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Business Intelligence (BI) in Firm Performance: Role of Big Data Analytics and Blockchain Technology

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Abstract: The analysis of the causes or drivers of the adoption of big data analytics and blockchain and their subsequent influence on firm performance has become a significant need as a direct result of the rapidly expanding popularity of business intelligence. The purpose of this research is to present a model that investigates the direct and indirect influence of business intelligence on firm performance through the mediating roles of the adoption of big data analytics and blockchain. The analysis is based on data collected from a representative sample of 387 employees from 12 Information technology (IT) firms operating in Croatia. The study investigates these connections using a structural equation modeling. The findings showed that business intelligence has a direct and significant influence on firm performance. In addition, business intelligence significantly and positively influenced the adoption of big data analytics and blockchain and, in turn, firm performance. Additionally, the adoption of big data analytics and blockchain technology signified and positively mediated the relationship between business intelligence and firm performance. Both the mediations were partial. Finally, the study also provides managerial implications, limitations and future directions.

Keywords: business intelligence; big data analytics; blockchain; firm performance; structural equation modeling (SEM)

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1. Introduction

Business intelligence combines all of the news sources into something beyond the sum of their components. It does this by pulling on the operational data provided by the enterprises' resource planning system and transforming it into meaningful intelligence that directly supports the company's strategic goals (Al-Mobaideen 2014). Business intelligence (BI) is universally acknowledged as the art of deriving business value from data; consequently, BI systems and communication infrastructure are required to integrate various data sources into a consistent standard framework in order to facilitate fact-checking and deep analysis across the firms. By recognizing the firm information systems, such as customer data, procurement information, employee information, production data, marketing and advertising activity data and any additional reference to crucial data (Khan 2019; Muntean and Cabau 2011), business intelligence tools have had the ability to make more smart judgments more efficiently (Sharda et al. 2014). Undoubtedly, the accuracy of the data on which a firm's decisions are based determines the quality of those judgments (Kilani 2022). When managers consider both the internal workings of the company and the external environment in which it functions, they can make both productive and profitable decisions. This necessitates continuously seizing newly emerging opportunities, taking calculated risks and maintaining a flexible stance in response to various new requirements (Muntean et al. 2010; Shi and Lu 2010).

Business intelligence initiatives help decision-makers to solve business problems in order to maximize business value. The primary objective of these initiatives is to increase profitability and productivity. According to Zeng et al. (2012), the resolution to a business challenge typically consists of a process that also involves business intelligence, while business intelligence on its own is rarely a sufficient answer to enterprise needs. Business intelligence suppliers are preoccupied with offering appropriate solutions for administrators, business intelligence solutions that are competent at implementing balanced scorecards, corporate reports and performance dashboards (Khatibi et al. 2020). This is related to managerial visions and a strategic planning tool that offers a global view of a company, transforming its strategy and mission into concrete and quantifiable goals (Muntean et al. 2010; Silahtaroğlu and Alayoğlu 2016).

With the accessibility of "big data" and blockchain technology in intelligent machines, the idea of "business intelligence" (BI) has emerged as an increasingly essential one (Agarwal and Dhar 2014). Over the course of the past two generations, the importance of the fields of business intelligence, blockchain and big data analytics, which are closely related to one another, has grown substantially in both the academic and commercial worlds (Chen et al. 2012; Daneshvar Kakhki and Palvia 2016). When integrated with big data and blockchain technology, these forms of business intelligence are able to carry out operations and actions that are both timelier and more relevant than those carried out by humans. Business intelligence is utilized in both testing and production environments by IT development businesses (Wamba-Taguimdje et al. 2020). The term "machine learning" refers to the process through which business intelligence might acquire new tools in order to investigate big data and automate decisions. The term "business intelligence" is most commonly used as an umbrella term to represent a system (Shollo and Kautz 2010) or methods and concepts (Sabherwal and Becerra-Fernandez 2013) that enhance decision-making by making use of reality support networks. Many concepts (such as "business intelligence", "business analytics" and "big data") are frequently interchangeable in research. Authors have described business intelligence in a variety of ways, including as "a process and a brand" (Jourdan et al. 2008, p. 121), "a process, a brand and a combination of methods, or a mixture of such" (Shollo and Kautz 2010, p. 87) or as "a good or service alone" (Seddon et al. 2017). Several of these findings come from a study that was carried out by Accenture and General Electric. According to the study, 89 percent of businesses believe that if they do not integrate big data and blockchain, they will lose market share (Columbus 2014).

Business intelligence (BI), blockchain technology, cloud computing services, big data and fifth-generation (5G) wireless networking are the five primary trends that are currently leading and influencing business (firm) performance. The term "big data" refers to the attempt to find techniques that can analyze the enormous volumes of information that are consistently produced. Big data uses computers to process information in order to gain insights or advantages over competitors. Big data analytics encompasses a wide variety of software programs, hardware technologies and business procedures that are all connected in some way to the phases of gathering, storing, accessing and analyzing large amounts of data (Bayrak 2015). "Big data" refers to the enormity of a large amount of unorganized data that is collected as part of the process of developing big data analytics. This type of data can only be analyzed and comprehended by using specialized software and hardware (Bayrak 2015). Analyzing social media data allows crucial aspects of marketing strategies to be automatically controlled using big data analytics and blockchain technology (Tan et al. 2013). These factors include the opinions of customers toward a brand, service or organization. On the other hand, the accessibility of big data presents practitioners and academics with new hurdles, even as it opens up previously unimaginable prospects for marketing intelligence. The analysis of large amounts of data focuses primarily on overcoming three distinct sorts of difficulties: storing, managing and processing (Kaisler et al. 2013).

Wang et al. (2022) noticed that firm performance is impacted by the capabilities and reliability of business intelligence (BI). In addition, performance affects a company's competitive advantage. Furthermore, BI capabilities affect BI reliability. Companies are actively contributing to the rapid development of big data technologies and are becoming more interested in the possibilities of big data. According to the Organization for Economic

Cooperation and Development (OECD), big data promises to produce increased value in various business operations and it has been singled out as the next big thing in technological advancement (Gunasekaran et al. 2017). In light of this, a recent study asserts that "big data is more than just a technological issue and for big data to be fully effective, it requires becoming an integral part of organizations" (Braganza et al. 2017). Recent research by Ji-fan Ren et al. (2016) examined the link between the value proposition of big data analytics options and the performance of companies. During this process phase, blockchain technology has forced technological communication methods to forge stronger ties with firm performance (Liu 2022). Blockchain technology, on the other hand, can boost a company's performance by increasing the number of innovations (Liu 2022). Companies can improve their performance by increasing their market share, expanding into new technologies, including blockchain and big data analytics (Braganza et al. 2017; Liu 2022), and developing higher-quality goods and services (Braganza et al. 2017). In light of this, this study approached the concepts of performance and performance as the predicted factor of big data analytics, blockchain technology and business intelligence.

