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Role of Big data Capabilities and Adoption in Innovation: Moderating Influence of Employee Engagement

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Abstract

Aim: South Korea's commitment to fostering a digitally well-informed society and its early embrace of mobile technologies has positioned the country at the forefront of the global mobile tech arena. South Korea has emerged as a global powerhouse in the technology sector, with its mobile tech industry playing a pivotal role in the country's economic landscape. Korean mobile tech companies have garnered international recognition for their innovation, cutting-edge technologies, and influential contributions to the global tech ecosystem. This descriptive and quantitative study investigates the intricate relationships among key variables, namely big data adoption, big data analytics capabilities, employee engagement, digital innovation, and innovative behavior within the framework of Korean mobile tech companies.
Methodology: TUtilizing a cross-sectional design and convenience sampling, data was collected from 213 managers working in this industry. The research draws on the Resource-Based View (RBV) and Dynamic Capability Theory to provide a comprehensive understanding of the interplay between these factors. The study employs Smart PLS (Partial Least Squares) for analysis, leveraging its suitability for complex structural equation modeling.
Findings:: Through this methodology, the research aims to uncover the nuanced connections between big data dynamics, employee engagement, and innovation within the unique context of Korean mobile tech companies. Smart PLS facilitates the simultaneous examination of multiple relationships and allows for the exploration of complex interactions, aligning with the multifaceted nature of the study's objectives.
Implications/Novel Contribution: The findings are anticipated to contribute valuable insights to both academia and industry by offering a robust examination of the mechanisms shaping innovation in Korean mobile tech companies. As organizations navigate the evolving landscape of technology and data-driven decision-making, the outcomes of this study aim to inform strategic decision-making and enhance the understanding of the factors influencing digital innovation and innovative behavior in this specific sector.

Keywords: Big data adoption, Big data analytics capabilities, Employee engagement, Digital innovation, Innovative behavior, Resource-based view, Dynamic capability theory

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INTRODUCTION

South Korea noticed a remarkable advancement in smartphone technology in the 2010s. South Korea's foray into the smartphone market was belated, in contrast to the United States, which led the way with IBM Simon in 1993 and found commercial success with the iPhone in 2007 (Park & Kim, 2021). The nation did not start producing smartphones in large enough quantities until about 2009. At first, South Korea's entry into the wireless telecommunications industry in the early 1980s behind Western markets by a decade or more (Lee, Yoon, Altmann, & Lee, 2021). This delayed start continued into the smartphone era in its early stages. Despite this, the Korean mobile industry progressively created its mobile technologies and came to compete with big names in the industry, such as Motorola and Nokia, who were the leading mobile manufacturers up until the 1990s. South Korea's smartphone market share eventually overtook Apple's iPhone, despite the country's gradual ascent to a significant domestic and international market share (Jin, 2018; Lee et al., 2021; Park & Kim, 2021).

The 2010s saw a notable surge in South Korea's smartphone technologies, which had been developing for the previous two decades. Before creating cutting-edge cell phones, Samsung Electronics and LG Electronics, the two largest handset manufacturers in the nation, went through many trial-and-error procedures (Lee et al., 2021; Park & Kim, 2021). These locally based-multinational enterprises made great strides in competing with international mobile

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telecommunications giants like Nokia and Motorola before eventually producing their smartphones; however, they did not gain a meaningful market presence until the late 1990s (Jin, 2018). Hence, to comprehend the context and reasoning behind the recent rise of the smartphone industry and culture in South Korea, it is necessary to look at a number of important factors, such as the regulations governing mobile telecommunications, the rivalry between service providers and handset manufacturers, and the fervor of users of mobile technology. The market is changing quickly because of the exceptional rate of technological advancement (Jin, 2018; Lee et al., 2021). Businesses release new items all the time and customers look forward to them. Every new product model is an invention, and the evolution of products shows how innovations have affected a certain product category over time cumulatively. Thus, it is possible to describe how products have evolved by looking at how product models have changed (Jin, 2018; Lee et al., 2021; Park & Kim, 2021).

Innovation is the production, integration, and application of novelties with added value in the social and economic spheres. It entails the growth and modification of markets, products, and services in addition to the implementation of contemporary production techniques and the creation of new organizational structures (Cosimato & Vona, 2021; Liu, Dong, Mei, & Shen, 2023). Conversely, advancements spurred or enabled by digital technology are particularly referred to as digital innovations (Al-Khatib, 2022; Zhe & Hamid, 2021). Modern technology innovations provide businesses with previously unheard-of chances for innovation, including wearables, the Internet of Things, smartphones, social networking, cloud computing, and market analytics (Di Vaio, Palladino, Pezzi, & Kalisz, 2021). In the current digital era, where social media and smartphones are commonly used, technology has become more affordable and accessible for the gathering, storing, analyzing, and usage of raw data (Akter, Michael, Uddin, McCarthy, & Rahman, 2022; Kapoor & Aggarwal, 2020). As a result, people all around the world are producing an ever-present and growing digital record known as big data (Ciampi, Demi, Magrini, Marzi, & Papa, 2021). Big data is widely acknowledged as a key component of technology in the future and has the potential to bring substantial benefits to enterprises (Arias-Pérez, Coronado-Medina, & Perdomo-Charry, 2022; Mendling, Pentland, & Recker, 2020).

Large volumes of data from many sources are gathered and processed using big data technologies (Maroufkhani, Tseng, Iranmanesh, Ismail, & Khalid, 2020). Modern firms are data-intensive by nature, and using big data analytics capabilities can provide new insights. The ability to analyze large amounts of data is crucial for changing how organizations operate, which promotes innovation and increases efficiency (Ibrahim, Abu Bakar, & Ahmad, 2024). Big data analytics capabilities help financial businesses detect and prevent fiscal fraud more efficiently Ibrahim et al. (2024) by creating profiles of individuals for more accurate client targeting (Mahmood, Ahmed, & Philbin, 2023). Furthermore, big data analytics capabilities make it possible for personalized strategies, better decision-support information, and informed decision-making (Awan et al., 2022). It is commonly agreed that big data analytics capabilities are essential for enterprises (Mahmood et al., 2023).

