

Article

Business Analytics Socio-Technical Perspective in Driving Market Orientation and Absorptive Capacity: Its Impacts on Innovation Ambidexterity

Ari Yanuar Ridwan ^{1,2,*} , Rajesri Govindaraju ¹  and Made Andriani ¹ 

¹ Industrial Engineering Department, Faculty of Industrial Technology, Bandung Institute of Technology, Bandung 40132, Indonesia; rajesri_g@mail.itb.ac.id (R.G.); mdandriani@mail.itb.ac.id (M.A.)

² Industrial Engineering Department, School of Industrial and Systems Engineering, Telkom University, Bandung 40257, Indonesia

* Correspondence: ariyanuar@telkomuniversity.ac.id

Abstract

This study examines the influence of business analytics, social capital, market orientation, and absorptive capacity on innovation ambidexterity in Indonesia's emerging market context. Drawing on the socio-technical perspective and dynamic capabilities views, the study develops a conceptual model and tests it with a disjoint two-stage SEM-PLS approach to examine the hierarchical component model using data from 218 large and medium-sized enterprises. The results show that business analytics significantly enhances social capital and builds socio-technical capabilities. Market orientation positively influences absorptive capacity, and both constructs act as complementary partial mediators. The study advances business analytics and sustainable innovation literature by strategically harnessing business analytics while acknowledging social capital. Some countries have practical manifestations of social capital in their communities that support their innovation activities. Furthermore, firms' business analytics adoption strategy must be tailored to local cultural values to harness economic and social performance. These findings also highlight the critical roles of market orientation and absorptive capacity in selecting insights with high potential utility from the vast data amassed and preserved by business analytics. This relationship, in turn, helps balance the competing activities of exploitative and exploratory to sustain innovation in an emerging market.

Keywords: business analytics; innovation ambidexterity; social capital; market orientation; absorptive capacity; socio-technical perspective



Academic Editors: Yan Yan, Jingjing Zhang and Yinghuan Wang

Received: 3 January 2026

Revised: 9 February 2026

Accepted: 24 February 2026

Published: 27 February 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The significant impact of innovation to sustain economic performance in developed and emerging economies is widely documented in the academic and practical literature [1]. Firms in emerging economies, in contrast to those in developed economies, encounter obstacles related to a dynamic business climate, barriers to market access and financial resources, and a lack of technological and support systems necessary to compete domestically and internationally [2–5]. In these circumstances, as the market environment is changing rapidly, firms should adopt an innovation ambidexterity strategy to develop and sustain a competitive edge [6]. It is known that ambidextrous organizations excel at responding to emerging markets and at selecting the most vital tangible and intangible resources to

compete [7,8]. Innovation ambidexterity has two driving factors—exploitative and explorative innovation, which correspond to incremental and radical innovation, respectively. Exploitative innovation focuses on enhancing existing products or services, while explorative innovation includes the quest for new products or services [9,10]. March [11] argued that organizations need to be ambidextrous—both exploitative and exploratory—to be competitive, though there is a trade-off between exploitative and exploratory activities. In recent years, the notion of ambidexterity has garnered significant attention as a research focus among numerous scholars [12]. While previous research shows that more firms agree that ambidextrous innovation has performance-enhancing benefits, the drivers and mechanisms to sustain exploitative and exploratory innovation activities remain a substantial challenge for firms [13].

On the other hand, business analytics (BA) is considered a strategic approach to augment sustainable innovation capabilities by leveraging current operations and exploring potential initiatives in emerging markets [8,14]. Business analytics is a compilation of technologies, methodologies, and software that involves collecting, curating, and analyzing data from disparate sources to enhance data-driven decision-making [15–19]. Henceforth, this study uses the all-encompassing term business analytics as a unified concept when referring to the related research on business intelligence, business analytics, and big data analytics [20,21]. Using advanced analytics helps firms predict future events, optimize strategies, identify growth opportunities, and stay competitive [15]. Business analytics helps firms create a work environment that facilitates both exploitative and exploratory innovation through data-driven decision-making. A wide range of previous research posits the vital role of business analytics in driving innovation ambidexterity [22]. Despite these, many organizations that have implemented business analytics still encounter challenges in realizing the expected competitive advantage [23]. Nevertheless, a more systemic understanding is needed of the processes involved in how business analytics drives sustainable exploratory and exploitative innovation strategies [24,25].

Hence, three key areas remain unexplored in current research regarding business analytics and innovation ambidexterity. First, existing studies mainly focus on markets with developed economies [26]. Although these studies offer highly valuable insights and potential opportunities, firms in developed countries face a contextually distinct strategic and operational environment compared to their counterparts in developing markets [27]. Information systems research in developed economies often presumes that enterprises can obtain essential skills and technological capabilities to stimulate innovation, a notion that may not hold in emerging economies [28]. Furthermore, firms' business analytics adoption strategy must be tailored to the local cultural values [28] to balance economic and social performances. Research on the swiftly expanding economies of Asia often highlights the significance of robust social networks [29]. Social capital may enhance engagement, coherence, and trust; help companies identify new prospects; facilitate adaptability to changing environments; and be essential for both exploitative and exploratory innovation activities [16]. Since the way organizations' social capital promotes innovation ambidexterity in the implementation of business analytics initiatives in Indonesia has been primarily unexamined, it is crucial to examine whether this social capital constitutes significant drivers or obstacles to firms' business analytics-driven innovation [3,16].

Second, companies need a strategic orientation and a vision for effectively utilizing information from business analytics [30–32]. In meeting this requirement, organizations differ in their strategy selection, reflecting their philosophy on how to conduct business to achieve superior performance [33]. Companies need to be aware of their resources available for innovation and their desired outcomes when deciding on a strategic orientation [33]. Strategic orientation is particularly important for companies in developing countries with

limited technical and financial resources [32]. Companies should select an orientation that aligns with their innovation goals rather than rushing to pursue multiple strategies simultaneously [34]. Market orientation is the most important orientation for competing in emerging economies [32] and is essential for driving innovation in volatile emerging markets [35]. However, previous research has overlooked the mediating role of market orientation [32].

Third, firms need market-related prior knowledge to increase their absorptive capacity [36]. We assert that market orientation and absorptive capacity serve as filters that facilitate the selection of insights with great potential utility from the vast data amassed and preserved by business analytics [32]. Market orientation helps firms focus on the most critical knowledge [32]. This method helps reduce bounded rationality and provides valuable insights for innovation—especially for firms in emerging markets with resource constraints [35]. Business analytics enables market orientation to determine the most efficient and successful strategies for storing and transmitting market information analytics [32]. Market-oriented approaches driven by business analytics capabilities necessitate an additional organizational dynamic capability—absorptive capacity—to adopt an ambidextrous innovation approach [37] comprehensively.

To address these three interrelated research gaps, we developed a model that utilizes the dynamic capability [23] view and the socio-technical perspective [38], to provide a robust theoretical framework [15]. We observe that the process and challenges of developing sufficient business analytics-social capital relationships have largely been overlooked so far. We chose to focus on these constructs to examine the potential benefits of business analytics implementation in dynamic markets in an emerging economy with strong social cultures within its communities. Despite certain constraints on access to managerial and financial support, firms in Indonesia have advantages in community culture that may enhance innovation. While prior research has recognized a positive correlation between business analytics and innovation, no empirical investigation has comprehensively examined the influence of business analytics, social capital, market orientation, and absorptive capacity on amplifying exploratory and exploitative innovation activities. We empirically supported the research model through a survey conducted among 218 large and medium-sized firms in Indonesia across various industrial sectors. The research was divided into several interrelated components. Following the introduction is the theoretical background and hypothesis development. Furthermore, the research methodology included survey instruments, the data and sample, and the data analysis techniques. Following the research methodology, the results consist of the examination of measurement and structural models. Based on these findings, we can offer some valuable insights regarding the theoretical and managerial implications. Lastly, we highlight the limitations and future research directions.

2. Theoretical Background and Hypothesis Development

2.1. Theoretical Underpinning

Building on theories of dynamic capabilities and social capital, we aim to investigate the interaction of business analytics, social capital, market orientation, and absorptive capacity to enable a firm to develop both exploratory and exploitative innovations simultaneously. Previously, the primary theoretical frameworks employed to analyze business analytics via the notion of IT capabilities [39] were the resource-based view (RBV) [16]. The Resource-Based View (RBV) emphasizes that competitive advantage arises from the unique collection of resources owned and managed by firms, positing that a company's distinctive IT capability is formed through a synergistic amalgamation of resources that are valuable, rare, inimitable, and non-substitutable (VRIN) [40]. Dynamic capabilities (DC) theory emerged primarily due to the limitations of resource-based theory [41], which generally

maintains a static perspective and overlooks the impact of external market volatility on organizations [42]. Dynamic capabilities are demonstrated by firms that seek, perceive, assess, and identify new market opportunities [43]. Seizing capabilities involves mobilizing resources to exploit identified opportunities, while reconfiguring involves the strategic renewal and transformation of the organization's resource base [43]. Birkinshaw and Zimmermann [44] associate seeking and sensing capacities with exploration, while selecting and seizing capabilities are connected to the exploitation of resources and opportunities [45]. More recent studies in the information systems domain have conceptualized absorptive capacity as a distinct type of dynamic capability [46]. Firm absorptive capacity (ACAP) refers to a firm's ability to assimilate external information, adapt it, and apply it for commercial purposes [47]. Absorptive capacity consists of four essential routines: acquiring, digesting, transforming, and utilizing knowledge [16,48]. This procedure relates to similar concepts in the dynamic capability literature [49].

This study presents a paradigm for business analytics socio-technical capabilities, anchored in dynamic capabilities and a socio-technical perspective, to develop a research model. This research endeavor will require identifying joint optimization and complementarities among technical and social information systems assets. This research distinguishes the linkages among distinct categories of IS assets and socio-organizational competencies [50]. Simultaneously, socio-technical theory elucidates the mutual interaction between the technological and social subsystems, which are essential for the adoption of business analytics [51]. Socio-technical challenges existed at the group level, where business units were hesitant to alter their work practices and adapt IT usage to integrate analytical insights [52]. These mechanisms are deemed essential for extracting value from investments in business analytics within the socio-technical systems in which they are applied and for gaining sustainable competitive advantages by balancing technical and social performance [52].