It was therefore proved that higher firm performance is influenced by advanced technologies (i.e., business intelligence, big data analytics and blockchain). It has been determined that the integrated business intelligence (BI) system is an effective and reliable tool for managing corporate capacity planning and executing supply chains. Business intelligence, with the adoption of big data analytics and blockchain, makes a substantial contribution to higher firm performance in the market. The vast majority of these systems can successfully carry out the feature in question; nevertheless, they lack the tools necessary for data analysis and reporting. It is possible to use BI tools to maintain a consistent path of innovation in information systems (Al-Measar 2015; Chou 2018). As a result, this research focused on IT firms in Croatia that use business intelligence with the intention of using big data analytics and blockchain. The objectives of the study are to (1) examine the influence of business intelligence on firm performance and (2) test the mediating roles of big data analytics and blockchain between business intelligence and firm performance.

2. Literature Review and Theoretical Framework

2.1. Underpinning Theory

According to the theory of signaling, an agent can minimize the information gap between themselves and their principal by sending a signal or communicating confidential information to the principal (Grover et al. 2018). The primary, who is typically portrayed by the shareholders of a firm, may view the signal as one that increases value, which could result in an increase in both the stock price (due to the shareholders' increased buying activity) and the value of the business. With big data and blockchain investments in technologies, techniques, skills and governance viewed as the leading innovators in social and media discussion, a company can gain significant effects via the signals created through these investment opportunities and other business intelligence initiatives (Wang 2010). Additionally, herd behavior, which refers to the practice of following the lead of the mob, is another hypothesis that underpins symbolic value (Grover et al. 2018). Some businesses may want to use new information technologies to demonstrate that they are up-to-date with industry trends and can compete effectively in order to maintain their customer base or their reputation (Grover et al. 2018). Herd behavior was shown to occur by Sun (2013), who demonstrated that it happens "when adopting a brand-new technology is motivated mostly by the monitoring of earlier adoptions and thoughts of ambiguity about the adoption of technology". As a result, if the study is to properly investigate the strategic ramifications of implementing business intelligence via big data analytics and blockchain on firm performance, the symbolic significance must not be overlooked. In addition, the resource-based view (RBV) suggests that the interaction between business intelligence and the technology framework produces heterogeneity as well as immobility for value (Grover et al. 2018). The logic of alternatives suggests that business intelligence could have a higher value because it provides options ranging from more extensive performance to opening doors to subsequent options (Grover et al. 2018). Therefore, the theoretical perspectives support the study model.

2.2. Business Intelligence (BI) and Firm Performance

Research on business intelligence that is based on the information system success model rarely analyzes the connection between business intelligence and the performance of the firm. This gap has indeed been noted and demands for a theoretically grounded investigation based on the merits of business intelligence have been made as a result (Sharma et al. 2014). Although it has been used as a basis for a number of BI studies that investigate the link between BI and firm performance from the standpoint of making decisions (Grover et al. 2018; Işık et al. 2013), it does not directly address the problem of firm performance. Therefore, studies that are based on this perspective often do not go beyond the intermediate benefits of BI, such as better decisions, quicker access to insights and greater environmental awareness. This type of research, while having obvious value, does not explicitly evaluate the mechanism by which these intermediate advantages influence business performance (Torres et al. 2018). There are few scientific viewpoints that are used to support BI research that clearly incorporate company performance as a dependent variable. One of those conceptual frameworks is the RBV of the firm (Elbashir et al. 2008; Torres et al. 2018). RBV is a firm-level theory of firms' competitive performance that implies that reserves are heterogeneously divided up across the economy and that agencies endowed with resource bases that are beneficial, rare, unique and non-substitutable adore business edge (Barney 1991). Based on the pieces of evidence in the literature, this study proposes the research hypothesis:

H1. *Business intelligence significantly and positively influences firm performance in Croatia.*

2.3. Business Intelligence, Big Data Analytics and Firm Performance

Within the context of assisting the adoption and deployment of big data, this study also investigates and reports on the possible influence of business intelligence on firm performance (Aydiner et al. 2019). "Big data adoptions" are those that transform large amounts of data into information that is both emotional and functional for businesses (Bayrak 2015). Business intelligence was conceptualized as a collection of information system applications in the model; these included market intelligence, financial intelligence, data gathering and decision-support systems. According to Ramanathan et al. (2017), organizations have the potential to realize considerable improvements in performance by adopting big data analytics in a manner that is aligned with their business operations and the firm's goals. A firm process is a cross-sectional and complicated situation that gathers information from all of an organization's operations and capabilities. Therefore, increasing firm performance requires both the analysis of interactions and the identification of prospective enhancements in favor of decision-making. Big data, which is included in BI apps and counts as one of the big data analytic components, improves company performance and economies by facilitating the smooth interchange of data and information between various business processes and outside partners.

By taking into consideration the resource-based view (RBV), one can determine the degree to which big data analytics has the potential to contribute to the development of a competitive advantage (Gunasekaran et al. 2017). As a result, it is essential to have a clear understanding of the distinctions between a firm's performance and its value (Ji-fan Ren et al. 2016). According to Kozlenkova et al. (2014), RBV recognizes business value as its core construct, which lies between rare, unique and non-substitutable resource base and firm performance.