Since the early 2010s, social media, mobile content, and corporate informatics have all contributed to the rapid proliferation of data and the digital transformation of business, government, and society (Maroufkhani et al., 2020). Big data is expected to play a major role in driving digital innovation by lowering costs, promoting new market development, and increasing innovative behavior. This prediction is shared by many research institutes and consulting organizations (Awan et al., 2021). The present breadth and depth of big data usage have fallen short of earlier estimates, notwithstanding these hopes. In 2016, the National Information Agency performed a survey that revealed that less than 1% of Korean enterprises were using big data (Su et al., 2022). Additional survey results show that a number of obstacles, including those pertaining to technology, management, data, internal capabilities, and external factors, are impeding the broad adoption of big data among businesses (Arias-Pérez et al., 2022).

Since it is now known that an individual's job attitudes have an impact on their inventive behavior in addition to their innate features, academics have turned their attention to studying the attitudinal elements that encourage innovative conduct. Sung and Kim (2021) "operationalized by the intensity and direction of cognitive, emotional, and behavioral energy" is one definition of employee engagement. It is thought that in order for people to participate in the difficult process of invention, they must possess this triple energy. Academics also agree that there isn't enough research done on the different situational and individual aspects that affect worker engagement, especially when it comes to the unique setting of creative behavior (Jaouadi, 2022).

According to Barreiro and Treglown (2020), engagement is typically understood in academic terms as a good and gratifying work-related frame of mind marked by vigor, devotion, and absorption. Attachment, according to Lu, Yu, and Shan (2022) definition of "employee engagement," is the favorable attitude that a worker has toward their workplace or employer. Nonetheless, there can be large differences in how different firms define employee engagement. Engagement is defined by Kwon and Kim (2020) as the dedication, enthusiasm, and active involvement of workers who choose to stay with the company. Engagement is a function of an employee's status because of social interactions at work and is positively correlated with improved organizational performance. Higher performance levels are typically shown by employees who find significance in their work, fit in with the business culture, and comprehend and support the policies of the organization (Wang, Xu, Zhang, & Li, 2020).

LITERATURE REVIEW

Resource-Based View and Dynamic Capability Theory

In order to address the study topic, and develop, and test a conceptual framework, we make use of resource-based theory and its extension, dynamic capabilities theory. While digital technologies offer new potential for non-technical businesses like banking, manufacturing, and retail as well as technological entities like IT corporations, achieving digital innovation necessitates a deep commitment to evolving technology (Kapoor & Aggarwal, 2020). Organizations should be focused on embracing developing digital technologies in order to transform them into creative digital solutions, given the current state of these technologies. When it comes to digital innovation, having digital capabilities is essential for combining digital technologies with the knowledge of digital experts. Digital capability, which refers to an organization's ability to create new products and processes and adjust to changing market conditions, can be understood as a dynamic capability based on insights from the dynamic capability theory (Freeman, Dmytriyev, & Phillips, 2021). A major contribution to the growing body of research on big data analytics capabilities has been made by the resource-based view. Still, little is known about how businesses might use big data analytics to enhance their skills (Bleady, Ali, & Ibrahim, 2018). Large, complicated, and real-time data quantities that necessitate sophisticated management, analysis, and processing techniques in order to extract information are generally referred to as "big data" (Shibin et al., 2020). By comparison, "big data analytics capabilities" include material resources like as technology and data, in addition to other fundamental resources like time and investments; on the other hand, human resources are made up of big data-related managerial and technical abilities (Kapoor & Aggarwal, 2020). The present discourse posits that intangible organizational resources significantly facilitate the creation of big data analytics capabilities. These intangible resources give an organization the ability to recognize and make use of a range of technology and human resources for procedures meant to develop organizational capabilities.

The resource-based view states that both tangible and intangible business resources help create long-lasting competitive advantages that are difficult for rivals to copy (Wheeler, 2002). The resource-based view highlights that in the context of big data, value is created by deriving insights from complex data bundles and related skills, using assets and capabilities that serve as a foundation for big data collection, storage, and analytics (Freeman et al., 2021). Manufacturing companies frequently depend on having innovative and distinctive intangible resources. According to Shibin et al. (2020), businesses can improve performance and create long-lasting competitive advantages by utilizing organizational assets, procedures, special capabilities, and expertise. According to Freeman et al. (2021), organizational big data analytics capabilities depend on an organization's resource base and are a good predictor of dynamic capabilities, which is consistent with the RBV (Shibin et al., 2020). Scholars explain the material and immaterial resources influencing a firm's capacity to integrate, develop, and reconfigure competencies to handle disruptive changes in the marketplace by combining the resource-based view with dynamic capabilities. The company's resource-based view places a strong emphasis on combining human and technology resources to generate value (Freeman et al., 2021). Although prior research has mostly used the resource-based view as the major theoretical lens to evaluate how big data analytics capabilities affect firm performance, work that is more recent highlights the significance of IT embeddedness in dynamic capabilities (Freeman et al., 2021; Kapoor & Aggarwal, 2020). According to Wheeler (2002), dynamic capabilities have the ability to sense, seize, and transform. Within this framework, the conversation delves into how customers can act as data analysts and how organizational creativity can be used to alter competences for big data-driven value creation.