Innovation ambidexterity aims to balance exploitative and exploratory innovation to facilitate both incremental and radical improvements that enhance sustainable organizational performance [10,53,54]. Exploitative innovations (EXPL) are incremental enhancements to existing products aimed at current consumers and markets. In contrast, exploratory innovations (EXPR) involve drastic transformations, embodied in new products designed to serve new customers and markets. Researchers have investigated ambidextrous drivers at intra-organizational and inter-organizational levels, concentrating on three mechanisms: structure, context, and leadership [55]. The organizational context is crucial when analyzing alignment (exploitation) versus adaptability (exploration) [56]. An ambidextrous organization that emphasizes structural processes distinguishes between exploration and exploitation as separate structural elements [10]. Strategic leadership is an increasingly important element in promoting ambidexterity [10]. A leadership mechanism that enables ambidexterity is essential, as it addresses resource-allocation issues and recognizes collaborations between the organization's senior executives' exploration and exploitation activities [55]. Research shows that managers can learn more about how to exploit and explore by drawing on various knowledge resources, including people at all levels of the company [55]. Within a firm, there are R&D, manufacturing, marketing, logistics, administration, and other units. There are also external contacts, such as suppliers, customers, banks, competitors, government agencies, and industry regulators. Social networks emphasized the quantity, duration, and intensity of interpersonal interactions [57]. Strong relationships in managers' social capital usually lead to positive actions, to help organizations learn and use new information more effectively and build sustainable relationships [16,57].

2.2. Business Analytics Socio-Technical Capabilities

Previous studies by Gupta and George [58] highlighted several business analytics resources—data, management, technical capabilities, and a data-driven culture—that collectively establish a business analytics capability that generates operational and strategic business value. In line with product/service innovation processes, researchers have examined the essential stages of data-driven innovation, including data collection, refinement, storage, dissemination, and presentation [59]. Hu, Wen [60] emphasized a business analytics system that provides functionality to manage the various stages of the data life cycle, from inception to disposal. The system typically has several discrete phases for various purposes. Belhadi, Zkik [61] proposed a three-layer framework for applying business analytics to the innovation process, comprising data warehousing, data aggregation, and data analytics. Oesterreich, Anton [62] have been employed to delineate BA technology for the acquisition, storage, analysis, and visualization of data. Mehdikhani, Valmohammadi [25] presented an enhanced framework of business analytics comprising four distinct dimensions: data acquisition, descriptive, predictive, and prescriptive analysis. Based on a well-known data value chain method, we delineated the proposed business analytics technological framework for the organization, which outlines the data value chain process for architectural alternatives across three tiers [63]: (1) data aggregation technology; (2) data analysis technology; and (3) data interpretation technology. Data aggregation technology can transform various types of enterprise data into formats suitable for data analysis platforms through three principal functions: data collection, data transformation, and data storage [25]. Data analytics technology collects many types of data and performs relevant analysis to extract insights through three primary forms of analytics: descriptive, predictive, and prescriptive [62]. Data interpretation technology produces reports to support managerial decisions and actions, encompassing comprehensive summaries that provide a holistic view to support evidence-based business decisions, enhanced alerts, and strategic guidance [63].

Social capital (SC) is a set of relationship processes within organizational networks that enable them to work together effectively for the common good [64]. Social capital (SC) and information systems (IS) interact and influence each other's use and development [65]. Prior research indicates that social capital is a multifaceted construct encompassing structural, relational, and cognitive social capital [16]. Structural social capital refers to the overall patterns of relationships among individuals, particularly the existence of network connections among them. Relational social capital is the quality that people in a network have built through their interactions over time. This part discusses trust, dependability, gratitude, mutual respect, and the act of giving and receiving. In intraorganizational contexts, such attributes among individuals and organizational units hinder opportunistic behaviors and promote a heightened propensity for collaboration and resource exchange. Organizational units that exhibit trust and respect are more inclined to establish intraorganizational strategic connections [16]. Cognitive social capital is the third part of social capital. Cognitive social capital includes elements such as shared code or a shared mindset that help group members understand their objectives. Shared values and interpretive frameworks among units foster partnerships, enhancing both individual and collective activities that benefit the organization, including in sustainable innovation activities. These resources, comprising a shared language, codes, and narratives, are fundamental components in our examination of knowledge sharing [16]. The focus of this research on social capital is on two main objectives: minimizing socio-technical inertia and maximizing inter-functional collaboration in business analytics adoption for sustainable innovation activities. Social capital encompasses all the tangible and potential resources that an individual or social group possesses, can access, or derive from their network of relationships [66]. Social

capital enables people to interact with one another, facilitating new connections within organizations, potentially enhancing the flow of knowledge among colleagues, and balancing social and economic performances [16].

H1. *Business analytics technological capabilities will positively impact business analytics-related social capital.*

2.3. The Effect of Business Analytics Technological Capabilities and Social Capital on Market Orientation

Strategic orientation denotes an organization's ability to adjust to changing external conditions and interact with its environment to sustain its competitive advantage [67]. Market orientation (MO), as part of organizational strategic orientation, alters the firm's culture by emphasizing customer needs, thereby improving corporate performance and increasing consumer value as a strategic priority [68]. Moreover, businesses must develop a culture that acknowledges and implements internal processes to enhance customer satisfaction, hence steering the organization's efforts toward attaining outstanding performance [69]. Market orientation is a strategic approach that focuses on building systems and processes to identify and meet current and future customer needs [70].

Market knowledge resources help a business stand out from its competitors [71]. These are unique, hard-to-copy skills that businesses possess, and knowing the market is very important [69]. Market knowledge is the company's knowledge of its customers and competitors [72]. Market orientation is a company's strategy to cultivate knowledge about its customers and competitors and create market-oriented innovation. Market orientation is very important for the company's success [72]. Consequently, the information supplied by the business analytics systems is a significant catalyst for market orientation. Inadequate market information from business analytics may raise concerns about its credibility, potentially adversely affecting usage behavior, and vice versa.

H2. *Business analytics' technological capabilities have a positive and direct effect on market orientation.*

Social capital significantly influences the ability to learn, integrate, reconfigure, and manage partnerships, including market orientation capabilities. Empirical evidence has demonstrated that social capital is an essential resource for all organizations [66]. Interdepartmental social ties reduce hierarchical barriers, improve knowledge dissemination and utilization, and promote the effective implementation of market orientation. Organizations that emphasize established personal social capital have achieved commercial success [73]. Thus, we formulate the following hypothesis:

H3. *Social capital positively and directly influences market orientation.*

2.4. The Impact of Business Analytics Technological Capabilities and Social Capital on Absorptive Capacity

Enterprise absorptive capacity (ACAP) refers to a firm's ability to assimilate external information, adapt it, and apply it to commercial purposes [47]. To acquire and maintain a sustainable competitive advantage, organizations are increasingly investing in enhancing their personnel, software, and IT infrastructure to build absorptive capacity [17]. Absorptive capacity is a fundamental concept in the domain of information systems [16], as evidenced by its substantial citations in IS academic journals [74]. Strategic IS specialists view absorptive capacity as a unique type of dynamic capability [36]. The notion of absorptive capacity as a dynamic capability shaped by business analytics has been explored in various academic studies [75]. Absorptive capacity consists of four essential routines,

namely acquiring, digesting, transforming, and utilizing knowledge [16,48]. This procedure relates to similar concepts in the dynamic capability routines [49]. We suggest the following hypotheses:

H4. *Business analytics' technological capabilities positively and directly influence absorptive capacity.*

Social capital fosters more committed relationships between units [66] and facilitates the creation of value through the exchange and integration of existing intellectual resources [76]. Knowledge seekers, including business units, who trust the expertise of sources to provide direction and influence their viewpoints, are more likely to heed, digest, and act upon that knowledge [16]. Organizations with social capital demonstrate greater absorptive capacity than those without it [77]. The preceding statements lead to the following hypothesis:

H5. *Business analytics-related social capital has a positive and direct effect on absorptive capacity.*

2.5. Mediating Role of Market Orientation and Absorptive Capacity

Companies with higher absorptive capacity are more likely to exhibit ambidextrous behavior, effectively balancing exploration and exploitation [78]. Business analytics encompasses a collection of technologies, including data collection, data analysis, and data visualization, which fosters an ideal environment for organizations to develop their absorptive capacity [63]. Conversely, the transfer of knowledge between business divisions facilitates intra-organizational knowledge flow and consolidation, thus enhancing the organization's knowledge base [47].

The availability of market data encourages business units to be more responsive, particularly when monitoring performance from a short-term perspective. Market information also helps firms stay alert to unforeseen issues and take proactive steps, resulting in long-term advantages [69]. Business analytics can enhance firms' strategic orientation, including market orientation, and indirectly affects business performance [30]. A strategic orientation is a company's approach to doing business, grounded in a set of strong principles [36]. Market orientation improves firms' innovation ambidexterity in emerging markets [3]. It is critical to emphasize that properly implementing a market orientation strategy to drive innovation ambidexterity in this emerging environment [25]. Converting emerging-market data into corporate actions is crucial to long-term planning and involves a significant decision-making process that can affect organizational changes [69]. Prior studies have also claimed that market information can only be converted into valuable knowledge through assimilation and comprehension, with market orientation and absorptive capacity being a critical precursor for guiding exploitative and exploratory activities [75,79].

Business analytics and social capital affect market orientation and absorptive capacity, a higher-level organizational capability [36], that helps companies find, combine, and use lower-level capabilities (such as operational and IT capabilities) to make organizations more successful [80]. Strong business analytics can indirectly enhance an organization's innovation potential by improving the fundamental processes that underpin dynamic capabilities. The organization's market orientation and absorptive capacity, in conjunction with business analytics insights and social capital, foster interactivity among business units and expand the knowledge base necessary for the development and implementation of exploratory and exploitative innovation. As a result, we suggest the following hypotheses:

H6. *Market orientation positively and directly influences absorptive capacity.*

H7a. *Market orientation and absorptive capacity mediate the relationship between business analytics-related social capital and exploitative innovation.*

H7b. *Market orientation and absorptive capacity mediate the relationship between business analytics-related social capital and explorative innovation.*

H8a. *Market orientation and absorptive capacity mediate the relationship between business analytics' technological capabilities and exploitative innovation.*

H8b. *Market orientation and absorptive capacity mediate the relationship between business analytics' technological capabilities and explorative innovation.*

This study formulates a conceptual research model (Figure 1) to illustrate how business analytics-related technological capabilities (aggregation, analysis, and interpretation technology) and business analytics-related social capital (structural, relational, and cognitive) within firms can indirectly affect innovation ambidexterity (explorative, exploitative) through a crucial mediating factor: market orientation and absorptive capacity (acquisition, assimilation, transformation, exploitation). The model proposes that business analytics enhances social capital and builds socio-technical capabilities. Market orientation and absorptive capacity act as mediators and play critical roles in acquiring, digesting, transforming, and utilizing insights with high potential utility from the vast data amassed and preserved by business analytics. This relationship, in turn, helps balance the competing activities of exploitative and exploratory to sustain innovation in an emerging market.

