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RESEARCH ARTICLE

The Role of Knowledge-Oriented Leadership in Fostering Innovation Capabilities: The Mediating Role of Data Analytics Maturity

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ABSTRACT The ability to continuously innovate has been widely realized as crucial for organizations to survive and be sustainable. One of the keys to successful innovation in a turbulent environment is leadership from top management and executives in organizations. Moreover, the role of knowledge-oriented leadership in promoting innovation within organizations has received considerable attention in recent studies. However, past studies have been more focused on the indirect impact of knowledge-oriented leadership instead of the direct impact of innovation capability. Therefore, this study examined both the indirect and direct impacts of knowledge-oriented leadership on fostering innovation capabilities through data analytics maturity. Data were collected from 114 participants working in medium and large organizations across different industries in Indonesia using a web-based questionnaire. Data were analyzed using partial least squares-structural equation modeling (PLS-SEM). Results show that knowledge-oriented leadership has a significant direct impact on innovation capabilities, especially on explorative innovation. The results also show that knowledge-oriented leadership has a strong indirect impact on both explorative and exploitative innovation through data analytics maturity. Hence, this study confirms that as a third-order construct comprising five dimensions (organizational culture, data governance, strategy management, skills and technology), data analytics maturity plays an important role in fostering explorative and exploitative innovation in companies.

INDEX TERMS Data analytics, exploitative innovation, explorative innovation, innovation capabilities, knowledge-oriented leaderships.

I. INTRODUCTION

In order to survive in a dynamic and highly competitive business environment, organizations are encouraged to continuously innovate. Continuous innovation utilizes knowledge assets to face challenges, seize opportunities, and maintain the organization's relevance and success in the long term. There are two main types of innovation, namely explorative and exploitative. Research shows that organizations that can introduce exploitative and explorative innovation simultaneously will improve the organization's financial performance [1]. Explorative innovation aims to create new products or processes that are different from existing products or processes, which requires new knowledge or changes to existing skills [2]. Exploitative innovation aims to meet existing customer needs and improve existing processes or products based on existing knowledge [2]. Through experimentation and continuous adaptation, innovation enables organizations to create a unique and difficult-to-replicate value proposition, which is then strengthened by technological advances [3]. However, most companies still experience difficulties balancing explorative and exploitative innovation

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due to the competition for scarce resources, which often leads to conflicts and inconsistencies between these activities [4].

The proliferation of digital technologies has revolutionized how organizations collect, store, and analyze data, enabling the use of data-driven decision-making to achieve strategic objectives. With the advent of big data and advanced data analytics, organizations are able to capture large volumes of data from diverse sources, including social media, sensors, and transactional systems [5]. Research also shows that organizations embracing data analytics are more likely to outperform their peers in innovation, productivity, and profitability [6]. Data analytics allows organizations to identify patterns, trends, and correlations in their data, enabling them to make accurate decisions [7]. Therefore, one of the areas that is starting to gain researchers' attention in the information technology literature is how data analytics can facilitate innovation [8].

The study in [9] also showed that there is a close and positive relationship between data analytics and innovation because data acquisition could encourage the formation of new knowledge. New knowledge produced from the data analytics process could support some types of innovation better than others [8]. Furthermore, a key factor contributing to increased innovation is the level of data analytics capabilities within an organization [10]. These capabilities could encourage organizations to build their data analytics maturity, which refers to their ability to effectively collect, analyze, and gain insight from large volumes of data [11]. Hence, to fully harness the power of data analytics, organizations need to invest in tangible assets such as tools, infrastructure, and technology [12], [13] and also in intangible assets such as human resources and strategy [14].

Despite the benefits of data analytics, many organizations still struggle to gain business value and insight from data analytics results [15]. Research showed that organizations could increase productivity by 5% and profitability by 6% if they successfully implement data analytics [15]. Hence, organizations need guidance to develop data analytics capabilities. One of the tools often used by organizations for guidance is the maturity model, which contains the success factors needed to build specific capabilities [5].

Past research has shown that knowledge-oriented leaders can create an innovation culture [16]. Previous studies have examined how leadership can increase innovation capability through various mediating variables. While authors in [16] used knowledge management as a mediating variable, study in [2] used organizational culture as a mediating variable. This study was executed in Indonesia, in which power distance is considered high, and the companies have a strong culture of following the leaders. In this context, it is interesting to investigate leadership's influence on exploitative and explorative innovation mediated by data analytics maturity. This study will contribute in two ways: firstly, to examine the data analytics maturity as a third-order construct, and secondly, to examine its mediating role in the relationship between knowledge-oriented leadership and both explorative and exploitative innovation.

II. THEORETICAL BACKGROUND

A conceptual framework is helpful as a ground base to develop a research model. This section explains the underlying concepts used to develop the hypothesis and build the conceptual framework based on extending the resource-based view from Barney [17].

A. RESOURCE-BASED VIEW ON DATA ANALYTICS

The resource-based view has been widely used by researchers to build research models. It argues that a firm's competitive advantages can be leveraged by deploying a set of specific resources that are "valuable, rare, imperfectly imitable and non-substitutable" [17]. A few scholars, such as [12], [13], and [14], adapted the resources-based view to build a conceptual model that helps organizations understand and organize their data analytics capabilities to get value from their data. They found that it is crucial for firms to build organizational capabilities, which are a firm's strength and competitive advantage. Hence, this study also proposes that data analytics maturity could be a key capability to build a firm's competitive advantage. For instance, authors in [12] and [13] identified three primary resources to build data analytics capability, namely intangible, tangible, and human resources. Furthermore, authors in [14] introduced three main dimensions of data analytics capability: infrastructure flexibility, management capabilities, and personnel capability. Therefore, this study aims to enrich the body of knowledge on data analytics, by proposing a new set of dimensions based on data analytics maturity model literature.

B. DATA ANALYTICS MATURITY

Data analytics capabilities are a company's ability to utilize analytical tools and processes to examine vast amounts of data to gain insights for decision-making [18]. Data analytics capabilities include statistical techniques, data visualization techniques, and dashboards that can hasten organizational decision-making processes [18]. Organizations may struggle to exploit the full potential of large amounts of data to make effective decisions and maintain a competitive advantage if the organization does not achieve a high enough data analytics maturity level. In other words, data analytics maturity can be described as an organization's ability to integrate, manage, and utilize relevant internal and external data sources into decision-making processes [19].

The use of data analytics is increasingly popular because it allows companies to make effective business decisions through the optimization of data-based business processes rather than relying solely on intuition [19]. Despite a growing interest in data analytics, only a small number of companies have the necessary analytical capabilities, including infrastructure, human resources, and effective management skills, to meet analytics requirements [19]. Although previous research has highlighted the relationship between data analytics and innovation [1], [20], there is a need for further research on how data analytics mediates the relationship between knowledge-oriented leadership and innovation capabilities, namely exploitative innovation and explorative innovation.

1) ORGANIZATIONAL CULTURE

The organizational culture dimension is the most widely used dimension in the data analytics maturity models developed by authors in [5], [11], [21], [22], [23], and [24]. The organizational maturity dimension focuses on understanding individual and collective attitudes toward big data and data analytics [25]. There are two main aspects of the organizational dimension, namely the individual aspect (skills) and the collective aspect (culture). The skills aspect evaluates the extent to which employees in the organization are aware of the potential of data analytics technology and have the skills to implement it. The culture aspect assesses the extent to which the organizational culture acknowledges data analytics as important and reliable [25]. Leidner and Kayworth [26] also defined culture as the norms, values, and patterns of organizational behavior that are explicitly and implicitly established over time and lead to a systematic approach to data collection, analysis, and distribution. While skills and culture may have different maturity levels, some studies combine aspects of skills and culture into a single dimension of organizational maturity. At the collective level, the maturity of a data analytics culture is determined by the level of confidence that an organization has in the results big data analytics provides [25]. Moreover, to transform into a data-driven organization, companies must prioritize the establishment of a suitable corporate culture, as well as leadership and communication strategies within the organization [27]. Hence, the ability to develop, acquire, and orchestrate human and organizational resources becomes crucial in providing support for data analytics activities throughout the organization [28]. Therefore, this research proposes that the dimensions of culture and skills should be separate from the dimensions of organizational maturity.

Data is used to create knowledge to help organizations make decisions [12]; hence, data-driven culture is considered as an important sub-dimension in organizational culture. The concept of an IT-business unit partnership is also a critical sub-dimension since collaboration and coordination in data analytics activities are important for IT technical issues and business strategy across the organization. Hence, coordination between IT departments and business divisions is crucial for developing data analytics maturity. Business–IT partnerships refer to a firm's ability to foster collaboration between IT and business units that use the technology, thus facilitating users' understanding of the potential power of data analytics [29], [30]. Collaboration and coordination between IT and business divisions and units is vital for organizations to benefit from data analytics utilization. Collaboration includes disseminating information about new technologies, managing data analytics projects, and sharing knowledge between members [5]. Hence, collaboration is also considered an important sub-dimension of organizational culture. Therefore, this research proposes splitting culture into three sub-dimensions: data-driven culture, collaboration, and IT–business partnerships.

