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Stevan Didijer
1911-2004

EDITOR'S NOTE **VOL 12. NO. 2 (2022)**

Business intelligence factors for decision making

In today's business world, data has become a highly valuable asset. Companies that can effectively harness their data to gain insights and make informed decisions have a significant competitive advantage. This is where business intelligence and real-time analysis come in. The authors will discuss various business intelligence applications. Such studies, e.g. improving competitive advantage through business intelligence, speed of innovation and quality of innovation in human capital and structural capital are becoming increasingly relevant (Niwash et al., 2022). It also expands the scope of competitive intelligence to include a wide range of factors (Cekuls, 2022; Cekuls, 2015; Tsuchimoto & Kajikawa, 2022). In this issue, authors will explore the primordial role of business intelligence and real-time analysis for big data, using a finance-based case study. Authors will also investigate the mediating role of business intelligence on the relationship between critical success factors for business intelligence and strategic intelligence and discuss the application of business intelligence in decision making.

Business intelligence refers to the process of gathering, analyzing, and visualizing data to provide insights that inform business decisions. Real-time analysis refers to the ability to analyze data as it is generated, providing immediate insights into current trends and events. Together, business intelligence and real-time analysis allow companies to make informed decisions based on real-time data.

Business intelligence plays a mediating role in the relationship between critical success factors for business intelligence and strategic intelligence. Critical success factors for business intelligence can include factors such as data quality, organizational support, and user adoption. By addressing these critical success factors, companies can improve their business intelligence capabilities, which in turn provides the data and insights needed to inform strategic decision-making.

Let's consider a financial services company that wants to improve its risk management processes. By implementing business intelligence and real-time analysis tools, companies can analyze a vast amount of data, including customer information, transaction data, and market data, in real-time. This allows the companies to identify patterns and trends that could signal potential risks and take corrective actions quickly. In addition, real-time analysis can help companies to detect and respond to different activities, reducing losses and maintaining customer trust.

Business intelligence provides critical insights into business operations, market trends, and customer behavior. By leveraging business intelligence, companies can make data-driven decisions that improve their overall performance. For example, a retailer can use business intelligence to analyze customer data and identify trends in purchasing behavior, allowing them to tailor their marketing efforts and improve customer loyalty.

In conclusion, the primordial role of business intelligence and real-time analysis for big data cannot be overstated. By leveraging these tools, companies can gain valuable insights into their business operations, market trends, and customer behavior. This allows them to make informed decisions that improve their overall performance and competitive advantage. The mediating role of business intelligence in the relationship between critical success factors for business intelligence and strategic intelligence further highlights the importance of effective business intelligence capabilities. Ultimately, the application of business intelligence in decision making is critical for companies to succeed in today's data-driven business environment.

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Sincerely Yours,

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Stevan Didijer
1911-2004

Introducing concepts: stairs of acceptance and project specific reputation score. Exploring public acceptance in three Finnish construction projects via large dataset media-analytics

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ABSTRACT The opposition to a deployed technology in large construction projects can grow step by step when transferred from a global level to local project delivery. Large construction projects with specific technology implementations put pressure on local public acceptance and community involvement. This pressure is transferred to project management, how to deal with the issue of stakeholder acceptance before, during, and after project execution. Hence, understanding public acceptance and project-specific reputation can prove beneficial. Utilized mostly in the company Market Intelligence function(MI), modern large dataset media analytics enables mining technology-related sentiments on global, regional, or local project levels. This paper measures the media sentiment towards three large Finnish construction projects. The specific interest is to investigate which stakeholder groups are visible through the editorial and social media and how these can be classified according to the level of required information or participation level. The aim is to gain a numerical value for project reputation, a concept belonging to the marketing field of studies. Relevant technology deployment indications are provided, and a stairs of acceptance concept is conceptualized to reflect the project-specific public acceptance. Specific needs to increase efforts at a local project level are indicated. The means to counteract local resistance can involve the mode of project execution or social marketing. The new algorithm-based method for measuring public acceptance and the introduced stairs of acceptance concept may bring project-level benefits by providing the added focus for increasing public acceptance.

KEYWORDS: Data-analytics, public acceptance, project reputation, complex project stakeholder analysis, sentiment analysis

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1. INTRODUCTION

Market Intelligence(MI) information and tools can be utilized in various functions of a company, also in the project management function, especially in the case of complex megaprojects. It is not just the local project execution that is affected by the drastic increase in information and the variety of channels providing open communication among project stakeholders. The global technology trends, as perceived by project stakeholders based on available information and communication, can influence the local project execution via technology acceptance. Examples can be drawn, for example, from coal combustion technology; its reputation globally has been so negative that there are implications for any future local coal power plant projects and local stakeholder management (Nuortimo 2020). Nevertheless, studies are scarce in terms of direct project management focus on public acceptance via modern digital media sentiment analytics, in order to take advantage of the vast sea of available market information from social media (SoMe).

This paper combines multiple aspects, it measures the media sentiment of three complex construction projects via a combination of large-scale media-analytics and a detailed classification to understand exactly what is measured, i.e., is it the project acceptance amongst a stakeholder group, or something else. It is also important to understand how the media-analytics compares to traditional methods. The difference is the pure amount of data; where traditional methods are very limited in coverage, the opinion mining on a global dataset can consist of several hundreds of thousands of data points (Nuortimo 2020, 2021). In this study, a new methodological approach is adopted to analyze the project sentiment. Human validation is applied to ensure data validity.

The paper starts from local project execution, including a specific focus on stakeholder management. To describe traditional, complex construction projects, the main participants in a construction coalition are usually the client, the architect, and the contractor. The interrelations between these participants determine the overall performance of the construction project to reach successful completion (Takim, 2009). The main contractor selects the sub-suppliers. The project alliance model, on the other hand, aims to reduce the length of the construction time and the construction costs through contractor involvement at an early stage of the design process. The project participants are paid on a net cost basis with participants jointly sharing the financial success or failure of the project at the completion, and the creation of a contractual partnership between all the parties (Scheublin, 2001). How these two execution models treat stakeholders differ, while in management theory and practice, the rise and role of stakeholders as major players in organizational dynamics are widely recognized and recorded, and the traditional view of the client as a single entity does not reflect the reality of stakeholder configurations for most projects (Newcombe, 2003). In Finland, large construction projects with different phases are executed with both traditional and alliance models, which utilize the expertise of different sub-suppliers and partners.

Today, the public acceptance is considered as the most critical issue, especially in areas without any prior experience, for example, a specific energy product. The widely discussed “Not in My Back Yard” (NIMBY) syndrome needs to be considered already in the project planning stage (Achillas *et al.*, 2011). Further, the NIMBY syndrome has been found to have several dimensions, including sociological, economic, political, and ethical (Beben, 2015). Strong protests by local communities can be observed especially in cities with high population densities (Ren *et al.*, 2016). The NIMBY syndrome is a part of the socio-political research field, whereas its influence has been notified also in the field of marketing research and tackled by, for example, social marketing, originally introduced by Philip Kotler (Stead & Hastings, 2018). In addition to using the alliance execution model, social marketing is a process where actions are aimed at triggering desired attitudes and behaviours by using marketing techniques, and marketing mix, containing cost, product benefits, communication, distribution, and people leaders (Beben, 2015). Especially in the Chinese WtE incineration projects, the NIMBY has been dealt with by a 6P model of the social marketing mix, based on the social marketing theory (Dong *et al.*, 2016).

To manage the stakeholders, complex construction projects attract interest from various stakeholders who express needs and expectations about the project, while these are often in conflict with each other, and it is unlikely that all of them can be fulfilled, requiring stakeholder management (Olander, 2007). Traditionally, stakeholder involvement has been researched by using questionnaires (Wang & Huang, 2006; Zanjirchi & Moradi, 2012).

In stakeholder theories, public acceptance has seldom been prioritized over hard financial values, while stakeholders can be classified stakeholders to groups. Construction engineers are seen to use the relation among the key stakeholders as the most important criterion of evaluating project success (Wang & Huang, 2006). The project stakeholders' project performance is also seen to positively correlate with each other; whereas project owners play the most important role in determining the project success, and project management organizations' performance has significant correlations with project success criteria as the single point of project responsibility (Wang & Huang, 2006).

When transferring the stakeholder acceptance measurement methods from questionnaires and interviews to digital age, numerical project reputation value is a new concept introduced in this paper, derived from automated media sentiment analysis via Likert scaling. Reputation is formed in the minds of stakeholders and is out of direct company control, making it rather challenging to manage (Argenti & Druckenmiller, 2004). Companies can have versatile reputations for various stakeholder groups. The analysis is committed with the help of media analytics, in this case black-box type media monitoring software. This takes place in the global context, where the mere manual analysis of content is no longer practical due to the sheer volume of data (Dhaoui et al., 2017; Wang et al., 2012), and therefore automated analysis is necessary. The computational analysis of vast amounts of data has only recently become truly viable due to developments in information technology (Chen et al., 2012). In this case, the possibility to measure large datasets with global, regional, and local levels, contributes to the build-up of stairs of acceptance concept, combining global and regional results from previous research (Nuortimo 2020; 2021) with project level studies presented in this paper and in Lehtinen (2021). One important project specific comparison point is the dissertation by Lehtinen (2021), highlighting the Raidejokeri project details studied with traditional methods, such as questionnaires and interviews.

This paper aims to 1) highlight the larger framework of acceptance and its measurement on global, regional, and local project levels via modern media-analysis, and 2) analyse via hybrid approach whether there are visible differences in project stakeholder communication of different groups, and how the general project reputation score can be calculated. Also, the human classification results via hybrid research approach are utilised to ensure validity of the measured sentiment.

This paper is organized as follows: First, literature review highlights the theoretical aspects related to the concept of public acceptance in different levels, and related stakeholder and project managerial aspects. Also, the method application, such as sentiment measurement related aspects, are discussed. Then the large-scale data-analysis is carried out based on the project name, to highlight general project visibility, sentiment, and development trend of three large construction projects, which in general, would be facing issues related to public acceptance and stakeholder management. Based on the research scope, Raidejokeri was selected as an example project to investigate the more detailed aspects. Finally, in discussion section, these views are combined to highlight theoretical, methodological, and managerial contributions.

2. LITERATURE REVIEW

Projects involve a variety of stakeholders whose opinions and interests may influence the success of delivering the project outcomes (Bourne & Walker, 2006). It is essential to increase the understanding of stakeholders' influence, attributes, concerns, and behaviour to understand how to engage them in the project management decision-making process (Aaltonen & Kujala, 2010). Also, the public, or members of public are stakeholders if they have interests in the project, and the acceptance or opposition by them may affect the project.

In general, the concept of stakeholders and their engagement are considered a part of stakeholder theory (Parmar et al, 2010). In this research paper, the general and the more focused area-specific attitudes of the public can be considered along the axis of global-regional-local acceptance. Global acceptance can be linked to potential country-level gains (Gough et al. 2002), or greater benefits for society in general (Kokkinos et al. 2018). It is generally described as socio-political acceptance, operating at the level of technologies, policies, key stakeholders, and the general public (Sovacool and Ratan, 2012). Related market acceptance involves the adoption of technologies by consumers and businesses (Sovacool and Ratan, 2012). Acceptance of a technology can be described as a "range of potential attitudes towards the technology, which are other than active opposition, namely apathy, passive acceptance, approval, and finally active support" (Hanger et al. 2016). In literature, it is generally described, that distinction can be made between different levels of acceptance taking place in different spheres (Wüstenhagen et al., 2007). The regional acceptance links to the perception of stakeholders and fairness (Gölz & Wedderhoff, 2018).