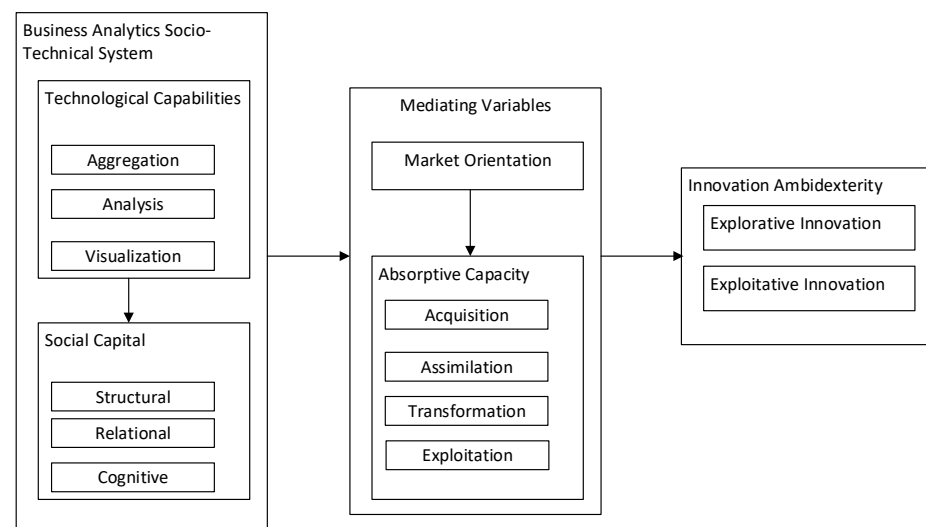


Figure 1. Conceptual research model. Source: Authors' work.

3. Research Methodology

3.1. Survey Instruments

The measurement instruments in this study were adapted from prior studies and selected following a thorough literature review. This study used three first-order formative constructs to measure the technological capabilities of business analytics (BA). These are data aggregation technology (3 items), data analysis technology (4 items), and data visualization technology (3 items). The BATC is a second-order construct of the formative-formative type adopted from Wang and Byrd [63]. Social capital (SC) is a reflective-reflective second-order construct comprising three first-order reflective constructs —structural capital (4 items), relational capital (4 items), and cognitive capital (3 items) —as measured by

Shuradze, Bogodistov [16]. Market orientation (MO) is measured using four items adopted from Gnizy [30]. Absorptive capacity (ACAP) is a reflective-reflective second-order construct comprising four first-order reflective constructs: acquisition (3 items), assimilation (4 items), transformation (4 items), and exploitation (3 items), adopted from Flatten, Engelen [80]. Innovation ambidexterity is measured by five items for exploitative innovation (EXPL) and five for exploratory innovation (EXPR), as derived from Jansen and Van Den Bosch [81]. Multi-item variables were measured using a 7-point Likert scale, ranging from 1 = strongly disagree to 7 = strongly agree. Table 1 details the measurement items used.

Table 1. Measurement items.

Constructs	Sub-Constructs	Items	Measurement Items	References
Business analytics' technological capabilities (BATC)	Data aggregation technology (AGG)	AGT1	Our company collects data from external sources and from various systems throughout our organization.	[63]
		AGT2	Our company maintains records that are consistent, visible, and easily accessible for further analysis.	
		AGT3	Our company stores data in appropriate databases.	
	Data analysis technology (ANT)	ANT1	Our company identifies essential business insights and trends to improve our products and services.	[63]
		ANT2	Our company identifies patterns to meet our business needs.	
		ANT3	Our company analyzes data in near-real or real time, enabling rapid responses to unexpected business events.	
		ANT4	Our company analyzes social media data to understand current trends across large populations.	
	Data visualization technology (INT)	VIS1	Our company provides systematic, comprehensive reporting to help identify feasible opportunities for business improvement.	[63]
		VIS2	Our company supports data visualization that enables users to easily interpret results.	
		VIS3	Our company provides near-real or real-time information on business operations and services within organizations and across systems.	
Social capital (SC)	Structural social capital (SSC)	SSC1	Our employees maintain close social relationships with one another.	[16]
		SSC2	Our employees spend a lot of time interacting with one another.	
		SSC3	Our employees know each other at a personal level.	
		SSC4	Our employees communicate frequently with each other.	
	Relational social capital (RSC)	RSC1	Our employees maintain close social relationships with one another.	[16]
		RSC2	Our employees spend a lot of time interacting with one another.	
		RSC3	Our employees know each other at a personal level.	
		RSC4	Our employees communicate frequently with each other.	
	Cognitive social capital (CSC)	CSC1	When interacting, our company's employees use common terms or jargon.	[16]
		CSC2	During discussions, our employees use clear communication patterns.	
		CSC3	When communicating, our employees use clear, understandable narratives.	
Market orientation		MO1	Our company's strategy for competitive advantage is based on our thorough understanding of our customers' needs.	[30]
		MO2	All our managers understand how the entire business can contribute to creating customer value.	
		MO3	Our company responds quickly to negative customer satisfaction information throughout the organization.	
		MO4	Our company's market strategies are driven in large part by our understanding of opportunities to create value for customers.	
Absorptive capacity (ACAP)	Acquisition (ACQ)	ACQ1	The search for relevant information concerning our industry is an everyday affair in our company.	[80].
		ACQ2	Our company motivates employees to use industry-specific information sources.	
		ACQ3	Our company expects its employees to handle information beyond the industry.	
	Assimilation (ASS)	ASS1	In our company, ideas and concepts are communicated cross-departmentally.	[80].
		ASS2	Our company emphasizes cross-departmental support in solving problems.	
		ASS3	In our company, information flows quickly, e.g., if a business unit obtains essential information, it promptly communicates it to all other business units or departments.	

Table 1. Cont.

Constructs	Sub-Constructs	Items	Measurement Items	References
Absorptive capacity (ACAP)	Transformation (TRF)	ASS4	Our company demands periodic cross-departmental meetings to exchange new developments, problems, and achievements.	[80].
		TRF1	Our company can structure and use the knowledge we collect.	
		TRF2	Our company is accustomed to absorbing new knowledge, preparing it for future use, and making it available.	
		TRF3	Our company successfully links existing knowledge with new insights.	
	Exploitation (EXP)	TRF4	Our company can apply new knowledge in its practical work.	[80].
		EXP1	Our company supports the development of prototypes.	
		EXP2	Our company regularly reconsiders technologies and adapts them according to new knowledge.	
		EXP3	Our company can work more effectively by adopting new technologies.	
Exploratory innovation (EXPR)		EXPR1	Our company accepts demands that go beyond existing products and services.	[81]
		EXPR2	Our company invents new products and services.	
		EXPR3	Our company experiments with new products and services in our local market.	
		EXPR4	Our company commercializes products and services that are entirely new to our unit.	
		EXPR5	Our company frequently takes advantage of opportunities in new markets.	
Exploitative innovation (EXPL)		EXPL1	Our company frequently refines the provision of existing products and services.	[81]
		EXPL2	Our company regularly implements minor adaptations to existing products and services.	
		EXPL3	Our company introduces improved but existing products and services to our local market.	
		EXPL4	Our company improves its efficiency in providing products and services.	
		EXPL5	Our company increases economies of scale in existing markets.	

3.2. Data and Sample

This study is cross-sectional, with data collection using a purposive sampling approach to establish an accurate representation of the target population. Survey data were gathered using a structured questionnaire accompanied by an introductory cover letter outlining the survey's purpose. The questionnaire underwent preliminary testing before distribution to the entire sample. We conducted pretests with 30 randomly selected participants, comprising 25 business analytics specialists from various industries and five academics from educational institutions. In previous research, Mandal [82] conducted a pretest with 61 respondents to assess the intelligibility of the survey questions. The pretest aimed to ensure that the questionnaire items were complete, precise, unambiguous, and understandable to the research subjects. The questionnaire items were then adjusted based on feedback from the pretest. Following the pretest survey, we sent the final questionnaire to 430 medium- and large-sized Indonesian companies via an online Google Forms poll from January to July 2024. We applied four main criteria for respondent selection, including location, years of adoption, knowledge, and position. First criterion, respondents working at medium (20–99 employees) and large enterprises (100 or more employees) in Indonesia, and firms that have implemented BA for more than three years. Second, participants demonstrated substantial knowledge in business analytics. Third, respondents hold a managerial, executive, or IT specialist position within the organization. Finally, we collected 218 responses, yielding an overall response rate of 50.7%.

Around 155 respondents are needed to achieve the minimum expected route coefficient, which ranged from 0.11 to 0.20, with statistical significance at the 5% level [83]. Thus, the sample size of 218 companies in our study was suitable for PLS-SEM analysis. The predominant responses were from business and IT executives. Table 2 illustrates the demographic characteristics of the sample. Respondents consisted of large organizations

(62%) and medium-sized companies (38%). The participants in this study originated from various industrial sectors in Indonesia: manufacturing (19.72%), health and pharmacy (2.29%), financial and banking (11.93%), mining and energy (9.17%), transportation and logistics (10.55%), utilities (1.83%), retail and consumers (13.76%), information technology (20.18%), consultancy (1.83%), communication and media (2.29%), and construction and property (6.42%). The respondents occupied the following roles: CEO (1.38%), Director (5.05%), Senior Manager (22.48%), Manager (55.50%), and IT Specialist (15.60%).

Table 2. Descriptive statistics of the sample and respondents.

Variable(s)	Sample (N = 218)	Percentage (%)
Industry		
Manufacturing	43	19.72
Health and pharmacy	5	2.29
Financial and banking	26	11.93
Mining and energy	20	9.17
Transportation and logistics	23	10.55
Utilities	4	1.83
Retail and consumers	30	13.76
Information technology	44	20.18
Consultancy	4	1.83
Communication and media	5	2.29
Construction and property	14	6.42
Firm size (No. of employees)		
20–100	83	38.07
>100	135	61.93
Total business analytics experience		
1–4 years	31	14.22
>4 years	187	85.78
Respondent's position		
CEO	3	1.38
Director	11	5.05
Senior Manager	49	22.48
Manager	121	55.50
Specialist	34	15.60

3.3. Common Bias Method

Common method bias (CMB) and outliers represent substantial challenges to survey-based business analytics research [75]. This study sought to address this issue by targeting key respondents with the expertise to complete the questionnaire: managers, organizational leaders, and IT specialists. We conducted a collinearity analysis using variance inflation factors (VIFs) to identify common method bias (CMB). A VIF threshold of 3.3 is appropriate for CMB tests using a factor-based PLS-SEM method, whereas a threshold of 5 is suitable for algorithms that account for measurement errors [84]. The results were clearly below 3.3, indicating that the proposed study model was devoid of CMB concerns. We examined the data to detect outliers using IBM SPSS Statistics (v. 22). We identified only a few outliers using a box plot and a stem-and-leaf diagram, but we retained them for further examination because there was no clear rationale [75].

