization, which have sparked the newest generation of organizational production mechanisms (Khan et al., 2022; Nylen & Holmstrom, 2015). Innovation has filled all spheres of economic and social life. Various factors connected to innovation have been highlighted, including

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transformations and agility (Kalaignanam et al., 2021), management information systems (Yoo et al., 2012), improved digital product and service innovation (Hinings et al., 2018), organizational change (Johnson et al., 2006), and knowledge management (Shahzad et al., 2020). Among these significant factors, the most critical is absorptive capacity, which has been largely overlooked.

The enterprise's ability to integrate and imitate new knowledge expanded from external sources is called "absorptive capacity" (Cohen & Levinthal, 1990), or the outcome of prior knowledge and organizational experiences. Furthermore, this concept was framed primarily as a cumulative individual pre-existing knowledge about corporate processes and technology. Prior knowledge helps understand related technologies and acquire new information, and in addressing related and unrelated trends that enable firms to deal with unexpected and divergent issues, such as current and potential markets or technological development. Prior knowledge addresses several criticisms, affects internal R&D intensity, and depends on the conducive learning environment within an organization (Lane et al., 2006).

Previous literature showed that absorptive capacity is the most significant determinant of organizational learning, knowledge transfer, and innovations resulting from external knowledge. In addition, absorptive capacity is positively related to strategic business performance and supports its connection with innovations (Tsai, 2001), knowledge transfer within the organization, and inter-organizational learning (Hindasah & Nuryakin, 2020). The present study unveils one of the novel areas for practitioners and researchers to achieve digital innovation through business analytics competencies, organizational absorptive capacity, and firm agility. Given the significance of business analytics competencies, this study first investigates one of the least discussed domains in the current literature; how do firms achieve digital innovation through alternative combinations of dynamic capabilities? How business analytics competencies predict a strong foundation for establishing digital innovation is also explored. Second, the mediating role of absorptive capacity and firm agility is also evaluated. The rest of the paper is organized as follows. Theoretical background and hypotheses development are discussed. Then, the research methodology is explained before the analysis. The final section highlights the discussion and conclusion by explaining its significant contribution to theory and practice.

Theoretical underpinning

Dynamic capability view (DCV)

This theory extends the domains of renowned resource-based view (RBV) (Wernerfelt, 1984), adding that resources are sufficient and capabilities are vital to enhance organizational performance (Denrell & Powell, 2016; Teece, 2017). Thus, on the notions of DCV, this study posits that the proposed relationships, that is, analytics competencies, are needed for modern firms to excel in their respective fields.

Literature review and hypotheses

Business analytics competencies (BAC) and digital innovation (DINN)

BAC is a transformation, a collection of different technologies and practices, that enhances a firm's ability to add knowledge and information and assimilate it for better performance (Flatten et al., 2011). This study investigates BAC with its three implications: objects, operations, and knowledge. The impact of BAC on performance has been measured, but few studies emphasize it with innovation in a single framework. Meanwhile, innovation is monitored continuously to anticipate dynamic changes (Pitt & Clarke, 1999). Therefore, innovation is associated with customers' demands (Rietzschel et al., 2007). This study cumulatively measures and analyzes the effect of BAC on digital innovation.

Customers can be driven toward innovation by the firm's innovative ideas, services, and products, that, as a result of the BAC can attract customers, as in the case of smartphone technologies, the latest software implications, and AI-based computing treatments in various sectors of an economy. Another view of resource orientation and dynamic capability suggests that innovation can be achieved by combining skills, resources, and technologies. Therefore, in the given context, innovation can be the outcome of BAC, which combines vital ingredients of objects, knowledge, and operations. Dynamic changes and responses, transfer of information skills, and knowledge are incorporated to result in innovation (Paladino, 2007). Grant (1996) argued that tactics and attributes of resources backed by competencies can result in innovation. Through BAC, modern firms can precisely predict market requirements and evolve their structures and strategies accordingly and disclose future customer aspirations (Gupta & Duggal, 2021). Extant literature identified the role of IT infrastructure in simplifying new knowledge exploration and exploitation for innovation purposes. Irfan et al. (2019) validated the positive influence of IT capabilities on organizational agility. Therefore, the present study proposes the idea of innovation as an outcome of BAC, which can produce all the essential elements. Thus, the following hypothesis is proposed;