2) DATA GOVERNANCE

Data governance refers to the framework that a company adopts to establish the rights and obligations associated with handling data as an asset of the company [31]. The main objective of data governance is to recognize data as a valuable resource for the organization [32]. In this context, data assets are defined as information with potential value and, therefore, require documentation [33]. The main difference between the concepts of governance and management is that governance refers to the decision-making process and the individuals responsible for making these decisions to ensure the management and utilization of resources. In contrast, management encompasses the execution of implemented decisions [34]. Khatri and Brown [34] identified five decision domains in data governance that must be considered as sub-dimensions of data governance maturity. This framework contains five interrelated decision domains: 1) data principle, 2) data quality, 3) metadata, 4) data access, and 5) data lifecycle. However, several adjustments have been made for this current study.

Data principles aim to establish requirements for using data assets that meet company data quality standards [35]. Hence, data quality is considered as a sub-dimension of data governance. In addition, the data life cycle is the process of defining, collecting, creating, using, maintaining, archiving, and deleting data [34]. Hence, data management becomes an important part of data governance, so this study uses the term data management to replace the term data life cycle.

Companies collect data from various sources, which often include inconsistent, incomplete, and incorrect data, causing complexities with data integration and standardization [27]. Therefore, companies must ensure data is gathered, stored, and managed in a secure, precise, and efficient manner [36]. Thus, security and privacy are the most frequently raised issues regarding using data as an asset. Therefore, this research uses the sub-dimension of data security and privacy.

Access to quality data is essential for organizations to make good decisions, especially in the innovation process. The utilization of external knowledge sources as opposed to solely relying on internal sources of knowledge, has garnered significant interest in the existing literature [37]. One of the success factors for explorative or radical innovation is the use of external knowledge [38]. Studies in the manufacturing industry reveal that innovation outcomes are enhanced when knowledge and information from external sources are utilized [39]. Furthermore, the rapid distribution of data results in increased knowledge-based value creation, accelerating the innovation cycle and the creation of new products [40].

Hausladen and Schosser [41] also argue that the management of data sources is important in organizations. Thus, external and internal data source diversity is vital to encourage the implementation of data analytics in the company's innovation process. Hence, data source diversity is also important for data governance. This research proposes splitting data governance into four sub-dimensions: data management, data quality, data security and privacy, and data source diversity.

3) SKILLS

Several studies have highlighted the importance of people as part of data analytics capability, such as [5], [7], [10], [21], [24], [42], [43], [44], and [45]. Instead of focusing on people, this study proposes to highlight skills, where this dimension focuses on developing employees' or organization members' abilities, knowledge, and competencies to support the use of data analytics. Moreover, employees are considered crucial stakeholders in the data collection process [46] because of the knowledge and skills they possess. Hence, to improve data analytics capabilities, companies must develop technical, relational, and business knowledge and skills [14].

Since data analytics depends on the competence of each individual in the company, it is important to separate the skills dimension from the organizational dimension. The skills dimension needs to be separated from the cultural dimension so that organizations can focus on building internal capabilities, such as the skills and knowledge needed to implement data analytics. In other words, the skills dimension focuses on the types of competencies that each individual or employee in the organization must have. Because employees' and managers' knowledge regarding digitalization and analytical capabilities can be seen as limited resources [42], companies need to increase employees' knowledge and abilities through training. Therefore, it is necessary to identify what kind of skills employees must master to encourage the use of data analytics in the company.

Studies in the field of data science develop methodologies and models that convert raw data into valuable information, knowledge, and actionable strategies [27]. This can be accomplished by utilizing significant big data sources, along with relevant technologies and techniques [27]. Moreover, acquiring data science skills is crucial for advancing data analytics proficiency because such skills empower organizations to effectively analyze and interpret vast quantities of data, which ultimately yields valuable insights [14]. Consequently, the mastery of data science skills is essential for employees to uncover patterns, correlations, and trends within data sets, promoting business growth and fostering innovation within organizations [47].

Analytical skills are closely related to problem-solving abilities. Data analytics frequently involves the use of data-driven approaches to identify and resolve complex business problems [48]. Thus, analytical skills allow employees to break down complicated problems into more manageable components, construct hypotheses, and assess them using appropriate analytical techniques [48]. Moreover, analytical skills empower employees to evaluate the effectiveness of data analytics initiatives, identify gaps in capabilities, and propose strategies to enhance data analytics maturity [27]. Therefore, analytical skills play a crucial role in improving data analytics maturity as they facilitate recognizing opportunities, optimizing processes, and fostering innovation in organizations [48].

Communication skills are also considered crucial for developing data analytics maturity. Xu et al. [48] argued that effective communication plays a vital role in conveying insights derived from data analysis to stakeholders. This includes the visual presentation of data, explanations of statistical analyses, and the interpretation of findings resulting from data analysis [48]. This is because data analysts are encouraged to be proficient in effectively communicating complex technical concepts to non-technical audiences, such as business unit managers. Moreover, data analysts frequently work within interdisciplinary teams, where effective communication is necessary for coordination, information sharing, and conflict resolution [49]. Hence, clear and concise communication guarantees that team members comprehend their respective roles and responsibilities, leading to more efficient and effective collaboration. Thus, this study proposes three skills: analytical, communication, and data science skills.

4) STRATEGY MANAGEMENT

The importance of strategy as a main capability in data analytics maturity has been mentioned in a number of studies [5], [24], [25], [27], [41], [42], [50]. The importance of strategic practices in data analytics initiatives lies in their potential to produce desired outcomes and performance [42]. Hence, organizations need a data science or analytics vision, strategy, and roadmap that can be utilized to overcome the challenges of moving toward a data-driven organization [27]. Notably, strategic IT alignment has been highlighted as a major success factor in IT investment [51]. Thus, strategic alignment in data analytics is important for improving the data analytics maturity level. Companies are also urged to develop a comprehensive strategy to make sure that the data analytics strategy supports business processes [42]. Therefore, strategy management is important for implementing the use of data analytics in organizations. Thus, this study proposes two main sub-dimensions in strategy management, namely data analytics strategy and strategic alignment.

5) TECHNOLOGY

An organization's ability to deploy and manage infrastructure, tools, and technology is becoming increasingly important [44]. Maroufkhani et al. [52] highlighted the successful use of technology as one of the main success factors in big data analytics adoption. The emergence of big data and open-source cloud computing have become significant ways to generate effective technology usage in supporting the company's data analytic capabilities [44]. Business intelligence (BI) technology in a data warehouse environment also offers flexibility in data administration and monitoring, enabling efficient analytical processing [35]. Thus, data warehousing and BI technology are considered sub-dimensions of technology capability.

Maturity in technology use is also required to ensure that data is accessed and employed through the utilization of the most potent and efficient software and hardware [27]. Hence, organizations need to identify and assess potential tools and suitable applications to exploit the capabilities of data analytics [53]. Cosic et al. [21] define IT tools as a separate dimension in data analytics maturity focused on supporting the data analysis process. They propose putting IT tools into two separate dimensions, namely business analytics technology and visualization analytics technology.

Authors in [25] and [43] highlighted the importance of IT infrastructure in the technology dimension. Moreover, the advancement of IT infrastructure is driven by the extent of technology employed in the storage and processing of data analytics [25]. Halaweh and Massry [54] argued that organizations should be supported by a comprehensive IT infrastructure, including high-capacity storage and powerful processors to facilitate extensive data analysis. The absence of flexibility in accessing adequate infrastructure for testing and deployment of data analytics solutions can impede data analysis [43]. Hence, this study also includes IT infrastructure capability as a sub-dimension of technology capability. Thus, this study proposes three main sub-dimensions in technology: IT infrastructure and capability, data analytics tools sophistication, and data warehouse and business intelligence (BI) technology. Appendix A describes the data analytics maturity dimensions used in this study.

C. INNOVATION CAPABILITIES

A company's innovation capability is defined as its ability, compared to its competitors, to collectively apply knowledge, skills, and resources in innovation to add value to the company [65]. In order to compete, companies are encouraged to innovate incrementally (exploitative innovation) and radically (explorative innovation) [66]. Therefore, ambidextrous organizations can carry out both types of product and process innovation [67].

Exploitative innovation ensures reliable implementation of current business processes, so the focus of exploitation is maintaining sustainable business processes to meet commitments to external and internal stakeholders, as well as meeting the efficiency levels required by the company [68]. Exploitative innovation is also designed to meet existing customer needs by building on existing organizational knowledge [2].

Explorative innovation experiments with new features and is related to flexibility [3]. Exploration activities are driven more by opportunities than internal process problems, and their main goal is to encourage innovation, growth, and effective and efficient utilization of business and technical opportunities [68]. Moreover, explorative innovation is aimed at new customers or market needs [2]. Therefore, in contrast to exploitation, which is driven by current practices, exploration focuses on future practices or new opportunities that may occur [68]. Thus, organizations with strong exploration capabilities are generally highly sensitive to external environmental changes.