3.4. Data Analysis Technique

This study used high-order constructs (HOCs) to model constructs at higher levels of abstraction. Subdimensions (LOCs), which are more concrete sizes and concepts, display low-order dimensions [85]. The hierarchical component model (HCM) is a data structure that depicts hierarchical relationships within a construct. The hierarchical component model

(HCM) has been a significant trend in the application of partial least squares structural equation modeling (PLS-SEM) [85]. This study employed a disjoint two-stage approach to evaluate higher-order structures (HOCs) as recommended by Becker and Cheah [85]. Initially, the disjoint two-stage method only uses LOC to link it to all model constructs, such as the causes and effects of high-level constructs [85]. The second phase of the disjoint two-stage method utilizes the first-stage LOC score as a metric for the HOC measurement model while maintaining the current construction measurement model [85]. During the initial phase, the model is assessed using PLS-SEM criteria [83] for LOC, excluding HOC from this evaluation. In the following phase, LOC functions as a metric for HOC [86]. At this point, it is important to use a standard set of criteria to evaluate the LOC measurements for both formative and reflective measurement models [83]. The LOC must meet the measurement model's assessment criteria to move on to the next stage [86]. This research employed the SmartPLS software (v. 3.3.3) to construct structural equation models using the PLS-SEM approach [86].

4. Results

4.1. Examination of the Measurement Model

We used the results of the measurement model evaluation to conduct a lower-order construct (LOC) measurement model analysis using the disjoint two-stage approach [85]. We evaluated indicator reliability, construct reliability, convergent validity, and discriminant validity for reflective construct measurement models [83]. Using the formative construct measurement model, we assessed collinearity among indicators and the significance and relevance of the outer weights. This level consisted of one second-order formative-formative type construct (BA), two second-order reflective-reflective type constructs (SC, ACAP), and three first-order reflective constructs (MO, EXPL, EXPR).

Table 3 presents the evaluation results for formative construct measurement methods, while Table 4 presents the results for reflective constructs. All reflective constructs exceeded the outer loading threshold (>0.7), indicating reliability [83]. The construct's internal consistency, as measured by Cronbach's alpha, composite reliability, and the reliability coefficient, exceeded the criterion of >0.7 [83]. All constructs' average variance extracted (AVE) surpasses the recommended value of 0.50 [83].

Table 3. Formative measurement model analysis.

	Outer Weight	T Statistics	p-Values	VIF	OLs
Stage 1-LOC Analysis (First-order constructs)					
AGT1 → AGT	0.256	2.137	0.033	1.511	0.737
AGT2 → AGT	0.671	5.431	0.000	1.789	0.949
AGT3 → AGT	0.235	2.032	0.042	1.580	0.744
ANT1 → ANT	0.262	2.226	0.026	1.509	0.728
ANT2 → ANT	0.353	2.479	0.013	1.617	0.801
ANT3 → ANT	0.378	2.600	0.009	1.311	0.747
ANT4 → ANT	0.333	3.470	0.001	1.357	0.734
VIS1 → VIS	0.256	2.137	0.033	1.256	0.765
VIS2 → VIS	0.671	5.431	0.000	1.442	0.738
VIS3 → VIS	0.518	4.566	0.000	1.232	0.770
Stage 2: Step 1 HOC analysis Second-order constructs					
AGT → BATC	0.355	3.029	0.002	1.533	0.722
ANT → BATC	0.233	3.029	0.002	2.098	0.880
VIS → BATC	0.582	4.958	0.000	1.884	0.913

Table 4. Discriminant validity–Heterotrait–Monotrait (HTMT) of the measurement model (reflective).

Stage 1-LOC Analysis (First-Order Constructs)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) ACQ									
(2) ASS	0.753								
(3) CSS	0.683	0.520							
(4) EXP	0.819	0.776	0.572						
(5) EXPL	0.686	0.492	0.499	0.609					
(6) EXPR	0.540	0.334	0.408	0.462	0.722				
(7) RSC	0.747	0.516	0.763	0.596	0.541	0.432			
(8) SSC	0.470	0.360	0.630	0.420	0.357	0.326	0.669		
(9) MO	0.679	0.567	0.399	0.717	0.650	0.595	0.509	0.360	
(10) TRA	0.801	0.741	0.495	0.848	0.506	0.455	0.531	0.405	0.711
	(1)	(2)	(3)	(4)					
(1) ACAP									
(2) EXPL	0.646								
(3) EXPR	0.495	0.722							
(4) MO	0.758	0.708	0.512						
(5) SC	0.749	0.588	0.495	0.685					

Table 4 demonstrates that the conservative Heterotrait–Monotrait ratio (HTMT) criterion, a more rigorous test of discriminatory validity than the Fornell–Larcker criteria, yielded no values exceeding 0.85 [83]. Consequently, all first-order reflective constructions were valid and reliable. Table 3 presents the indicators for the formative constructs. The variance inflation factor (VIF) stays within the recommended range (<5) [83]. The next stage entailed assessing the significance of the outer weights. In multiple regression, the outer weight is the standard resultant coefficient. Table 3 shows that the outer weights are significant and applicable [83]. This result means that all first-order formative constructs were valid and reliable.

The second phase of the disjoint two-stage methodology incorporates the initial stage LOC. In this phase, the LOC score is a parameter in the HOC measurement model [85]. As shown in Tables 3 and 4, the analysis of the second-order construct measurement revealed that all reflective and formative constructs were valid and reliable.

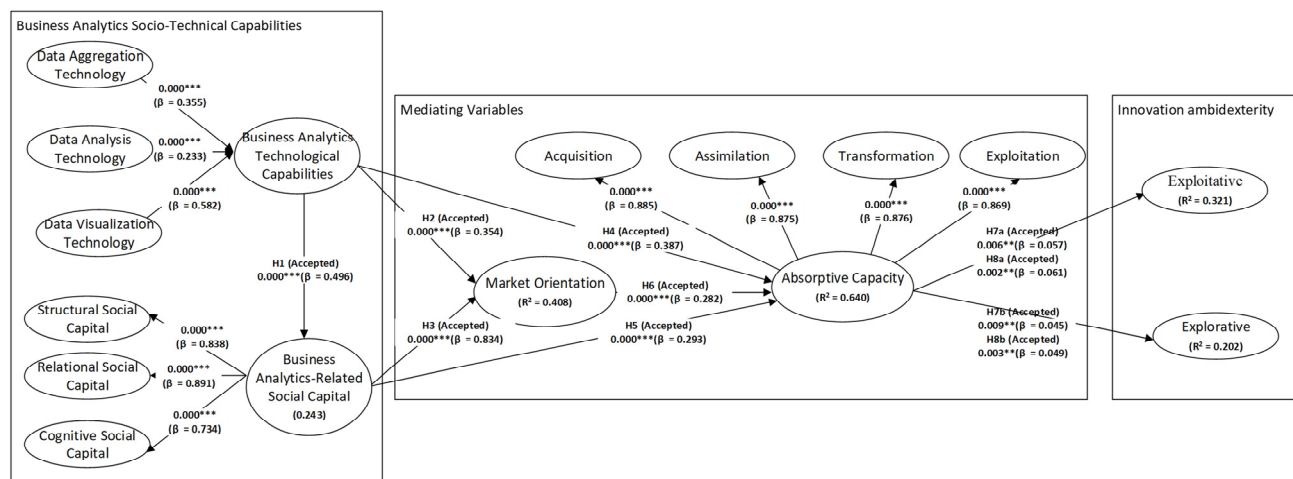
4.2. Examination of Structural Models

After assessing the measurement model, the structural model was examined to determine the links among the constructs. Before we examined the structural model [87], We used the VIF criterion to assess multicollinearity among exogenous variables and bootstrapping with 10,000 samples to test the significance and relevance of path coefficients [88]. Table 5 indicates that multicollinearity was not an issue in this study, since VIF remained below the advised threshold of <3.3 [83]. Next, we performed hypothesis testing using the Bias-Corrected and Accelerated (BCA) method with 10,000 bootstrap samples (two-tailed) and set the significance level at 5% [83]. Table 5 presents the path coefficients, t-values, and p-values, indicating that all relationships were statistically significant. The investigation's findings empirically supported all hypotheses; therefore, we accepted H1, H2, H3, H4, H5, H6, H7, H8 (Figure 2).

Table 5. Structural model-path coefficients result.

	Relationship	Inner VIF	β	t-Value	p-Value	Support	Bias-Corrected 95% Confidence Interval	F2
H1	BATC $\rightarrow$ SC	1.537	0.496	7.584	0.000 ***	Yes	[0.358–0.616]	0.377
H2	BATC $\rightarrow$ MO	1.564	0.354	5.580	0.000 ***	Yes	[0.241–0.616]	0.159
H3	SC $\rightarrow$ MO	1.323	0.384	6.029	0.000 ***	Yes	[0.236–0.536]	0.188
H4	BATC $\rightarrow$ ACAP	1.423	0.387	6.166	0.000 ***	Yes	[0.233–0.456]	0.270
H5	SC $\rightarrow$ ACAP	1.323	0.293	4.815	0.000 ***	Yes	[0.211–0.336]	0.151
H6	MO $\rightarrow$ ACAP	1.495	0.282	4.169	0.000 ***	Yes	[0.228–0.302]	
H7a	BATC $\rightarrow$ MO $\rightarrow$ ACAP $\rightarrow$ EXPL		0.057	2.750	0.006 **	Partial	[0.038–0.126]	
H7b	BATC $\rightarrow$ MO $\rightarrow$ ACAP $\rightarrow$ EXPR		0.045	2.626	0.009 **	Partial	[0.028–0.102]	
H8a	SC $\rightarrow$ MO $\rightarrow$ ACAP $\rightarrow$ EXPL		0.061	3.023	0.002 **	Partial	[0.031–0.111]	
H8b	SC $\rightarrow$ MO $\rightarrow$ ACAP $\rightarrow$ EXPR		0.049	3.076	0.003 **	Partial	[0.026–0.101]	
N1	BATC $\rightarrow$ EXPL	1.803	0.286	3.521	0.000 ***	Yes	[0.118–0.434]	0.173
N2	BATC $\rightarrow$ EXPR	1.803	0.342	4.827	0.000 ***	Yes	[0.205–0.486]	0.192
N3	SC $\rightarrow$ EXPL	1.678	0.154	2.149	0.032 *	Yes	[0.004–0.289]	0.171
N4	SC $\rightarrow$ EXPL	1.678	0.182	1.997	0.046 *	Yes	[0.001–0.353]	0.189

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ (two-tailed test); SRMR: 0.061; NFI: 0.819; Chi-Square: 594.313. H = Hypothesis; N = Not hypothesized.