Local acceptance is linked to three types of factors, namely personal (age, gender, education), place attachment (bonds, awareness, behavioral, etc.), and project-related factors (perceived impacts, procedural justice, and trust). Nevertheless, project-related factors are seen as the most important ones in explaining local acceptance, or the lack of it (Devine-Wright, 2012). Local community acceptance can be considered as the most specific level (Sovacool and Ratan, 2012) and it concerns the energy by communities affected by the technology developed and is constructed nearby (Roddis et al., 2018). So, it seems evident, that community acceptance is a key player in implementing technologies on the local level. One essential factor, which can affect to resistance, is how public perceives the cost and benefit distribution (Shaw et al., 2015).

As the acceptance can be considered either as that by individuals or the overall public acceptance, transparency is particularly essential for building and maintaining the public acceptance, both in terms of the decision-making process, as well as the possibilities to influence it (Hildebrand et al. 2012). Furthermore, it can be possible to determine suitable levels of public participation that would positively influence public acceptance (Heldt et al. 2016). After all, it is the public engagement strategy that creates public acceptance through the pathway of communication and engagement (Mulyasari et al., 2021). Gaining public acceptance not only requires communication and dissemination of information, or elaborate risk assessment but also acknowledging different moral stakeholder viewpoints and accommodating a variety of values (Correljé et al. 2015).

As to tackle challenges on project level, social marketing is proposed as a technique to achieve social change as an effective approach to engage the public in terms of projects that influence them or their surroundings (Wong-Parodi et al. 2011). Social marketing can also be used to identify engagement strategies to increase understanding (McCarthy & Eagle, 2020). Social marketing can further be seen as an intervention design with support for planned behavior theory (Tapp et al. 2015). Stakeholder participation is specifically highlighted as important for social marketing efforts (McHugh et al. 2018).

As project reputation is a concept introduced in the marketing research field, the evaluation of project reputation is dependent on the nature and timing of such evaluation, and the stakeholder perspective (McLeod et al. 2012). Project reputation has also been linked to project performance (Badewi, 2016), indicating some linkage to public engagement and acceptance. Product and process perspectives have been highlighted as drivers of project reputation with linkages to stakeholders (Olawale et al. 2020). The main relation of reputation and acceptance seems to be that even things with good reputation are not necessarily accepted due various reasons in some stakeholder groups, such as political, ideological, or religious. The decision-making should be aware that stakeholder reactions may not be aligned with the overall project reputation.

Project managers attempt to predict the stakeholder reactions during the decision-making and choose suitable solutions to manage the stakeholders (Yang et al. 2009). The stakeholder management involves the stakeholder analysis that is prone to interpretations and the interpretation process is affected by how the information is obtained, filtered, and processed (Aaltonen, 2011). It is the project manager's perception of stakeholder attributes that is seen as critical to the view of stakeholder salience in the stakeholder classification (Mitchell et al. 1997). Nonetheless, effective stakeholder analysis should understand the possible trade-offs that do not compromise the project purpose, identify the extent to which the needs and concerns are possible to be fulfilled, and understand the consequences of non-fulfilment (Olander & Landin, 2008). Stakeholder relationship analysis is an alternative approach to predicting stakeholder behaviour and demands (Rowley, 1997). These normative guidelines on classifying stakeholders by assuming an objectively analysable environment form a good share of stakeholder research and have their use in classifying stakeholders and in evaluating their impact along with attributes, attitudes, and interdependencies. Nevertheless, certain interconnectedness of stakeholder concerns can produce a chain effect leading to conflicts and resistance, making the understanding of concern interdependencies also beneficial (Mok et al. 2017). The overall understanding of stakeholder dynamics and the impacts on project management is important for evaluating project viability (Aaltonen et al. 2015). Nevertheless, different interpretations are possible from similar stakeholder analysis processes (Aaltonen, 2011).

Project stakeholder analysis can be seen to have the primary aims to identify, prioritise, and make the appropriate decisions (Yang, 2014). Data collection is necessary to identify stakeholders, followed by interpretation to give meaning to identify, and to further classify. Aaltonen (2011) divides the stakeholder analysis process phases into data collection, stakeholder identification and classification, and strategy formulation and decision-making. A variety of methods have been discussed in conjunction with stakeholder analysis and linkages to stakeholder process steps (Table 1). Nevertheless, the methods to cover the stakeholder analysis and their application can entail challenges in terms of identification and the characterisation of the stakeholders (Jepsen & Eskerod, 2009). However, these methods are mainly concentrated on local project level without the possibility to gain a global view of the applied technology and related acceptance, which can be influential for example in complex projects when the technology to be implemented has a poor reputation.

As project stakeholders play a significant role in the project execution, stakeholder analysis is not enough, but adequate stakeholder management with a systematic process is needed (Karlsen, 2002). Understanding stakeholder behaviour is necessary for stakeholder management (Berman et al. 1999). Also, following the plan is not enough as a project can be successful only if the stakeholders contribute as they evaluate the success (Eskerod & Jepsen, 2013). Stakeholder management can be seen as organisation-focused or issue-focused, depending on whether the focus is on the organisation's welfare or an issue that affects relationships with other societal groups (Roloff, 2008).

Factors affecting the stakeholder management process from the project implementation perspective, either positively or negatively are listed as 1) analysing stakeholder concerns and needs, 2) communication of benefits and negative impacts, 3) evaluation of alternative solutions, 4) project organisation, and 5) media relations (Olander & Landin, 2008). One perspective is that even unpopular decisions can be pushed through by using alliances between inner stakeholders coined with powerful outside stakeholders to gain power (Newcombe, 2003) to work towards project objectives.

Meeting the project objectives often necessitate the appropriate inclusion of the public (Sterry & Sutrisna, 2007). However, the general public is often seen as a secondary stakeholder (Newcombe, 2003), and is traditionally seen to result in low-level risk impact on projects, even if the public may have high interests in the project and are impacted by the project (Manowong & Ogunlana, 2010). Nevertheless, in some instances, the successful project outcome necessitates that the public is regarded as a key stakeholder (Yuan, 2017), whereas it is the media that plays a vital role in informing and educating the public during the stakeholder participation process (Li et al. 2013). The public as a participating stakeholder can provide beneficial public awareness (Xie et al. 2014). Addressing the problem of the public being in the margins and moving them to the centre has been discussed for some projects (Henjewele et al. 2013).

Not in my Backyard (NIMBY) effect, produced by factors such as known risks, values,

Table 1. Examples of stakeholder analysis methods, stakeholder management, and linkages to process steps.

Method	Source	Process step
Interviews	(Brugha & Varvasovszky, 2000; Raum, 2018)	Data collection/ Stakeholder identification
Brainstorming	(Colvin et al. 2016)	Stakeholder identification
Stakeholder lists	(Yang et al. 2011)	Stakeholder prioritisation
Stakeholder led categorisation	(Reed et al. 2009)	Stakeholder prioritisation
Stakeholder salience	(Mitchell et al. 1997)	Stakeholder prioritisation
Power/ Interest matrix	(Olander & Landin, 2008)	Stakeholder prioritisation
Social network analysis	(Rowley, 1997)	Stakeholder identification/ prioritisation
Strategic/ Intrinsic	(Berman et al. 1999)	Stakeholder management
Factors affecting the stakeholder management process	(Olander & Landin, 2008)	Stakeholder management

and feelings of unfairness, is one form of the potential negative outcome of the public opinions being overseen (Tcvetkov et al. 2019). Nevertheless, it has been noted that the NIMBY label is masking issues that the project has not addressed (Devine-Wright, 2012). The public opposition to the projects is further labelled as NIMBYism (Cass & Walker, 2009). The general attitude of the public towards the project can be positive, but they just do not want it in proximity and is a form of local opposition (Carley et al. 2020).

Today, the social media acts as a catalyst for the rapid spread of public opinions, reflecting the acceptance or opposition by the public. Social media, in general, is seen to consist of Web 2.0 -labelled applications, such as Twitter, Facebook Instagram, and YouTube, which enable creating and sharing different kinds of information (Kumar & Singh, 2020). Social media enables two way communication between stakeholder groups, thus a project organisation can benefit from different SoMe sources in attempts of understanding the external stakeholder network and stakeholders' online behaviour. Or alternatively enhancing the sense of community that helps planning the following communication with specific stakeholders (Williams et al., 2015; Turkulainen et al., 2015). However, stakeholder communication research on social media channels is only in the very early stages and studying the details and effectiveness of social media communication in complex projects is essential for developing a more contextualised understanding of stakeholder engagement (Lehtinen, 2021). This is one of the research gaps addressed in the paper.

As a way to implement new ways of tackling very diverse flow of social media based information, and advance research methods typical for questionnaires and interviews in a wider scale, opinions can be determined by the means of sentiment analysis, which is increasing in the social media (Chaudhary et al., 2018). This includes multiple IT-related aspects, such as 1) what the sentiment is measuring, 2) what is the accuracy, and 3) How to get to the detailed subject level, thus bringing multidisciplinarity into this type of research approach. Previous studies have applied sentiment analysis to for example online reputation management (Olaleye et al., 2018). Zervas et al. (2021) studied the online reputation via customer ratings, and Rust et al. (2021) created the automated reputation tracker. As an example of similar project acceptance measurement via an automated approach, public acceptance of an energy technology has been modelled previously for example via a Deep Neural Network algorithm, which is a hybridisation of fuzzy logic and a deep neural network algorithm (Buah *et al.*, 2020). This work utilizes a hybrid approach (Nuortimo 2021), with an aim to 1) discover trends and directions from a larger dataset, 2) reach basis for project comparison, both large scale and detailed level, 3) define project reputation score and details for smaller dataset classification, described in the next section, and 4) compare classification results to a larger scale automatic measurements to form a bigger picture.

3. RESEARCH METHOD: HYBRID APPROACH

This research paper utilises two stepped hybrid approach: 1) Projects' yearly data is obtained from black-box media monitoring software, commonly used in the company's MI-function and summarised. 2) More detailed project-level analysis is carried out via manual classification of hits to discover the project stakeholder related details and distil implications to managerial actions.

Opinion mining on a large media dataset is utilised in the first step with the help of a commercial black box media monitoring software M-Adaptive (Nuortimo, 2020, 2021). This is done in compilation with a more detailed human-based analysis to clarify the content details related to the project stakeholders. Figure 1 illustrates the applied hybrid approach. The used software (M-Brain, 2015) has the capability to utilise a large dataset covering 236 regions, 71 languages in 3 million social media platforms and 100,000 news outlets, both social media (SoMe) and editorial media sources. The software includes different lexicons for several languages, from which the algorithm defines the first local sentiments for a document and then compares those to the search terms. The results are presented for the entire document, indicating the sentiment (neutral, negative, positive, mixed, or unknown). The algorithm applies the same consistent logic for the text in all the documents. The accuracy of sentiment classification is approximately 80 %. The analysis by machine is objective, and should any mistake take place, they are made in a predictable manner. The benefits include avoiding dependency on individuals, and the ability to deal with a vast quantity of data. After the opinion mining, the project sentiments are grouped and compared to each other, and the human made classification is the final step.

The two-step approach helps in focusing on the aspects of project stakeholder related issues, firstly, it reveals the projects media visibility, and the sentiment, enabling comparison to other projects and discover development trends during time and project progress. In the second stage, a detailed human made classification analysis of the projects can complement the big picture with insights. These insights can include issues such as: explanation on why the project sentiment was negative or positive; support for converting negative issues to positive project stakeholder communication; understanding whether the positive/negative media hit measure project reputation, local project resistance, stakeholder views in format of electronic word to mouth communication (eVOM), or something external to project environment, related fairly random items, such as the existence of endangered species in the project site, as was the case in the Raidejokeri project.

Table 2. Selected Finnish construction projects.

Project	Alliance model (yes/no)	Sector	Schedule	Location	Description
Fennovoima/ Hanhikivi1	No	Large nuclear	2014–2022/5 terminated	Pyhäjoki, Finland	Nuclear Power Plant
Naistenlahti 3	No	Medium sized CHP plant	2020–2023	Tampere, Finland	Bio-plant (combined heat and power) that burns renewable biomass
Raidejokeri	Yes	Light rail system construction (Tram)	2019–2024	Helsinki & Espoo, Finland	Cross-Regional Public Transport: Tramline to connect the cities of Helsinki and Espoo.