As a result, the implementation of big data results in the provision of standardized tools that may support, diagnose and enhance performance inside an organization (Sharma et al. 2014; Torres et al. 2018; Sun et al. 2017). Other studies have focused explicitly on the effect of big data analytics on decision-making performance without evaluating its effect on firm performance (Appelbaum et al. 2017; Gunasekaran et al. 2017; Sun et al. 2017). This is despite the fact that many studies state that business intelligence and big data adoption provide better value creation, leading to firm performance (Bayrak 2015). Nevertheless, business analysis and the applications of business analysis have a wider influence on a firm's value and business operations when a company changes its organizational structure and its procedures. As a result, the adoption of big data analytics and all of its components is the primary focus of our research. In light of this, we offer the following hypothesis concerning the link between business intelligence and the adoption of big data analytics: data analysis and e-commerce structures are ingrained in business intelligence in a conceptual framework as the most common information system applications and tools because of their ability to respond to "so what" and "now what" queries and their ability to improve service standards while simultaneously reducing spending (Sivarajah et al. 2017). Finally, the study proposes the following research hypotheses:

H2a. *Business intelligence significantly and positively influences the adoption of big data analytics in Croatia.*

H2b. *The adoption of big data analytics significantly and positively influences firm performance in Croatia.*

H2c. *The adoption of big data analytics significantly and positively mediates the relationship between business intelligence and firm performance in Croatia.*

2.4. Business Intelligence, Block Chain and Firm Performance

Blockchain technology is a game-changing innovation that has ushered in novel ideas for the safe and confidential exchange of data and information. This cutting-edge technology is made up of a string of blocks that, when combined with shared and dispersed networks, make it possible to safely keep every transaction that has been made (Salah et al. 2019; Lahami et al. 2022). The hashing, global consensus methods and digital signatures are some examples of the fundamental technologies that have been implemented in order to achieve this objective. As no centralized authority is required for the completion of any transaction, third parties are unnecessary for its confirmation and verification (Litke et al. 2019). Through the use of a hypothetical application scenario, the benefits of blockchain technology in terms of providing provenance and traceability to essential products are brought into focus (Krichen et al. 2022). Lighter consensus approaches are necessary in addition to standard ones in order to bridge the performance gap that exists between a public blockchain and a regular database.

The blockchain is an indestructible digital blockchain platform of financial relationships that is capable of being designed to record not only financial transactions but almost anything of value. The blockchain was initially developed to record money transactions. The utilization of blockchain technology releases auditors from the duty of having to check repetitive transfers so that they can instead concentrate on complex operations and internal control systems It also verifies that the digital performance of tangible assets is legitimate, it guarantees that the agreement is authored in compliance with standards and it alters both the scope and the methodologies of individual opinions (EY 2017). As part of this process, official key performance metrics were developed so that all of our hard work was directed in the appropriate direction, resulting in measurable accomplishments (Zhang et al. 2020). According to Kim and Shin's (2019) research, which examined the influence of blockchain technology on partnerships and firm performance, blockchain technology has a significant influence on firm performance. They explained that GPS could indeed track goods all across their life span, which is beneficial in the procedures of composting, reprocessing and renewability. Kouhizadeh et al. (2019) clarify the implementation of blockchain technology by using the instance of a monitoring system. As the history of each transaction is preserved in blockchain ledgers, blockchain technology can also be used to monitor the efficiency of the circularity management process. PBV sheds light on the differences in firm performance that can be attributed to the utilization of specific and transferable firm operations. Processes are defined as "an exercise or set of exercises that firms in different industries may perform," and PBV explains how these differences come about (Bromiley and Rau 2014). In the theory of practice-based view (PBV), organization is the dependent variable. Blockchains, on the other hand, are practices that are integrated throughout firm performance (Rehman Khan et al. 2022). The emergence of technology based on blockchain could play a significant role in the radical transformation of monetary and organizational performance.

While the mainstream finance literature studied corporate branding and its impact on business performance by using data sets that contained organizations that operate under established regulatory regimes, other researchers looked at the topic from a different perspective (Akyildirim et al. 2020). Shitanda et al. (2020) also showed the findings that blockchain technology significantly and positively influences firm performance in Kenya. The purpose of this study was to investigate the impact that blockchain technology has had on business performance in Kenya and to compare those findings to the procedures that are currently being utilized by insurance companies. Although well-established blockchain systems have already been chosen to suit the requirements of these novel applications, it is still necessary to conduct extra-dimensional and hands-on assessments of the performance of these public blockchains (Pongnumkul et al. 2017). These details are necessary for practitioners to comprehend the constraints and choose the appropriate platform to use for their own applications. There are still a lot of obstacles that need to be overcome before blockchain technology can become widely used. Dinh et al. (2017), the authors of a recent work that will soon be published, investigated the performance of blockchain technology and mentioned performance review as a research area. When it comes to the adoption of blockchain technology, performance is one of the most significant concerns. This is because it is vital to provide a credible alternative to preexisting financial platforms. The following provides a synopsis of the contributions made by this paper. In the first step of this research project, a standardized procedure for analyzing a blockchain platform is offered. Both of the blockchain technologies in Croatia are evaluated with up to 10,000 transactions to determine how they perform in terms of throughput and latency using this firm performance approach, which is used to evaluate the current condition of the markets in Croatia. Therefore, the study proposes the following research hypotheses:

H3a. *Business intelligence significantly and positively influences the adoption of blockchain in Croatia.*

H3b. *The adoption of blockchain significantly and positively influences firm performance in Croatia.*

H3c. *The adoption of blockchain significantly and positively mediates the relationship between business intelligence and firm performance in Croatia.*

Finally, Figure 1 shows the conceptual framework before a detailed discussion of the literature review.