**Figure 2.** Results of SmartPLS SEM model. *** $p < 0.001$, ** $p < 0.01$.

To assess the model's explanatory power, we used the coefficient of determination (R^2) (Table 6). The R^2 values for the two dependent variables—0.408 for MO and 0.640 for ACAP—indicated modest predictive accuracy for BATC and SC. The F2-effect metric evaluates the relative impact of each predictor construct on R^2 and its practical importance [86]. Table 5 presents the F2 values. BATC exhibited a medium effect size (F2) on MO (0.159) and ACAP (0.270). SC demonstrated a medium effect size (F2) on MO (0.188) and ACAP (0.151).

Table 6. Construct cross-validated redundancy.

	SSO	SSE	Q2	R2
Social Capital (SC)	854.000	425.211	0.421	0.243
Absorptive capacity (ACAP)	872.000	441.177	0.494	0.639
Market orientation (MO)	872.000	673.894	0.227	0.408
Exploitative Innovation (EXPL)	1090.000	891.205	0.182	0.397
Explorative Innovation (EXPR)	1090.000	949.660	0.129	0.242

Stone–Geisser's Q2 approach uses the blindfolding procedure to assess a model's predictive accuracy [86]. Table 6 shows that ACAP (Q2 = 0.494), MO (Q2 = 0.227), EXPL

($Q2 = 0.182$), and EXPR ($Q2 = 0.129$). These values were considered moderately to strongly predictive, thereby increasing the model's utility across a broader range of populations. The standardized root mean square residual (SRMR) is the primary global indicator of model fit [83]. Table 5 presents the results of the proposed model, with an NFI of 0.819, indicating a suitable model fit, and an SRMR of 0.061 (<0.08), signifying robust explanatory capability [88].

We further conducted a mediation analysis of the structural model results (Table 5). The results indicate that MO and ACAP partially (complementarily) mediate the relationship between BATC on EXPL and EXPR. MO and ACAP also play complementary partial mediation roles in the relationship between SC on EXPL and EXPR. Partial complementary mediation occurs because the direct and indirect effects are significant and point in the same direction [87]. The results of the mediation effect analysis indicated that all mediation hypotheses had complementary partial mediation effects (Table 5). Therefore, we can confidently state that MO and ACAP mediate the relationship between BATC and SC regarding EXPL and EXPR. Thus, H7 and H8 were confirmed.

5. Discussion and Conclusions

This research model comprises three higher-order constructs: business analytics technological capability, social capital, and absorptive capacity. Empirical results indicate that second-order construct visualization technology ($\beta = 0.582$) makes a significant contribution to business analytics, followed by analysis technology ($\beta = 0.355$) and aggregation technology ($\beta = 0.233$). Second-order construct relational social capital contributes the most ($\beta = 0.891$), next to structural capital ($\beta = 0.838$) and cognitive capital ($\beta = 0.734$). Consequently, the second-order construct of absorptive capacity, which encompasses acquisition, exploitation, assimilation, and transformation, contributes more significantly to acquisition ($\beta = 0.885$), followed by transformation ($\beta = 0.876$), assimilation ($\beta = 0.875$), and exploitation ($\beta = 0.869$).

Several model constructs, such as social capital, market orientation, and absorptive capacity, empirically show relatively high HTMT values, although still within acceptable limits [83]. Although theoretically interrelated, this study examines the distinct roles of Social Capital (SC), Market Orientation (MO), and Absorptive Capacity (ACAP) in building a BA implementation model to support innovation ambidexterity. In this study, the development of social capital is designed to help companies minimize socio-technical inertia and maximize inter-functional collaboration in business analytics adoption for sustainable innovation activities [66]. Social capital enables people to interact with one another, facilitating new connections within organizations, potentially enhancing the flow of knowledge among colleagues, and balancing social and economic performances [16]. Market orientation (MO) is part of organizational culture development, emphasizing consumer value as a strategic priority and helping companies identify and meet current and future customer needs [70]. Market orientation helps firms focus on the most critical emerging market knowledge and provides valuable insights for innovation [35]. Enterprise absorptive capacity (ACAP) refers to a firm's ability to assimilate external information. ACAP consists of four essential routines: acquiring, digesting, transforming, and utilizing knowledge [48]. Firms need market-related prior knowledge to increase their absorptive capacity effectively [36]. Market orientation and absorptive capacity serve as filters that facilitate the selection of insights with great potential utility from the enormous data amassed and preserved by business analytics to support exploitative and explorative innovation activities [32].

Findings related to hypothesis 1 indicate that business analytics capabilities will positively impact social capital development, and this finding has been supported. The result

shows that business analytics can serve as a key technological tool for integrating social capital into organizational processes (H1), consistent with the existing literature, such as Gao and Sarwar [38]. Hypothesis 2 (H2) is supported, demonstrating that business analytics' technological capabilities have a significant impact on market orientation. This finding is supported by previous research, such as Gnizy [30]. Meanwhile, the results of hypothesis 3 (H3) demonstrate that social capital has a significant impact on market orientation, as supported by Ramírez-Solis, Llonch-Andreu [89]. Looking at hypotheses H4 and H5, the study's results showed that both business analytics' technological capabilities and social capital have a significant effect on absorptive capacity. Prior research by Wang and Byrd [63] supports hypothesis 4 (H4), while an earlier study by Shuradze and Bogodistov [16] supports hypothesis 5 (H5).

Hypothesis 6 (H6) showcased a substantial and resilient relationship between market orientation and absorptive capacity. This finding is consistent with previous research conducted by Ibarra-Cisneros and Demuner-Flores [90], which examined the influence of market orientation on absorptive capacity.

Hypothesis 7a (H7a) proposes that market orientation and absorptive capacity mediate the influence of business analytics' technological capabilities on exploitative innovation, and hypothesis 7b (H7b) proposes that they mediate the influence of business analytics' technological capabilities on exploratory innovation. Hypothesis 8a (H8a) proposes that market orientation and absorptive capacity function as mediators in the influence of social capital on exploitative innovation, and hypothesis 8b (H8b) on explorative innovation. We present evidence for the complementary partial mediating roles of market orientation and absorptive capacity in supporting the interaction between business analytics' technological capabilities and social capital in fostering both exploitative and exploratory innovative ambidexterity. While prior research has recognized a positive correlation between business analytics and innovation, no empirical investigation has comprehensively examined the influence of business analytics, social capital, market orientation, and absorptive capacity on amplifying exploratory and exploitative innovation activities. This concept represents a significant advancement that amplifies the results of prior studies, including those by Gao and Sarwar [38], Božič and Dimovski [75], Lozada and Arias-Pérez [1], and Shuradze and Bogodistov [16]. Based on these findings, we can offer valuable insights into the theoretical and managerial implications, while also outlining several limitations in the subsequent section.

5.1. Theoretical Contributions

This study enriches the information systems research and innovation management literature by examining the empirical mechanisms by which business analytics drives innovation ambidexterity. We offer two valuable insights regarding the theoretical contributions. First, we extend prior research by adopting a socio-technical perspective to investigate the interaction effects of business analytics technological capability and social capital on sustaining exploitative and exploratory innovation successes in emerging market conditions. The social-technical perspective emphasizes the acquisition of resources and the development of sustainable competitive advantage by optimizing social and technical interactions. This research demonstrates that the development of business analytics technology enables firms to build social capital. Higher business analytics technology enhances the efficient exchange and communication of information between business units, thereby increasing social capital. Organizations require integrating business analytics and social capital to facilitate knowledge exchange across specialties within their units. Using a socio-technical perspective, this study demonstrates that implementing business analytics technology must be accompanied by the development of firms' social capital. The development of social cap-

ital helps firms to prevent the emergence of socio-technical inertia and enhance sustainable business performance. Socio-technical inertia refers to the reliance on social and technical capabilities that emerge from their interaction and combined optimization. It describes an organization's resistance to change and indicates the effort required to transform it through business analytics systems. Scholars have typically investigated the advantages of computer platforms in enhancing social capital, demonstrating that, with stronger personal connections—where people share ideas and goals—reciprocity continues to facilitate the development of social exchanges [91]. Business analytics provides a decision-support environment that facilitates decision-making across business departments. Moreover, aligning this business analytics technological development with the organization's social capital enhances collaboration and improves the innovation processes by integrating technology, culture, and tasks across the organization [92].

Second, using the dynamic capability view, we expand existing knowledge on how market orientation and absorptive capacity mediate the link between business analytics socio-technical capability and firm innovation ambidexterity. The results show that market orientation and absorptive capacity play complementary partial mediating roles in the relationship between business analytics socio-technical capabilities and innovation ambidexterity. This study suggests that the impact of business analytics and social capital on innovation ambidexterity depends, to some extent, on market orientation and absorptive capacity. This study proposes that the socio-technical capability of business analytics is positively correlated with the organization's dynamic capabilities—market orientation and absorptive capacity—thereby driving innovation ambidexterity. This study has an important finding that expands the understanding of market orientation and absorptive capacity in emerging economies. Market orientation and absorptive capacity are considered the primary capabilities of a firm that enhance the organization's ability to develop the finest knowledge regarding exploitative and explorative innovation efforts. A market-oriented strategy, combined with the capability for knowledge acquisition, assimilation, transformation, and exploitation, is necessary to effectively convert business analytics investments into exploitative and exploratory innovation capabilities. Market orientation leads the firm toward collecting appropriate knowledge in emerging economies, and through its organizational absorptive capacity, it integrates this knowledge to fuel both exploitative and exploratory innovation activities. A combination of market orientation strategy and absorptive capacity enhances a firm's capability to align internal resources with external opportunities and foster both exploitative and exploratory innovation activities.