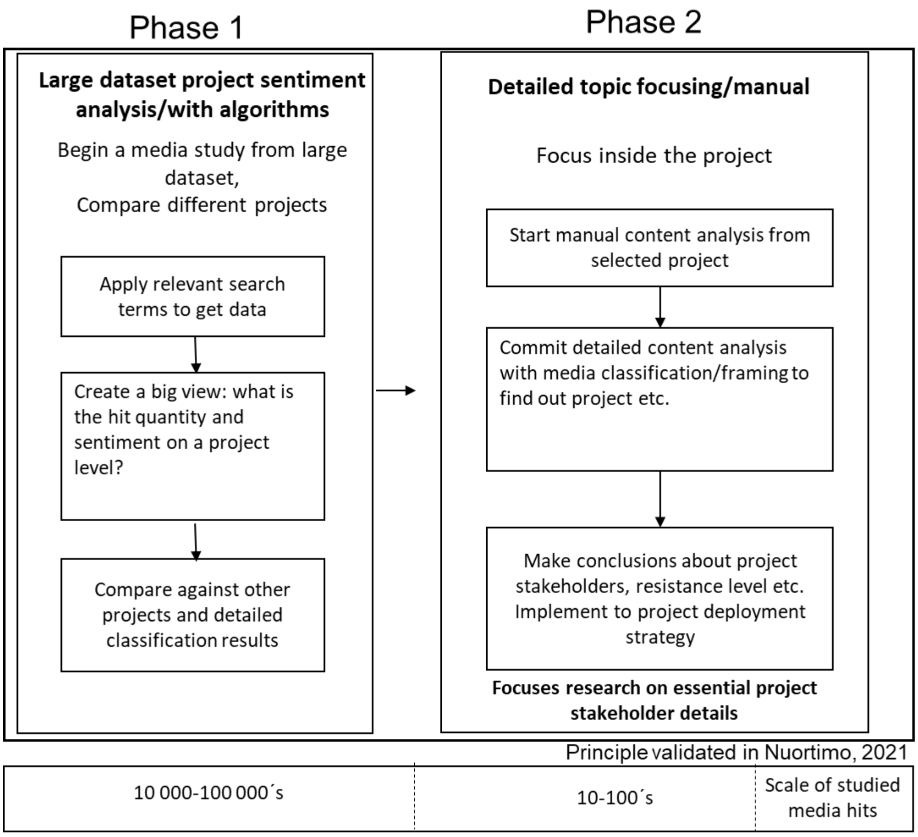

Figure 1. Hybrid approach (Nuortimo, 2021) as a research method – algorithm-based mining of media, and focused manual analysis.

When the sentiment of communication is likert scaled with scale of 1–5 (positive 4–5, negative 1–2, neutral + mixed 3, it is possible to get a numerical value for different stakeholder groups such as construction companies, electronic word to mouth based on local residents, tram users, politicians, governmental communication, local editorial press, and trade press. By calculating the numerical value, it is possible to gain total project reputation score, which can be used to compare projects, and to understand support or opposition in terms of more specific issues. The selected projects are described in table 2.

Figure 1 depicts the two-stepped hybrid approach used in this paper.

4. DATA-ANALYSIS FROM A LARGE DATASET TO DETAILED LEVEL

This section presents the results media-based data-analysis covering two years, 2020 and 2021, with the aim to gain a) quantity/sentiment comparison between projects, b) understand development trend, and c) indication of the most interesting project for further detailed study. The total amount of analysed hits was 11 780, mainly in Finnish language due to the projects' origin.

4.1 First stage: Two year media analysis data covering three Finnish construction projects

Table 3 summarises the identified relevant media analysis data for the three construction projects over the two year period based on the media-based data mining of a vast amount of data.

From the overall large dataset based media-analytics on three projects, some general comparisons can be made concerning the project sentiment and the communication volume. Trend analysis can also be made over the course of the projects. If, for example, the communication in social media (SoMe) should turn negative at some point, the reasons could be investigated. Also, the popularity of the project, project reputation, can be compared amongst the projects. Whereas the two-year media sentiments and the amount of communication indicate that the Raidejokeri tram project with an alliance execution model has received the majority of the communication (total hits 7131–4559 editorial/ 2572 SoMe), with a mostly neutral and positive sentiment (Figures 2 and 3). Fennovoima project received the second most communication (total of 4185 hits – 2788 editorial, 1397 SoMe), editorial sentiment being mostly positive and SoMe mostly neutral. The regional Kyvo 3 CHP-power plant, Naistenlahti project received the least attention (464 total hits – 375 editorial, 89 SoMe).

From the figure 2 it is visible, that Raidejokeri sentiment is neutral and positive, while Fennovoima had slightly better positive score in the editorial media, but not in the social media. Naistenlahti being the smallest and a regional project to build a CHP powerplant, it received mostly neutral communication especially in the social media. None of the project data gained from the large dataset implicate significantly large negative communication. Based on general comparison, indicative conclusions could include, that the projects are

Table 3. Analysed media hits summarised.

Project/ sector/ schedule	Analysis time frame/ months	Total editorial hits/av.hits/ month	Total SoMe hits/ av.hits/month	Editorial Sentiment % positive/ negative/ neutral	Social media Sentiment % positive/ negative/ neutral
Fennovoima/ Large nuclear/ 2014-terminated 24.5.2022	2.1.2020– 20.12.2021/ 24months	4569/190	1397/ 58	36%/ 10%/ 48%	23%/13%/60%
Naistenlahti 3/ Medium size CHP plant/ 2020–2023	2.1.2020– 20.12.2021/ 24 months	375/15	47/2	29%/ 2%/ 65%	11%/4%/79%
Raidejokeri/ Public transport/ 2019–2024	31.12.2019– 20.12.2021/ 24 months	4559/ 379	2572/190	31%/4% /62%	26%/4%/67%

generally accepted, and that Raidejokeri could be a target for further studies, specifically taking into account the focus of this paper.

The more specific Fennovoima project hits are presented as Figures 4 and 5. From Figure 4, it can be seen that the SoMe sentiment is slightly less positive, and more neutral and negative.

The trend of media-attention for Fennovoima has been increasingly more positive both in editorial media and SoMe (Figure 5).

Figures 6 and 7 present the two-year project media sentiment distribution for Naistenlahti 3 project, for which the sentiment has been more positive in the editorial media, and slightly decreasing from 2020 to 2021.

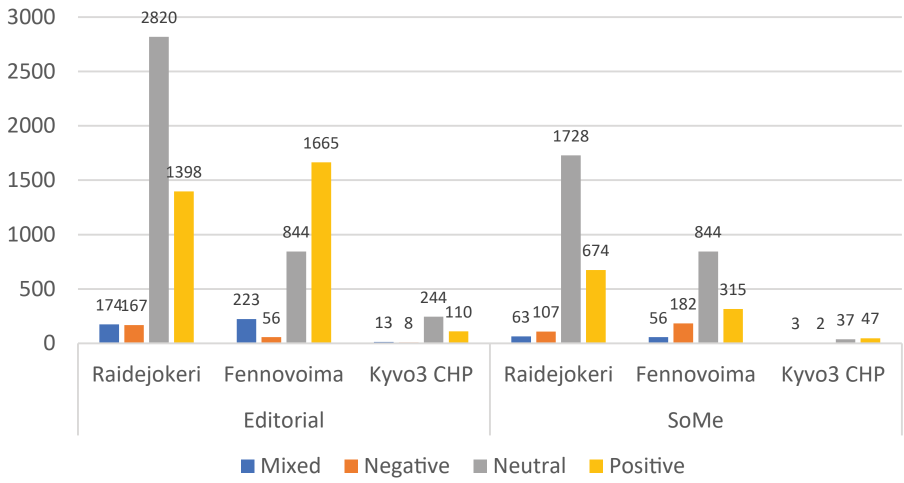

Figure 2. Media visibility and sentiment distribution of the projects over two year period.

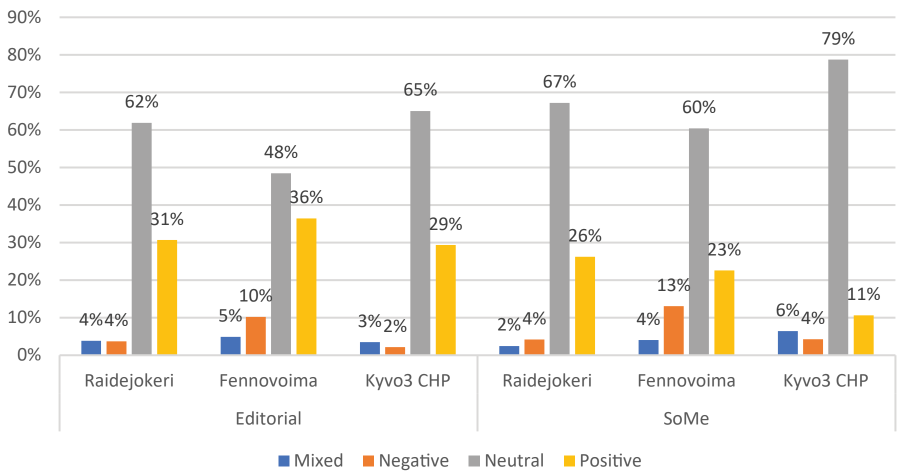

Figure 3. Media sentiment distribution of the projects over two year period.

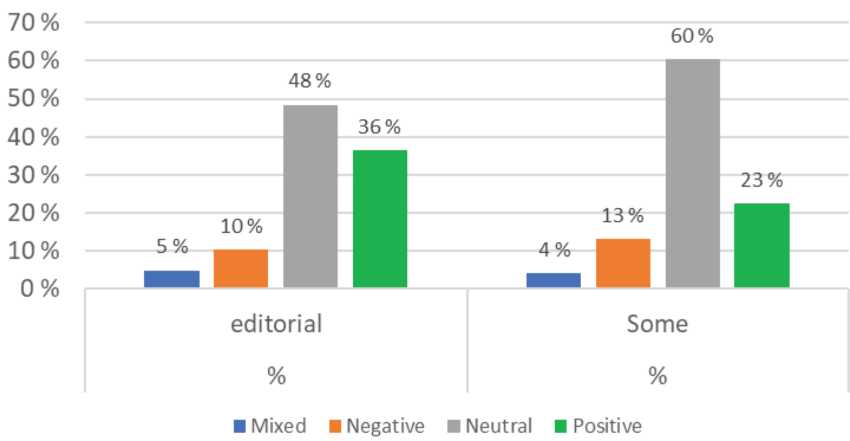

Figure 4. Sentiment of 2020 & 2021 opinion mined media hits – Fennovoima.

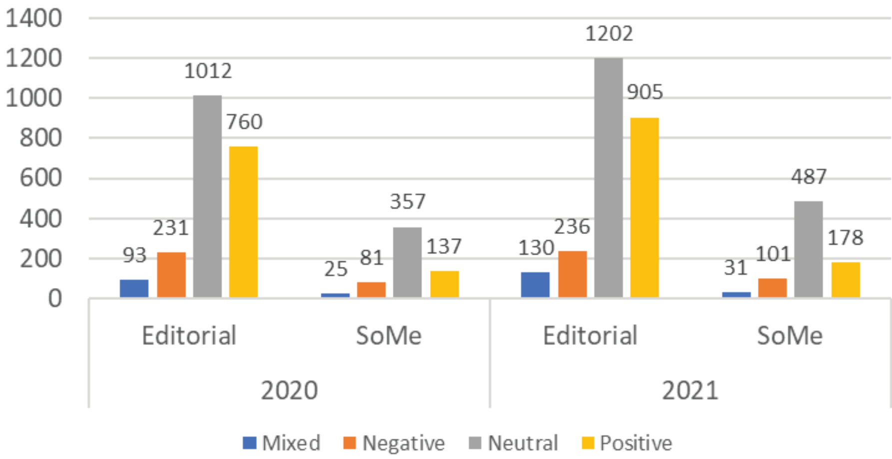

Figure 5. 2020 & 2021 opinion mined media hits – Fennovoima, yearly trend.