Big Data Analytics Capabilities

Big data analytics capabilities are often utilized to indicate a company's ability to handle large and complex datasets, improving its ability to conduct studies at high speed, high variability, and high visual clarity (Ibrahim et al., 2024; Park & Kim, 2021). A process that includes problem-solving, presenting solutions based on knowledge or fresh experiential ideas, endorsing these ideas, and putting these ideas into action to further the objectives of the business is known as innovative behavior (Al-Khatib, 2022). Different academics have defined innovative actions in different ways. For example, it is defined as conduct that is purposefully intended to introduce and apply new concepts and practices within groups and organizations in order to improve their performance by Park and Kim (2021). Zheng, Zhang, Wang, and Hong (2022) describes it as the long-term development and implementation of novel concepts within human relationships. While Zheng et al. (2022) describe innovative conduct as products, services, procedures, etc., given by champions of creative ideas, Zheng et al. (2022) say that innovative behavior entails generating or actualizing ideas and non-role behavior. Innovation is the process of choosing original concepts and incorporating them into workflows for finished goods. Innovative conduct is taking original concepts that people or groups have generated or presented and turning them into useful resources. An action eventually improves job performance by effectively changing work processes (Kör et al., 2021). Innovation in digital technology has drastically changed the commercial environment. Previously, the first online shopping pages were just inferior copies of old-fashioned mail-order catalogs. The e-commerce revolution has broadened the scope of innovative digital enterprises. Modern internet retailers, such as Amazon and Zappos, provide more than just convenient and reasonably priced goods (Jaouadi, 2022; Kör, Wakkee, & van der Sijde, 2021). They promote unique consumer goods by providing brand experiences and proposed solutions. Traditional firms, including grocery store chains and taxi services, have been able to gain a strategic competitive advantage by investing in online digital technologies. The creation of new goods through the integration of digital and physical components is what defines digital innovation (Liu et al., 2023). It entails presenting novel ideas, implementing novel behavioral strategies, or constructing completely new entities for people. Utilizing a company's information resources to encourage innovative behavior among employees is made possible in large part by the capabilities of big data analytics Sung and Kim (2021). Big data analytics capabilities are described by Kör et al. (2021) as a comprehensive process that includes data gathering, analysis, utilization, and interpretation across several functional divisions. The objectives of this process are to generate corporate value, get practical insights, and establish a competitive edge (Liu et al., 2023). These skills are essential for putting flexible and economical operational plans into practice. Prior research has investigated the connection between digital innovation and big data analytics skills (Al-Khatib, 2022; Zhe & Hamid, 2021), as well as innovation capability (Di Vaio et al., 2021). The claim made is that large data analytics capabilities will probably direct data analytics toward building flexible, economical, lead-time-improving, and on-time delivery solutions. These capabilities allow businesses to get valuable insights for efficient decision-making by departing from conventional methods of utilizing data (Akter et al., 2022). According to Cosimato and Vona (2021) who view the resource-based view theory as a strong framework for explaining the relationship between data analytics and innovative behavior, the theoretical foundation of the theory supports the notion that big data analytics capabilities play a crucial role. Therefore:

H1: Big data analytics capabilities have a direct effect on digital innovation.

H2: Big data analytics capabilities have a direct effect on innovative behavior.

Big Data Adoption

Due to its significant operational and strategic advantages, big data adoption has evolved into a stimulus that can maximize the efficacy and efficiency of businesses (Arias-Pérez et al., 2022; Park & Kim, 2021; Ibrahim et al., 2024). In order to improve performance, businesses using big data approaches should transform data into intelligence and comprehensible visions (Ciampi et al., 2021; Mahmood et al., 2023). Because big data adoption speeds up work by increasing process speed, it can therefore improve a firm's agility and overall performance (Su et al., 2022). According to Al-Khatib (2022), the absence of a link between big data adoption and innovative behavior was primarily brought about by the lack of relevant data, since the business value that these investments produced was absent. According to Mahmood et al. (2023), adopting new systems or technologies may not succeed if they are viewed as being excessively difficult or complex. Technological obstacles arise when, for example, collaborative procedures are changed; therefore, new technology must be simple to use in order to be easily adopted (Zhe & Hamid, 2021). Because advanced technologies add uncertainty and complexity to their adoption, it is critical that employees learn about the innovation as soon as possible. According to Al-Khatib (2022), complexity has a major role in the implementation of innovations, and as a result, decision-makers' acceptance of new ideas is seldom unanimous. It has been demonstrated that complexity has a detrimental impact on technology adoption when compared to other innovative technological components (Awan et al., 2022).

Since their creation, acceptance models have experienced modifications and developed into new models. These further variables add to our understanding of the aspects that firms consider when deciding whether to use big data adoption. Because digitalization brings about changes in social systems (such as norms, processes, and structures) as well as technological systems, digital innovation is intrinsically socio-technical (Al-Khatib, 2022; Jaouadi, 2022). Contextualizing digital innovation is coming up with creative digital solutions that change other companies' offerings, services, and business processes. Thus, "the development of new products, services, or solutions by utilizing digital technology" is how we describe digital innovation (Di Vaio et al., 2021). According to Cosimato and Vona (2021), big data, cloud computing, artificial intelligence, augmented and virtual reality, the Internet of Things, and cyber-physical systems are some of the digital technologies used in innovation. However, social media, mobile technology, analytics, and embedded devices are all included in the definition of digital technology given by (Lee et al., 2021). Numerous studies, such as Akter et al. (2022) (Kapoor & Aggarwal, 2020), have explored the adoption of big data technologies and its direct implications on digital innovation. Therefore:

H3: Big data adoption has a direct effect on digital innovation.

H4: Big data adoption has a direct effect on innovative behavior.

Moderating Role of Employee Engagement

When workers find purpose in their work, identify with the company's values and policies, and actively participate in their positions, there is usually a higher level of engagement. Employee engagement is defined as a strong desire and commitment, as well as a willingness to make discretionary efforts to help the business flourish (Wang et al., 2020). It goes beyond simple satisfaction with employment arrangements or basic loyalty to the employer. Essentially, long-term changes in people's working conditions, expectations for their jobs, and working methods are related to changes in employee engagement. When force-based treatments are used, employee community growth is significantly higher in organizations than when organizational impact groups are the only strategy used (Lu et al., 2022). Positive and proactive behavior at work that combines emotional attachment with motivational drive is a sign of engaged employees. High-consciousness managers successfully convey their dedication to accomplishing organizational objectives, fostering an engaged culture within the company.