D. KNOWLEDGE ORIENTED LEADERSHIP

Good leadership is closely related to the ability of top-level executives or senior managers to instill the practice of data-based decision-making in the organization [44], [69]. Researchers such as [7], [10], [21], [23], [44], [45], [54], [55], and [70] emphasize the importance of good leadership to encourage the application of data analytics. Furthermore, data analytics is resource-intensive and relies on collaboration between different units [7]. Therefore, the influence of management support and attitudes towards change are key factors in determining technological innovation adoption [71], [72]. Knowledge is an important aspect of leadership for effectively implementing data analytics. Therefore, the leadership term used in this study is knowledge-oriented leadership, where managers are able to simultaneously support exploration (i.e., creation) and exploitation innovation (i.e., storage, transfer, and application) initiatives [16].

III. MODEL DEVELOPMENT

A. THE DEVELOPMENT OF DATA ANALYTICS MATURITY AS A THIRD-ORDER CONSTRUCT

Recent research argues that the power of data analytics to influence business outcomes can be formed indirectly by developing higher-order dynamic capabilities [14], [73]. Therefore, data analytics is repeatedly identified as a multidimensional hierarchical construct with lower-level sub-dimensions that define the main dimensions [74]. For example, research by Gupta and George [12] and Wamba et al. [14] suggest data analytics capabilities as a higher-order construct because data analytics capabilities are the result of the orchestration of tangible assets, intangible assets, and human skills.

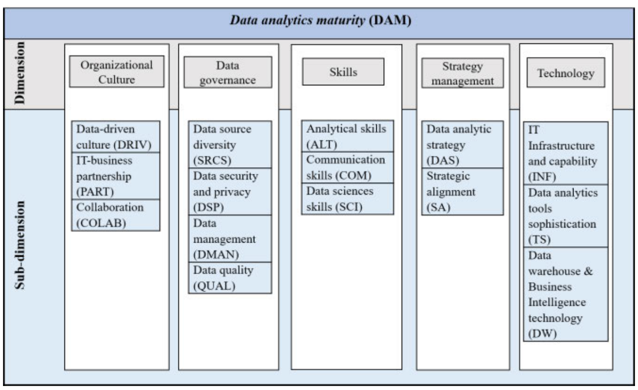

FIGURE 1. Data analytics maturity model.

Sarstedt et al. [75] also argue that higher-order constructs can reduce collinearity among formative indicators by reorganizing indicators and constructs across concrete sub-dimensions of more abstract constructs. In general, a higher-order modeling approach allows the pathways and relationships in the model to be more easily understood [74]. Another important thing to consider in building a data analytics maturity model is the detailed dimensions of existing maturity models [76]. Therefore, this research will develop a data analytics maturity model by considering existing dimensions from previous models. The data analytics maturity construct in this research will be conceptualized as a third-order construct composed of five second-order constructs (organizational culture, data governance, skills, strategic and technology management) and 15 first-order constructs. Fig. 1 shows the data analytics maturity model proposed in this research, and Fig. 2 displays the high-level construct for data analytics maturity.

FIGURE 2. Higher-order construct of data analytics maturity.

B. THE INFLUENCE OF DATA ANALYTICS MATURITY ON INNOVATION CAPABILITIES

Companies can analyze and understand large volumes of diverse big data using data analytics [77], thereby allowing them to recognize gaps that open up opportunities or areas for improvement that can be tackled through innovation [14]. For instance, data analytics can identify customer needs, detect operational inefficiencies, monitor competitors, and develop predictive models of market conditions [20], [78]. Strong data analytics capabilities enable companies to elevate performance levels across departments, from marketing, sales, operations, and supply chain management. Wamba et al. [14] found that organizations with data analytics and big data capabilities exhibited better innovation capabilities due to collecting valuable information from large and diverse data.

High data analytical capabilities have the potential to support or even replace human decision-making by automating responses to the insights that are generated [28]. By leveraging data analytics, companies are able to consolidate the flow of knowledge about existing products and market trends throughout the organizations using integrated technologies [1], [59]. Therefore, companies with a certain level of maturity in applying data analytics will be more able to balance exploitative and exploratory innovation activities. Thus, this research hypothesizes that data analytics maturity could increase organizations' explorative and exploitative innovation capabilities. Fig 3. shows the conceptual model proposed in this research. The dotted lines represent indirect effects, while the solid lines represent direct ones. Hence, this study proposes the following hypotheses:

H1: Data analytics maturity has a significant positive impact on explorative innovation

H2: Data analytics maturity has a significant positive impact on exploitative innovation

C. THE INFLUENCE OF KNOWLEDGE-ORIENTED LEADERSHIP ON DATA ANALYTICS MATURITY

The significance of knowledge-oriented leadership for innovation has grown during the transition from the industrial era to the knowledge era [79]. Leadership plays a dominant role in enabling organizations to acquire, apply, and share corporate knowledge, which drives the spread and implementation of new commercial ideas [79]. Because data analytics requires a lot of data and analytical tools to produce knowledge, corporate leaders must secure, absorb, understand, and integrate new knowledge and ideas [80]. Furthermore, knowledge-oriented leaders will base decisions and activities on their insights. However, data analytics activities are not formed and carried out only as technical activities but need to be developed as capabilities across the company [20]. Therefore, knowledge-oriented leadership is needed to support every data analytics activity in the company and establish data analytics maturity. Hence, this study proposes the following hypothesis:

H3: Knowledge-oriented leadership has a significant positive impact on data analytics maturity

D. THE INFLUENCE OF KNOWLEDGE-ORIENTED LEADERSHIP ON INNOVATION CAPABILITIES

Leaders can facilitate knowledge sharing and collaboration among employees by providing the necessary resources and incentives, thereby breaking down silos to promote cross-functional collaboration and generating new insights and ideas for innovation [16]. Because explorative and exploitative innovation involve very different activities, they require different skills and leadership styles [2]. Leadership also plays an important role in balancing the forces of VOLUME XX, 2017 3 exploration, such as innovation

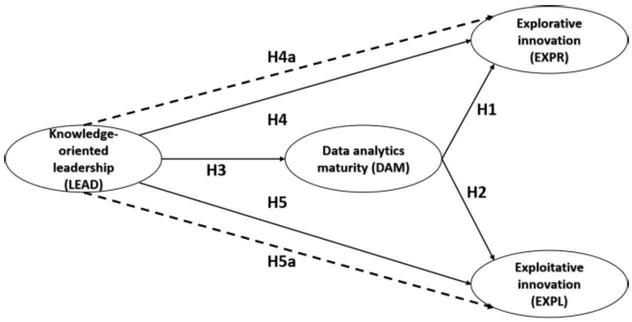

FIGURE 3. Conceptual model.

and change, and the forces of inertia for exploitation [81]. Leaders must make decisions and take actions that resolve these contradictory forces, enabling the company to balance exploration and exploitation innovation [2], [82] which will be possible when leaders or managers encourage their employees to participate in knowledge-based activities [83]. Thus, knowledge-oriented leaders will encourage company members to continue to innovate while balancing exploitative and explorative innovation. Thus, this study hypothesizes that knowledge-oriented leadership will increase exploitative and explorative innovation capabilities. While Table 1 shows the role of each variable used in this research, this study proposes the following hypotheses:

H4: Knowledge-oriented leadership has a significant positive impact on explorative innovation

H4a: Data analytics maturity positively mediates the relationship between knowledge-oriented leadership and explorative innovation

TABLE 1. Roles and description of research variables.

Variable	Role	Description
Data analytics maturity (DAM)	Mediating variable	Data analytics maturity refers to an organization's ability to effectively collect, analyze, and derive insights from large volumes of data.
Exploitative innovation (EXPL)	Outcome variable	Exploitative innovation is designed to meet the needs of emerging customers or markets by offering new designs, markets, and distribution channels [3]
Explorative innovation (EXPLR)	Outcome variable	Explorative innovation is designed to meet the needs of existing markets and customers by improving established designs, expanding existing products, and increasing the efficiency of distribution channels [3].
Knowledge-oriented leadership (LEAD)	Independent variable	Knowledge-oriented leadership refers to managers who simultaneously support exploration (i.e., creation) and knowledge exploitation (i.e., storage, transfer, and application) initiatives [16].

H5: Knowledge-oriented leadership has a significant positive impact on exploitative innovation

H5a: Data analytics maturity positively mediates the relationship between knowledge-oriented leadership and exploitative innovation

IV. RESEARCH METHOD

A. SURVEY INSTRUMENTS

Questionnaire items were developed based on past research. The items were measured using a Likert scale ranging from 1 (“Strongly disagree”) to 5 (“Strongly agree”). For example, the items to measure knowledge-oriented leadership were adapted from Donate and De Pablo [16], who used four indicators: leadership creates an environment for responsible behavior, managers promote learning from experience, managers promote the acquisition of external knowledge, and managers reward employees who share knowledge. The indicators to measure exploitative and explorative innovation as dependent variables are based on Jansen et al. [3] and comprise six items for explorative innovation and six items for exploitative innovation.