H1: *The BAC of a firm positively affects digital innovation.*

Business analytics competencies (BAC), organizational absorptive capacity (OAC), and firm agility (FA)

Organizational resources are not limited to physical; they can also be human, financial, and technological, among others. Integrated capabilities can improve organizational performance (Cegarra-Navarro & Dewhurst, 2006; Grant & Verona, 2015). Additionally, such capabilities can outlay a design to meet external and internal organizational outcomes (Felin & Foss, 2009). Modern businesses rely heavily upon core competencies to improve organizational performance (Qu et al., 2021). Business analytics has been explained differently, such as an act by knowledgeable executives that helps them collect consistent data and make the right decisions to run a smooth organization (Rialti et al., 2019; Tabesh et al., 2019). BAC is also considered a transformation, a collection of different technologies and practices, that can enhance a firm's ability to add and assimilate knowledge and information for better performance (Mandal, 2019).

OAC involves different learning approaches to enhance a firm's performance, such as exploitative, transformative, and exploratory learning. OAC is divided into two dimensions and subsets (Todorova & Durisin, 2007; Zahra & George, 2002), namely potential and realized absorptive capacities. Assimilation and acquisition of knowledge can be linked to potential absorptive capacity while the firm's ability to transform and assimilate this knowledge into operations can be called realized absorptive capacity. These distinctions are apparent in literature (Ali et al., 2016; Camisón & Forés, 2010; Khan & Tao, 2022). Acquisition and assimilation of the latest and market-based knowledge turn into productivity in the long term, whereas firms that solely focus on exploitations may fail to sustain the pace of organizational performance (Volberda et al., 2010).

Finally, FA can transform unpredictable customer situations into profitability in a highly competitive and dynamic environment (Goldman et al., 1995) and create opportunities for changes (Mikalef & Pateli, 2017; Yusuf et al., 1999). Al-Nimer (2019) stated that FA helps upgrade organizational processes and technologies as per the market needs. Moreover, this ability can make an organization rediscover, review, and respond to dynamic changes (Doz & Kosonen, 2010).

Extant literature reflects BAC as a subset of IT capabilities (Khin & Ho, 2019). BAC can combine analytics resources and processes acquired by a firm with expertise, operations, and processes (Tippins & Sohi, 2003). BAC is explained with its three dimensions, namely, objects, operations, and knowledge. For modern firms, competitive advantage is the primary concern that may be triggered through the outcomes of BAC, which involves all the essential elements that result in OAC and digital innovation. With the above crucial components, BAC can result in OAC and FA. Handled proficiently and effectively, BAC provides the much-needed information required by a firm (Wang et al., 2019); statistical and real-time information not only solves contemporary issues but also enhances its knowledge absorption capacity and increases its agility compared with its competitors. Thus, the following hypotheses are proposed;

H2: *BAC positively affects the OAC of manufacturing firms.*

H3: *BAC positively affects the FA of manufacturing firms.*

Firm's agility (FA) and digital innovation (DINN)

The concept of agility is relatively longstanding, given its introduction in 1991 in the Iacocca Institute, United States (Kale et al., 2019). Agility is a swift response to market trends based on the firm's capabilities, and a result of dynamic changes in response to market needs. FA is generally examined in the primary area of IT and operations, and its effect on firm performance is the standard theme of most academic research. Swafford et al. (2006) and Khan et al. (2020) linked value chain agility with business performance. Chen (2019) argued that dynamic market changes determine the speed of FA, which may not directly influence firms' financial performance. However, Degroote & Marx (2013) found a positive association between FA and the firm's performance in the manufacturing industry.