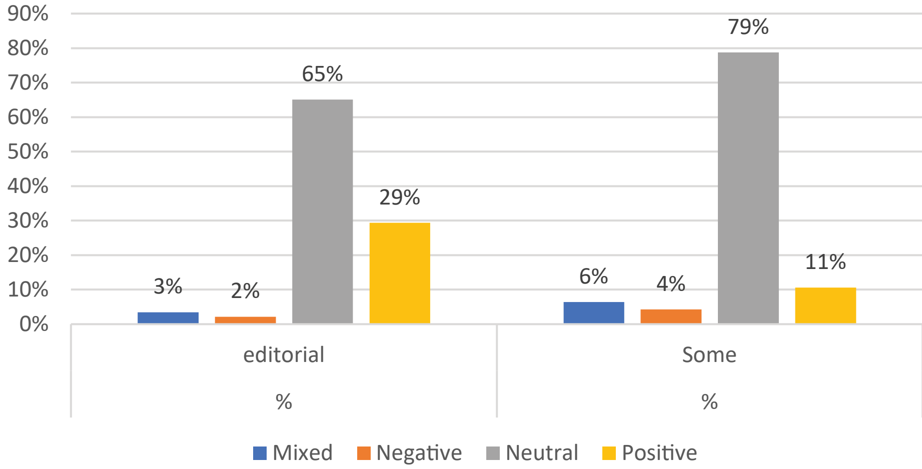

Figure 6. 2020 & 2021 opinion mined media hits – Naistenlahti 3.

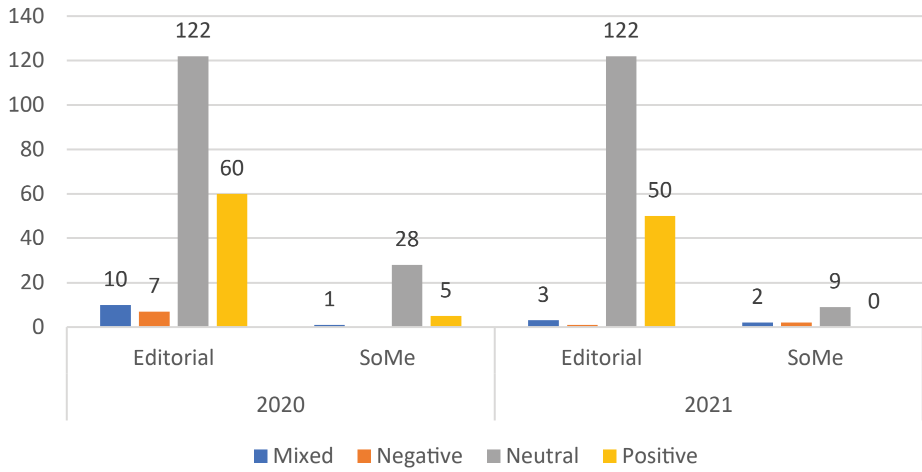

Figure 7. 2020 & 2021 opinion mined media hits – Naistenlahti 3.

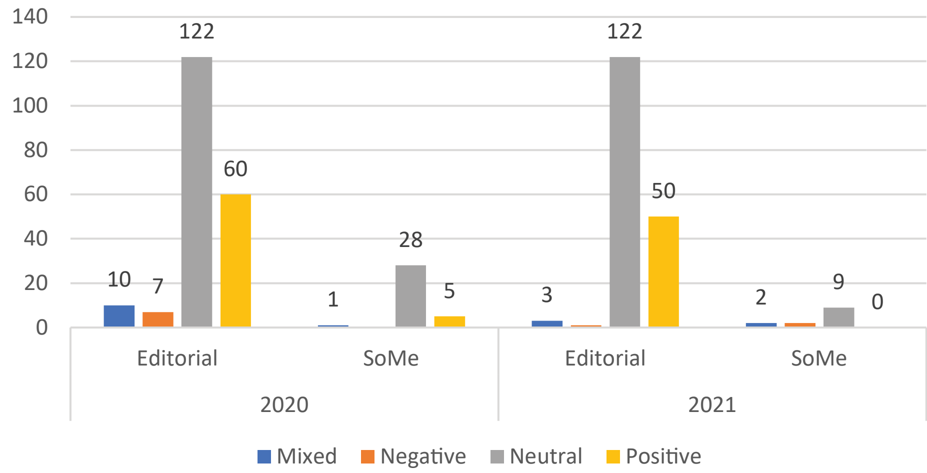

Figure 8. 2020 & 2021 opinion mined media hits – Raidejokeri.

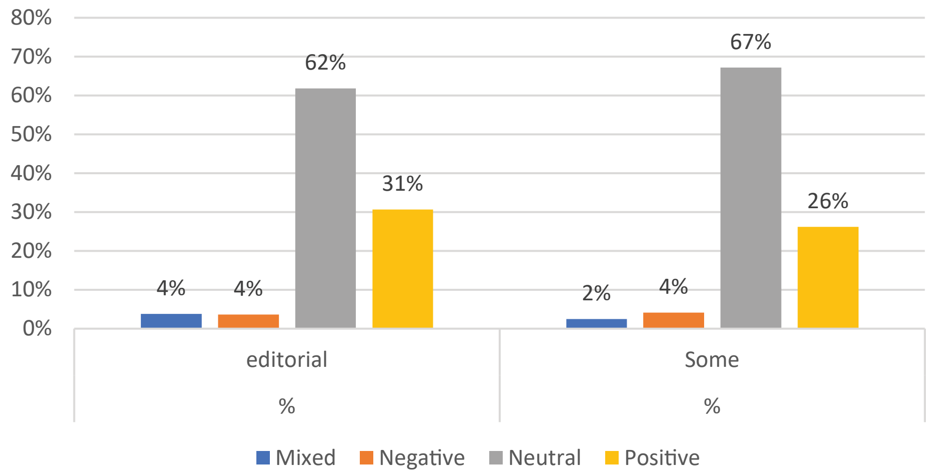

Figure 9. 2020 & 2021 opinion mined media hits – Raidejokeri.

The Figures 8 and 9 present the two-year media sentiment distribution for the Raidejokeri project, and give an indication that the editorial media has been slightly more positive, and trend has been somewhat increasing from 2020 to 2021.

From the first stage, general conclusions can be made to aid in highlighting the general project sentiment, and to guide the further research stages, namely the classification of Raidejokeri project related hits. One important target is to obtain information on what the project sentiment is actually measuring, whether it is project acceptance, reputation, or something else, and to finally reach the goal to defining project specific reputation value.

4.2 Second stage: Classification analysis of the media hits

The project of interest was selected based on large-dataset media-analysis stage, where Raidejokeri gathered most of the positive and neutral media attention both in the editorial and social media. The project was the only one executed with an alliance model, hence the interest was also focused on how the alliance model execution is visible in the media-feed.

The classification structures for the project related media hits are described as tables 4–6. Total of 45 hits were classified manually for the period of 22.1.2020–3.4.2021 to understand what the media hit sentiment actually measures, whether it is as accurate as implicated (app. 80 %), and to clarify the project specific communication details. It was noted that all selected hits were relevant, and somehow related to Raidejokeri project. In general, "Raidejokeri" was the specialised search word giving mostly results related to the project, due to the uniqueness of the word. Table 4 presents general results, the general sentiment.

It is visible from table 4 that media hit sentiment seldom measures direct project acceptance or resistance. Nevertheless, it is possible to identify major stakeholder classes.

Table 4. Classification analysis of Raidejokeri project hits.

Topic correct	Sentiment correct	Major stakeholder class visible	Company generated editorial/ SoMe	Activist generated editorial/ SoMe	Positive measures acceptance	Negative measures resistance
45	37/ 82%	43	9	3	4	1

Table 5. Classification of Raidejokeri project hits.

Sentiment reflects project reputation	Positive	Negative	Neutral
28	15	1	11

It is visible from table 5 that the sentiment is mostly an indication of project reputation amongst different stakeholders, not necessarily direct acceptance. This is mainly related to automated sentiment calculation, where only positive and negative expression are identified from text without direct relation to content. Table 6 illustrates classified hits with likert scaling from sentiment value and calculating the average, combining both topic and sentiment classification with deeper insight.

Table 6. Likert scaled values for different measured stakeholder groups based on the 27 hits measuring project reputation (Scale 1–5: 1–2 negative – 3 neutral + mixed – 4–5 positive).

Project stakeholder	Value
Construction companies	4
eVom: residents, tram users, politicians	3,6
Government/local authority communication	3,5
Local/national editorial press	3,3
Trade press	4,2
Total project reputation score	3,6

It is visible from the Table 6 that the project participants, such as construction companies, have highly positive active communication, which can then be compared against other stakeholder groups. This also includes eVOM (Electronic word to mouth communication), such as editorial press, authorities, and individuals. In general, the project reputation score for Raidejokeri is a bit above medium(3), which is in-line with the large amount of neutral hits in the first step's larger data series. This indicates that the project reputation is already indicatively visible from the larger data series but does not imply direct acceptance. The reputation is generally on the level that is not directly hindering or stopping the project execution, and the details listed in appendix 1 can be used by project management to counteract issues rising during the project execution and find out positive outcomes of alliance execution model.

General Raidejokeri project related issues included reaching targeted goals, project being executed according to environmental regulations, increased project schedule but higher cost, project hold-ups, experiences utilised from similar projects, and random issues, such as the endangered species on the project site. These can be utilised to gain managerial implication for project managers in the construction alliance. This also implicates possibilities to utilise company's MI function in co-operation with project management, to generate measurable data from changes in stakeholder reactions and random items influencing to project execution.

5. DISCUSSION

Understanding the influence of public acceptance on technology development and deployment for different technologies in general, and in terms the acceptance of individual projects, and the acceptance of technologies with linkages to projects can be beneficial for addressing the relevant project related acceptance of opposition. The literature focuses on acceptance from a variety of perspectives, whereas the complex project stakeholder management related acceptance has not been measured widely by the means of algorithm-based opinion mining, nor has the results been compared to wider acceptance contexts. The literature concerning co-operation between company's MI-function and project management is scarce. Nevertheless, opinion mining results not being fully conceptualized and the relevant technologies developing, certain caution is necessary to understand what the opinion mined sentiments are actually measuring. Also, the acceptance or opposition may not be completely visible directly from the gained opinion mining results. Hence, project stakeholder reputation score is applied in this study. The reputation score is a concept applied in the marketing domain.

Due to the previous absence of a method for measuring global, or large regional acceptance, there has been a gap in explaining the influence distilled from the global level to the local project execution. The stairs of acceptance concept conceptualised in Figure 9 and is intended to reflect the project-specific public acceptance. The approach implies the reverse top to bottom order in which the technology deployment acceptance issues would be feasible to be targeted. This approach is compiled by the unification of acceptance studies to global opinion mining results. In general, the global level includes global agreements, general public sentiment, and the global technology reputation. The regional issues include country level politics, regulations, local subsidies, and the local level implies the local project implementation and site location related issues. As an energy technology related example, in the global level, agreement such as Glasgow COP-agreements guide the technology selection and would be required to be tackled before specific project implementation, and policies & regulation on regional level, with finally tackling local project deployment related issues.