Organizational culture comprises several sub-dimensions, such as data-driven culture, IT-business partnership, and collaboration. The measurement items of data-driven culture are based on Gupta and George [12], Hajiheydari et al. [55], and Cosic et al. [69], and indicators of IT-business partnership are based on Ravichandran et al. [60] and Tian et al. [61]. The sub-dimension of collaboration is measured by four items from Brinch et al. [42] and Hornick [50].

On the one hand, data governance comprises four sub-dimensions: data sources diversity, data security and privacy, data management, and data quality. Data source diversity was measured by two indicators related to how the company collects data either from internal sources or both external and internal data sources. Data security and privacy were measured by three indicators from Paul et al. [84]. Additionally, measurement items of data management were adapted from Gupta and George [12]. Seven indicators were also used to measure the sub-dimension of data quality, which were adapted from Wang and Strong [85].

Analytical, communication, and data science skills were also operationalized based on past research from Matin et al. [86], Power [87], and Tippins and Sohi [88]. Furthermore, the measurement indicators of data analytics strategy, strategic alignment, and IT infrastructure and capability were adapted from Akter and Wamba [89]. Additionally, six measurement items from Ghasemaghaei et al. [53] were used to measure data analytics tools’ sophistication. Indicators of data warehouse and business intelligence technology were adapted from Gupta and George [12]. The complete questionnaire can be seen in Appendix B.

B. SURVEY PRE-TESTING

The questionnaire was first tested before being distributed to the full sample of respondents. Pre-testing was carried out on 15 randomly chosen respondents– ten respondents who were experts on data analytics from the service, finance, manufacturing, and technology sectors and five who were academics at educational institutions. These fifteen respondents had a background in data analytics to ensure they could understand the questionnaire questions so that the researchers could test whether the questions were clear enough and easy to understand. Huang et al. [90] also randomly pre-tested ten respondents to confirm the clarity of the survey question items. Respondents were asked to fill out the survey and provide feedback regarding the appearance and content of the survey questions. The questionnaire items were then modified based on the pre-test feedback.

C. DATA COLLECTION

The questionnaire was compiled in Google Forms for easy access and data collection. The questionnaire was distributed to medium-sized companies (20–99 employees) and large-sized companies (100 or more employees) in Indonesia. There were three criteria for selecting respondents: the respondent's position in the company could be no lower than a junior manager, the company implements data analytics in daily activities, and the respondent has experience in using data analytics. The respondents' departments or divisions were not taken into account, assuming that data analytics can be utilized in all company divisions, including human resources, marketing, operations, finance, IT, supply chain, and research and development. The questionnaire was distributed from May – October 2023, and 181 respondents filled out the questionnaire. However, 67 respondents did not meet the research criteria. Therefore, only 114 samples were processed for analysis using SmartPLS software version 3.0.

D. MEASUREMENT MODEL

The measurement model shows how the observed variables can represent latent variables to be measured, so validity and reliability testing was carried out [91]. These tests evaluated each measurement item's accuracy (reliability) and convergent and discriminant validity [91].

1) CONVERGENT VALIDITY

Validity refers to whether a research instrument's measurement attributes are valid. Outer loading is a table containing loading factors showing the magnitude of the correlation between indicators and latent variables used in validity testing. The validity testing procedure measures convergent validity and compares the item score (component score) with the construct score, producing a loading factor value, where validity is considered good if the component or indicator correlates > 0.70 with the construct to be measured [91]. However, for research in the early stages of development, a loading factor of 0.5– 0.6 is considered sufficient [92]. Measurement evaluation was done by using the coefficient path algorithm function in Smart PLS version 3.0 to obtain measurement model test results. In addition, the AVE measure is used to assess convergent validity testing [91]. An AVE value of ≥ 0.5 confirms convergent validity [91].

2) INTERNAL CONSISTENCY RELIABILITY

Reliability measures whether results can be trusted and whether they provide relatively consistent measurements. In order to measure reliability, coefficient alpha or Cronbach alpha and composite reliability are used. A measurement item can be reliable if it has an alpha coefficient value >0.6 [91], [93] and the accepted composite reliability value is >0.7 [94]. The Cronbach alpha value is the lower limit for reliability, and composite reliability (CR) is the upper limit for internal consistency reliability [94]. Additionally, rho_a values usually lie between these limits and represent the construct's internal consistency reliability, assuming the model is correct [94]. Hair et al. [94] also suggested that the CR and CA values should not exceed 0.95 to avoid indicator redundancy, which would impact content validity.

3) DISCRIMINANT VALIDITY

Discriminant validity assessment ensures that the reflective construct has the strongest relationship with its indicators (e.g., when compared with other constructs) in the PLS-SEM path model [94]. Three criteria are used to assess discriminant validity: the Fornell-Larcker criteria, cross-loadings, and the heterotrait-monotrait ratio of correlations (HTMT) [94]. Because the model construct is first-order reflective and higher-order formative, the discriminant validity value is only carried out in stage 1 for the first-order reflective constructs. In the case of the embedded two-stage approach, the model must be assessed only in the first stage because stage two uses the latent variable scores from the output of stage one as a single item, which makes validation on the basis of items meaningless [75]. Therefore, discriminant validity assessment is only carried out in the first stage.

E. STRUCTURAL MODEL

According to Hair et al. [94], there are several criteria used to test the structural model, namely, the significance of path coefficients, R^2 value, predictive power (Q^2), and effect size (f2). Before testing the structural model, it is necessary to identify whether there is collinearity between constructs. The variance inflation factor (VIF) value checks collinearity between constructs, with the maximum accepted VIF limit value being 5 [91].

1) SIGNIFICANCE TESTING

Besides testing the hypotheses, significance testing was used to see whether each low-order construct was a high-order dimension [94]. In other words, significance testing can confirm whether each sub-dimension (e.g., data-driven culture, collaboration, and IT-business partnership) is forming the construct of data analytics maturity dimension (e.g., organizational culture). Significance testing in this study uses bootstrapping techniques with a confidence level of 0.05 or 5%. Because the relationship between variables (positive or negative) was clear, a one-way (1-tailed) test was used. In using one-tailed hypothesis testing, the statistical t-value must be > 1.64.

2) R-SQUARE

The R-square (R^2) measures the changes in exogenous variables to endogenous variables [94]. If the R-square (R^2) value is 0.67, then the model is considered good, 0.33 value is considered moderate, and 0.19 is weak [92]. R-square is also referred as the predictive power of a sample [94].

3) Q-SQUARE

To assess the predictive relevance of the PLS path model, the Q-square (Q^2) value needs to be calculated [94]. As a guideline, the Q^2 value should be greater than zero for a particular endogenous construct to indicate the predictive accuracy of the structural model for that construct sample [94]. In other words, if the Q^2 value is less than 0 (zero), it will show that the model lacks predictive relevance. However, if the calculation results show a Q^2 value of more VOLUME XX, 2017 3 than 0 (zero), then the model can be said to have predictive relevance. As a rule of thumb, Q^2 values higher than 0, 0.25, and 0.50 depict the PLS path model's small, medium, and large predictive relevance sample [94]. Q^2 results can be seen in the blindfolding algorithm in SmartPLS software.

4) F-SQUARE

The effect size (f^2) is a measure that quantifies the magnitude of the difference or relationship between variables. The condition is that if the f^2 value is 0.02, the latent predictor has a small influence, 0.15 has a medium influence, and 0.35 has a large influence at the structural level sample [94]. Hair et al. [91] argue that the f^2 value may be redundant for the results of path coefficients. This is because the ranking order of the predictors in explaining the dependent (endogenous) construct in the structural model is often the same when comparing the size of the path coefficient and the size of the f^2 effect. However, the f^2 results and the significance of the path coefficients may differ, for example, due to mediation effects [91], [94]. Since this research has a mediating variable, this research still includes the f^2 value.

V. RESULTS

A. RESPONDENTS' PROFILE

Table 2 shows that out of 114 respondents, 11.40% respondents were from medium companies (20–99 employees) and 88.60% were from large companies (100 or more employees). Furthermore, 68.52% of respondents had more than four years of work experience, which indicates that the majority of the respondents already have knowledge about the implementation of data analytics tools. In terms of company age, it is harder to confirm exploitative innovation in younger companies (1–9 years) since most young companies are likely to focus on expanding their business by capturing new opportunities by creating new products and services rather than strengthening their existing innovation processes. Around thirty percent of the companies surveyed were aged 1–9 years and thus focused on building their core business. Thus, smaller companies are more likely to use explorative innovation.

Moreover, firm size may also influence the results of this research because large-sized companies dominate this research. Business activities in large-sized companies are more mature than in medium-sized companies. Mature companies usually do exploitative innovation as part of their daily business activities because they are more focused on using existing knowledge to optimize their production process, resulting in modifying or configuring their existing products. Hence, exploitative innovation activities may function better than explorative innovation in larger and more mature companies.