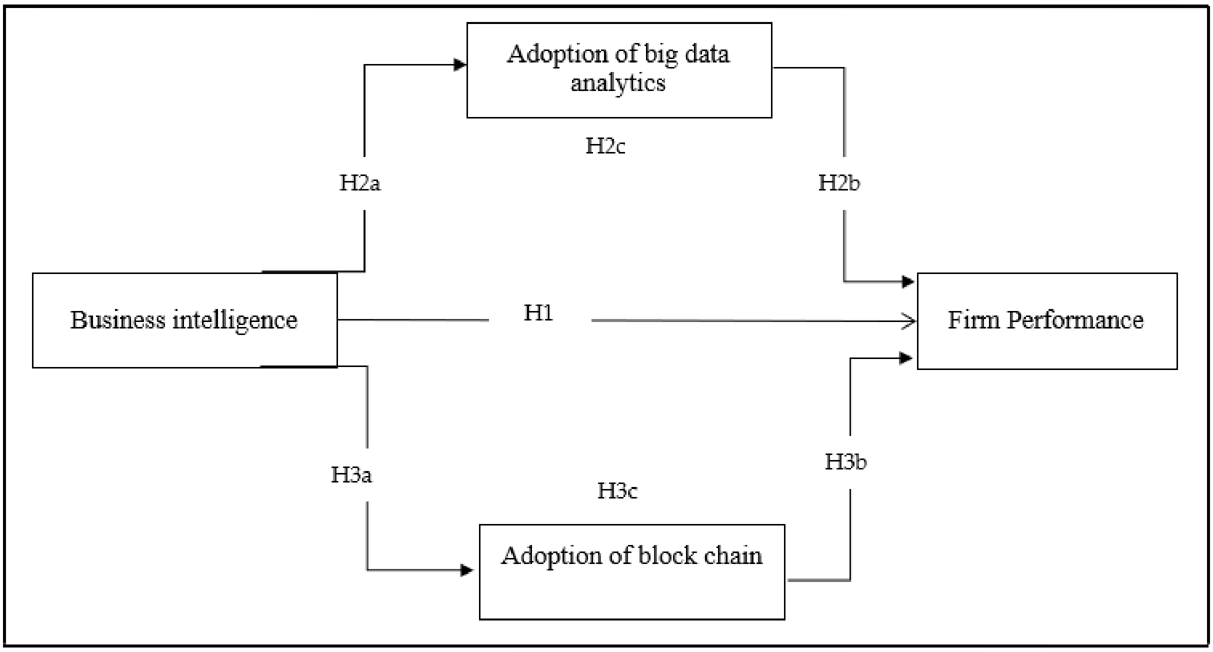

Figure 1. Conceptual model.

3. Research Methodology

3.1. Research Design

This study used a quantitative research method (Creswell et al. 2008). This study used a survey questionnaire to collect quantitative data from the employees of IT firms in Croatia. This study used the validated and developed scales from previous research and literature studies. This study targeted 12 IT firms because these are the ones that use new, advanced technologies by using business intelligence services to facilitate daily transactions with the customers.

The quantitative research method offers three perspectives to collect and analyze the data: (1) using quantitative approaches to extract prospective data from analysis and understand in detail what is happening upstream and downstream to evaluate how the operations and maintenance decision-making affect the firm's performance (Niu et al. 2019); (2) the operational progression from tend to answer management systems that can help experts analyze larger datasets utilizing available analytical and numerical techniques (O'Dwyer and Renner 2011); and (3) the mixture that results from of the implementation of both quantitative methods. In the quantitative survey, the research method used was a survey based on sampling and the instrument used to gather information was a questionnaire. It consisted of open-ended and closed-ended questions and used nominal and ordinal scales to measure responses. The research was carried out with the assistance of 387 respondents who were knowledgeable in the subject matter. The employees who indicated their willingness to participate in the poll were sent an email containing a link to the survey questionnaire.

3.2. Population and Sample Size

The study targeted employers from 12 IT firms in Croatia. This research aimed to determine the most important aspects that could impact firm performance by using business intelligence in 12 IT firms to determine whether advanced information technologies increase firm performance or not. In a broader sense, IT firms have an immediate requirement for a model that can guide the successful implementation of business intelligence in the firm performance of Croatian IT firms. Consumers in Croatia, who have suffered through years of economic downturn, are now in a position to raise their spending and have a fresh sense of hope about their country's economy. Because the European Commission began tracking this measure for Croatia in February 2018, the economic sentiment reached its best level ever, scoring 118.8 out of a possible 100 points in February 2018. When purchasing at conventional retail establishments, Croatian customers have a preference for domestic brands; however, when buying online, they have a high preference for global online merchants (40 percent of Internet users buy largely from foreign sites). Despite this, e-commerce is a long way from attaining its full potential because businesses only make 14 percent of their revenues through this channel (the average in the EU is 20 percent) (Eurostat 2020). Therefore, the Croatian market is the hub of online business and monetary transactions using technological tools, including business intelligence, blockchain and big data analytics. The researcher received 78 more responses but felt that there might be more. Finally, on 9 September 2022, the researcher received 61 additional responses, bringing the total to 387. The study also includes the demographic information of the employees in the IT firms, including gender, qualification, firm size, marketing experience and BI systems experience.

Finally, the study adapted the items of measurement scales from the previous studies so that the study uses valid and reliable measurement scales. The study adapted eight items of firm performance from the studies of Aydiner et al. (2019) and Ramanathan et al. (2017). The study adapted six items of business intelligence from the studies of Aydiner et al. (2019) and Hindle and Vidgen (2018). The study used modified versions of the adoption of big data analytics and the adoption of blockchain technology from the study of Maroufkhani et al. (2020). There were seven items for each construct. All measurement items were measured on a five-point Likert scale ranging from 1 = never to 5 = always. The study also used the demographic characteristics of the respondents, including gender (male = 1, female = 2), qualification (1 = school level, 2 = graduation, 3 = master degrees and 4 = PhD degree), firm size (1 = <50 employees, 2 = 50–100 employees and 3 = >100 employees), marketing experience (1 = <5 years of experience, 2 = 5–8 years of experience, 3 = 9–10 years of experience and 4 = >10 years of experience) and business intelligence (BI) system experience (1 = <1 year of experience, 2 = 1–2 years of experience, 3 = 3–4 years of experience and 4 = >4 years of experience).

3.3. Data Analysis

To test the hypotheses and examine the proposed model, the current study applied a widely known technique of partial least squares (PLS) based on component structural equation modelling (SEM) using Smart PLS 4.0 (Richter et al. 2020). The study used partial least square (PLS) SEM to ensure the reliability and validity of the measurement constructs (Dash and Paul 2021; Hair et al. 2017; Henseler et al. 2015). The PLS-SEM technique provides accurate and statistically robust results even with a small sample size and complex model (Sharif et al. 2021). First, the study ran an algorithm technique with 5000 subsamples to test the validity and reliability of the measurement constructs. Second, the study ran the bootstrapping technique with 5000 subsamples to examine the effect of independent variables on dependent variables because Hair et al. (2017) argued that the bootstrap samples need to be at least greater than the number of valid inferences in the initial data set, but the authors recommended using 5000 instead (Dash and Paul 2021). In addition, the study tested the model's adequacy and accuracy.