5.2. Practical Implications

In practice, this study helps consultants and managers involved in deploying business analytics better understand the mechanisms and pathways for practical implementation in emerging markets. In general, managers should improve innovation ambidexterity by utilizing business analytics, social capital, market orientation, and absorptive capacity. Successfully integrating these four capabilities in fostering innovation ambidexterity remains a key challenge for managers. First, regarding business analytics capabilities, the study suggests that managers should enhance three interrelated technologies: data visualization, data analysis, and data aggregation. Companies leverage business analytics aggregation technologies (e.g., data warehouses) to integrate and improve market consistency of data from multiple sources, analyze data using data analytics technologies (e.g., descriptive, predictive, prescriptive), and visualize data for informed business decision-making. Business analytics aggregation technology identifies the relevant data required from the market and integrates it into business analytics for reporting, monitoring, evaluation, and decision-making. Data aggregation serves as a foundation for data analysis and interpretation.

However, many firm providers face challenges, including the lack of data standards, integration difficulties, data overload, and difficulties in gathering high-quality data. Therefore, managers should recognize the significance of data aggregation tools when deploying business analytics systems. Following aggregation technology capability, firms require expertise in advanced analytics techniques, including the development of descriptive, predictive, and prescriptive analytical models. Furthermore, the insights from business analytics should be accessible to all participants in the innovation process, accompanied by a clear explanation of the significance and limitations of the findings using visualization technology. The business analytics visualization technology enables the firm to consolidate data and visualize its innovation efforts [63], distinguishing between exploratory and exploitative activities.

Second, regarding social capital, firms should focus on enhancing relational capital, fostering structural capital, and driving cognitive capital. Advancements in business analytics technologies may have increased socio-technical barriers to companies integrating them into their operations. Integrating business analytics resources with organizational mechanisms related to social capital—such as structural, relational, and cognitive capital—can help alleviate this burden. Managers should also strive to build trust among colleagues from different business units and clearly convey their vision and goals for implementing business analytics to their members.

For instance, to improve structural capital, firms can establish a cross-functional team and a steering committee to utilize business analytics [16]. Regarding relational capital, various programs, such as team-building workshops or retreats, and sharing sessions across business units [89]. Conducting training sessions to familiarize participants with business analytics, aligning unit visions, and forming joint problem-solving groups can improve cognitive social capital among them. Business analytics technology literacy among managers is crucial for fostering a culture of data-driven innovation and ambidexterity. For example, companies can facilitate this literacy by providing educational materials, such as Frequently Asked Questions (FAQs) and video tutorials, to introduce novice users to the fundamentals of business analytics systems. This approach can encourage managers to read, learn, and understand new features, thereby improving the quality of decision-making. In addition to progressive and regular corporate cultural values training, the company also ensures that managers maintain technical proficiency and stay up to date with the latest developments in business analytics technology.

Third, in building sustainable innovation, some countries have practical manifestations of social capital in their communities that support their innovation activities, for example, through *compadrazgo* (Ecuador) and *guanxi* (China) [28]. Indonesian society employs a similar approach, the *gotong royong* culture. *Gotong royong* is an Indonesian expression originating from the term “gotong,” which signifies “to work,” and “royong,” which denotes “together” [93]. The tradition of *gotong royong* has been transmitted through generations and modified in diverse ways throughout Indonesia. *Gotong royong* is characterized by strong solidarity among individuals and groups, as evidenced by the mutual support that pervades daily life. It is a potential sustainable innovation strategy in Indonesia, grounded in social capital within community culture, to help address business challenges and resource constraints [93]. Previous research has shown that *gotong royong* is an essential social capital for Indonesian people [93]. Three key behaviors generally explain the indicators of *gotong royong* culture: helping each other, making decisions together, and respecting others [94]. The emergence of digital platforms has also strengthened the spirit of *gotong royong* in reducing economic and social problems [95]. Firms should embed the *gotong royong* spirit into their corporate culture and innovation activities as part of their social capital, thereby fostering economic and social performance.

Fourth, Market orientation is not a marketing orientation but rather a part of the entire organization's culture. Every department must have a market-oriented culture, regardless of whether it is related to the marketing function. Business analytics collects information about its market (customers and competitors) and then disseminates this information to various departments and functions. Each department, according to its function, plays a role in customer satisfaction and in sustaining a competitive advantage. Furthermore, firms must develop absorptive capacity to enhance their market orientation strategy. Inter-functional coordination is necessary to disseminate market intelligence on customers and competitors to all business units. A shared understanding across business units regarding customers and competitors eliminates barriers to balancing exploration and exploitative innovation activities. Each department has a role in meeting customer needs and understanding competitors' positions.

Fifth, regarding innovation ambidexterity, this study finds that firms are more inclined to pursue exploitative innovation activities than exploratory ones. It is generally simpler for companies to improve their existing products than to develop entirely new ones. As a result, managers often focus on exploitative strategies to quickly capitalize on opportunities [10]. This result indicated that companies in Indonesia find it easier to enhance existing products and services than to develop new ones for unexplored markets, as they perceive exploitative innovation to yield better and faster returns on valuable resources than exploratory innovation [75]. Another possible explanation is that firms rely much more on basic analytics than on advanced business technology as the primary predictor of exploration. Therefore, most companies use business analytics to interpret past events and then incorporate new practices into their products or services. The firms lack sufficient business analytics expertise, hindering their ability to utilize advanced tools and techniques, such as predictive and prescriptive analytics, to generate more sophisticated reports for managers and senior executives.

Along with developing the ability to utilize advanced tools and techniques to sustain exploration and innovation activities, firms should empower their employees to think creatively, enabling them to develop new ideas for products and services or improve existing ones. Additionally, firms require a framework that supports both exploring new markets and exploiting existing opportunities to foster innovation ambidexterity. Firms can establish an integrated innovation management system that encompasses the entire process, from early development to the diffusion of innovation. All employees are encouraged to submit their ideas through this system, and executives can effectively evaluate the sustainability of exploratory and exploitative innovation activities.

5.3. Limitations and Recommendations for Future Research

Every study has limitations that invite further research, and this one is no exception. First, the advanced study may be replicated using a mixed-methods approach that combines surveys and semi-structured interviews with managers to gain deeper insights and better understand the interrelated constructs. Second, this study did not examine potential differences by respondent's industry type. Future research could examine whether there is a significant disparity in the effects of this pathway on innovation ambidexterity across industry segments. Third, because of Indonesia's unique characteristics, these findings may not apply to other countries. While these traits are pertinent to various nations, their influence and relative significance may differ. Fourth, more detailed research is required to investigate through a variety of theoretical lenses, such as information processing theory and institutional theory.

5.4. Conclusions

This study examines the distinct roles of social capital, market orientation, and absorptive capacity in building a business analytics implementation model that supports innovation ambidexterity. We expand existing knowledge on how market orientation and absorptive capacity mediate the link between business analytics, socio-technical capability and firm innovation ambidexterity. The results show that market orientation and absorptive capacity play complementary partial mediating roles in the relationships between business analytics, socio-technical capabilities and innovation ambidexterity. This study contributes to the fields of information systems and innovation management by examining the role of business analytics in helping organizations balance exploration and exploitation. In practice, this research offers guidance to stakeholders and corporate officials, helping them formulate business analytics implementation strategies that foster innovation ambidexterity, particularly in an emerging economy with strong social cultures within its communities.

Author Contributions: Conceptualization, A.Y.R., R.G. and M.A.; methodology, A.Y.R., R.G. and M.A.; software, A.Y.R.; validation, A.Y.R.; investigation, A.Y.R., R.G. and M.A.; writing—original draft preparation, A.Y.R., R.G. and M.A.; writing—review and editing, A.Y.R., R.G. and M.A.; supervision, A.Y.R.; project administration, A.Y.R.; funding acquisition, A.Y.R. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Industrial Engineering Department, School of Industrial and Systems Engineering, Telkom University, Indonesia (PID number: 003/SDM12/2021).

Institutional Review Board Statement: This study is waived from ethical review by the Institutional Committee due to its non-interventional nature and minimal risk, the guaranteed confidentiality of the participants' data, the voluntary nature of their participation, and the intended use of the collected data for academic publication.

Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study.

Data Availability Statement: Data are provided in the article.

Acknowledgments: The authors sincerely acknowledge the respondents for their consent, which enabled us to complete the analysis. The authors also acknowledge the anonymous reviewers for their helpful comments and the administrators for their support throughout the publishing process.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Lozada, N.; Arias-Pérez, J.; Henao-García, E.A. Unveiling the effects of big data analytics capability on innovation capability through absorptive capacity: Why more and better insights matter. *J. Enterp. Inf. Manag.* **2023**, *36*, 680–701. [\[CrossRef\]](#)
2. Elidjen, E.; Pertiwi, A.; Mursitama, T.N.; Beng, J.T. How potential and realized absorptive capacity increased ability to innovate: The moderating role of structural ambidexterity. *VINE J. Inform. Knowl. Manag.* **2022**, *55*, 15–33. [\[CrossRef\]](#)
3. D'souza, C.; Nanere, M.; Marimuthu, M.; Arwani, M.; Nguyen, N. Market orientation, performance and the mediating role of innovation in Indonesian SMEs. *Asia Pac. J. Mark. Logist.* **2022**, *34*, 2314–2330. [\[CrossRef\]](#)
4. Asni, N.; Agustia, D. Does corporate governance induce green innovation ? An emerging market evidence. *Corp. Gov.* **2022**, *22*, 1375–1389. [\[CrossRef\]](#)
5. Jaidi, N.; Siswantoyo; Liu, J.; Sholikhah, Z.; Andhini, M.M. Ambidexterity Behavior of Creative SMEs for Disruptive Flows of Innovation: A Comparative Study of Indonesia and Taiwan. *J. Open Innov. Technol. Mark. Complex.* **2022**, *8*, 141. [\[CrossRef\]](#)
6. Ju, M.; Elliott, M.T. Antecedents of organizational ambidexterity: An empirical investigation of foreign ventures in an emerging market. *J. Bus. Ind. Mark.* **2024**, *39*, 350–365. [\[CrossRef\]](#)
7. Moreno-Luzon, M.; Gil-Marques, M.; Lloria, M.B.; Salas-Vallina, A. Quality-oriented human resource practices (QHRP), ambidextrous culture and organizational ambidexterity: A study of green agro-food companies. *Eur. J. Manag. Bus. Econ.* **2024**, *33*, 253–271. [\[CrossRef\]](#)