FA requires three meta-skills for its successful implementation, namely, leadership unity, resource fluidity, and strategic sensitivity; the mix of these skills makes an organization agile and proactive (Wang et al., 2022; Kumkale, 2016). Subsequently, the role of FA with similar organizational outcomes has been well explored. According to Kumkale (2016), FA results in a competitive advantage. Modern firms have to keep an eye on external changes and respond promptly. The rapid response to market changes swiftly makes a firm agile and improves performance. Thus, FA can result in DINN, either speeding up its process or establishing its base. The present study separates itself from previous literature by stating that FA is an enabler of DINN; FA enables a firm to be quickly equipped with the needed resources and capabilities to achieve DINN. Thus, the following hypotheses are proposed;

H4: *FA positively affects the DINN of manufacturing firms.*

H5: *FA mediates the relationship between BAC and DINN.*

Organizational absorptive capacity (OAC) and digital innovation (DINN)

OAC emphasizes the upgrading of systems, knowledge, capabilities, and resources to "absorb" pressure from concerned stakeholders (Todorova & Durisin, 2007). Innovation assures competitiveness, social benefits, and community well-being (Caputo et al., 2019). Previous literature highlighted the significant role of OAC in achieving innovation and competitiveness (Shahzad et al., 2020). Adopting innovative and digital technologies affects operational efficiency, and thereby corporate innovation (Shahzad et al., 2022a; Teece, 2017). However, the indirect relationship between OAC and DINN has not been well considered. For example, Overby et al. (2006) found a relationship between knowledge reach and agility level for organizational performance. Mao et al. (2015) studied the relationship between IT and knowledge capabilities on FA. In addition, FA has been investigated to achieve versatile outcomes, such as meeting customer requirements, managing new products strategically, and completing organizational tasks on time (Jin et al., 2022; Corte-Real et al., 2017).

OAC develops a proactive conception to respond to dynamic changes for better performance. The present study follows Kale et al. (2019), who linked OAC to agility. Consequently, the OAC and FA relationship can further be explained with the former's sub-dimensions, namely, acquisition and application (Shahzad et al., 2022b).

Skills and capabilities are vital to gaining agility and improved performance. In this era of globalization and digital technologies, companies strive to attain up-to-date and timely information through analytics, which helps them alter their products and services (digital innovation) as needed. Thus, the following hypotheses are proposed;

H6: *OAC positively affects DINN.*

H7: *OAC mediates the relationship between BAC and DINN.*

The above hypotheses can be shown in a conceptual framework in Fig. 1 below.

Methodology

Sample and data collection

The study sample included employees of manufacturing firms in Pakistan. Employees involved in strategic decision-making and management with appropriate information to implement the strategies were selected given that they play a critical role in attaining and sharing knowledge (Yusr et al., 2017). Data to validate the relationship between constructs were collected through a questionnaire adapted from literature, which has used a similar approach because employees signify a company as a whole (Ooi, 2014). A total of 1500 emails were sent through a web link containing the questionnaire related to the study constructs and a cover letter. Employees' email addresses were collected through an email extracting software used on the company's website. The response rate was approximately 37.8%. The return responses were 567 questionnaires. After removing incomplete and missing response questionnaires to avoid biases, 493 questionnaires remained and were used for final analysis. Table 1 presents the details of demographics. The data collection continued from September to December 2021.

Constructs measurement

The primary constructs in this study are Business analytical competence (BAC), Organizational absorptive capacity (OAC), Firm Agility (FA), and Digital Innovation (DINN). The survey instrument to measure these constructs was adapted from previous studies. BAC and OAC are higher-order constructs with subdimensions, which in turn have different items. By running the initial partial least squares (PLS) algorithm, we scored latent variables as items for BAC and OAC to convert into second-order constructs.