Kwon and Kim (2020) emphasized the differences in meaning and concepts of big data, big data analytics, and big data analytics capabilities and big data adoption. A range of subject areas was identified by their systematic examination; some research focused on data and its attributes, while others used the term analytics to highlight the procedures, instruments, and methods needed for data analysis. When the focus turns to the significance of hidden values recovered by analytical procedures, the meaning of big data analytics capabilities and big data adoption might become clear. According to Lu et al. (2022) significant work is required to extract useful insights from big data due to its distinctive characteristics, which include volume, velocity, and variety. Conventional analytical methods might not be sufficient for these kinds of data According to Barreiro and Treglown (2020) good big data analytics capabilities and big data adoption practices are essential to big data success. They maintained that while there are many different big data analytics capabilities and big data adoption methodologies, converting big data into useful values requires organizational resources including organizational learning and a data-driven culture. Big data analytics capabilities and big data adoption have become more often used to denote a company's ability to successfully apply big data and obtain value for the business (Wang et al., 2020). An active circumstance of work characterized by vitality, devotion, and absorption is called employee engagement (Mendling et al., 2020; Sung & Kim, 2021). Engaged employees show enthusiasm and energy for their work, frequently devoting their whole attention to it (Shibin et al., 2020; Zhe & Hamid, 2021). Employees can improve their sense of responsibility and emotional connection to their work by investing in cognitive, emotional, and social resources. This will lead to them devoting more time and effort to their tasks, which will ultimately help them achieve good work performance

(Awan et al., 2022). Employees who are highly engaged at work also tend to have a strong sense of self at work and expect positive results from their employment, including good performance (Akter et al., 2022; Shibin et al., 2020). Work engagement and job performance are positively correlated, according to numerous research (Jaouadi, 2022). Arias-Pérez et al. (2022) suggests that work engagement and innovative behavior are significantly influenced by innovation and that these factors positively correlate with digital innovation. Our main claim is that the relationship between the adoption of big data analytics capabilities, digital innovation, and inventive behavior is moderated by work engagement (Lu et al., 2022; Taher, 2011).

H5: Employee engagement has a moderating impact on big data analytics capabilities and digital innovation.

H6: Employee engagement has a moderating impact on big data analytics capabilities and innovative behavior.

H7: Employee engagement has a moderating impact on big data adoption and digital innovation.

H8: Employee engagement has a moderating impact on big data adoption and innovative behavior.

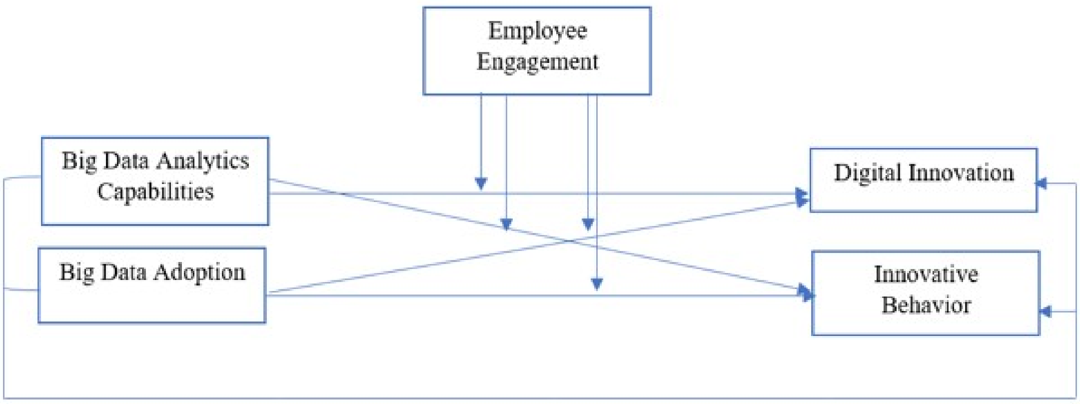

Figure 1. Conceptual framework

RESEARCH METHODOLOGY

The research methodology, comprising the study's nature, variables, adaption process, validation, data analysis, data collection, and instrument design, is covered in this part. The temporal horizon of the study was a cross-sectional design, and it was quantitative and descriptive in character. By comprehending the connections between employee engagement, digital innovation, big data adoption, big data analytics capabilities, and creative behavior, this strategy aims to contribute to the body of knowledge in this field.

Using a questionnaire as the data recording tool, a survey methodology was used to gather primary data for this study. Convenience sampling was used as a non-probability sampling strategy because the population was unknown. A total of 250 questionnaires were issued, with the target audience being managers in Korean mobile tech companies. With 213 correctly completed questionnaires in the final dataset, the response rate was 84%. Participants were informed that participation was entirely voluntary and that they were under no obligation to reply. Only those who wished to take part were asked to complete the questionnaires. Participants were advised that their data would be treated with confidentiality and that their responses would remain anonymous.

A questionnaire was used as the research tool, and it had three primary elements. The goal of the study was explained, response guidelines were supplied, and it was assured that the data submitted would only be used for research in the first portion. While the second segment was used to gather demographic data, the third section included items pertaining to the causes under investigation. Employee engagement functioned as the moderating variable in this study, whereas the adoption of big data and big data analytics skills were the independent variables. Innovative behavior and digital innovation were the result criteria. The prediction ability of big data analytics was evaluated using four items that were altered from Su et al. (2022). The third predictive variable, big data adoption, was evaluated by adjusting five items from the Maroufkhani et al. (2020). The study's moderating variable, employee involvement, was measured using a modified version of the 4-item (Heslina & Syahruni, 2021). The Zhe and Hamid (2021) scale was adapted with five new items to assess the outcome variable, digital innovation. For the other outcome variable, innovative conduct was measured using a 5-item scale adapted from (Kör et al., 2021). The questionnaire was assessed for face validity, content validity, and reliability after the adaption process. While content validity confirmed that the items adequately examined the constructs, face validity made sure the items seemed relevant to the respondents. To make sure the products were internally consistent, reliability tests were carried out. The validity and reliability of the data were guaranteed by the meticulous selection of tools and procedures, and the statistical analysis strategy selected was intended to make a substantial contribution to the body of knowledge currently available in this subject.