For the demographic information, the study used IBM SPSS software to do the frequency analysis. Table 1 shows the demographic information (N = 387).

Table 1. Demographic information.

		Frequency	Percent	Valid Percent	Cumulative Percent
Gender	Male	343	88.6	88.6	88.6
	Female	44	11.4	11.4	100.0
	Total	387	100.0	100.0	
Qualification	School level	6	1.6	1.6	1.6
	Bachelor	75	19.4	19.4	20.9
	Master degree	257	66.4	66.4	87.3
	PhD degree	49	12.7	12.7	100.0
	Total	387	100.0	100.0	
Firm size	<50 employees	102	26.4	26.4	26.4
	50–100 employees	248	64.1	64.1	90.4
	>100 employees	37	9.6	9.6	100.0
	Total	387	100.0	100.0	
Marketing experience	<5 years of experience	42	10.9	10.9	10.9
	5–8 years of experience	141	36.4	36.4	47.3
	9–10 years of experience	110	28.4	28.4	75.7
	>10 years of experience	94	24.3	24.3	100.0
	Total	387	100.0	100.0	
BI system experience	<1 year of experience	20	5.2	5.2	5.2
	1–2 years of experience	78	20.2	20.2	25.3
	3–4 years of experience	124	32.0	32.0	57.4
	>4 years of experience	165	42.6	42.6	100.0
	Total	387	100.0	100.0	

3.4. Common Method Bias (CMB)

A common method variance (CMV) might be an issue in situations where self-report surveys are employed to collect data. If participants have a tendency to provide vital information when finding survey items that are not otherwise related, data from self-report surveys may result in the creation of misleading correlations (Podsakoff et al. 2003). The study uses a Harman's single factor test in addition to a common latent factor (CLF) since several of the methods utilized in this investigation have the potential to encourage the development of CMV (Chang et al. 2010; Podsakoff et al. 2011). According to the findings of the Harman test, a single component cannot account for more than 24% of the variance, while there were four factors with eigenvalues that were higher than 1, each of which explained 40.1% of the total variance, which is lower than 50%. The findings of these tests imply that the common method variation is not present and that it does not affect the outcomes in any way.

4. Results

The analysis used PLS-SEM route modeling because this method was the most appropriate for the non-normal dataset and fairly significant sample size that were present in our research. The PLS-SEM methodology employs extremely broad, non-rigid distributional assumptions in addition to non-parametric evaluation metrics focused on prediction (Richter et al. 2020). The PLS-SEM method is particularly useful for doing analyses of indirect effects using several mediators (Taylor et al. 2008). For the PLS-SEM analysis and bootstrapping; the results are given in accordance with recent recommendations (Chin 2010).

4.1. Assessment of Measurement Model

Following this, the convergent validity was evaluated by analyzing the factor loadings of the construct items and the extracted average variance (AVE). The item loadings of all four constructs were tested using the algorithm technique with 5000 subsamples and the loading should be higher than 0.70, which is the established guidance for proving satisfactory convergent validity (Chin 2010; Ringle et al. 2015). Other than that, all of the outer loadings that were associated with the final scale items met or exceeded the threshold set by the scholars. The addition of the item did not have a detrimental effect on the construct's dependability, nor did it make a significant difference to the AVE; hence, the inclusion of the item was kept. Every single one of the AVE values that were measured was higher than the recommended 0.50. (Richter et al. 2020). Last but not least, the Fornell–Larker criterion (Fornell and Larcker 1981) was applied in order to evaluate the discriminant validity of the measurement scales. The fact that no latent variable correlations were higher than the square root of the AVE is evidence that the discriminant validity was satisfactory. The study ran a series of algorithms because there were some items that had lower factor loadings than 0.70. The study deleted one item of big data analytics (BDA4 = 0.674), two items of business intelligence (BI1 = 0.668, BI5 = 0.687), one item of blockchain (BC7 = 0.600) and one item of firm performance (FP1 = 0.649) from the measurement model due to lower factor loadings. Finally, Table 2 shows that the factor loading and AVE values were within the threshold values, meaning the study meets convergent validity.

Table 2. Validity and reliability.

Constructs	Item Code	Factor Loading	AVE	Cronbach Alpha (α)	Composite Reliability
Business intelligence (BI)	BI2	0.746	0.598	0.776	0.856
	BI3	0.769			
	BI4	0.787			
	BI6	0.791			
Adoption of big data analytics (BDA)	BDA1	0.760	0.622	0.878	0.908
	BDA2	0.743			
	BDA3	0.787			
	BDA5	0.782			
	BDA6	0.833			
	BDA7	0.825			
Adoption of blockchain (BC)	BC1	0.727	0.580	0.855	0.892
	BC2	0.724			
	BC3	0.777			
	BC4	0.799			
	BC5	0.767			
	BC6	0.772			
Firm performance (FP)	FP2	0.778	0.612	0.894	0.917
	FP3	0.705			
	FP4	0.838			
	FP5	0.778			
	FP6	0.803			
	FP7	0.787			
	FP8	0.782			

Every first-order construct was evaluated by a reflective measurement and, as a result, it was subjected to tests of convergent and discriminant validity (Chin 2010; Sharif et al. 2021). Concerning the concept of convergent validity, the reliability index was evaluated by looking at the significance of the construct loadings. Each variable item's factor loadings are significant at the p.001 level. In terms of construct reliability and validity, the study demonstrates a high level of internal consistency in aspects of composite reliability and Cronbach alpha (Cronbach's $\alpha \geq 0.70$, composite reliability ≥ 0.70) (Chin 2010; Ringle et al. 2015; Sharif et al. 2021). All of the extracted average variances (AVE) are clearly higher than 0.50, which demonstrates that convergent validity has been established (Fornell and Larcker 1981). Finally, the study also ensures good composite reliability and Cronbach alpha for all four constructs (Table 2).

The study assessed the discriminant validity of the construct indices by comparing the loading of each indicator on the first-order construct to the loading it had on the other constructs. The study demonstrates that all first-order construct loadings are greater than 0.70 (Chin 2010; Richter et al. 2020) and it also shows that the loading that each indicator contributes to the corresponding latent variable construct is the greatest (Fornell and

Larcker 1981). It is proof of the discriminant validity of the notions that every square root of the AVE in the diagonal of the measurement constructs is higher than the correlation with the other constructs (Richter et al. 2020; Taylor et al. 2008). Finally, the study ensures discriminant validity, including cross loadings (Table 3) and Fornell–Larcker criterion (Table 4).