Business analytics capability

Business analytics competence is a high-order construct with three subdimensions: (1) BA Objects (BAOB) has five items; (2) BA Operations (BAOP) has six items; and BA Knowledge (BAKN) has four items. BAOB measures the firm's competency in hardware, software, and personnel support related to business analytics. BAOP measures the firm's implementation of business analytics processes, work-related routines, and practices. BAKN measures the extent to which a firm has technical knowledge about business analytics systems and applications. A 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was adapted to collect the information.

Organizational absorptive capacity (OAC)

OAC measures the firm's ability to obtain, assimilate, transform, and exploit external knowledge to create value (Liu et al., 2014). OAC is adapted from measures developed by Wang et al. (2019). The scale consists of 13 items and four subdimensions; (1) Acquisition (PACAQ) denoted by Potential absorptive capacity (PAC) has four items, measuring the firm's ability to identify and obtain critical knowledge essential for its operations; (2) Assimilation (PACAS) have three

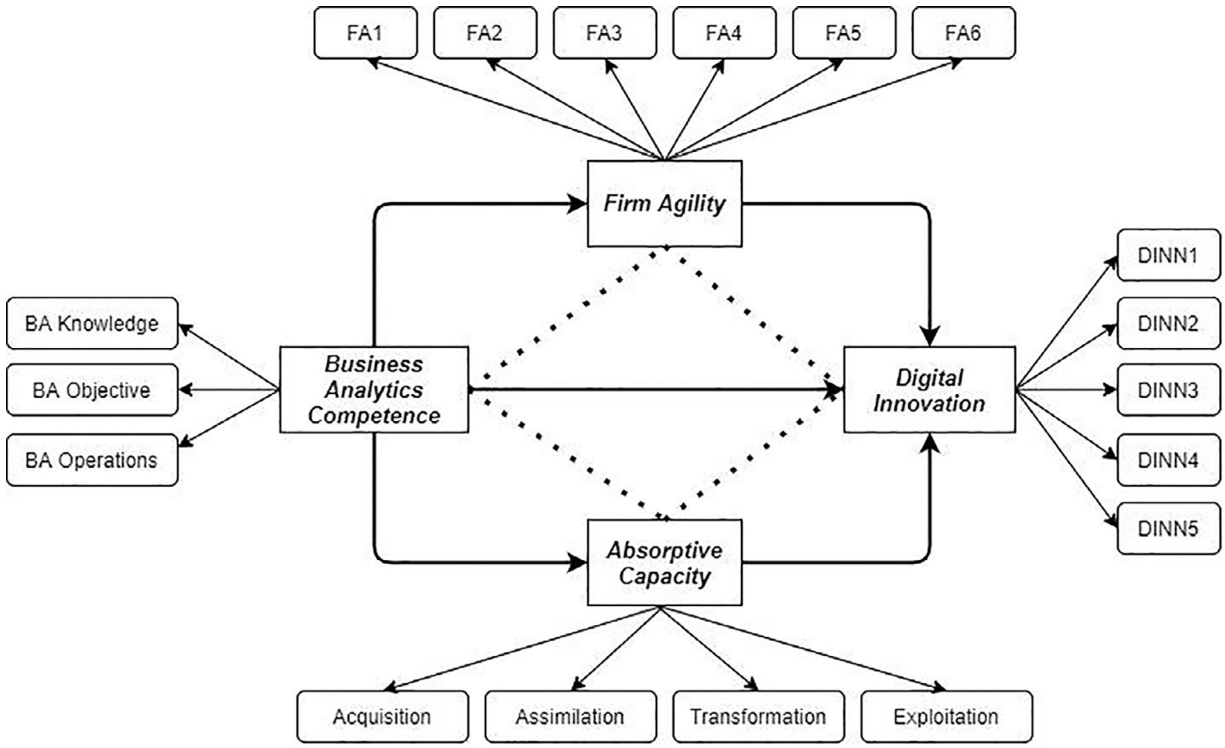

Fig. 1. Conceptual framework.

items, measuring the firm's ability to absorb and understand the acquired knowledge; (3) Transformation (RACT) related to realized absorptive capacity (RAC) has three items, measuring the firm's ability to combine new with existing knowledge; and (4) Exploitation (RACE) has three items, measuring the firm's ability to use the acquired knowledge to achieve its objectives. A 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was used to tap participants' responses on absorptive capacity.