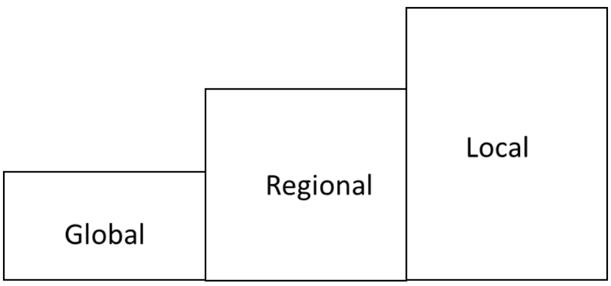

Figure 9. Stairs of acceptance

The stairs of acceptance concept can be used to emphasise the order and scale of required actions in technology development and deployment concerning the public acceptance or opposition. For example, the focus can be on power production technologies (Table 7). The approach can be used to highlight a) the general top-down approach in reaching technology acceptance to facilitate deployment, and b) increase the needed stakeholder management actions and local communication, including social marketing at the local level. The tasks of stakeholder management and local communication can be specifically challenging if the technology is not accepted at the global level, as is the case with coal and nuclear energy technologies (Nuortimo 2021). This approach also combines the benefits of co-operation between company's MI function in order to analyse global media(incl SoMe) coverage in order to make generalizations for project management concerning global-, regional- and local acceptance, as well as monitor weak signals influencing project execution in a local level, such as endangered species in the project site.

The results from the studied energy technology projects in this paper, namely Fennovoima and Naistenlahti are in-line with global and regional results. This is despite the facts that it is evident that a) the opinion mining results do not directly measure the acceptance, and merely provide an indication of it, and b) the errors in a large datasets need to be considered, such as the sentiment measurement accuracy and the influence of applied search words. In case of Fennovoima nuclear project, the chain of reasoning was visible as follows: Nuclear power sentiment globally was negative, while in Finland the overall sentiment was positive, and also for Fennovoima in general (Editorial sentiment: 36 % positive/ 9 % negative/ 49 % neutral: SoMe sentiment: 23 % positive/ 13 % negative/ 61 % neutral). The project was eventually cancelled mostly due to issues related to the Russian sub-supply linked to geopolitical issues, also one relevant topic to monitor in company's MI function.

In case of small-scale projects with well-known technology, the easy application and positive product reputation, such as solar PV panels, this type of acceptance chain is clearly positive in global, regional, and local project levels. However, in the detailed classification phase the indication was that the media analysis does not necessarily directly measure the acceptance, so the global and regional results are mostly indicative, and do not in any case present causality. On the contrary to nuclear, a WTE or coal project, if a neighbour installs solar panels on their roof, no one is likely to pay attention, which is an indication of high product reputation.

In the case of the focus project Raidejokeri, Tram-technology is well-established, and the acceptance issues are more related to project implementation level, to issues such as large demolition works and other project specific issues, such as endangered species at the construction site. The Raidejokeri is a bit separate path from energy technology acceptance but is suitable for methodological testing, due to having communication of multiple stakeholders in a large volume, and the applied alliance project execution model.

Table 7. Three stepped classification of energy technologies.

Techno-logy	Globally accepted/	Regionally accepted	Project accepted
Solar PV	Yes	Yes	Yes
Wind	Yes	Yes	Differs, mostly accepted
Bio	Yes	Moderate	Differs, mostly accepted
WTE	Yes	Yes	No, differs regionally
Coal	No	No	No, not accepted almost everywhere
Nuclear	No	No, differs	No, differs regionally

5.1 Methodological implications

In terms of project level sentiment measurement technologies, while new data-mining technologies such as opinion mining based on a large dataset can provide insight in all levels (global – regional – local) with generally moderate accuracy, the main question is what the project sentiment is measuring. Does the project sentiment measure acceptance or something else? In this paper, the indication is, that it is not necessary always acceptance, granted in the form of a social license, instead, the result on detailed project level could be labelled as "project reputation amongst the stakeholder group". This paper also introduced a project specific reputation score for different stakeholder groups, which can be calculated based on media hit sentiment classification, providing a numerical comparable value by following the Likert scaling by the sentiment classification. This is an approach which is comparable to current reputation scores formulated via questionnaires and interviews, utilised for different research purposes.

5.2 Managerial implications

This paper provides a new way of thinking for stakeholder management in complex projects, highlighting the co-operation between MI-function and project execution. Large construction projects may benefit from starting the stakeholder planning from the global perspective, by first thinking about general technology acceptance. This can provide new insights to the project implementation phase. Also, there is a possibility to monitor and measure the project stakeholder reputation as a numerical value with easy comparison to different project participants. It is possible to highlight how the project participants reputation has a score 4,2, but public only has 3,2, with implications to aid further guiding the positive stakeholder communication to most relevant

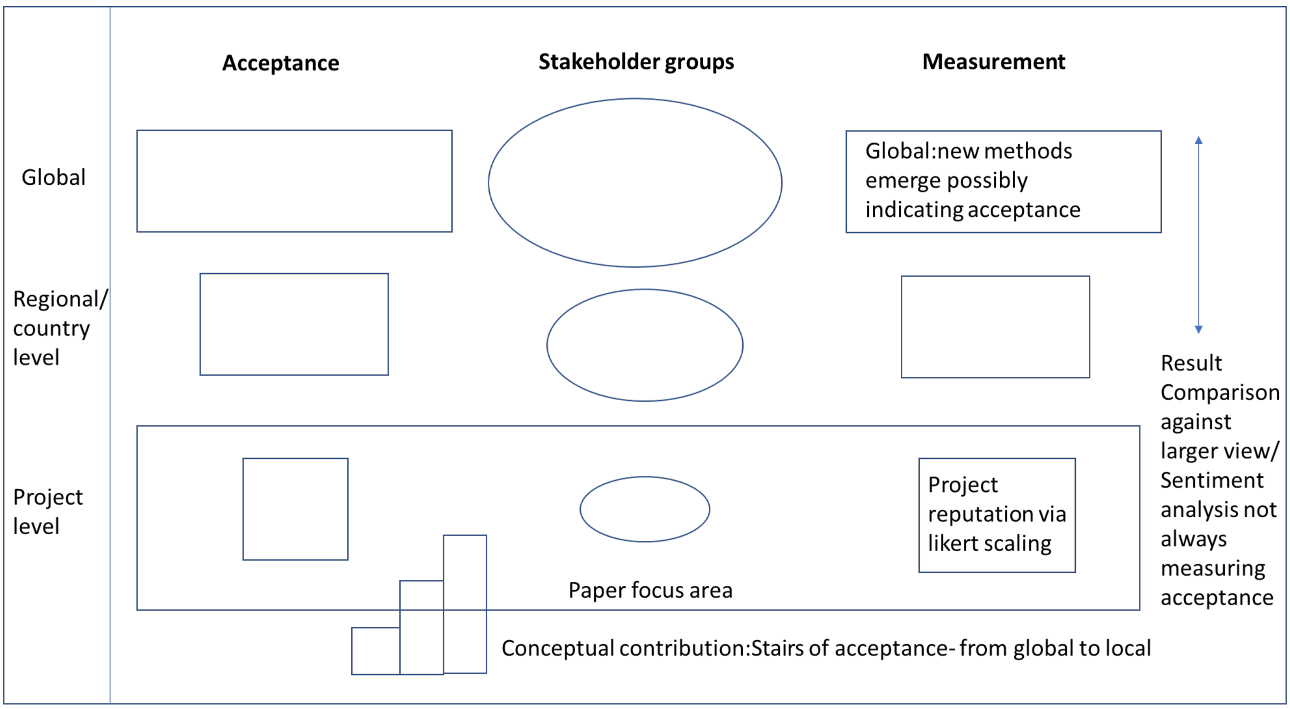

Figure 10. Summary of main paper contribution.

groups, and addressing issues as they emerge. In case of Raidejokeri project, the product reputation score of 4,2 in trade press clearly indicates the efforts to convey positive reputation for the project and alliance model, visible also in the content classification, while the reputation amongst the tram users 3,6 could indicate, that they do not read trade press. Local press score was 3,3. In case of other projects, general project reputation score could be compared against other projects to highlight the differences and find out ways to improve.

5.3 Summary of contribution

Figure 10 summarizes the main findings of this research paper.The main contribution of this research include highlighting the co-operation between MI-function and project management in order to discover how the acceptance can vary at different levels, while the largest efforts are required on the local project level, depending on the project type/scale/technology in question. To gain acceptance for a technology the approach should be from top to bottom, from global to local, by addressing different stakeholder groups.

When new measurement technologies are concerned, in project level, while new data-mining technologies such as opinion mining from large dataset, applied in the MI-function, can provide insight in all the levels with generally moderate accuracy, the question is:what is project sentiment measuring, is it acceptance or something else? In this paper, the indication is, that it is not necessary always acceptance, granted in the form of a social license, instead, the result on detailed project level could be labeled as “project reputation amongst the stakeholder group”. This paper also introduced project specific reputation score for different stakeholder groups, which can be calculated based on media hit sentiment classification as a final step, providing a numerical comparable value after likert scaling from sentiment classification. This is an approach which is comparable to current reputation scores formulated via questionnaires and interviews, utilized for different marketing research purposes.

6. CONCLUSIONS

This research paper highlights how company’s MI function can co-operate with complex project execution project management. This comes from issues, such as a technology can face different acceptance levels, whether it relates to global, regional, or local project delivery. Algorithm-based data mining, utilised from company’s MI function, is applied in this study to reveal the project and technology related media sentiment. It is realised how the development of data-analysis is what influences the measurement of global, regional, and local stakeholder sentiment. The project specific reputation can be calculated based on the media sentiment and the conceptualised stairs of acceptance model can be used to emphasise and address the order and scale of required actions. The stairs of acceptance visualises the possible opposition faced by a project starting from the global level and ending to a local project delivery, where the resistance level can be the highest, and also the effort required to support technology deployment, especially in case of unpopular large scale project deliveries. The application of a hybrid approach is presented as a way to measure stakeholder influence from the media feed. The main project specific result is that automatic sentiment detection is about 80 % accurate, and does not necessarily indicate direct acceptance or resistance as a form of a social license, but contribute to the presented project reputation score. It was calculated, that Raidejokeri project’s project reputation was 3,6 in a scale 1-5, and the most positive stakeholder group involved trade press.

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Appendix 1. Classification of media hits.

1	2		3	4	5	6	7	8	9	10	11	12	13	14	15
Channel	**Sub.cat.**	**Date (UTC)**	**Content**	**Sentiment reviewed**	**Autom. sentiment correct**	**Local resistance/ nimby**	**Major stakeholder class visible**	**Company generated editorial/ Some**	**Activist generated**	**Positive measures acceptance**	**Negative measures resistance**	**Sentiment measures project reputation**	**Relates to project model/ alliance**	**Implications to project execution/ deployment**	**Scale**
Editorial	Online only	03/04/2021	Mentioning of project in job advertisement, to help in transportation to work	positive	yes	no	no	no	no	no	no	yes	no	no	4
Editorial	Trade magazine	01/04/2021	Alliance model provides possibilities to transfer silent information	positive	yes	no	yes	no	no	no	no	yes	yes	no	4
Editorial	Trade magazine	01/04/2021	Editorial article concerning project, Sweco manager interview	neutral	yes	no	yes	no	no	no	no	yes	yes	no	3
Editorial	Trade magazine	01/04/2021	Alliance pioneer project provides skills development possibilities	neutral	yes	no	yes	no	no	no	no	yes	yes	no	3
Editorial	Trade magazine	01/04/2021	Experiences utilized from Tampere alliance model	neutral	yes	no	yes	no	no	no	no	yes	yes	no	3
Editorial	Govern-mental	31/03/2021	Set goal was reached	neutral	yes	no	yes	no	no	no	no	yes	yes	Set goal was reached	3
Editorial	Research	27/03/2021	dissertation IEM	mixed	yes	no	yes	no	no	no	no	yes	yes	no	3
Editorial	Govern-mental	19/03/2021	Raidejokeri is built according to environmental principles	positive	yes	no	yes	yes	no	no	no	yes	yes	Project is execut-ed according to environmental regulations	4
Editorial	Govern-mental	18/03/2021	increased project execution schedule	neutral	yes	no	yes	no	no	no	no	yes	yes	Increased project schedule	3
Editorial	Govern-mental	18/03/2021	new services and residents to Oulunkylä due to project	neutral	yes	no	yes	no	no	no	no	yes	no	no	3
Editorial	Govern-mental	16/03/2021	Raidejokeri as significant regional project	positive	yes	no	yes	no	no	no	no	yes	yes	no	4
Blog		14/03/2021	Raidejokeri improves transportation	positive	yes	no	yes	no	yes	yes	no	yes	yes	no	4
Blog		01/03/2021	Discussion of car use, raidejoker as example of public transportation	positive	yes	no	yes	no	yes	yes	no	yes	no	no	4
Editorial	Organiza-tion	18/02/2021	YIT partner communication	neutral	yes	no	yes	yes	no	no	no	yes	yes	no	3