B. TWO-STAGE APPROACH FOR MODEL EVALUATION

According to Ringle et al. [95] and Becker et al. [96], high-order PLS-SEM can be carried out using repeated indicators or a two-stage approach. A two-stage approach was used in this study to test the research model because it can overcome problems in reflective-formative higher-order constructs and is more suitable for small sample sizes [75]. It begins by applying a repeated indicators approach to form the first stage of the two-stage approach, where testing is only carried out to assess outer loading without checking the consistency or reliability of the model [74], [75]. Then, in the second stage, the construct scores in the form of latent variables from the results of stage 1 are used as indicators in the high-level construct measurement model [74], [75].

Since this research uses a third-order construct model, the test was carried out in three stages. In the first stage, testing was carried out for lower-order constructs to obtain construct values as latent variables from each lower-order variable. Model assessment for first-order variable components was carried out to see the direct relationships between measured items and the construct. In the second stage, the latent variable scores from the first-order components are used to obtain latent variables for the second-order construct. In the third stage, the second-order latent variable scores were used as indicators for the third-order construct. The higher-order construct of data analytics maturity in this research consisted of 15 first-order constructs, five second-order constructs (organizational culture, data governance, skills, strategy management, and technology), and data analytics maturity as a third-order construct.

Since the indicators of the first-order construct are reflective, in the first stage, the model was measured by the loading factor, Average Variance Extracted (AVE), Cronbach alpha, and composite reliability values. In the second stage, the latent variable first-order scores (ALT, COLAB, COM, DAS, DMAN, DRIV, DSP, DW, INF, PART, QUAL, SA, SCI, SRCS, and TS) were indicators for the second-order construct measurement. In the third stage, the latent variable scores from the second-order construct (organizational culture, data governance, skills, strategy management, and technology) were used to measure the third-order construct (data analytics maturity). Therefore, their validity and reliability must be tested at all three stages.

C. MEASUREMENT MODEL EVALUATION

The measurement model is evaluated by considering internal consistency reliability, convergent validity, and discriminant validity. The measurement model is considered valid if the AVE value is more than 0.5 [91] and the outer loading is more than 0.6 [92]. The outer loading values shown in Appendix B and AVE values shown in Table 3 confirm that all constructs are valid since the AVE is > 0.5 and the outer loading is >0.6. Furthermore, the measurement model is considered reliable if the Cronbach alpha (CA) value is more than 0.6 [91], [93] and the composite reliability (CR) value is more than 0.7 [94]. Table 3 also shows that all constructs are reliable since the Cronbach alpha and CR values are > 0.6 and 0.7, respectively. Hence, the measurement items could be considered as reliable.

Discriminant validity is also used to measure the validity of the model built using three criteria: cross-loadings, Fornell-Larcker, and HTMT. Since the square root value of AVE for each latent variable is greater than the correlation between other latent variables, the Fornell-Larcker value in this research has already met the validity criteria. Additionally, the value of HTMT in this study is also below the threshold value of 0.90, as suggested by [97]. Furthermore, the cross-loading value in this study also shows that the correlation between the constructs and their indicators is higher than the correlation with indicators from other constructs. Hence, based on the cross-loadings, Fornell-Larcker, and HTMT threshold values, all constructs in first-order reflective can be considered valid (see Appendix C and Appendix D).

D. STRUCTURAL MODEL EVALUATION

The structural model can be verified by evaluating the coefficient of determination values (R^2), the effect size of path coefficients (f^2), predictive relevance (Q^2), and the significance of path coefficient. Before testing the structural model, the VIF value is examined, and results in Table 4 show that the VIF value for each indicator in this study is less than 5, indicating no multicollinearity between constructs.

Besides the VIF value, Table 4 also shows the t-value and p-value results for the second-order and third-order constructs which indicates significant results for all relationships between constructs. The results confirm that the 15 first-order constructs are dimensions for the five second-order constructs. Furthermore, the five second-order constructs of organizational culture, data governance, skills, strategy management, and technology were confirmed as dimensions of the data analytical maturity construct because the p-value was significant (< 0.05).

The results of R^2 show that the structural model explains 34.5% of the variance for data analytics maturity ($R^2 = 0.345$), 46.3% of the variance for exploitative innovation ($R^2 = 0.463$), and 45.3% of the variance for explorative innovation ($R^2 = 0.453$). Hence, all the R^2 values represent a moderate level of predictive power [94].

The structural model is also evaluated by examining the effect size (f^2) value, which assesses exogenous constructs' contribution to an endogenous variable. In this study, the effect size of the relationship between data analytics maturity and exploitative innovation can be considered a large effect size ($f^2 = 0.420$), the effect size of the relationship between knowledge-oriented leadership and data analytics maturity is also considered a large effect size ($f^2 = 0.526$), and the effect size of the relationship between data analytics maturity and explorative innovation can be considered as medium effect size ($f^2 = 0.320$). However, the effect size of the relationship between knowledge-oriented leadership and explorative innovation ($f^2 = 0.060$) and between knowledge-oriented leadership and exploitative innovation only shows a small effect size ($f^2 = 0.025$).

TABLE 2. Profile of respondents.

Characteristic	Total sample (N=114)	Proportion (%)
Sector of industry		
Agriculture	2	1.75%
Mining	6	5.26%
Manufacture	14	12.28%
Energy (electricity, gas, and water)	4	3.51%
Construction	1	0.88%
Trade, Restaurants and Hospitality	7	6.14%
Transportation and warehousing	5	4.39%
Information and Communication Technology (ICT) and telecommunication	29	25.44%
Finance and Insurance	32	28.07%
Community, Social, and Personal Services	4	3.51%
Consumer goods	5	4.39%
Pharmacy	2	1.75%
Other	3	2.63%
Size of company		
20 – 99	13	11.4%
100 or more	101	88.6%
Age of company		
1 - 4 years	12	10.53%
5 - 9 years	19	16.67%
10 - 50 years	60	52.62%
>50 years	23	20.18%
Respondent's position		
Chairman/ President/CEO	2	1.85%
Vice President	10	9.26%
Director	5	4.63%
Senior Manager	34	31.48%
Junior Manager	63	58.33%
Total data analytics experience		
1 – 2 years	27	23.69%
3 years	13	11.40%
>4 years	74	64.91%

TABLE 3. Measurement model results.

Level	Construct	Indicator	CA	CR	AVE
First Order	Organizational Culture (C)	Data-Driven Culture (DRIV)	0.784	0.860	0.607
		IT-Business Partnership (PART)	0.910	0.937	0.788
		Collaboration (COLLAB)	0.785	0.862	0.610
	Data Governance (DG)	Data Source Diversity (SRCS)	0.649	0.845	0.733
		Data Security and Privacy (DSP)	0.847	0.908	0.767
		Data Management (DMAN)	0.799	0.882	0.714
		Data Quality (QUAL)	0.909	0.928	0.647
	Skills (S)	Analytical Skills (ALT)	0.923	0.950	0.867
		Communication Skills (COM)	0.890	0.932	0.820
		Data Science Skills (SCI)	0.927	0.940	0.662
	Strategy Management (SM)	Data Analytic Strategy (DAS)	0.854	0.932	0.873
		Strategic Alignment (SA)	0.817	0.916	0.845
	Technology (T)	IT Infrastructure and Capability (INF)	0.932	0.957	0.881
		Data Analytics Tools Sophistication (TS)	0.893	0.919	0.654
		Data Warehouse & Business Intelligence Technology (DW)	0.833	0.882	0.600
	Exploitative Innovation (EXPL)		0.926	0.942	0.731
	Explorative Innovation (EXPR)		0.913	0.933	0.701
	Knowledge Oriented Leadership (LEAD)		0.765	0.850	0.588
Second Order	Data Analytics Maturity (DAM)	Organizational Culture (C)	0.657	0.814	0.595
		Data Governance (DG)	0.782	0.861	0.610
		Skills (S)	0.828	0.897	0.744
		Strategy Management (SM)	0.775	0.899	0.816
		Technology (T)	0.850	0.909	0.769
Third Order	Data Analytics Maturity (DAM)		0.910	0.933	0.737

TABLE 4. T-values, P-values, and VIF values.