8. Shamim, S.; Zeng, J.; Khan, Z.; Zia, N.U. Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technol. Forecast. Soc. Change* **2020**, *161*, 120315. [\[CrossRef\]](#)
9. O'Reilly, C.A.; Tushman, M.L. The Ambidextrous Organization. *Harv. Bus. Rev.* **2004**, *82*, 74–81.
10. O'Reilly, C.A.; Tushman, M.L. Ambidexterity as a dynamic capability: Resolving the innovator's dilemma. *Res. Organ. Behav.* **2008**, *28*, 185–206. [\[CrossRef\]](#)
11. March, J.G. Exploration and Exploitation in Organizational Learning. *Organ. Sci.* **1991**, *2*, 71–87. [\[CrossRef\]](#)
12. Kassotaki, O. Review of Organizational Ambidexterity. *SAGE Open* **2022**, *12*, 21582440221. [\[CrossRef\]](#)
13. Dzenopoljac, A.; Dzenopoljac, V.; Muhammed, S.; Abidi, O.; Kraus, S. Intra-organizational knowledge sharing, ambidexterity and firm performance: Evaluating the role of knowledge quality. *J. Knowl. Manag.* **2024**, *28*, 132–155. [\[CrossRef\]](#)
14. Alaskar, T.H.; Alsadi, A.K.; Aloulou, W.J.; Ayadi, F.M. Big Data Analytics, Strategic Capabilities, and Innovation Performance: Mediation Approach of Organizational Ambidexterity. *Sustainability* **2024**, *16*, 5111. [\[CrossRef\]](#)
15. Ashrafi, A.; Zareravasan, A. An ambidextrous approach on the business analytics-competitive advantage relationship: Exploring the moderating role of business analytics strategy. *Technol. Forecast. Soc. Change* **2022**, *179*, 121665. [\[CrossRef\]](#)
16. Shuradze, G.; Bogodistov, Y.; Wagner, H.T. The role of marketing-enabled data analytics capability and organisational agility for innovation: Empirical evidence from German firms. *Int. J. Innov. Manag.* **2018**, *22*, 1–32. [\[CrossRef\]](#)
17. Persaud, A.; Zare, J. Beyond Technological Capabilities: The Mediating Effects of Analytics Culture and Absorptive Capacity on Big Data Analytics Value Creation in Small- and Medium-Sized Enterprises. *IEEE Trans. Eng. Manag.* **2024**, *71*, 7147–7159. [\[CrossRef\]](#)
18. Božič, K.; Dimovski, V. Business intelligence and analytics for value creation: The role of absorptive capacity. *Int. J. Inf. Manag.* **2019**, *46*, 93–103. [\[CrossRef\]](#)
19. Kristoffersen, E.; Mikalef, P.; Blomsma, F.; Li, J. Towards a business analytics capability for the circular economy. *Technol. Forecast. Soc. Change* **2021**, *171*, 120957. [\[CrossRef\]](#)
20. Marjanovic, O. A novel mechanism for business analytics value creation: Improvement of knowledge-intensive business processes. *J. Knowl. Manag.* **2022**, *26*, 17–44. [\[CrossRef\]](#)
21. Mikalef, P.; Pappas, I.O.; Krogstie, J.; Giannakos, M. Big data analytics capabilities: A systematic literature review and research agenda. *Inf. Syst. e-Bus. Manag.* **2018**, *16*, 547–578. [\[CrossRef\]](#)
22. Yoshikuni, A.C.; Dwivedi, R.; Filho, A.R.d.A.V.; Wamba, S.F. Big data analytics-enabled dynamic capabilities for corporate performance mediated through innovation ambidexterity: Findings from machine learning with cross-country analysis. *Technol. Forecast. Soc. Change* **2025**, *210*, 123851. [\[CrossRef\]](#)
23. Mikalef, P.; Boura, M.; Lekakos, G.; Krogstie, J. Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment. *Br. J. Manag.* **2019**, *30*, 272–298. [\[CrossRef\]](#)
24. Shi, Y.; Toorn, C.V.; McEwan, M. Exploration–Exploitation: How business analytics powers organisational ambidexterity for environmental sustainability. *Inf. Syst. J.* **2024**, *34*, 894–930. [\[CrossRef\]](#)
25. Mehdikhani, R.; Valmohammadi, C.; Taraz, R. The influence of business analytics on supply chain ambidexterity: The mediating role of market learning. *VINE J. Inform. Knowl. Manag.* **2024**, *55*, 951–977. [\[CrossRef\]](#)
26. Shamim, S.; Zeng, J.; Shafi Choksy, U.; Shariq, S.M. Connecting big data management capabilities with employee ambidexterity in Chinese multinational enterprises through the mediation of big data value creation at the employee level. *Int. Bus. Rev.* **2020**, *29*, 101604. [\[CrossRef\]](#)
27. Alshahrani, M.A.; Salam, M.A. Entrepreneurial orientation and SMEs performance in an emerging economy: The mediating role of absorptive capacity. *J. Res. Mark. Entrep.* **2024**, *26*, 1–24. [\[CrossRef\]](#)
28. Lee, Y.; Cortes, A.F.; Zhuang, Y.; Herrmann, P. Social capital and organizational ambidexterity: The moderating effect of absorptive capacity. *Int. J. Emerg. Mark.* **2021**, *16*, 1793–1812. [\[CrossRef\]](#)
29. Putnam, R.D. Social Capital and Public Life. *Am. Prospect.* **1993**, *4*, 1–11.
30. Gnizy, I. Big data and its strategic path to value in international firms. *Int. Mark. Rev.* **2019**, *36*, 318–341. [\[CrossRef\]](#)
31. Ciampi, F.; Demi, S.; Magrini, A.; Marzi, G.; Papa, A. Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation. *J. Bus. Res.* **2021**, *123*, 1–13. [\[CrossRef\]](#)
32. Song, J.; Xiang, Y.; Huang, B.; Xie, Y.; Li, Y. Exploring How Big Data Analytics Management Capability Fuel Market Performance: Evidence From a Mediated Moderation Model. *IEEE Trans. Eng. Manag.* **2024**, *71*, 9080–9093. [\[CrossRef\]](#)
33. Gangwani, K.K.; Bhatia, M.S. The effect of market orientation and technology orientation on industry 4.0 technologies and market performance: Role of innovation capability. *Ind. Mark. Manag.* **2024**, *118*, 231–241. [\[CrossRef\]](#)
34. Kim, H.; Hur, D. Feeling torn? The conflicting effects of market and entrepreneurial orientations on manufacturing SMEs' innovation performance. *Eur. J. Innov. Manag.* **2024**, *27*, 233–262. [\[CrossRef\]](#)
35. Sengura, J.D.; Mu, R.; Zhang, J. Towards Frugal Innovation Capability in Emerging Markets within the Digitalization Epoch: Exploring the Role of Strategic Orientation and Organizational Ambidexterity. *J. Theor. Appl. Electron. Commer. Res.* **2024**, *19*, 2000–2029. [\[CrossRef\]](#)

36. Lichtenthaler, U. Determinants of absorptive capacity: The value of technology and market orientation for external knowledge acquisition. *J. Bus. Ind. Mark.* **2016**, *31*, 600–610. [[CrossRef](#)]
37. Randhawa, K.; Wilden, R.; Gudergan, S. How to innovate toward an ambidextrous business model? The role of dynamic capabilities and market orientation. *J. Bus. Res.* **2021**, *130*, 618–634. [[CrossRef](#)]
38. Gao, J.; Sarwar, Z. How do firms create business value and dynamic capabilities by leveraging big data analytics management capability? *Inf. Technol. Manag.* **2024**, *34*, 219–232. [[CrossRef](#)]
39. Bharadwaj, A.S. A resource-based perspective on information technology capability and firm Performance. *MIS Q.* **2000**, *24*, 169–196. [[CrossRef](#)]
40. Barney, J.; Wright, M.; Ketchen, D.J. The resource-based view of the firm: Ten years after 1991. *J. Manag.* **2001**, *27*, 625–641. [[CrossRef](#)]
41. Eisenhardt, K.M.; Martin, A.J. Dynamic capabilities: What are they? *Strateg. Manag. J.* **2000**, *21*, 1105–1121.
42. Helfat, C.E.; Peteraf, M.A. The dynamic resource-based view: Capability lifecycles. *Strateg. Manag. J.* **2003**, *24*, 997–1010. [[CrossRef](#)]
43. Teece, D.J. Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance. *Strateg. Manag. J.* **2007**, *28*, 1319–1350. [[CrossRef](#)]
44. Birkinshaw, J.; Zimmermann, A.; Raisch, S. How Do Firms Adapt to Discontinuous Change? Bridging The Dynamic Capabilities And Ambidexterity Perspectives. *Calif. Manag. Rev.* **2016**, *58*, 36–58. [[CrossRef](#)]
45. Malik, M.; Andargoli, A.; Chavez, R.; Mikalef, P. A relational view of how social capital contributes to effective digital transformation outcomes. *J. Strategic. Inform. Syst.* **2024**, *33*, 101837. [[CrossRef](#)]
46. Božič, K.; Dimovski, V. The Relationship between Business Intelligence and Analytics Use and Organizational Absorptive Capacity: Applying the DeLone & Mclean Information Systems Success Model. *Econ. Bus. Rev.* **2020**, *22*, 191–232. [[CrossRef](#)]
47. Cohen, W.M.; Levinthal, D.A. Absorptive Capacity: A New Perspective on Learning and Innovation. *Adm. Sci. Q.* **1990**, *35*, 128–152. [[CrossRef](#)]
48. Zahra, S.A.; George, G. Absorptive capacity: A review, reconceptualization, and extension. *Acad. Manag. Rev.* **2002**, *27*, 185–203. [[CrossRef](#)]
49. Pavlou, P.a.; Sawy, O.a.E. Understanding the ‘Black Box’ of Dynamic Capabilities. *Manag. Sci.* **2011**, *92521*, 239–273. [[CrossRef](#)]
50. Schryen, G. Revisiting IS business value research: What we already know, what we still need to know, and how we can get there. *Eur. J. Inf. Syst.* **2013**, *22*, 139–169. [[CrossRef](#)]
51. Gillani, F.; Ali, K.; Sadiq, S.; Cao, D.; Ma, X. Unpacking Digital Transformation: Identifying key enablers, transition stages and digital archetypes. *Technol. Forecast. Soc. Change* **2024**, *203*, 123335. [[CrossRef](#)]
52. Mikalef, P.; van de Wetering, R.; Krogstie, J. Building dynamic capabilities by leveraging big data analytics: The role of organizational inertia. *Inf. Manag.* **2021**, *59*, 103412. [[CrossRef](#)]
53. Raisch, S.; Birkinshaw, J.; Probst, G.; Tushman, M.L. Organizational Ambidexterity: Balancing Exploitation and Exploration for Sustained Performance. *Organ. Sci.* **2009**, *20*, 685–695. [[CrossRef](#)]
54. Gibson, C.B.; Birkinshaw, J. The Antecedents, Consequences, And Mediating Role of Organizational Ambidexterity. *Acad. Manag. J.* **2004**, *47*, 209–226. [[CrossRef](#)]
55. Raisch, S.; Birkinshaw, J. Organizational Ambidexterity: Antecedents, Outcomes, and Moderators. *J. Manag.* **2008**, *34*, 375–409. [[CrossRef](#)]
56. Kowalczyk, M.; Buxmann, P. An ambidextrous perspective on business intelligence and analytics support in decision processes: Insights from a multiple case study. *Decis. Support Syst.* **2015**, *80*, 1–13. [[CrossRef](#)]
57. Kumalaningrum, M.P.; Ciptono, W.S.; Indarti, N.; Purnomo, B.R. Ambidexterity in Indonesian SMEs: A Systematic Review and Synthesis for Future Research. *Cogent Bus. Manag.* **2023**, *10*, 1. [[CrossRef](#)]
58. Gupta, M.; George, J.F. Toward the development of a big data analytics capability. *Inf. Manag.* **2016**, *53*, 1049–1064. [[CrossRef](#)]
59. Akter, S.; Hossain, M.A.; Lu, Q.; Shams, S.M.R. Big data-driven strategic orientation in international marketing. *Int. Mark. Rev.* **2021**, *38*, 927–947. [[CrossRef](#)]
60. Hu, H.; Wen, Y.; Chua, T.S.; Li, X. Toward scalable systems for big data analytics: A technology tutorial. *IEEE Access* **2014**, *2*, 652–687. [[CrossRef](#)]
61. Belhadi, A.; Zkik, K.; Cherrafi, A.; Yusof, S.r.M.; El Fezazi, S. Understanding Big Data Analytics for Manufacturing Processes: Insights from Literature Review and Multiple Case Studies. *Comput. Ind. Eng.* **2019**, *137*, 106099. [[CrossRef](#)]
62. Oesterreich, T.D.; Anton, E.; Teuteberg, F.; Dwivedi, Y.K. The role of the social and technical factors in creating business value from big data analytics: A meta-analysis. *J. Bus. Res.* **2022**, *153*, 128–149. [[CrossRef](#)]
63. Wang, Y.; Byrd, T.A. Business analytics-enabled decision-making effectiveness through knowledge absorptive capacity in health care. *J. Knowl. Manag.* **2017**, *21*, 517–539. [[CrossRef](#)]
64. Nugroho, M.A.; Jusoh, R.; Salleh, N.A.M. The Role of Alignment Between IS Strategy and Social Capital on the IS Capability and Business Performance Relationship: A Cross-Sectional Survey. *IEEE Access* **2020**, *8*, 52760–152771. [[CrossRef](#)]