DATA ANALYSIS

Assessment of Measurement Model

A measure's convergent validity is determined by how well it correlates with other measures that measure the same construct (J. F. Hair, Risher, Sarstedt, & Ringle, 2019). Since every concept in this study was modeled as reflecting, a large percentage of the variance should be shared by the indicators (J. F. Hair et al., 2019). Convergent validity was evaluated by looking at indicator reliability (outer loadings), Average Variance Extracted (AVE), and Individual Reliability (CR), as indicated in Table II. The majority of the goods had loadings more than the 0.4 criterion. The convergent validity was confirmed by the AVE values, which were all more than 0.5 (J. Hair, Hollingsworth, Randolph, & Chong, 2017; Hair Jr, Howard, & Nitzl, 2020). The reliability of the measurements was then evaluated using Composite Reliability (CR), which ranks the indicators according to how reliable each one is on its own. The measures were deemed reliable since all of the composite reliability CR values were higher than 0.7 (J. Hair et al., 2017; J. F. Hair et al., 2019; Hair Jr et al., 2020).

Table 1: Discriminant validity

Construct	Item	Loadings	CA	CR	AVE
Big Data Adoption	BDA1	0.849	0.899	0.925	0.713
	BDA2	0.829			
	BDA3	0.873			
	BDA4	0.884			
	BDA5	0.783			
Big Data Analytics Capabilities	BDAC1	0.854	0.927	0.948	0.821
	BDAC2	0.920			
	BDAC3	0.925			
	BDAC4	0.923			
Digital Innovation	DI1	0.909	0.945	0.958	0.820
	DI2	0.899			
	DI3	0.911			
	DI4	0.912			
	DI5	0.897			
Employee Engagement	EE1	0.729	0.771	0.851	0.590
	EE2	0.711			
	EE3	0.814			
	EE4	0.812			

Cont.....

Construct	Item	Loadings	CA	CR	AVE
Innovative Behavior	IB1	0.876	0.915	0.937	0.748
	IB2	0.790			
	IB3	0.891			
	IB4	0.886			
	IB5	0.879			

In the event that the threshold is exceeded by the level of HTMT, discriminant validity is compromised. The criterion indicates that each construct's HTMT ratio needs to be smaller than 0.85 in order to demonstrate convergent validity (J. Hair et al., 2017; J. F. Hair et al., 2019; Hair Jr et al., 2020). As can be seen in Table 3, every construct satisfies the requirement, establishing discriminant validity. The constructs' mean, standard deviation, and correlation are displayed in Table 3. Table 3 results support the acceptability of all items as trustworthy indicators for their respective constructs, hence validating first-order reflective measures.

Table 2: Reliability and validity

	BDA	BDAC	DI	EE	IB
Big Data Adoption	0.844				
Big Data Analytics Capabilities	0.727	0.906			
Digital Innovation	0.692	0.768	0.906		
Employee Engagement	0.626	0.466	0.441	0.768	
Innovative Behavior	0.538	0.762	0.800	0.467	0.865