Level	Construct	Indicators	VIF	T Statistics	P Value
Second Order	Organizational Culture (C)	Data-Driven Culture (DRIV)	1.159	6.217	0.000
		IT-Business Partnership (PART)	1.420	17.489	0.000
		Collaboration (COLAB)	1.432	19.699	0.000
	Data Governance (DG)	Data Source Diversity (SRCS)	1.224	8.886	0.000
		Data Security and Privacy (DSP)	1.849	25.176	0.000
		Data Management (DMAN)	1.727	17.643	0.000
		Data Quality (QUAL)	1.851	35.788	0.000
	Skills (S)	Analytical Skills (ALT)	2.513	64.500	0.000
		Communication Skills (COM)	1.763	17.130	0.000
		Data Science Skills (SCI)	1.923	23.495	0.000
	Strategy Management (SM)	Data Analytic Strategy (DAS)	1.668	30.060	0.000
		Strategic Alignment (SA)	1.668	51.074	0.000
	Technology (T)	IT Infrastructure and Capability (INF)	2.050	32.559	0.000
		Data Analytics Tools Sophistication (TS)	2.321	39.256	0.000
		Data Warehouse & Business Intelligence Technology (DW)	1.945	31.750	0.000
Third Order	Data Analytics Maturity (DAM)	Organizational Culture (C)	1.960	20.257	0.000
		Data Governance (DG)	3.253	37.882	0.000
		Skills (S)	3.377	36.938	0.000
		Strategy Management (SM)	2.296	30.176	0.000
		Technology (T)	3.182	43.356	0.000

This study measures predictive relevance (Q^2) using the blindfolding algorithm in SmartPLS. The value of Q^2 should be more than zero (0) to indicate that variables have good predictive relevance [91]. Table 5 presents the Q^2 values for the endogenous variables, namely data analytical maturity (DAM), explorative innovation (EXPR), and exploitative innovation (EXPL). The model has met predictive relevance because the Q^2 value is more than zero. The Q^2 values of exploitative and explorative innovation are classified as medium values, which means that both models have been constructed well.

The hypotheses in this research were tested using the PLS bootstrapping technique. The hypothesis testing was set at a significance level of 0.05% and one-way (1-tailed). Based on the results, all hypotheses are supported except for the

TABLE 5. Q-square results.

Variable	R Square	R Square Adjusted	Interpretation
Data Analytics Maturity (DAM)	0.345	0.339	Moderate
Exploitative Innovation (EXPL)	0.463	0.453	Moderate
Explorative Innovation (EXPR)	0.453	0.444	Moderate

direct relationship between knowledge-oriented leadership and exploitative innovation. Table 6 shows the results of hypotheses testing in this research. Even though the results of hypotheses testing in Table 6 show that knowledge-oriented leadership has no direct influence on exploitative innovation, the f^2 value indicates that knowledge-oriented leadership still has a small effect on explorative and exploitative innovation.

TABLE 6. Hypotheses results.

Hypothesis	Path	T-value	P-value	Results
H1	DAM →EXPR	6.611	0.000	Accepted
H2	DAM→EXPL	7.353	0.000	Accepted
H3	LEAD→DAM	9.688	0.000	Accepted
H4	LEAD→EXPR	2.632	0.004	Accepted
H4a	LEAD→DAM→EXPR	5.060	0.000	Accepted
H5	LEAD→EXPL	1.595	0.056	Rejected
H5a	LEAD→DAM→EXPL	5.755	0.000	Accepted

Besides testing direct effects, indirect effects are also examined through the mediation effect. Table 7 shows that data analytics maturity mediates the relationship between knowledge-oriented leadership and explorative innovation and between knowledge-oriented leadership and exploitative innovation. Specifically, it shows that data analytics maturity fully mediates the influence of knowledge-oriented leadership on exploitative innovation. However, data analytics maturity only partially mediates the relationship between knowledge-oriented leadership and explorative innovation since knowledge-oriented leadership already directly affects explorative innovation. Findings also suggest that knowledge-oriented leadership has a stronger indirect impact on exploitative and explorative innovation rather than the direct impact.

In regards to model fit, it is important to know that the term model fit has different meanings in the contexts of CB-SEM and PLS-SEM [98]. The goodness-of-fit statistics for CB-SEM come from the difference between the empirical covariance matrix and the theoretical model, while PLS-SEM focuses on the difference between the observed variable or dependent variable values and the values predicted by the model [94], [99]. The criteria used to measure model fit in PLS-SEM is the standardized root mean square residual (SRMR), which can be interpreted as the difference between the observed model correlation and the implied model [94]. A good fit model is a model that meets a threshold SRMR value of < 0.08 [100]. In this study, the SRMR value is 0.073, which is <0.08. Therefore, the research model already met the model fit criteria.

VI. DISCUSSION

A. THEORETICAL CONTRIBUTIONS

The study findings enrich the data analytics literature in several ways. First, results show that knowledge-oriented leadership positively impacts data analytics maturity in organizations. Data analytics is resource-intensive and relies on collaboration between different departments [7]. Support

TABLE 7. Mediation effect.

Relationship between construct	Specific indirect effect	T Statistics	P Values	Results
Knowledge Oriented Leadership → Data Analytics Maturity → Explorative innovation	0.303	5.819	0.000	Significant
Knowledge Oriented Leadership → Data Analytics Maturity → Exploitative innovation	0.344	5.021	0.000	Significant

from top management is necessary to build a supportive environment with sufficient resources to accelerate IT innovation [72]. Knowledge-oriented leaders also promote that knowledge creation in an organization is vital for organizational development and competitive advantage [101]. Hence, organizations will encourage the use of technology to support data analytics processes.

Furthermore, knowledge-oriented leaders will encourage members to make decisions based on data analytics. Such leaders can create a knowledge-sharing culture characterized by openness to ideas so that members of the organization are comfortable sharing information with each other [2]. Therefore, organizational members will be encouraged to utilize tools and data sources to gain new insights. Thus, knowledge-oriented leadership can increase the company's data analytics maturity.

Second, the findings show that knowledge-oriented leadership directly impacts explorative innovation but not exploitative innovation. This may be because 88.6% of the companies in this research were large companies. Previous studies have investigated the impact of firm size and age on innovation performance. Firm size positively influences innovation performance [102], [103] because larger firms often have more diversified resources, such as financial capital and workforce, which enables them to invest in new types of innovation [103]. Diverse expertise in larger firms also contributes to innovative and creative thinking by enabling companies to accumulate a larger store of technological knowledge and skills [104]. Thus, larger firms may invest more resources in explorative innovation. By contrast, smaller companies may be more agile and flexible in responding to market changes [103], allowing them to adopt radical or explorative innovation quickly.

In this study, 73% of firms were aged more than ten years, which can be considered as mature organizations. Firm age may influence innovation [105], [106] because as a firm ages, its capabilities and expertise expand, enabling it to effectively and efficiently execute its operations [107]. Older companies tend to innovate more because they are more likely to build upon their well-established innovative activities [107]. Hence, the exploitative innovation activities that result in modifying existing products could already

TABLE 8. Descriptions of the data analytics maturity dimensions.

No	Data analytics maturity dimension (Second-order construct)	Data analytics maturity sub-dimension (First-order construct)	Description	Used by
1	Organizational culture	Data-driven culture (DRIV)	Data-driven culture displays patterns of behavior, practices, and beliefs that are consistent with the principles of analytical decision-making [55].	[10], [12], [55]–[58]
		Collaboration (COLAB)	Collaboration is the ability of organizational members to work together to develop and achieve goals using data analytics [5].	[5], [42], [50]
		IT–business partnership (PART)	An IT–business partnership is a collaborative relationship between the IT department and business units. in which IT executives are involved in solving complex business-related problems, corporate planning, and strategy creation, and business managers participate in overall IT management, IT decision-making, and IT planning [59].	[51], [60], [61]
2	Data governance	Data source diversity (SRCS)	Diverse knowledge sources, both external and internal to the organization, are important to encourage the implementation of analytical data in the innovation process.	Proposed dimension
		Data security and privacy (DSP)	Data security refers to security requirements regarding accessibility, authenticity, availability, confidentiality, integrity, privacy, and data reliability [35].	[7], [27], [52], [54], [55], [62]
		Data management (DMAN)	Data management comprises data preparation and data integration activities including mechanisms to retrieve data, ensure data quality, and integrate data with existing data in a central repository [21].	[21], [27], [41]
		Data quality (QUAL)	Data quality refers to the ability to meet user needs consisting of data accuracy, timeliness, completeness, and credibility. Poor data quality is the main obstacle for companies to grow data analytics competencies because of the increasing number of data sources [34].	[7], [10], [53], [54], [62]
3	Skills	Analytical skills (ALT)	Analytical skills are used to solve problems by describing data and information to develop creative and rational solutions [63].	[53], [62]
		Data science skills (SCI)	Data science skills involve utilizing technology, models, and data to produce useful information [27].	[27]
		Communication skills (COM)	Organizational members foster a culture of open communication and trust [21] by developing the ability to translate analytical data concepts into everyday business language [64].	[5], [10], [21]
4	Strategy management	Data analytic strategy (DAS)	The data analytics strategy is part of the company's long-term strategy, specifically, the identification of opportunities and the integration of analytical operations, analytical infrastructure, and analytical models to achieve the mission and vision of the organization [36].	[36].
		Strategic alignment (SA)	Strategic alignment refers to aligning the data analytics strategy with the organization's business strategy in a two-way relationship [21].	[10], [21], [27], [55]
5	Technology	IT infrastructure and capability (INF)	Infrastructure refers to the maturity of the IT environment developed by an organization to acquire, manage, and extract knowledge [25]	[7], [25], [43], [54], [57]
		Data analytics tools sophistication (TS)	sophistication of data analytics tools refers to the complexity of the tools that represent the degree of technological proficiency within the organization [53]	[41], [50], [53], [62]
		Data warehousing and business intelligence technology (DW)	BI technology capabilities are the ability to develop and utilize analytical applications, such as reports, dashboards, scorecards, online analytical processing (OLAP), and data visualization technologies that display output in a user-friendly format that is easy to understand by non-technical users [21].	Proposed dimensions

operate efficiently and effectively without further guidance from top management. The results of this study suggest that knowledge-oriented leadership does not directly affect exploitative innovation and only directly influences explorative innovation.