Firm's agility

FA refers to the firm's speed of responding to the external environment's dynamic changes (opportunities and threats) (Tallon & Pinsonneault, 2011). How easily can a firm adjust according to unforeseen opportunities and threats in the marketplace? Following Sambamurthy et al. (2003), we used an eight-item scale to tap the responses on three different terms—customer responsiveness, business partnership, and operations. Responsiveness to changes in customer demand, product innovation, and pricing is used to measure customer agility. The adaptiveness of the suppliers' network is used to evaluate the business partnering agility. Lastly, operational agility is measured by the response times to new product launches, expanding the existing market, changing the firm's product mix, and acquiring and implementing new technology. A 5-point Likert scale (1 = strongly Disagree to 5 = Strongly Agree) was used to tap participants' responses on FA.

Table 1
Demographics.

Respondent Profile		(*n* = 493)	
Attributes	Distribution	Frequency	(%)
Gender	Male	281	0.57
	Female	176	0.36
	Prefer not to say	36	0.07
Age (Years)	20 to 29	123	0.25
	30 to 39	198	0.40
	40 to 49	109	0.22
	More than 50	63	0.13
Education	Undergraduate	139	0.28
	Graduate	170	0.34
	Post Graduate	101	0.20
	Others	83	0.17
Managerial Level	Low Level	125	0.25
	Middle Level	222	0.45
	Top Level	146	0.30
Job Experience (Years)	Less than 5	145	0.29
	6 to 10	178	0.36
	11 to 15	123	0.25
	More than 15	47	0.10

Digital innovation (DINN)

To measure DINN, we adopted a 6-items scale developed by Paladino (2007) and used by Khin and Ho (2019). A 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was used to tap participants' responses about DINN.

Data analysis and results

PLS structural equation modeling (SEM) was used for data analysis as suggested by Hair et al. (1995). The main attraction of this technique is that researchers can estimate complicated models with multiple constructs, indicator variables, and structural paths without enforcing data distribution assumptions. PLS-SEM is a causal predictive approach to SEM that accentuates predictions when estimating statistical models, the structure of which is intended to explain causal relationships (Sarstedt et al., 2014). PLS-SEM measures the partial model structures demarcated in a path of the relationship of different variables using Principal Component Analysis (PCA) and original least squares (OLS) regression (Mateos-Aparicio, 2011).

PLS-SEM is advantageous in many ways, working efficiently with small sample size, many constructs, and related questions by calculating the separate OLS regression for measurement and structural models. PLS-SEM also works with abnormal data distributions better than other statistical methods. In terms of statistical power, PLS-SEM ranked top among other analysis methods (Hair et al., 2017), indicating that all the significant relationships in the data are obtained. Table 2 presents the details.

Common method bias (CMB)

The first step in SEM is to evaluate the CMB that arises from errors or biases in measurement methodology (Podsakoff et al., 2003). Data related to this research constructs are collected simultaneously from the same respondents; therefore, CMB may exist. A valid measure to test CMB is the inner VIF developed by Kock (2015), which uses a full collinearity test. Inner VIF is calculated by considering each variable dependent once, and the threshold value is 3.3, as suggested by Kock (2015). All the values of inner VIF, as reported in Table 2, are according to the standard, and hence CMB is not a severe issue in this study.

Measurement model

SEM consists of two different models, namely, measurement and structural. Various validity and reliability measures, such as composite reliability, explain the measurement or outer model. By contrast, the structural model assesses the hypothesized relationship of multiple study constructs based on values such as beta coefficient, t value, and p-value (Higgins, 1995). The measurement model consists of different reliability and validity measures, such as convergent validity, discriminant validity, and internal consistency. Cronbach's alpha confirms the composite reliability and internal consistency. Factor loadings measure the construct validity and average variance extracted to verify the convergent validity. In addition, discriminant validity is measured by the Fornell-larker criterion (Henseler, Ringle, & Sarstedt, 2015).