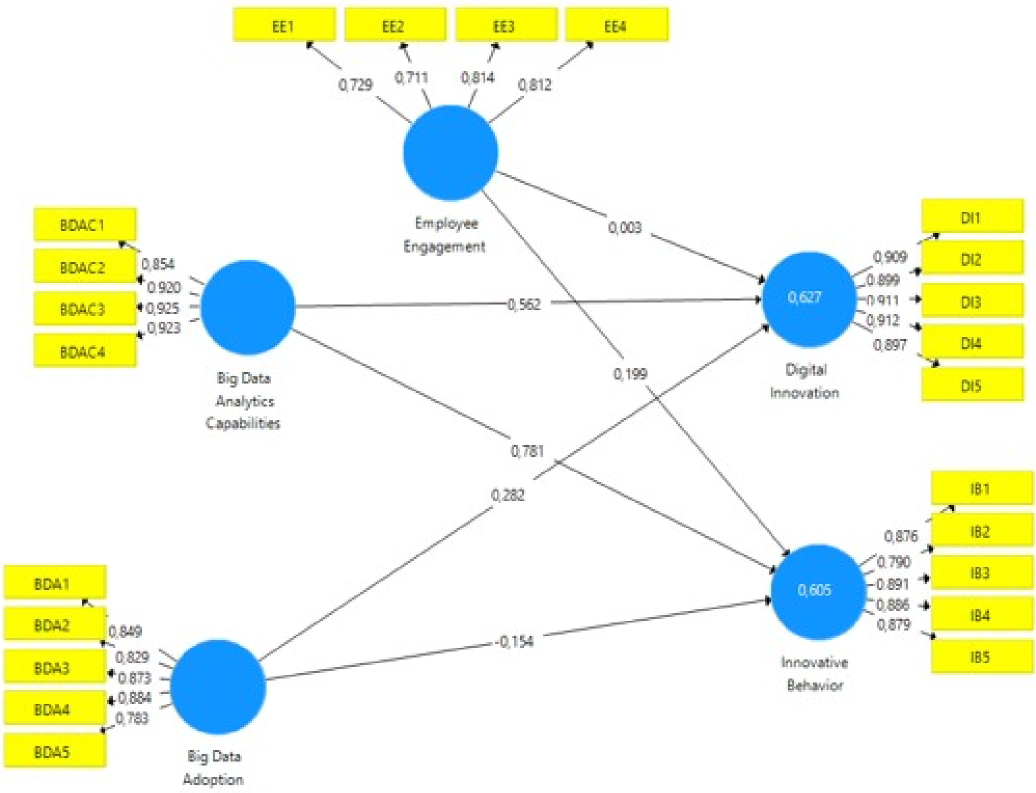

Figure 2. Assessment of measurement model

Assessment of Structural Model

Using SmartPLS 3.0, a non-parametric bootstrapping process with 5000 iterations was used to assess the relevance of the study's hypotheses. Hair Jr et al. (2020), this stage was carried out following the validation of the psychometric properties for the outer model by the researchers. Testing the structural model (inner model) comes next after the performance of the outer model has been verified. Table 4 provides specific R-squared values for each construct. Utilizing Edwards' adequacy coefficient (R2a) with Hair Jr et al. (2020), we followed the recommendations made by Hair Jr et al. (2020). To do this, add up all of the formative items' squared correlations with each formative construct, then divide the total by the total number of indicators.

Table 3: Assessment of *R* square

	R-Square	Adjusted *R*-Square
Digital Innovation	0.627	0.624
Innovative Behavior	0.605	0.602

To evaluate the theories, we employed structural equation modeling with Partial Least Squares (PLS). PLS should be used for a number of reasons: Construct scores are more dependable than sum scores in PLS, a structural equation modeling technique used to estimate composite factor models. PLS can assist in detecting a wide range of measurement model misspecifications and has enough information to estimate various weights. After the researchers have confirmed the psychometric properties for the outer model, they will use SmartPLS 3.0 to perform a non-parametric bootstrapping approach with 5000 iterations to assess the significance of the hypotheses in this study (Hair Jr et al., 2020).

The results of this study demonstrate a direct relationship between big data analytics capabilities and digital innovation (=0.566, T-value=11.895, p-value=0.000). The results of this study demonstrate a direct relationship between big data analytics capabilities and creative behavior (=0.775, T-value=15.638, p-value=0.000). The results of this study demonstrate a direct relationship between digital innovation and big data adoption (=0.337, T-value=6.445, p-value=0.000). The results of this study demonstrate a direct relationship between innovative behavior and big data adoption (=-0.182, T-value=1.363, p-value=0.021). The results of this study demonstrate that digital innovation and big data analytics capabilities are moderated by high employee engagement (=0.163, T-value=2.566, p-value=0.011). The results of this study demonstrate that innovative behavior and big data analytics skills are moderated by employee engagement (=-0.265, T-value=4.706, p-value=0.000). The present study shows that employee engagement has a moderating impact on big data adoption and digital innovation (=0.109, T-value=2.106, p-value=0.036). The present study shows that employee engagement has a moderating impact on big data adoption and innovative behavior (=-0.283, T-value=5.180, p-value=0.000).

Table 4: Hypothesis testing

	Original Sample	*T* Statistics	*p* Values	Decision
Big Data Analytics Capabilities -> Digital Innovation	0.566	11.895	0.000	Supported
Big Data Analytics Capabilities -> Innovative Behavior	0.775	15.638	0.000	Supported
Big Data Adoption -> Digital Innovation	0.337	6.445	0.000	Supported
Big Data Adoption -> Innovative Behavior	-0.182	1.363	0.021	Supported
Moderating Effect 1 -> Digital Innovation	0.163	2.566	0.011	Supported
Moderating Effect 2 -> Digital Innovation	-0.265	4.706	0.000	Supported
Moderating Effect 3 -> Innovative Behavior	0.109	2.106	0.036	Supported
Moderating Effect 4 -> Innovative Behavior	-0.283	5.180	0.000	Supported

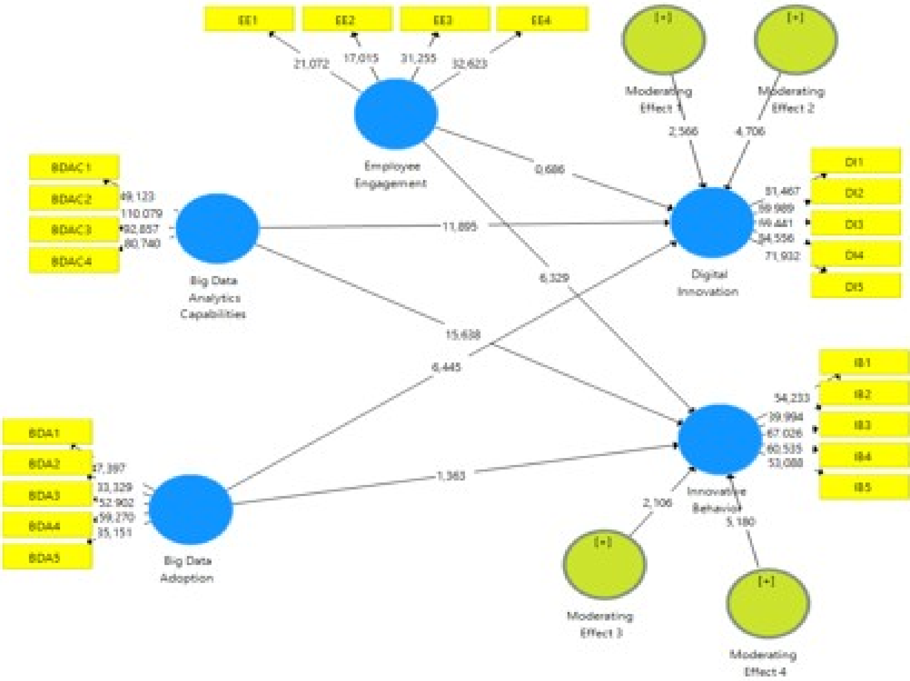

Figure 3. Assessment of Structural Model

Plotting the simple slopes associated with significant interactions that is, the low and high values of the moderating variables allows us to examine the interaction effects (below fingers). We next looked at these slopes to see if they had any statistical significance. The relationship between buffering and discovered insights is seen in the figures below. The fact that the deployment of big data analytics and the presence of high skills considerably boost the engagement level of people with low self-efficacy is particularly remarkable. The moderation study, which is shown in the following figures, shows that employee engagement modifies the link in the other way between digital innovation and innovative behavior and big data analytics capabilities and adoption.