Consequently, data analytics maturity plays a crucial role in mediating the relationship between knowledge-oriented leadership and exploitative innovation. This study shows that data analytics maturity has a full mediating effect on exploitative innovation and a partial mediating effect on explorative innovation. Knowledge-oriented leadership means emphasizing the importance of knowledge and taking advantage of opportunities to innovate [16]. Knowledge-oriented leadership possibly has a direct effect on explorative innovation rather than on exploitative innovation because leaders who encourage experimentation, risk-taking, and learning from failure create an innovation culture within the organization. Hence, they foster an environment where

TABLE 9. Measurement items.

No	Indicators	Items	Measurement items	Outer loading	Reference
1	Data-driven culture (DRIV)	DRIV1	We are willing to override our own intuition when data contradict our viewpoints	0.648	[12]
		DRIV2	We continuously coach our employees to make decisions based on data	0.801	
		DRIV3	We continuously assess and improve the business rules in response to insights extracted from data	0.808	
		DRIV4	We routinely use data and business analytics (BA) tools to solve problems and make decisions	0.845	[55], [21]
2	IT-business partnership (PART)	PART1	Our IS department and business units understand the working environments of each other very well	0.910	[60], [61]
		PART2	There is a high degree of trust between our IS department and business units	0.899	
		PART3	The goals and plans for IT projects are jointly developed by both the IS department and business units	0.908	
		PART4	Conflicts between IS departments and business units are always resolved through dialogue and mutual adjustment	0.831	
3	Collaboration (COLAB)	COLAB1	Our company is used to sharing information	0.829	[42]
		COLAB2	Interaction between employees is always well established in our company	0.844	
		COLAB3	Our company is used to involving employees from across divisions/units to work on functional projects	0.761	
		COLAB4	In our company, data analytics projects/work often involve many employees with various areas of expertise and different roles	0.681	[50]
4	Data sources diversity (SRCS)	SRCS1	1. Our company often only collects data sources that come from internal companies for the data analysis process	0.793	Proposed dimension
		SRCS3	3. Our company often collects data sources from internal and external companies for the data analysis process	0.915	
5	Data security and privacy (DSP)	DSP1	1. Only authorized individuals have access to the database system	0.818	[84]
		DSP2	2. The IT system could prevent unauthorized access as well as protection against personal data breaches	0.913	
		DSP2	3. The IT system could prevent unauthorized changes to information in the database	0.893	
6	Data management (DMAN)	DMAN1	1. We have access to very large, unstructured, or fast-moving data for analysis	0.856	[12]
		DMAN2	2. We integrate data from multiple internal sources into a data warehouse or mart for easy access	0.871	
		DMAN3	3. We integrate external data with internal to facilitate high-value analysis of our business environment	0.806	
7	Data Quality (QUAL)	In my organization, data used in data analytics:			[85]
		QUAL1	is reliable	0.782	
		QUAL2	has an appropriate level of details	0.807	
		QUAL3	is secure	0.770	
		QUAL4	is timely	0.752	
		QUAL5	is relevant to the task at hand	0.833	
		QUAL6	is accurate	0.842	
		QUAL7	is up-to-date	0.840	
8	Analytical skills (ALT)	ALT1	Our data analytics users are knowledgeable when it comes to utilizing such tools.	0.909	[88]
		ALT2	Our data analytics users possess a high degree of data analytics expertise.	0.939	
		ALT3	Our data analytics users are skilled at using data analytics tools	0.945	
9	Communication skills (COM)	COM1	Data analytics users in our company have excellent abilities in delivering messages related to work	0.883	[86]
		COM2	Data analytics users in our company have excellent listening skills when discussing work-related matters	0.916	
		COM3	Data analytics users in our company have excellent abilities in providing feedback regarding work	0.917	
10	Data Science skills (SCI)	Data analytics users in this company have sufficient skills in the following areas:			[87]
		SCI1	Performing data aggregation, cleaning, manipulation and processing for large, complex and distributed data sources	0.801	
		SCI2	Utilizing data mining, machine learning, or analyzing graphs	0.876	
		SCI3	Performing optimization method and mathematical programming	0.822	
		SCI4	Performing problem formulation, hypothesis testing, statistical inference, interpreting results from analysis of complex data sets	0.830	
		SCI5	Utilizing statistics methods including classical, Bayesian/Monte Carlo, forecasting	0.809	
		SCI6	Utilizing statistical tools (e.g.: R, SAS, SPSSS, Stata)	0.787	

TABLE 9. ***(Continued.)*** **Measurement items.**

No	Indicators	Items	Measurement items	Outer loading	Reference
		SCI7	Utilizing structured Query Language (SQL), Hadoop and programming in languages like Python or Java	0.816	
		SCI8	Utilizing unstructured data processing methods (e.g:: Text mining or text analysis)	0.764	
11	Data analytics strategy (DAS)	DAS1	The DA plan contains quantified goals and objectives	0.935	[89]
		DAS2	The DA plan contains detailed action strategies that support company direction	0.934	
12	Strategic alignment (SA)	SA1	The DA plan aligns with the organizational mission, goals, objectives, and strategies	0.913	[89]
		SA2	We prioritize major BDA investments by the expected impact on business performance	0.926	
13	IT Infrastructure and capability (INF)	INF1	Our company has the foremost available analytics systems to connect the remote, branch, and mobile offices into central office	0.948	[89]
		INF2	Our company provides multiple analytics interfaces for users to have access to all platforms and applications	0.934	
		INF3	Reusable software modules are widely used for end-users to create their own analytics applications to meet a variety of needs during analytics tasks	0.933	
14	Data analytics tools sophistication (TS)	In our organization, we use tools that			[53]
		TS1	Provide information processing and retrieval capabilities	0.751	
		TS2	Perform modelling and simulation	0.804	
		TS3	Perform natural language analytics (extracting information from unstructured sources such as social media)	0.732	
		TS4	Provide real-time insight	0.793	
		TS5	Identify problems	0.891	
		TS6	Evaluate different alternatives	0.870	
15	Data warehouse & Business intelligence technology (DW)	DW1	We have explored or adopted different data visualization tools	0.742	[12]
		DW2	We have explored or adopted new forms of databases such as Not Only SQL(NoSQL)	0.816	
		DW3	We have explored or adopted open-source software for big data analytics	0.815	
		DW5	We utilize data warehouses to store large amounts of data from internal and external sources	0.795	
16	Knowledge-oriented leadership (LEAD)	LEAD1	1. Leadership has been creating an environment for responsible employee behavior and teamwork	0.744	[16]
		LEAD2	2. Managers promote learning from experience, tolerating mistakes up to a certain point	0.743	
		LEAD3	3. Managers promote the acquisition of external knowledge	0.721	
		LEAD4	4. Managers reward employees who share and apply their knowledge	0.854	
17	Exploitative innovation (EXPL)	EXPL1	We frequently refine the provision of existing products and services.	0.873	[3]
		EXPL2	We regularly implement small adaptations to existing products and services.	0.867	
		EXPL3	We introduce improved, but existing products and services to our local market	0.845	
		EXPL4	We improve our efficiency in providing products and services	0.844	
		EXPL5	We increase economies of scales in existing markets	0.835	
		EXPL6	Our unit expands services for existing clients	0.865	
18	Explorative innovation (EXPR)	EXPR1	Our unit accepts demands that go beyond existing products and services	0.722	[3]
		EXPR2	We invent new products and services	0.894	
		EXPR3	We experiment with new products and services in our local market	0.869	
		EXPR4	We commercialize products and services that are completely new to our unit.	0.852	
		EXPR5	We frequently utilize new opportunities in new markets	0.896	
		EXPR6	Our unit regularly uses new distribution channels	0.774	

employees feel empowered to generate new ideas and take calculated risks.

From a more transactional perspective, knowledge-oriented leadership increases the willingness of organizational members to exploit existing knowledge [108]. When an organization has knowledge-oriented leadership, the organization will more intensively encourage the development and use of data to create knowledge [16]. However, in the context of exploitative innovation, other mediating factors are needed to transform employees' innovation intention into concrete behavior, such as innovation activities. Thus, the results of this study suggest that knowledge-oriented leadership has a strong indirect influence on innovation capabilities through data analytics maturity. Hence, the indirect impact of knowledge-oriented leadership is stronger than the direct impact on innovation capabilities. The findings also indicate that exploitative innovation is leveraged through data analytics maturity because knowledge-oriented

TABLE 10. Fornell-Larcker results for first-order reflective constructs.