1	2		3	4	5	6	7	8	9	10	11	12	13	14	15
Twitter		09/02/2021	Project as an example of increased investments to public tram transportation	neutral	yes	no	yes	no	yes	yes	no	yes	no	no	3
Twitter		08/02/2021	Project as an example of increased investments to public tram transportation	neutral	yes	no	yes	yes	no	no	no	yes	yes	no	3
Facebook		02/02/2021	2–4 graders in elementary school went to see the project	positive	yes	no	yes	yes	no	yes	no	yes	yes	no	5
Editorial	Business/ Economics	22/01/2021	Finland as a forerunner in Alliance model projects, not the cheapest project execution model, but acts as a solution for typical problem in large construction project	positive	yes	no	yes	no	no	no	no	yes	yes	no	4
Facebook		22/01/2021	Tekniikka & talous visited project site, alliance model works, project partly half year ahead of schedule	neutral	no	no	yes	no	no	no	no	yes	yes	no	3
Editorial	Online only	20/01/2021	Job advertisement	positive	yes	no	yes	yes	no	no	no	yes	no	no	4
Editorial	News agency	19/01/2021	project execution phase begins	positive	yes	no	yes	no	no	no	no	yes	yes	project phase begins	4
Instagram		18/12/2020	Instagram posting about work experiences from project organisation company	positive	yes	no	yes	yes	no	no	no	yes	no	no	5
Facebook		16/12/2020	Complaints against project were rejected. Resulted schedule delay will overcome	positive	no	yes	yes	no	no	no	no	yes	no	yes	5
Twitter		26/11/2020	Project participant communication(videos), environmental friendly, commences in advanced schedule	Positive	no	no	yes	yes	no	no	no	yes	yes	no	5
Editorial	Trade magazine	08/11/2020	Project price estimate	neutral	yes	no	yes	no	no	no	no	yes	yes	Cost level established	3
Editorial	Govern-mental	22/10/2020	Good experiences from Tampere are predecessor for Raidejokeri alliance model	positive	yes	no	yes	no	no	no	no	yes	yes	positive experiences from other similar projects	4
Editorial	Regional/ Local	01/07/2020	Project on hold	negative	no	yes	yes	no	no	no	yes	yes	no	Project on hold	2
Editorial	National/ Major	29/05/2020	Flying squirrel sighting as a setback for new tramway project, appeals from non-governmental organizations suspend construction works – If an exceptional permit is not granted, ”it must be contemplated whether Raidejokeri can be completed or not”	negative	no	no	yes	no	no	no	no	no	no	Yes. Negative impact on project schedule	2

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Elaborating the Role of Business Intelligence (BI) in Healthcare Management

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ABSTRACT The sector of healthcare is one of the most growing and developing sector of the current economy. The leaders of healthcare system need keys that would help them to advance business processes, decision-making, communication between physicians, administration and patients, as-well-as effective data access. In this case, Business Intelligence (BI) systems may be useful.

BI is a new multidisciplinary research field that is being used in a variety of industries. It entails extracting information from large amounts of data and delivering it to stakeholders in a decision-making context that is correct. Many BI applications in the healthcare industry attempt to analysing data, predictions, supporting decision-making, and attaining total sector improvements. In today's rapidly evolving health-care industry, decision-makers must cope with increasing demands for administrative and clinical data in order to meet regulatory and public-specific standards. The application of BI is realized as a viable resolution to this problem.

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As the current data on BI is mainly focusing on the area of industry, So the aim of the current input is to adapt and translate the present research findings for the health-care industry. For this reason, various BI definitions are explored and consolidated into a framework. The objective of this review is to give an overview of how to use BI to aid decision-making in healthcare companies. Along these the sector specific requisites for effective BI-application and role in future are discussed.

KEYWORDS: Business Intelligence; BI; Healthcare; Management; Medical

1. INTRODUCTION

The rapid growth of technology use in the business environment has generated huge amounts of digital data resulting from the volume of transactions. Technological advances have made the use of Information Technology (IT) tools and techniques a necessity for streamlining operations in all businesses and industries (Goodman et al., 2010). Not only for business operation and development, but also for supporting decision-making based on real information through the adoption of BI technologies. Every organization intends to become an intelligent and successful organization and gain a modest advantage on their market by applying new technologies and inventive BI-solutions especially in the healthcare sector (Ashrafi et al., 2014; Gurjar & Rathore, 2013).

The healthcare sector involves a variety of numerous stakeholders, including physicians, medical personals, government, insurance-companies, service providers, regulating-agencies, medical providers, and people that are looking for dependable and safe services (Olszak & Batko, 2012). Maintaining and dealing with, all these relationships between all stakeholders is very challenging task without use of new technology. Moreover, because these relationships include human life and wellness, they are more sensitive than those in other industries and businesses. For these motives, it is important to implement information technology (IT) in health-care industry to achieve the advantages of using IT toward improving services and facilitating-processes (Singh, 2012).

From the previous literature, the healthcare sector has huge amounts of data, and there is dire need to gather and process this information to make accurate and timely decisions-based on current data. One of the solutions to improve the decision-making process is BI tools is used to transform raw data into smart information and knowledge (JINPON et al., 2011). BI technologies capture the organization's strategy and apply their tools to help and manage and refine business information to make more effective business decisions in various scopes (Rouhani et al., 2012). They give the healthcare industry the ability to transmit large amounts of data from multiple sources into a single repository, allowing for analysis and drill-down into certain elements while also ensuring operational procedure prudence and providing a decision-making mechanism.

As BI becomes more important for the industry of health-care, it is the objective of this review to show an actual image of the BI in healthcare context. We trust that a well knowledge of the perspectives and meaning of BI might improve communication gap between the many organizations and individuals that uses the term of BI and probably increase its adoption. For this purpose, we looked at a variety of 'intelligence' definitions. As the portion of the BI literature focuses on industrial sector, we considered its importance in healthcare context in order to generate the ideas about applying BI in a healthcare sector. Finally, the review will discuss the future consequences of BI in healthcare management and provide an outlook for future research in the field

2. BUSINESS INTELLIGENCE (BI)

In 1865, the term "Business Intelligence (BI)" was coined, and now, after 157 years, it is tough to see a business today without a BI tools, especially while dealing with huge amount of digital electronic information (Tavera Romero et al., 2021). In today's world, a digital BI system is crucial in collecting, analysing, and processing business digital information in different fields including healthcare (Shao et al., 2022).

To explore the benefits of adopting BI in the healthcare, this review must first define the BI and its core concept techniques and technologies. The expression BI was introduced by an IBM scientist in 1958, as he defined it as the "ability to understand the interrelatedness of current data in many sides as to lead decision in respect of a wanted purpose and gain the competitive advantage" (Luhn, 1958). In recent years, BI was described as "concepts, methods and tools to improve and restructure the organization process and decision" (Kumari, 2013). BI was also well-defined by, Zeng et al. as "the process of extraction, handling, and diffusion and analysis of information that has an objective, the reduction of uncertainty when making strategic decisions" (Zeng et al., 2006).

BI by its definition contains of three (03) main stages: data-storage-integration, analysis, and information presentation stages (Bordeleau et al., 2018). Currently, various BI components are used to support decision-making as a part of integrated systems and suites or as distinct technologies.

The core BI components are (Aruldoss et al., 2014; Lee et al., 2022) i). Data Warehousing (DW), which provides thematic storage space for integrated, aggregated, and analysed data. ii). Extract Transform Load (ETL) tools, which transfer the data from transaction or operational systems to DWs. iii). On Line Analytical Processing (OLAP) tools which allow operators access to analyse and model business problems and share the stored information from DW. iv). Data Mining (DM) tools are used to determine the patterns, regularities, generalizations, and rules in data-resources. v). Ad-hoc inquiry and reporting tools for utilizing and creating different reports; and presentation which includes multimedia and graphical interfaces to provide operators with info in a accessible and comfortable form.

BI package aids users in comprehending complicated relationships and processes. through easily customized, assimilated graphic reports that help in making informed and timely decisions, taking actions that will improve further performance, and recognizing how their activities effect the entire company (Lale, 2022). BI dashboard solutions are commonly used in the presentation phase of many business sectors to communicate information to stakeholders and end-users (Monteiro, 2021).

BI tools are used presently to help the healthcare sector in making precise diagnosis and treatment, both in short and long-term care (Johnson et al., 2021). In many cases, they are used to estimate alternative treatments based on data analysis. In addition, they are also utilized for the administrative healthcare institute's perspective to assess and report on the cost and benefit of many operations in departments and units (Ameen et al., 2018).

BI in Healthcare Industry

The healthcare system has seen significant disturbances in recent years due to over dependence on medical services (Azizi et al., 2019). In addition, the COVID-19 pandemic brought about a number of difficulties that nearly took down the healthcare systems in many nations globally (Malik, 2022). As a result, adopting tech-driven techniques to enhance and optimize their operations became crucial for healthcare businesses. However, the demand for BI application development services in the healthcare industry has significantly increased. Due to the pandemic of COVID-19, the global Healthcare Business Intelligence market size is predictable to be worth 4.75 USD billion in 2022 and is forecast to a readjusted size of USD 8.37 billion by 2028 with a CAGR of 9.9% during the review period **(Figure. 1)** (Al-Sarawi et al., 2020).

In 2021, North America dominated the market, accounting for 43.4 percent of total sales followed by Europe (19.75%), Asia Pacific (18.13%), Middle East (9.52%), and

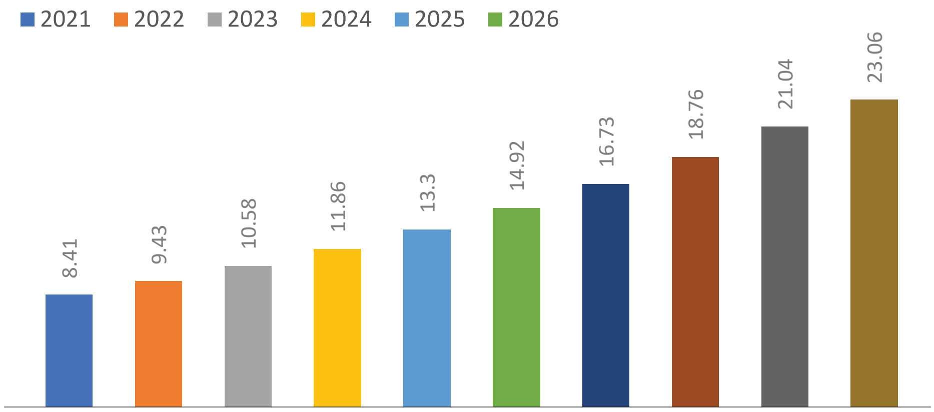

Figure 1. The global healthcare business intelligence market size, 2021–30 (USD Billions).

Latin America (9.2%) (THUO, 2021). The rise of the healthcare industry is attributable to the growth of the healthcare BI market in North America. According to forecast, the Asia-Pacific region is expected to grow the fastest. The healthcare BI market growth in this region is being influenced by giving awareness regarding BI tools and solutions in healthcare infrastructures. Additionally, the local government is also working to expand the healthcare industry, which is fuelling the region's healthcare BI market. Furthermore, the local government is also investing in the growth of healthcare BI **(Figure. 2)** (Bu & Wu, 2022).