Table 3. Cross loadings.

	Adoption of Block Chain (BC)	Adoption of Big Data Analytics (BDA)	Business Intelligence (BI)	Firm Performance (FP)
BC1	**0.727**	0.319	0.393	0.433
BC2	**0.724**	0.390	0.447	0.508
BC3	**0.777**	0.414	0.429	0.509
BC4	**0.799**	0.535	0.489	0.489
BC5	**0.767**	0.431	0.444	0.551
BC6	**0.772**	0.455	0.473	0.553
BDA1	0.447	**0.760**	0.525	0.455
BDA2	0.433	**0.743**	0.464	0.507
BDA3	0.388	**0.787**	0.514	0.457
BDA5	0.466	**0.782**	0.533	0.490
BDA6	0.431	**0.833**	0.531	0.542
BDA7	0.488	**0.825**	0.542	0.483
BI2	0.480	0.529	**0.746**	0.529
BI3	0.429	0.424	**0.769**	0.452
BI4	0.394	0.517	**0.787**	0.405
BI6	0.500	0.550	**0.791**	0.489
FP2	0.567	0.535	0.505	**0.778**
FP3	0.424	0.345	0.330	**0.705**
FP4	0.531	0.541	0.530	**0.838**
FP5	0.469	0.441	0.480	**0.778**
FP6	0.535	0.497	0.509	**0.803**
FP7	0.574	0.450	0.444	**0.787**
FP8	0.541	0.550	0.511	**0.782**

Note: In Table 3, bold values show the higher cross-loadings of the same construct than the blurred cross-loadings of another con-struct.

Table 4. Fornell–Larcker criterion.

	Adoption of Block Chain (BC)	Adoption of Big Data Analytics (BDA)	Business Intelligence (BI)	Firm Performance (FP)
Adoption of Blockchain (BC)	**0.762**			
Adoption of big data analytics (BDA)	0.560	**0.789**		
Business intelligence (BI)	0.587	0.657	**0.773**	
Firm performance (FP)	0.669	0.620	0.610	**0.783**

Note: Diagonal values represent the square roots of AVE and below values represent correlation coefficients. Bold values represent the square roots of AVE and below values represent correlation coefficients.

4.2. Assessment of the Structural Model

Examining the structural model involves factoring in an assessment of the path coefficients as well as the R^2 values for the amount of variance that is explained (Richter et al. 2020; Sharif et al. 2021). More specifically, the study tested all of the predicted model's relationships by specifying the mediating interactions on their own. In addition, the coefficients and t-statistics can be generated using bootstrapping using 5000 resamples. Each of the expected direct effects as well as the outer values of the latent factors is accounted for in the SEM-PLS route model (Chin 2010). The value of the route coefficients is a representation of the extent of the direct impacts. Increasing the coefficients of the several channels in the mediational chain yields a calculation that may be used to determine the indirect impacts

(Taylor et al. 2008). The bias-corrected 95% bootstrap approach is used to evaluate the significance of each impact (Taylor et al. 2008).

The study tested the research hypotheses by using a SEM approach (Table 5 and Figure 2). The study examined the direct and indirect effects of business intelligence on the performance of IT firms in Croatia. The study found that business intelligence significantly and positively influences firm performance (beta = 0.201***, *t*-value = 3.634, *p*-value = 0.000) and H1 is accepted. This means that business intelligence has a direct impact on the performance of Croatian IT firms. Business intelligence significantly and positively influences the adoption of big data analytics (beta = 0.657***, *t*-value = 17.321, *p*-value = 0.000) and the adoption of blockchain (beta = 0.587***, *t*-value = 15.529, *p*-value = 0.000); therefore, H2a and H3a are accepted. On the other hand, the adoption of big data analytics significantly and positively influences firm performance (beta = 0.262***, *t*-value = 4.233, *p*-value = 0.000), and H2b is accepted. The adoption of blockchain significantly and positively influences firm performance (beta = 0.404***, *t*-value = 7.499, *p*-value = 0.000), and H3b is accepted. The study showed that business intelligence has the strongest effect on the adoption of big data analytics in firm performance than blockchain technology. Additionally, the adoption of blockchain has a higher effect on firm performance as compared to the adoption of big data analytics.