	ALT	COLAB	COM	DAS	DG	DMAN	DRIV	DSP	DW	EXPL	EXPR	INF	LEAD	PART	QUAL	SA	SCI	SRCS	TS
ALT	0.931																		
COLAB	0.507	0.781																	
COM	0.654	0.546	0.906																
DAS	0.653	0.468	0.540	0.934															
DG	0.753	0.643	0.629	0.687															
DMAN	0.673	0.578	0.621	0.550	0.707	0.845													
DRIV	0.256	0.329	0.329	0.360	0.411	0.361	0.779												
DSP	0.580	0.433	0.400	0.526	0.732	0.569	0.377	0.876											
DW	0.637	0.499	0.490	0.516	0.613	0.559	0.225	0.443	0.775										
EXPL	0.516	0.508	0.513	0.488	0.580	0.393	0.356	0.433	0.489	0.855									
EXPR	0.481	0.457	0.354	0.505	0.580	0.325	0.363	0.391	0.560	0.762	0.837								
INF	0.649	0.438	0.555	0.686	0.678	0.627	0.259	0.510	0.608	0.506	0.457	0.938							
LEAD	0.452	0.588	0.263	0.450	0.499	0.305	0.384	0.409	0.361	0.488	0.526	0.378	0.767						
PART	0.480	0.521	0.490	0.431	0.507	0.394	0.318	0.327	0.445	0.438	0.457	0.391	0.501	0.888					
QUAL	0.728	0.564	0.579	0.620	0.934	0.586	0.354	0.606	0.531	0.537	0.549	0.669	0.446	0.468	0.804				
SA	0.505	0.374	0.402	0.633	0.533	0.399	0.299	0.422	0.520	0.588	0.613	0.543	0.475	0.270	0.476	0.919			
SCI	0.690	0.494	0.502	0.545	0.613	0.581	0.226	0.369	0.628	0.432	0.363	0.581	0.328	0.348	0.589	0.431	0.814		
SRCS	0.305	0.439	0.329	0.387	0.606	0.334	0.186	0.394	0.399	0.338	0.359	0.235	0.313	0.295	0.352	0.341	0.295	0.856	
TS	0.604	0.473	0.540	0.566	0.608	0.578	0.185	0.358	0.665	0.528	0.515	0.687	0.417	0.448	0.574	0.577	0.574	0.334	0.809

leaders who provide technical and non-technical resources will support the data analytics environment, boosting new product innovation by modifying existing products and processes.

Third, the results show that data analytics maturity significantly impacts both explorative and exploitative innovation. This result aligns with Mikalef et al. [20], who found big data analytics capabilities positively influence exploitative and explorative innovation. Liao et al. [1] stated that data analytics can enable the smooth flow of knowledge within an organization by integrating tools and technology. In this way, the organization constantly updates information regarding products developing in the market. As a result, managers gain insight into the different needs of each work unit so they can allocate different resources for exploration and exploitation innovation [109]. Data analytics can also help organizations use knowledge assets to facilitate innovation strategies and better performance [110]. By utilizing diverse internal and external data sources, employees will be encouraged to utilize data analytics, thereby encouraging continued exploitation and exploration innovation.

B. MANAGERIAL IMPLICATIONS

This study has several implications for business practitioners. First, executives need to implement data analytics by considering the five dimensions of the maturity model (organizational culture, data governance, skills, strategy management, and technology) along with the 15 crucial success factors (sub-dimensions). Thus, to fully benefit from data analytics implementation, top management must consider dividing company resources to support those five maturity dimensions.

Second, companies should not only focus on hard dimensions (technology, skills, and data governance) but also on soft dimensions such as organizational culture and strategy management. Top management should provide appropriate technology and efficient data governance and upgrade employees' skills through training. Managers also need to create a data-driven culture and align the data analytics strategy with the business strategy to start creating a data analytics environment.

Third, to build data analytics maturity, managers should build leadership capabilities focused on knowledge and data as primary information sources for decision-making. The results of this study indicate that knowledge-oriented leadership influences innovation capabilities in companies. In regard to explorative innovation, managers could support experimentation and exploring new opportunities in product or process innovation by providing a sufficient budget. Moreover, to fully boost exploitative innovation, managers could strengthen the flow of information within the company

TABLE 11. HTMT results for first-order reflective constructs.

	ALT	COLAB	COM	DAS	DMAN	DRIV	DSP	DW	EXPL	EXPR	INF	LEAD	PART	QUAL	SA	SCI	SRCS	TS
ALT																		
COLAB	0.605																	
COM	0.718	0.664																
DAS	0.735	0.579	0.619															
DMAN	0.782	0.745	0.737	0.666														
DRIV	0.285	0.404	0.380	0.418	0.437													
DSP	0.653	0.528	0.452	0.615	0.684	0.443												
DW	0.721	0.625	0.566	0.610	0.680	0.291	0.518											
EXPL	0.557	0.592	0.568	0.546	0.456	0.395	0.484	0.551										
EXPR	0.518	0.536	0.394	0.563	0.384	0.411	0.436	0.636	0.822									
INF	0.699	0.521	0.608	0.769	0.725	0.275	0.565	0.684	0.544	0.490								
LEAD	0.536	0.739	0.317	0.548	0.383	0.485	0.498	0.435	0.576	0.622	0.440							
PART	0.521	0.613	0.543	0.490	0.461	0.373	0.366	0.508	0.475	0.498	0.426	0.595						
QUAL	0.794	0.669	0.643	0.704	0.686	0.396	0.687	0.603	0.583	0.593	0.728	0.525	0.516					
SA	0.577	0.473	0.471	0.755	0.495	0.356	0.509	0.626	0.673	0.704	0.619	0.593	0.312	0.551				
SCI	0.739	0.585	0.550	0.607	0.671	0.262	0.413	0.717	0.463	0.387	0.621	0.379	0.375	0.638	0.494			
SRCS	0.388	0.585	0.426	0.506	0.460	0.233	0.509	0.525	0.427	0.429	0.307	0.412	0.392	0.430	0.444	0.379		
TS	0.666	0.570	0.606	0.649	0.686	0.222	0.405	0.768	0.580	0.566	0.751	0.503	0.495	0.639	0.672	0.635	0.423	

by encouraging knowledge sharing and collaboration. Therefore, managers in Indonesian companies should create and nurture a mature data analytics environment to foster both explorative and exploitative innovation because a supportive environment will balance explorative and exploitative innovation within the company.

C. LIMITATIONS AND FUTURE RESEARCH

While this study offers new insights on the use of data analytics to support innovation, there are some limitations that need to be addressed as well as new opportunities for future research. First, the sample size of this study is relatively small and focused only in one country, Indonesia. Hence, future research could increase the sample size, for example, by gathering data from different countries.

Second, as this research was quantitative, it may not fully explain the role of each data analytics maturity dimension. Future studies may conduct longitudinal research to investigate how technology, skills, and data governance play crucial roles as hard dimensions in data analytics maturity while culture and strategy management serve as soft dimensions. Future studies could also examine how different industries encourage both exploitative and explorative innovation by improving hard and soft dimensions of data analytics maturity.

Third, since this study does not specify a certain size of companies, future research may focus on particular sizes rather than combining two or three-size groups to investigate the role of knowledge-oriented leadership in specific sizes of companies. For example, large-sized companies may give different results in fostering innovation capabilities through data analytics maturity.

VII. CONCLUSION

This study investigated the role of knowledge-oriented leadership on innovation capabilities by highlighting the importance of data analytics maturity as the mediating variable. The results indicate that knowledge-oriented leadership indirectly impacts both exploitative and explorative innovation. However, knowledge-oriented leadership has a strong direct influence on explorative innovation. Nonetheless, the results suggest that through data analytics maturity, knowledge-oriented leadership could foster both explorative and exploitative innovation within organizations. Hence, data analytics maturity fully mediates only the relationship between knowledge-oriented leadership and exploitative innovation. The findings also indicate that data analytics maturity plays a crucial role in enabling organizations to effectively utilize knowledge in decision-making. Organizations that have developed strong data analytics capabilities are better equipped to collect, analyze, and utilize data for innovation. Furthermore, the results suggest that knowledge-oriented leadership is a key driver of both exploitative and explorative innovation. Therefore, organizations must focus on developing knowledge-oriented leadership and enhancing their data analytics maturity to foster a culture of innovation that encompasses both explorative and exploitative activities. Ultimately, organizations that prioritize and invest in both knowledge-oriented leadership and data analytics are more likely to achieve successful and sustained innovation capabilities.

APPENDIX A
DESCRIPTIONS OF THE DATA ANALYTICS MATURITY DIMENSIONS

See Table 8.

APPENDIX B
MEASUREMENT ITEMS

See Table 9.

APPENDIX C
FORNELL-LARCKER RESULTS FOR FIRST-ORDER REFLECTIVE CONSTRUCTS

See Table 10.

APPENDIX D
HTMT RESULTS FOR FIRST-ORDER REFLECTIVE CONSTRUCTS

See Table 11.

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