3. HOW DOES BI WORKS?

BI supports in operational and strategic decision-making. According to Gartner research,

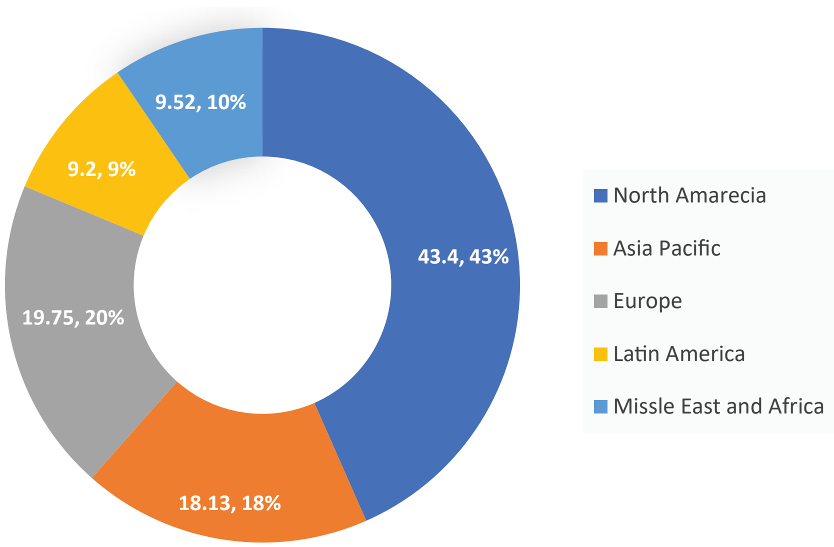

Figure 2. The global healthcare business intelligence market share, 2021 (%).

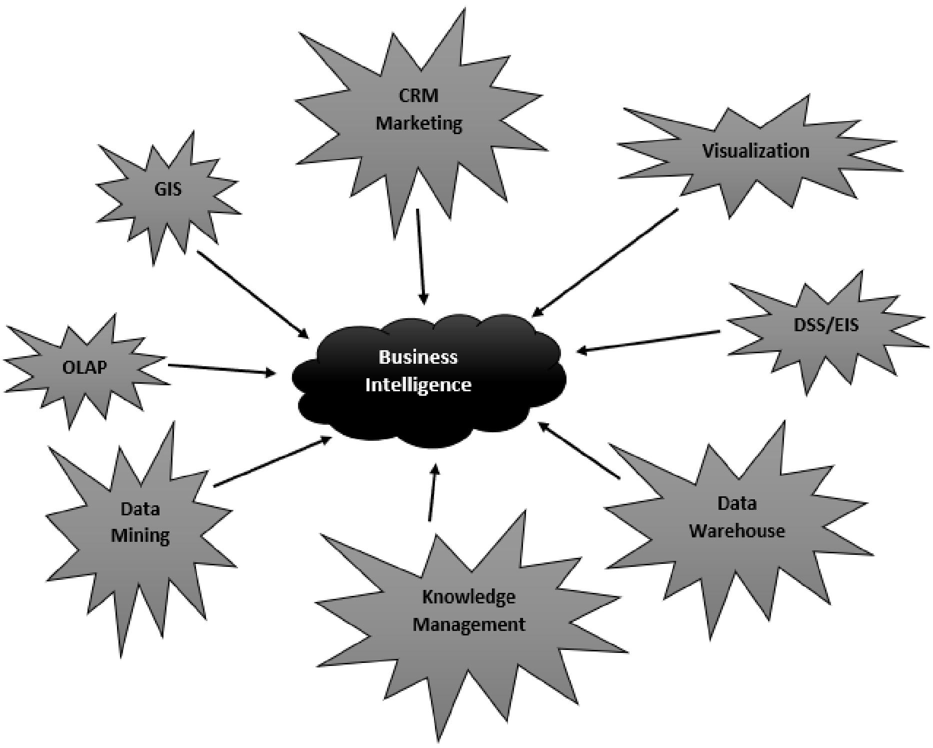

Figure 3. Relationship of Business Intelligence to other Information Systems.

CRM: Customer Relationship Management, GIS: Geographic Information Systems, OLAP: On-Line Data Processing, DSS: Decision Support Systems.

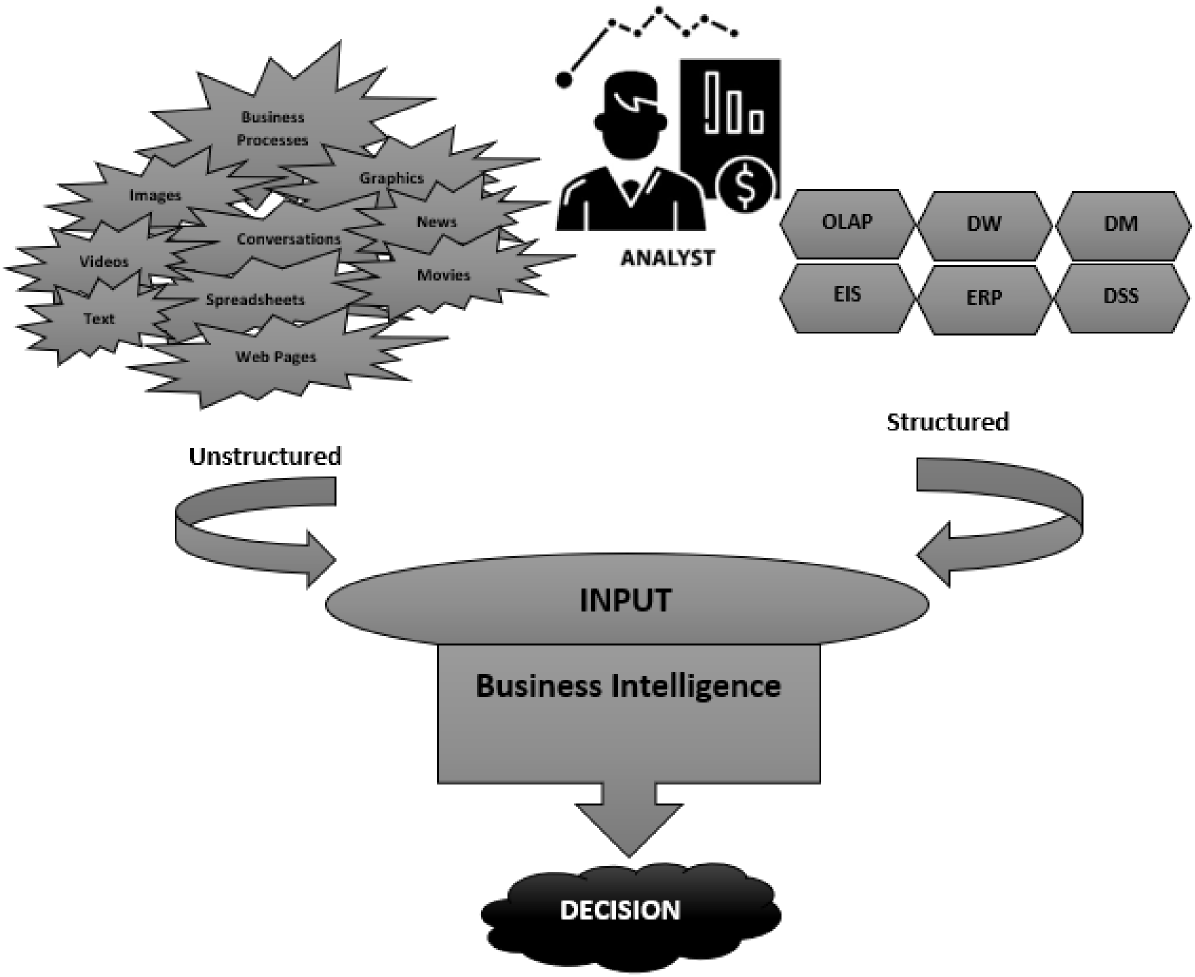

Figure 4. Structured and unstructured inputs to BI system and final decision-making.

DM: Data Mining, OLAP: On-Line Analytic Processing, EIS: Executive Information Systems, DW: Data Warehouse, ERP: Enterprise Requirement Planning.

the following is the hierarchy of strategic BI use (Massey, 2008):

1. Management of corporate performance.
2. Monitoring business activities, optimizing customer-relations, and support of traditional decision.
3. Standalone packaged BI solutions for specific strategies or operations.
4. Management reporting of BI.

One implication of this ranking is that it is insufficient to simply report on a company's and its competitor's performance, despite this being a strength of many existing software solutions. Another implication is that too many businesses still see BI as an inward-looking activity, just like DSS and EIS did before it.

BI is a logical progression from a number of earlier decision-supporting tools. Data warehouse development as a repository, the improvements in data cleaning that produced a single truth, increased hardware and software capabilities, and the boom of Internet technologies that provided the prevalent user interface, all came together to produce a richer BI environment than was previously available. BI gathers data from numerous different systems. The information systems that BI uses are shown in **Figure 3.**

BI transforms data into usable information that can then be analysed by humans to produce knowledge. Some of the tasks that are performed by BI are following:

- Making predictions based on historical facts, present and past performance, and predictions of directions in which the future will go.
- Impacts of changes and potential outcomes are analysed using "what if" questions.
- Ad-hoc access to the data to address particular, unusual questions.
- Strategic perception.

Figure 4 illustrates the assortment of information inputs that can be used to provide the intelligence required for decision-making.

3.1 Benefits of Business Intelligence (BI) in Healthcare Domain

The advantages of BI include intelligent-data-analytics, cost-reduction, improved service quality, transparency, and greater visibility etc (Kamble & Gunasekaran, 2020). Monitors data in real-time and remotely. Creates graphic indicators for each process, monitor its evolution, and define strategic actions. Risk analysis and accurate information tracking. Anticipates fault identification. Monitors the evolution of what happens in the hospital.

Every day, technology changes the way we live. One of these shifts is taking place in the healthcare industry (Diamandis & Kotler, 2020). Healthcare setting is a business around for centuries with current medicine which helps to extend the lifespan. However, the new inventions are established to create this process pointedly more useful and user friendly (Liu et al., 2020).

BI is an innovation that states the assembled and usage of data to improve the strategic plannings and business operations. Healthcare BI made on this same context but in this situation, the patient data in question is assembled through different channels (Conboy et al., 2020). BI in context to healthcare management has a slightly different purpose than that explained prior with BI alone. With BI healthcare, different healthcare organizations are still trying to improve operations and reduce costs, but primarily focuses on the improvement of patient-care (Arefin et al., 2020). Below discussed are some benefits of BI in healthcare management.

3.1.1 Cost Reduction

Globally, the health-care is a business, while clinicians and doctors are in the role to helps the patients, but still money is a driver which must be acknowledged. Running a hospital or medical practice is expensive with tools, resource costs, pharmaceuticals, and equipment's, it all adds up. However, the healthcare BI packages can helps to reduce these costs different ways.

BI healthcare software package can track populations and accomplish analysis to better comprehend the probability of infections and illness in specific locations. BI healthcare tools can expand information and communication sharing among various organizations and even between the countries (Bordeleau et al., 2018).

3.1.2 Turning a Physician to a Data-Scientist

BI tools might be difficult to use and comprehend. However, as healthcare has evolved, so have the business intelligence systems that support it. Doctors and other healthcare professionals now have a simple way to extract data without having to know how to code or work with databases.

Front-line employees are more productive and effective when they use self-service tools. They give healthcare providers real-time access to information, allowing them to make better decisions and judgements faster. Furthermore, these self-service tools enable the patients for easy modification, allowing them to comprehend the information that are being offered (Ahn et al., 2019).

3.1.3 Personalized Medicine

In years back, Patient treatment used to be more of a guessing game than anything else. As the time proceeded and evidence and data were shared between clinicians, researcher, and physicians about what medications worked and what did not work when it came for the treatments of specific disease, better option for treatment were refined and discovered.