The effectiveness of the measurement model can be carried out in three steps. First, factor loadings must be evaluated to confirm the reliability of related indexes. Second, overall composite reliability can be assessed by Cronbach's alpha and composite reliability value provided by SEM results. Cronbach's alpha was used to measure the material composite reliability. By contrast, composite reliability is measured by the load index and its error variance. The average variance was extracted to measure the constructs' convergent validity. Table 3 reports the reliability and validity results, where the factor loading of each item surpasses the standard of 0.50. Cronbach's alpha values were also higher than the standard value of 0.70, composite reliability, and average variance extracted (AVE) greater than the minimum standard values. These values indicate the goodness of the measurement model and higher composite reliability (Nunnally & Bernstein, 1994). Cronbach's alpha results show a high internal consistency. Overall, the measurement model results confirm the reliability and validity of internal consistency.

Discriminant validity

Discriminant validity measures the differences in the study constructs in the context of the same structural model (Hair et al., 2019). Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratio are the two popular measures used to confirm discriminant validity.

Fornell-Larcker Criterion. This technique measures the AVE's square root, which must be greater than the inter-construct correlation to confirm discriminant validity (Henseler, Ringle, & Sarstedt, 2015). The research model's shared variance is less than the AVE's square root. Table 4 reports the Fornell-Larcker criterion results and all the values of the square root of AVE are greater than the inter-construct correlation in the same column.

HTMT Ratio: Henseler et al. (2014) suggested another measure to test the discriminant validity. Innovation in the context of PLS-SEM and based on the Monte Carlo simulation, HTMT is the ratio between trait correlations and trait correlations. HTMT ratio is considered a more accurate or better measure of discriminant validity. The threshold HTMT value is 0.90, as recommended by (Henseler et al., 2015). Table 5 reports the HTMT ratio results, and all the values are lower than the threshold of 0.90, confirming the discriminant validity.

Table 2
Inner VIF (Common method bias).

	ACQ	ASSIM	BAKN	BAOB	BAOP	DINN	EXP	FA	TRAN
ACQ		2.112	2.119	2.126	2.136	2.051	2.086	2.140	1.894
ASSIM	1.537		1.532	1.547	1.543	1.543	1.554	1.482	1.519
BAKN	1.587	1.570		1.592	1.575	1.544	1.539	1.589	1.572
BAOB	2.363	2.360	2.375		2.088	2.382	2.333	2.242	2.370
BAOP	2.806	2.790	2.803	2.518		2.697	2.771	2.510	2.784
DINN	2.360	2.429	2.389	2.466	2.327		2.334	2.448	2.437
EXP	1.848	1.885	1.844	1.871	1.873	1.801		1.871	1.876
FA	2.534	2.287	2.526	2.542	2.342	2.557	2.443		2.511
TRAN	1.840	2.008	2.039	2.066	2.048	2.052	2.035	2.076	

Structural model

The second model in PLS-SEM is a structural model that explains the hypothesized relationship between study constructs. Path coefficient indicates an independent variable's change into a dependent variable, and the path value ranges between −1 to +1. Table 6 illustrates the hypothesis testing results. BAC is positively and significantly associated with OAC as indicated by the coefficient value and sign (β = 0.705), while t value and p-value (t-stat = 13.635, $p < 0.001$) confirm the significance of the relationship. Similarly, the relationship between BAC and FA is positive, as depicted by the coefficient sign and value (β = 0.754), and this relationship is significant at the 1% level, as shown by (t-stat = 12.234, $p < 0.001$). According to the coefficient value (β = 0.532), absorptive capacity is positively related to digital innovation, and this relationship is significant as indicated by t value and p-value (t-stat = 6.656, $p < 0.001$). Results also show that FA is positively and significantly related to DINN.