DISCUSSION

The purpose of this research was to explore and understand the relationships between big data adoption, big data analytics capabilities, employee engagement, digital innovation, and innovative behavior in the context of Korean mobile tech companies as well as resource-based view and dynamic capability theory. All hypotheses were accepted.

The present study shows that big data analytics capabilities have a direct effect on digital innovation and innovative behavior. According to Kör et al. (2021), concentrating only on big data analysis is sufficient. They argue that creating value with big data entails a series of interrelated steps, highlighting the critical roles of the data provider and their ability to obtain relevant data to provide favorable results. The body of current big data literature has consistently emphasized that organizations must make the necessary investments in technology infrastructure to attain BDA capabilities and produce the necessary big data outputs (Awan et al., 2022). In order to improve the inputs for data analysis, capabilities, and value creation activities including knowledge development, creativity, and decision-making, businesses should place a strong emphasis on the big data value chain. The findings point to the larger significance of technical administration since it has a somewhat stronger impact on BDA capacities and decision-making performance than relational governance. Companies and data suppliers should have appropriate agreements in place to guarantee data quality, communication, and comprehension of big data. Views should be exchanged in order to improve the firm's comprehension of the data (Su et al., 2022).

The present study shows that big data adoption has a direct effect on digital innovation and innovative behavior. Firm productivity will increase significantly as a result of BDA assets and capabilities (Lu et al., 2022; Taher, 2012). The beneficial effects of BDA on various invention types to improve innovative behavior were found by Taher (2011) and Wheeler (2002). According to Su et al. (2022), adopting BDAs would probably aid businesses in improving their innovative behavior. According to Ciampi et al. (2021), Zhe and Hamid (2021), mobile tech companies would be divided into tangible and intangible forms based on the big data-related talents of employees. For instance, digital innovation and innovative behavior inside a company comprises intangible resources, whereas data and technology are considered physical resources. According to (Jaouadi, 2022), intangible resources are essential because they can help decision-makers become more knowledgeable and expand their perspective, which will help them make wise choices. "The information derived via BDAC provides firms with real-time information," according to Mahmood et al. (2023) enabling organizations to perform better. The current research, which draws inspiration from earlier studies on big data adoption, views the entire term as an innovation that is necessary for businesses to successfully adopt innovations. Accordingly, the incorporation of big data may help shape innovative behavior. Then, it can motivate businesses to employ big data for several objectives, including enhancing operations, facilitating decision-making, maintaining competitive advantage, and fostering business growth (Al-Khatib, 2022).

The present study shows that employee engagement has a moderating impact of big data analytics capabilities and adoption on digital innovation and innovative behavior. Workers in strong mental health are more confident in their ability to overcome barriers in the innovation process and are more willing to stick with it while developing and implementing new ideas Ibrahim et al. (2024), Park and Kim (2021) and Wang et al. (2020). Kapoor and Aggarwal (2020) and Maroufkhani et al. (2020) claim that technological advances have completely changed the way businesses and consumers exchange information and communicate. Park and Kim (2021) and Wang et al. (2020) points out that keeping a firm current with cutting-edge technology can be costly, as utilizing it frequently entails significant expenses, particularly for small enterprises. Lu et al. (2022) define innovation as the creation and investigation of novel ideas, approaches, products, and services. Not only does idea production happen in the early stages of brainstorming, but it also happens throughout the continuous cognitive process of problem-solving and action. Idea promotion is a set of socio-psychological exercises designed to find possible allies, sponsors, backers, and coworkers, as well as to build an advocacy coalition that can assist in bringing ideas to life. Lastly, concept realization is the process of continuously creating prototypes, bringing new goods and services to market, and materializing fresh models in order to provide unique values both inside and outside of the company (Shamim, Zeng, Khan, & Zia, 2020). Businesses should understand that employee engagement has a significant impact on the success of digital innovation and creative behavior projects, and that the adoption of cutting-edge technologies is not the only factor that matters. Strategic decision-making for companies seeking to efficiently use human and technology resources to spur innovation is informed by this comprehensive viewpoint.

Theoretical and Practical Implications

The results of the research will have a significant impact on how manufacturing companies handle the difficulties presented by big data analytics. The results demonstrate that the following elements massive data collection, technology investment, innovative analytics techniques, technology and management personnel, organizational learning culture, and embedded big data decision-making are critical for realizing business value from big data investments. Firms may only create value benefits by combining the entire effect of the aforementioned competencies. As a result, practitioners should be aware of several implications of the current study's findings. First and foremost, managers need to focus more on big data analytics capabilities and develop strategic plans that are grounded in data-driven analysis. Secondly, it is imperative to establish an organization-wide data-driven culture, which involves enhancing the competencies of data managers, broadening the range of data-driven decision-making options, and fostering the development of decision-making skills that integrate both analytical and intuitive insights. Additionally, during the hiring process, employers ought to focus more on choosing staff members with management and big data technological expertise. The goal of this research is to address the important question of whether and how big data might stimulate digital innovation and creative behavior in businesses. To that aim, we broaden our investigation to include the idea that big data analytics adoption and capabilities are critical competencies that businesses need to develop in order to reap significant benefits from their big data usage. Based on the well-known resource-based view, we claim that the acceptance and capabilities of big data analytics are not just technical but also require the development of a variety of non-technical resources in order to create a complete framework. Furthermore, we hope to close this gap by offering empirical support for the suggested theoretical framework. While the value of big data analytics capabilities, adoption, and big data, in general, has frequently been communicated anecdotally with little empirical support, particularly in the context of digital innovation and innovative behavior, we hope to do so. By showing how big data analytics adoption and capabilities favorably impact a firm's dynamic capabilities, this study makes a substantial contribution to the big data literature. This fortifies both inventive behavior and digital innovation. Additionally, this research adds to the empirical investigation of the processes by which big data analytics impacts innovative behavior and digital innovation. From a practical point of view, the knowledge gained from this study can help Korean mobile tech companies and, by extension, other businesses in comparable situations. The role of the digital innovation process has drawn attention from academics to provide additional theoretical and empirical contributions, that relate to the research direction for digital innovation and digital technology. This might be the result of businesses shifting toward decision-making that is done on their own, and because BDA capability is a more comprehensive concept that includes management ability, technology infrastructure, and human skill (Maroufkhani et al., 2020). Because the BDA construct is multifaceted, its ability to impact the quality of decision-making is independent of mediators like data-driven insights. Still, more research is required on this matter.