65. Yang, S.; Lee, H.; Kurnia, S. Social Capital in Information and Communications Technology Research: Past, Present, and Future. *Commun. Assoc. Inf. Syst.* **2009**, *25*, 23. [\[CrossRef\]](#)
66. Nahapiet, J.; Ghoshal, S. Creating organizational capital through intellectual and social capital. *Acad. Manag. Rev.* **1998**, *23*, 242–266. [\[CrossRef\]](#)
67. Aloulou, W.J. Impacts of strategic orientations on new product development and firm performances: Insights from Saudi industrial firms. *Eur. J. Innov. Manag.* **2019**, *22*, 257–280. [\[CrossRef\]](#)
68. Narver, J.C.; Slater, S.F. The of Effect Orientation on a Market Business Profitability. *J. Mark.* **1990**, *54*, 20–35. [\[CrossRef\]](#)
69. Qu, Y.; Mardani, A. Market orientation, technological opportunity, and new product innovation performance. *J. Bus. Res.* **2023**, *162*, 113841. [\[CrossRef\]](#)
70. Ramachandran, I.; Lengnick-Hall, C.A.; Badrinarayanan, V. Enabling and leveraging ambidexterity: Influence of strategic orientations and knowledge stock. *J. Knowl. Manag.* **2019**, *23*, 1136–1156. [\[CrossRef\]](#)
71. Grant, R.M. Toward a Knowledge-Based Theory of The Firm. *Strategic. Manag. J.* **1996**, *17*, 109–122. [\[CrossRef\]](#)
72. Kohli, A.K.; Jaworski, B.J. Market Orientation: The Construct, Research Propositions, and Managerial Implications. *J. Mark.* **1990**, *54*, 1–18. [\[CrossRef\]](#)
73. Ramírez-Solis, E.R.; Llonch-Andreu, J.; Malpica-Romero, A.D. How beneficial are relational capital and technology orientation for innovation? Evidence from Mexican SMEs. *Int. J. Innov. Stud.* **2022**, *6*, 1–10. [\[CrossRef\]](#)
74. Gao, S.; Yeoh, W.; Wong, S.F.; Scheepers, R. A literature analysis of the use of Absorptive Capacity construct in IS research. *Int. J. Inf. Manag.* **2017**, *37*, 36–42. [\[CrossRef\]](#)
75. Božič, K.; Dimovski, V. Business intelligence and analytics use, innovation ambidexterity, and firm performance: A dynamic capabilities perspective. *J. Strategic. Inform. Syst.* **2019**, *28*, 101578. [\[CrossRef\]](#)
76. Chuang, M.Y.; Chen, C.J.; Lin, M.J.J. The impact of social capital on competitive advantage: The mediating effects of collective learning and absorptive capacity. *Manag. Decis.* **2016**, *54*, 1443–1463. [\[CrossRef\]](#)
77. Zardini, A.; Ricciardi, F.; Rossignoli, C. The relational capital of the IT department: Measuring a key resource for creating strategic value. *J. Intellect. Cap.* **2015**, *16*, 835–859. [\[CrossRef\]](#)
78. Akbari, M.; Baghersad, V.; Harandizadeh, M.; Giglio, C.; Padash, H. Absorptive capacity and technological innovation: Ambidexterity and research and development. *Manag. Decis.* **2025**. [\[CrossRef\]](#)
79. Huma, S.; Muslim, S.; Ahmed, W. Understanding the role of organizational intellectual capital on developing absorptive capacity to strategize innovation ambidexterity. *Rev. Int. Bus. Strategy* **2024**, *34*, 433–453. [\[CrossRef\]](#)
80. Flatten, T.C.; Engelen, A.; Zahra, S.A.; Brettel, M. A measure of absorptive capacity: Scale development and validation. *Eur. Manag. J.* **2011**, *29*, 98–116. [\[CrossRef\]](#)
81. Jansen, J.J.P.; Van Den Bosch, F.A.J.; Volberda, H.W. Exploratory innovation, exploitative innovation, and performance: Effects of organizational antecedents and environmental moderators. *Manag. Sci.* **2006**, *52*, 1661–1674. [\[CrossRef\]](#)
82. Mandal, S. An examination of the importance of big data analytics in supply chain agility development: A dynamic capability perspective. *Manag. Res. Rev.* **2018**, *41*, 1201–1219. [\[CrossRef\]](#)
83. Hair, J.F.; Hult, G.T.M.; Ringle, C.M.; Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed.; SAGE Publishing: Thousand Oaks, CA, USA, 2022; p. 355.
84. Kock, N. Common Method Bias in PLS-SEM. *Int. J. e-Collab.* **2015**, *11*, 1–10. [\[CrossRef\]](#)
85. Becker, J.M.; Cheah, J.H.; Gholamzade, R.; Ringle, C.M.; Sarstedt, M. PLS-SEM's most wanted guidance. *Int. J. Contemp. Hosp. Manag.* **2023**, *35*, 321–346. [\[CrossRef\]](#)
86. Sarstedt, M.; Hair, J.F.; Cheah, J.H.; Becker, J.M.; Ringle, C.M. How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australas. Mark. J.* **2019**, *27*, 197–211. [\[CrossRef\]](#)
87. Hair, J.; Alamer, A. Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Res. Methods Appl. Linguist.* **2022**, *1*, 100027. [\[CrossRef\]](#)
88. Henseler, J.; Hubona, G.; Ray, P.A. Using PLS path modeling in new technology research: Updated guidelines. *Ind. Manag. Data Sys* **2016**, *116*, 2–20. [\[CrossRef\]](#)
89. Ramírez-Solis, E.R.; Llonch-Andreu, J.; Malpica-Romero, A.D. Relational capital and strategic orientations as antecedents of innovation: Evidence from Mexican SMEs. *J. Innov. Entrep.* **2022**, *11*, 42. [\[CrossRef\]](#)
90. Ibarra-Cisneros, M.A.; Demuner-Flores, M.d.R.; Hernández-Perlines, F. Strategic orientations, firm performance and the moderating effect of absorptive capacity. *J. Strategy Manag.* **2021**, *14*, 582–611. [\[CrossRef\]](#)
91. Moreira, A.C.; Navaia, E.C.; Ribau, C. The Importance of Exploration and Exploitation Innovation in Emerging Economies. *J. Open Innov. Technol. Mark. Complex.* **2022**, *8*, 140. [\[CrossRef\]](#)
92. Karina, R.; Siti-Nabiha, A.K.; Jurnal, T. Big data integration in performance management and control: A socio-technical perspective. *J. Account. Organ. Change* **2025**. [\[CrossRef\]](#)
93. Lukiyanto, K.; Wijayaningtyas, M. Gotong Royong as social capital to overcome micro and small enterprises' capital difficulties. *Heliyon* **2020**, *6*, 110–120. [\[CrossRef\]](#)

94. Humaedi, M.A.; Wibowo, D.P.; Hariyanto, W.; Rahmat, S.; Susilo, T.; Wijayanti, F.; Hakim, F.N.; Martino, M.; Wijaya, G.; Andari, R.N.; et al. Shifting collective values: The role of rural women and gotong royong in village fund policy. *Hum. Soc. Sci. Commun.* **2025**, *12*, 411. [[CrossRef](#)]
95. Faedlulloh, D.; Karmilasari, V.; Meutia, I.F.; Yulianti, D. Examining Social Capital for Urban Societies in the Midst of Covid-19 Through Digital Gotong Royong. *Adv. Soc. Sci. Educ. Humanit. Res.* **2021**, *606*, 202–208.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.