H5 and H6 illustrate the mediation effects of OAC and FA between BA and DINN. Results for OAC are significant, confirming its mediation effect between BA and DINN as proposed in H5 (β = 0.375, t-stat = 5.254, and $p < 0.010$). Furthermore, results indicate that the relationship between BA and DINN is mediated by FA. This relationship is significantly positive, as indicated by the different statistical values (β = 0.203, t-stat = 3.503, and $p < 0.001$).

Discussion and conclusion

This study examines the impact of business analytics competence on digital innovation through organizational absorptive capacity and firm agility. Absorptive capacity cultivated by business analytics competence enhances responsiveness (firm agility) to dynamic changes in the marketplace and results in digital innovation.

Findings show that BAC positively influences OAC, thereby supporting H1. BAC enhances a firm's capability in acquiring and combining new learning with existing knowledge than transforming and exploiting these to achieve organizational objectives. The findings are in line with existing literature that similarly reports IT competencies enhance the OAC (Wang et al., 2019). Further results indicate a positive relationship between OAC and FA, confirming H2. These findings demonstrate that knowledge reach and richness, learning capabilities, and strategic learning enhance the FA and improve its speed to change behavior according to market requirements (Kale et al., 2019).

H3 is also supported by the results that FA positively affects DINN, confirming the outcomes (Côrte-Real et al., 2017). FA is considered the primary capability of a firm that enhances the organization's speed to respond to dynamic changes in the environment (changes in customer demand, competition, and products), which results in

Table 3
Reliability and validity of constructs.

Item Codes	Factor Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)	Variance Inflation Factor (VIF)
BA Knowledge		0.910	0.937	0.787	
BAKN1	0.857				2.274
BAKN2	0.901				3.262
BAKN3	0.906				3.308
BAKN4	0.884				2.598
BA Objective		0.906	0.930	0.728	
BAOB1	0.790				1.885
BAOB2	0.850				2.488
BAOB3	0.868				3.087
BAOB4	0.885				3.428
BAOB5	0.870				2.695
BA Operations		0.908	0.929	0.686	
BAOP1	0.738				1.767
BAOP2	0.820				2.224
BAOP3	0.848				2.647
BAOP4	0.860				2.863
BAOP5	0.853				2.786
BAOP6	0.845				2.796
Acquisition		0.884	0.928	0.811	
ACQ1	0.897				2.539
ACQ2	0.905				2.517
ACQ3	0.900				2.428
Assimilation		0.784	0.874	0.699	
ASSIM1	0.810				1.492
ASSIM2	0.843				1.782
ASSIM3	0.854				1.731
Exploitation		0.848	0.908	0.767	
EXP1	0.845				1.903
EXP2	0.889				2.084
EXP3	0.892				2.289
Transformation		0.823	0.894	0.738	
TRAN1	0.858				1.889
TRAN2	0.839				1.762
TRAN3	0.880				1.922
Firm Agility		0.805	0.860	0.508	
FA1	0.621				1.665
FA2	0.659				1.733
FA3	0.757				1.790
FA4	0.790				2.314
FA5	0.697				1.861
FA6	0.737				1.433
Digital Innovation		0.858	0.898	0.637	
DINN1	0.772				1.878
DINN2	0.819				2.117
DINN3	0.806				1.876
DINN4	0.816				2.057
DINN5	0.779				1.748

innovative solutions (innovative products). FA leads the firm toward knowledge collection worldwide and integrates it to fuel continuous innovation. Lastly, the findings report a positive relationship between BAC and DINN, confirming H4 (Aydiner et al., 2019). According to DCV, innovation can be achieved through the combination of skills, resources, and capabilities; therefore, in the given context, we believe that innovation can be the outcome of BAC, which is the combination of vital ingredients of objects, knowledge, and operations. This idea of BAC incorporates dynamic changes and responses, transfer of information skills, and the ability to result in innovation (Paladino, 2007).