Limitations and Future Research

First, the sample group is restricted to Korean mobile tech startups, which stand out for their distinct resources and structural flexibility when compared to larger enterprises. Future research should broaden the model's scope to incorporate more types of organizations, especially large corporations, to determine how broadly relevant the findings are. Second, additional research is needed to validate the conceptual framework among mobile tech companies in both developed and developing countries, as the study solely examined Korean enterprises within a specific time period. Thirdly, the cross-sectional form of the study makes it more difficult to use questionnaire surveys to test hypotheses and establish causation in the relationships between variables. In order to get more accurate and dependable results over an extended period of time, a longitudinal study is required because big data analytics adoption and capabilities are not always evident. Lastly, by including additional components discovered in recent studies like organizational culture, competitive pressure, and technological infrastructures future research could enhance the conceptual framework. Subsequent investigations that tackle these constraints will augment our understanding of the complex mechanisms that support the adoption, efficaciousness, and impacts of big data analytics on organizational outcomes. Furthermore, the research's reliance on a survey-based methodology and the subjectivity of the variables employed increase the risk of cognitive bias, which could compromise the study's objectivity. To increase the robustness of ensuing contributions, researchers are encouraged to look into the same subject using a range of informant sources and case-based methodologies. Future research should seek to conduct more objective surveys with personnel of different positions within the organization and at different moments in time to validate the statistical results. The current study collected data through questionnaire surveys. Furthermore, it is advised to use the structural equation modelling methodology to develop a more precisely defined relationship between variables, hence providing a stronger theoretical foundation for the study. Furthermore, contextual factors were overlooked in this study, which explores the moderating influence of employee involvement in the conversion of big data analytics skills into digital innovation and innovative behavior. Future research should examine whether contextual factors mediate the adoption and successful use of data analytics capabilities, given that the value of big data analytics capabilities may change throughout various corporate contexts. Closing this study gap will advance our understanding of the complex interactions between contextual factors and big data's effects on organizational outcomes by offering insightful information and useful implications.

CONCLUSION

By highlighting the significance of big data adoption, big data analytics capabilities, employee engagement, digital innovation, and inventive behavior within the particular context of Korean mobile tech companies, this study provides a significant contribution to the growing body of empirical knowledge. Utilizing the viewpoints of the Resource-Based View and Dynamic Capability Theory, the study emphasizes how important big data adoption and analytics capabilities are to raising a company's effectiveness and efficiency. However, it is crucial to acknowledge the study's limitations, including its focus on a specific industry and geographical context. The generalizability of the results may be influenced by the unique characteristics of Korean mobile tech companies. Future research endeavors could expand the scope to include a broader range of industries and geographic locations to enhance the external validity of the findings. In practical terms, the insights derived from this research offer guidance to Korean mobile tech companies in navigating the complex interplay between big data dynamics, employee engagement, and innovation. The emphasis on dynamic capabilities reinforces the need for continuous adaptation, learning, and strategic flexibility in the rapidly evolving landscape of mobile technology. This study contributes to the growing body of literature on big data and innovation, providing a nuanced understanding of how these factors interconnect within the context of Korean mobile tech companies. As organizations worldwide grapple with the challenges and opportunities presented by technological advancements, the findings of this research offer relevant implications for those seeking to leverage big data analytics for enhanced innovation and organizational success.

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APPENDIX

Variables	Items	Source
Big Data Analytics Capabilities	1. We have access to very large, unstructured or fast-moving data for analysis 2. We integrate data from multiple internal sources into a data warehouse or mart for easy access 3. We integrate external data with internal to facilitate high-value analysis of our business environment 4. We have explored or adopted parallel computing approaches (e.g. Hadoop) to big data processing	(Su et al., 2022)
Big Data Adoption	1. Big data is used as an essential tool in every department (volume). 2. Big data is used for decision-making in your organization (diversity). 3. Big data is used in the functional area of operation (depth). 4. Big data is used in the functional area of management (depth). 5. Our organization use advanced analytical techniques (e.g. simulation, optimization, regression) to improve decision-making.	(Maroufkhani et al., 2020)
Employee Engagement	1. At my job, I feel strong and vigorous. 2. I am enthusiastic about my job. 3. My job inspires me. 4. When I get up in the morning I feel like going to work	(Heslina & Syahruni, 2021)
Digital Innovation	1. Please indicate your level of agreement or disagreement with the statements below 2. We are committed to use digital technologies in developing our new solutions 3. Our solutions have superior digital technology 4. New digital technology is readily accepted in our organization 5. We always look out for opportunities to use digital technology in our innovation	(Zhe & Hamid, 2021)
Innovative Behavior	1. I try to create/adapt new and creative ways of doing business. 2. I develop new ideas to solve problems that arise during my work. 3. I explore new products or services 4. I pay attention to issues that are not part of my daily work. 5. I look for opportunities to improve things.	(Kör et al., 2021)