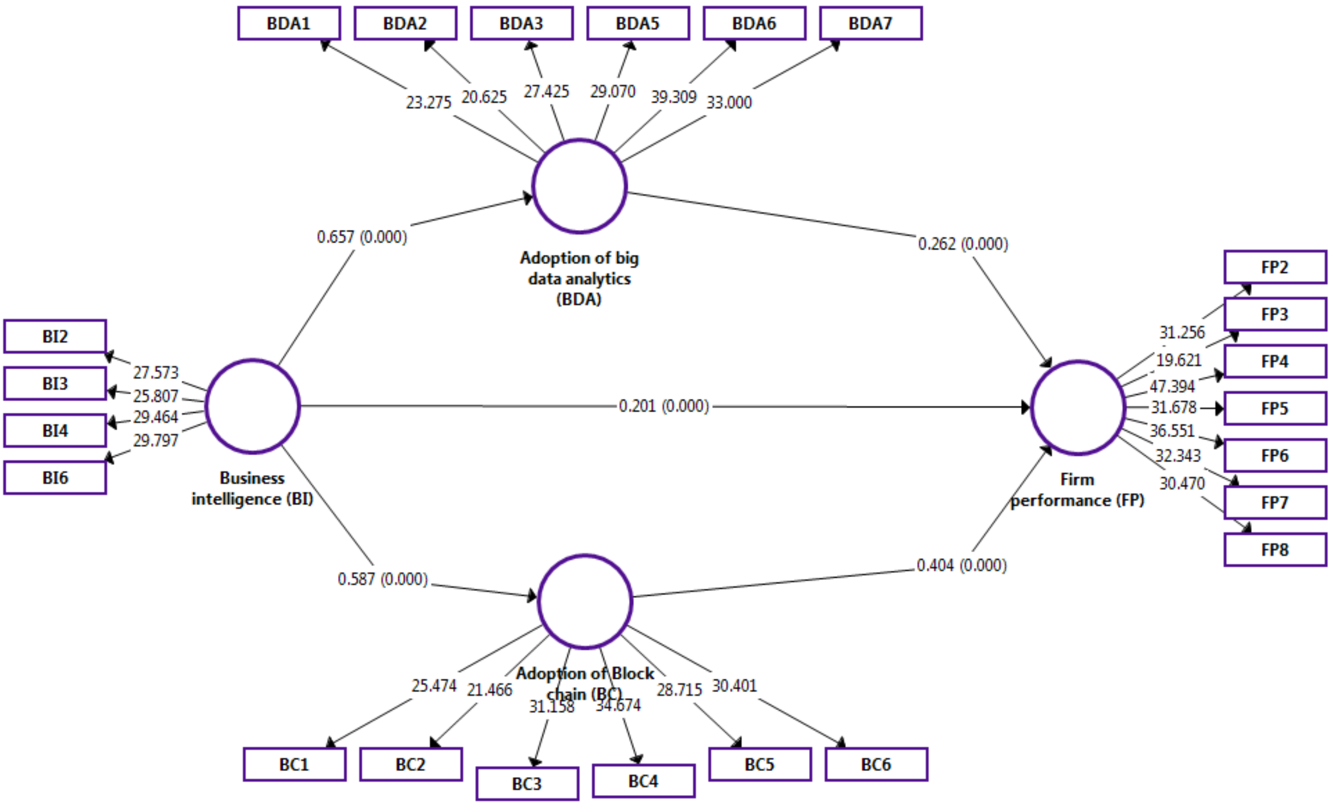

Figure 2. Structural equation modeling (SEM).

Additionally, the study examined the mediating roles of both big data analytics and blockchain technology between business intelligence and firm performance (Table 6). The study proved that the adoption of big data analytics significantly and positively mediates the relationship between business intelligence and firm performance (beta = 0.172***, *t*-value = 4.112, *p*-value = 0.000), and H2c is accepted. Meanwhile, the adoption of blockchain technology significantly and positively mediates the relationship between business intelligence and firm performance (beta = 0.237***, *t*-value = 6475, *p*-value = 0.000), and H3c is accepted. The study clarified that both the mediations were partial mediations because the direct effects were also significant but the mediating role of the adoption of big data analytics has a stronger effect than the direct effect between business intelligence and firm performance. It means business intelligence produces higher firm performance when the firm follows the adoption of big data analytics in marketing.

Table 5. Direct effects.

	Estimate	*t*-Statistics	*p*-Values
H1. Business intelligence (BI) -> Firm performance (FP)	0.201	3.634	0.000
H2a. Business intelligence (BI) -> Adoption of big data analytics (BDA)	0.657	17.321	0.000
H2b. Business intelligence (BI) -> Adoption of blockchain (BC)	0.587	15.529	0.000
H3a. Adoption of big data analytics (BDA) -> Firm performance (FP)	0.262	4.233	0.000
H3b. Adoption of blockchain (BC) -> Firm performance (FP)	0.404	7.499	0.000

Note: *p*-value measures the size of the difference relative to the variation in your sample data. *t*-statistic is the ratio between the estimate and the estimated standard error. Bootstrapping with 5000 subsamples.

Table 6. Mediating effects.

	Estimate	*t*-Statistics	*p*-Values
H2c. Business intelligence (BI) -> Adoption of big data analytics (BDA) -> Firm performance (FP)	0.172	4.112	0.000
H3c. Business intelligence (BI) -> Adoption of blockchain (BC) -> Firm performance (FP)	0.237	6.475	0.000

Note: *p*-value measures the size of the difference relative to the variation in your sample data. *t*-statistic is the ratio between the estimate and the estimated standard error. Bootstrapping with 5000 subsamples.

4.3. R^2 and Adjusted R^2

R^2 tells the strength of the effect when an exogenous construct explains the amount of variance in the endogenous construct (Henseler et al. 2015). R^2 value varies from the recommended criterions such as an R^2 value equal to 0.25 or higher value indicates a weak effect, a value equal to 0.50 or higher indicates a moderate effect and a value equal to 0.75 or higher indicates a strong effect (Chin 2010; Richter et al. 2020; Sharif et al. 2021). Table 7. shows that business intelligence explained 34.5% of the total variance in the adoption of blockchain, which is a weak effect. Additionally, business intelligence explained 43.2% of the total variance in the adoption of big data analytics, which is also a weak effect. Business intelligence explained 55.5% of the total variance in firm performance, which is a moderate effect. However, the study showed that there was good variation in each exogenous construct in endogenous construct.

Table 7. R^2 and adjusted R^2.

	R Square	R Square Adjusted
Adoption of blockchain (BC)	0.345	0.343
Adoption of big data analytics (BDA)	0.432	0.431
Firm performance (FP)	0.555	0.552

5. Discussion

This study conducted research in Croatia by targeting 12 IT firms. The study used an online survey questionnaire to collect the data from the management and employees of these IT firms. The study applied a SEM technique to analyze the relationship between business intelligence and firm performance in the presence of the adoption of big data analytics and blockchain technology. The study uploaded the survey questionnaire on social media platforms and gathered data from 387 top managerial officers. The study found the results that business intelligence directly and significantly enhanced firm performance of the Croatian IT firms. Although this conceptual model is affiliated with the mobility perspective, which is broadly used in the research on how IT affects firm performance, the treatment of the firm capacity to sense, confiscate and reshape opportunities is inconsistent throughout the IT agility literature (Chen et al. 2012). The model makes a clear distinction between each of these aspects and, as a result, it helps to create a more accurate perception of the connection that exists between business intelligence and firm performance. It does this by elucidating the nature of the connection between business intelligence and firm performance and then providing empirical validation of that connection (Torres et al. 2018).