Theoretical and practical implications

A post-pandemic business environment presents numerous reasons for manufacturing firms to consider the significant role of BAC and innovation through OAC and FA. Manufacturing firms face colossal competition and must develop new ideas before their

Table 4
Fornell-Larcker criterion (Discriminant validity).

	ACQ	ASSIM	BAKN	BAOB	BAOP	DINN	EXP	FA	TRAN
ACQ	0.901								
ASSIM	0.473	0.836							
BAKN	0.438	0.394	0.887						
BAOB	0.508	0.417	0.406	0.853					
BAOP	0.512	0.417	0.468	0.708	0.828				
DINN	0.608	0.447	0.532	0.568	0.638	0.798			
EXP	0.546	0.424	0.492	0.492	0.448	0.596	0.876		
FA	0.503	0.506	0.458	0.671	0.709	0.601	0.519	0.713	
TRAN	0.642	0.482	0.461	0.494	0.527	0.576	0.523	0.500	0.859

Table 5
Heterotrait-Monotrait ratio HTMT (Discriminant validity).

	ACQ	ASSIM	BAKN	BAOB	BAOP	DINN	EXP	FA	TRAN
ACQ									
ASSIM	0.562								
BAKN	0.486	0.463							
BAOB	0.566	0.494	0.445						
BAOP	0.571	0.494	0.515	0.781					
DINN	0.696	0.545	0.600	0.643	0.722				
EXP	0.628	0.518	0.553	0.560	0.508	0.694			
FA	0.586	0.627	0.526	0.759	0.811	0.714	0.620		
TRAN	0.749	0.600	0.531	0.569	0.606	0.680	0.623	0.603	

Table 6
Hypothesis testing.

	Hypothesized Paths	Coefficient	T-Statistics	P Values
H1	Business Analytics Capability -> Digital Innovation	0.789	11.970	0.000**
H2	Business Analytics Capability -> Absorptive Capacity	0.705	13.635	0.000**
H3	Business Analytics Capability -> Firm Agility	0.754	21.234	0.000**
H4	Firm Agility -> Digital Innovation	0.270	3.677	0.000**
H5	Business Analytics Capability -> Firm Agility -> Digital Innovation	0.203	3.503	0.000**
H6	Absorptive Capacity -> Digital Innovation	0.532	6.656	0.000**
H7	Business Analytics Capability -> Absorptive Capacity -> Digital Innovation	0.375	5.254	0.000**

competitors. The present findings can guide practitioners and academics to shift their focus on generating innovation through BAC, OAC, and FA. Expanding the scope of DCV and RBV, this study concludes that OAC is one of the most neglected areas in recent research to expedite DINN, especially after the pandemic affected the business world. Moving through transition and radical changes after COVID-19, it is equally essential for manufacturing firms to adapt to market changes and develop competencies. To obtain knowledge, transform, and exploit in a post-pandemic business scenario, firms must make decisions based on BAC. Expanding the concurrent discussion on organizational resources, astute capabilities, and dual approach, this study attempts to link BAC to DINN through OAC and FA, a relationship that has not been well considered.

Consequently, the management of manufacturing firms can consider the capabilities perspective, which can result in DINN. The present findings also provide the basis for evaluating innovation beyond the limits of market pressures and customer demands in a post-pandemic business world, as innovation can be linked to an organization's inherent skills and capabilities. Generating innovation is more convenient through OAC and FA in manufacturing firms. This study can managers to be agile and seek capabilities such as OAC and FA, which can ultimately result in DINN. More specifically, the findings can help the firms of developing countries that are not known for innovation. BAC outcomes can prove vital to enhancing a firm's performance.

Limitations

This study is limited to Pakistan manufacturing firms, with high competition and greater demand to accommodate DINN. In future investigations, firms from different sectors can be taken to cross-check this relationship. In addition, manufacturing firms are still developing and still have to go a long way to establish themselves as one of the most innovative industries. The findings can prove interesting if the same framework is used to investigate the relationships in an established industry.

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