Secondly, the study examined that business intelligence more strongly influenced the adoption of big data analytics than blockchain because the Croatian IT firms would recommend utilizing big data analytics in order to enhance and store big data and information (Aydiner et al. 2019). It also proved that big data analytics is the priority of the marketers to enhance business-to-customer (B–C) relationships. Business intelligence is the capabilities of digital computer technologies to assist businesses in locating and analyzing vital data connected to their business that may be applied to a variety of different business sectors (Aydiner et al. 2019; Bayrak 2015). With the assistance of business intelligence, firms are able to more easily develop novel and useful corporate insights (Barney 1991). Users of business intelligence are assisted in drawing inferences from analyzed data (Chen et al. 2012; Elbashir et al. 2008). Data scientists delve deep into the particulars of the data at hand, applying sophisticated statistical methods and predictive analytics in order to identify patterns and make predictions on future patterns. On the other hand, the adoption of big data analytics and blockchain significantly and directly impacted firm performance but in this case, blockchain highly enhanced firm performance. Elbashir et al. (2008) demonstrated that blockchain is a public, open-source, blockchain-based, decentralized computing platform with smart contract capabilities.

According to Gunasekaran et al. (2017), blockchain is an application for improving firm performance that is intended to serve as a foundation for the development of a wide range of industries. When evaluating the effects of blockchain adoption, new performance proposals emerge as relevant. These new measures cope with the lateral restructuring of online transactions as well as the capacity and resources of the firms. Furthermore, these new measures of firm performance are relevant. The implementation of blockchain technology has the potential to result in more efficient transaction administration. However, when the study tested the mediating roles of the adoption of big data analytics and blockchain technology, the researcher found that the adoption of big data analytics is a strong technology that has a higher potential to increase firm performance rather than the adoption of blockchain.

5.1. Managerial Implications

The results of this research have four massive implications for marketing firms and other organizations that want to get the most out of the money they invest in business intelligence and analytics. To begin, the findings of this research provide credence to the idea that business intelligence, big data analytics and blockchain can be considered a sort of capital plan that, in the long run, has an effect on a firm's performance. This research provides empirical data that could be used as a foundation for company executives wanting to justify investments in business intelligence by establishing the causal link that connects business intelligence and firm performance. The study was conducted to provide this evidence. The big data analytics and blockchain framework provides intuitive theoretical advice that practitioners could rely on to better grasp the complicated interactions that are required to extract benefits from big-data-based business intelligence. This is possible because big data aligns well with traditional business intelligence functions within firm performance (Işık et al. 2013). According to the results, in order for firms to fully capitalize on business intelligence resources, they will need to transform big-data-based business intelligence from a technical asset into a firm competence that is essential to achieving success in a competitive environment. Despite the fact that this is not a novel concept, the calls for businesses to implement it are often motivated by imperatives stemming from their finances, structures or cultures (Daneshvar Kakhki and Palvia 2016; Grover et al. 2018). Because of the work that we have done, businesses now have a new lens through which they can view the utilization of their big-data-based resources as a significant action that can enable companies to continually create and adapt in reaction to business intelligence that is constantly changing (Gunasekaran et al. 2017; Hindle and Vidgen 2018). Secondly, the research results highlight the significance of opportunity cost in realizing the value of business intelligence investments and recommend that the advancement of mutual understanding, policymaking and planning ought to be regarded as essential components of big data and blockchain capabilities. This is because opportunity usurpation is a key factor in realizing the benefits of big-data-based business intelligence investments. This indicates that businesses should make investments in firm policies that enable successful information and communication among various stakeholders, in addition to making technical investments in business intelligence infrastructure and employees. Although businesses are frequently advised to streamline decision-making and take proactive measures to ensure that important solutions and plans can be made in a timely manner in response to possibilities, the firms embed this recommended method in a chain of events that translates business intelligence investments into improved firm performance.

The model that the study proposed offers managers whose involvement in business intelligence, big data analytics and blockchain technology is growing (Davenport 2014). These technologies allow them to undertake an incorporated evaluation of the impact that business intelligence, big data analytics and blockchain technology have on firm performance. It is essential to educate IT managers on the various value-generating options offered by business intelligence, big data analytics and blockchain technology solutions and the processes by which these opportunities can be translated into improvements in the company's performance, because the changes may be profound (Orlikowski and Scott 2015). The findings of our study indicate that business intelligence, big data analytics and blockchain technology continue to hold the promise of adding value. The implementation of blockchain technology solutions paves the way for higher firm performance, the introduction of ground-breaking new products and the potential to outperform rival businesses. Implementing solutions for business intelligence enables the firm to provide superior goods and services to its clientele, thereby winning their satisfaction. The findings on the firm performance and the explored mediation impacts will make it easier to scale up solutions for business intelligence, big data analytics and blockchain technology. According to these findings, IT managers should take customer satisfaction as a key strategic objective to ensure an improvement in their companies' financial performance. Even so, managers ought to be mindful that some distinctions could emerge based on the particular IT objects they wish to engage in (George et al. 2014; Orlikowski and Scott 2015). These findings were published by (George et al. 2014; Mayer-Schönberger and Cukier 2013; Orlikowski and Scott 2015).

5.2. Limitations and Future Directions

The findings of the research need to be interpreted with a number of significant limitations in mind. Despite the lack of empirical studies to support a preference for one modeling approach over another, the mediation model is compatible with other theorizing in the sense of big data analytics and blockchain. This study used a convenience sampling technique in collecting data; however, the researcher faces biases and the findings are not generalized. The study only used a survey questionnaire (i.e., quantitative method), so mixed method research should be used to explore more factors in implementing new technologies in firm performance. This is a unique research model that conceptually examines the mediations of the adoption of big data analytics and blockchain; however, the study targeted only the perceptions of the IT firms and not their practical jobs. This lends credence to its use as a basis for the selection of one modeling framework over another. As a result, the mediation technique was chosen by the study to represent the aspects of other dynamic capabilities in this work. Further consideration should be given to the possibility that detecting, seizing and converting operate in comparison, have interaction or portray first-order factors of a higher-order concept; even so, future research should expand upon the post-hoc assessment that was revealed here and further investigate the possibility that these three processes exist. Secondly, due to its non-random nature, this study used a convenient sample, which is prone to selection bias. In order to solve this problem, two strategies were utilized, including the use of different access points to enhance the features of the sample in Croatia. Thirdly, this research made use of evaluations that were based on people's perceptions of firm performance by adopting business intelligence, big data analytics and blockchain. Such measurements include the self-reported assessments of the individuals who participated in the research, which may be prevalent in research on capacities and strategic management. Verifying the conclusions of this study would benefit from additional research in the future that investigates the data sources utilized by third parties. Fourthly, the information that was gathered places a strong emphasis on business intelligence in relation to the particular facets of the sense–seize–transform paradigm.

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