Healthcare data intelligence helps the clinicians, researcher, and physicians to understand why some treatment option that suitable for one patient might or might not work for another patient. Healthcare Business-analytics can further determine the risks of specific treatment options based on a patient's medication and condition. Now the treatments options can be personalized because of BI, based on definite genetic blueprints, allowing for more precise treatment (Alloghani et al., 2018).

3.1.4 Caregivers' Evaluation

As previously stated, healthcare is a business, and one of the fundamentals of business is customer service. Patients who visit a doctor or visit a medical facility are considered as customers in healthcare system. These patients are not only concerned with how they are treated in the healthcare facility, but also how much empathy is or is not shown in the given situation to the patient, the information they receive, and many more.

Like restaurants reviews, the healthcare facilities can also be reviewed by patients and information's like this are collected through different BI tools. Clinical business intelligence software can analyse data about caregivers inside an organization and use it to improve patient care (Esteves et al., 2019).

3.1.5 Patient Satisfaction Improvements

Patient happiness and satisfaction is influenced by health analytics in several ways. Personalised and better treatment option ensures that the patients receive services focuses on their specific condition and diseases. Personalised treatment options results in enhanced patient outcomes, leading to overall better quality of life. In addition, hospital and clinical BI helps to make the healthcare facilities more effective and efficiently improving waiting times and overall the health service levels (Bordeleau et al., 2020).

1. Improving care of patient: BI offers complete data on the health of patient's by relating different types of medical records and reports. Understanding the current symptoms, history, inherited risks, and the probability of relapse permits clinicians to produce optimal-conditions for in-patient-care and accurately plan the home visits.
2. Guessing the requirements of patients: BI can guess the events at the macro and micro levels. For example, forecast of occurrence of the patients during flu-season and determination of patients who will requires hospitalization.
3. Individual treatment option: BI analyses and collects large amounts of the data, and findings hidden relationship. Which allows the physicians to adapt the treatment option for an individual patient according to their needs. For example, it will help to determine the current state of patient, the likelihood of death during a surgery, and the tendency to increased blood clotting.
4. Making quick decisions: BI rations the external and internal patient data in a single-core and offers easy access for different healthcare institutes. In serious cases, when the physicians do not have adequate information about patient, it is conceivable to receive information of the patient from other institutes and deliver timely assistance.
5. Financial planning: BI takes economical, operational, and clinical data, creating it easier to track key performance indicators (KPIs). For health staff, it is a prospect to find the feasibility of certain costs and invoicing, optimize calculation, and distribution of funds between departments.

3.2 Tools of Business Intelligence in Healthcare Domain

BI software's of healthcare is a subset of BI-software beset to the healthcare-market. These tools allow medical professionals to review data from a variety of sources in a more efficient manner. These sources could include patient medical records and files, but they can also include extra information like financial records and more to help the facility better plan its care and treatment (Gastaldi et al., 2018). Healthcare BI tools interface with other software in a medical setting, but it's important to note that they're not the same as EMR and EHR software.

3.2.1 Tableau

Tableau is a market leader in the business intelligence field, it helps the healthcare setting to create and publish the dashboards in a very easy way. Tableau offers some built-in data preparation capabilities that makes gathering of information process easier. Tableau also includes several ready-to-use templates for healthcare consumers, which aids implementation even more by allowing firms to dive down into their data more rapidly.

It supports healthcare firms in becoming more data-driven in order to improve patient experiences and outcomes through confident decision-making aided by visual-analytics. The users of various degrees of technical expertise can easily use this platform to explore the data filtering by dragging and dropping and in natural language enquiries. Tableau provides both SaaS and self-hosted deployment options (Carlisle, 2018).

3.2.2 Power BI

Power BI is a Microsoft product; thus, it will be familiar to Office users. It also has direct integration with other Microsoft programs like as SharePoint, PowerPoint, Azure and Excel, and allow users' model, analyse, and graphically present the data in reports and dashboards of various types. With a built-in AI engine, the Power BI is quite intuitive and simple to use which allows users to analyse the patient's clinical data easily and quickly. Power BI enables to gain actionable and deeper insights that link the gaps between clinical data and decision-making. It is a popular choice for businesses of all sizes (from small businesses to large corporations) because of its cost-effectiveness, ease of use, and scalability (Powell, 2018).

3.2.3 Sisense

Sisense, like Tableau, offers healthcare-specific integrations. Sisense, on the other hand, goes a step further with a healthcare analytics module designed exclusively for healthcare data and information. Sisense allows user to pipe the data from different data sources so that user will integrate all of the various touchpoints in a single-interactive-dashboard.

Sisense is also a complete BI and data discovery platform that makes analytics available to everyone. Based on single-stack-technology, Sisense contains all the things that are important for data analysis, preparation, and visualizations in a single-architecture. It can do thousands of queries on large amounts of clinical data, returning results at a faster rate than in-memory processing, which allows the users for making decisions very quickly. Sisense's healthcare analytics module is created specifically to evaluate the healthcare data, which is one of the prime benefits for healthcare providers. Sisense is also one of the greatest data integration solutions on the market. Integration is not only viable, but also simple, when the users are connecting to data sources or other software such as ERP and invoicing software (Lousa et al., 2019).

4. FUTURE PERSPECTIVES

In various industries, BI is now widely regarded as a key driver for the better understanding organizational outputs and measuring them in real time in order to make improvements and changes. To make accountable decisions about the use of rare resources of the healthcare system it is important to recognise the tools or sources of efficiency, that can contribute more to improve the outcomes. Manager and users of healthcare sector, require real-time information to well manage the data and to make the knowledge and information which could improve the quality of health services and reduces the risks. Healthcare-specific analytical skills, on the other hand, are already incorporated in other fundamental operational applications as well as medical devices and equipment's. Occasionally they have been effectively put forth as stand-alone intelligence-applications (Tavera Romero et al., 2021). For example, significant-intelligence is built into Clinical-Decision-Support (CDS) applications, Computerized-Provider-Order-Entry (CPOE) systems, telemedicine devices and hand-held computing tablets seen everywhere in clinics, hospitals, and healthcare infrastructures. While the main aim of these technologies is not only analysis, but to make it more valuable (Bisheh et al., 2021).

The future of healthcare BI will be defined by the convergence of business and policy issues, as well as the deployment of increasing analytical capabilities to tackle these challenges. It appears that providing real-time data is essential. In near future BI will be taken in closer contact with healthcare system, if the managers and users want to effectively support the data management, evidence-based-practices and to understand the correlations between them. Safety and quality can be only improved and measured when variation in regional or local differences is eradicated, when the consequences are measured, and when teams from the multi-disciplines sing from the same song sheet. BI's worth for healthcare will therefore not primarily be in information provision and simplifying communication. Rather, its contribution is in enabling new ways of working, allowing the integration of organization and information and the measurement of outputs in real time (Tavera Romero et al., 2021).

However, three critical challenges must be addressed in order to comprehend the future direction of BI in healthcare: (a) The most critical business and policy issues in healthcare today; (b) The emerging trends in the field of business intelligence capabilities in healthcare sector; and (c) The potential analytical applications of healthcare that are now being overlooked. Parallel to this, there is a need to enhance emerging analytical capabilities in order to produce applications that can address these difficulties, particularly in areas like:

1. Patient satisfaction and service evaluation: including patient engagement, experience, loyalty, happiness, relationship measurement and the last and important one tracking and measuring the voice of patient.
2. Management of healthcare marketing: developing and measuring the growth of healthcare branding, trust management, reputation, customer and patient segmentation, patient lifetime value and profitability.
3. Financial stability in the healthcare sector: increase in productivity, maximizing profits, Streamlining the processing of claims, control of waste and costs, costs according to activity.
4. Analysis of healthcare operations: Measurement and management of partners,

opportunities for collaboration, improvement in agility, asset and working capital management.

5. Development of health-care personnel: provider commitment, measurement of the provider's experience, and analysis of the provider's voice, measurements of learning and development, knowledge, innovation, culture and analytics of intangible value.

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The primordial role of Business Intelligence and Real Time Analysis for Big Data : Finance-based case study

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ABSTRACT This study is about big data and its relationships with business intelligence and real time analysis. Few studies have studied this relation and fewer the parameters and variables of the characteristics and relations. In this study, this is presented in the literature review then for the research method, it is a questionnaire to finance sector leaders managers –unit of analysis-with lickert scale, yes and no questions and comments about the characteristics and relations of big data with real time analysis and business intelligence. The analysis uses SPSS for windows and NVIVO 12 for the quantitative and qualitative analysis. The results of the analysis present concrete and concise models in which big data is in relation to real time analysis and business intelligence. It also provides a thematic analysis leading to the development of a new framework model that lead to the definition of the characteristics and relationships. There are various theoretical and managerial implications for the big data management and possible finance sector. The future research is to scale the questionnaire to a survey basis, to modify the origins of the questions to a complete lickert scale and to elaborate on new links with big data using the new conceptual framework.

KEYWORDS: Big data, Business intelligence, Real time analysis, characteristics, relationships

1. INTRODUCTION

There is no doubt that business intelligence (BI)-based decision-making must be effective if competitiveness is to be maintained for long-term growth. Big data collection and analysis are now vital due to the quick advancement of information and communication technologies, which has led to a significant surge in academic research on big data and big data analysis (BDA) (Dong-Hui & Hyun-Jung, 2018). We agree with this particular point of view, however, many of these research are unrelated to BI since businesses do not fully grasp and use the concepts. How does big data differ from earlier methods of data analysis? Supporting internal corporate strategies is the main objective of conventional small data analytics, which all managers are more or less familiar with. But big data also provides a promising new perspective: finding fresh ways to provide clients with high-value goods and services (Ge, 2018).

In other words, digital transformation in the corporate world refers to the incorporation of digital technologies across all functional divisions, from product development to customer service. This idea is crucial for a company's and its economy's overall sustainable growth. Based on this reality, the researcher investigated the significance of digital transformation for overall strategic performance inside a firm through the use of big data, the Internet of Things, and blockchain-based capabilities (Bhatti, 2021). As Paradza and Daramola (2021) argues that to maintain their profitability and long-term sustainability, organizations must obtain enough business value (BV) from the implementation of business intelligence (BI). Many organizations that have implemented BI, however, nevertheless do not comprehend the subtilities that determine the realization of BV from BI. Also, a new way to look at this is that Governments in the United States and other countries are using data analytics more and more to enable data-driven decision making. The research community has, however, paid little attention to how various players (producers and consumers) inside governments, in particular municipal governments, employ the tools, methodologies, and outcomes of data analytics. This study investigates the primary elements that affect the application of data analytics from a socio-technical perspective (Cronemberger (2018).

The current trends of big data is in relation to critical decision making, real time analysis, analytical methods and business intelligence. Previous studies lack research in forming an exact relationships among big data and real time analysis and business intelligence so further studies is needed to clarify the business intelligence and real time analysis characteristics involved in the development of big data. Considering the demand for research about business intelligence big data and real time analysis, what influence the characteristics of these variable are not yet presented in extensive research conducted that describe and develop the construct of big data, business intelligence and real time analysis. There is little empirical research on these variables and little incentive to make the research to incorporate also about the relationships among big data, business intelligence and real time analysis. In the literature, there is not yet a strong sense and meaning about the relationship among these variables. The aspect about the links about these constructs is neglected and not taken into consideration. The intent of this study is to provide exact meanings about the variables and their relationships.

The objectives and purposes of this study is to help identify the characteristics and relationships among big data, business intelligence and real time analysis. As planned, the objectives of this study provide an overview of how it will reached the investigation on the variables of the study. The purpose is to understand exactly the mission of conducting research about big data and business intelligence and become much clearer. The purpose of this study can be divided according to the research questions to various sub purpose as a first purpose there is the identification of the characteristics of big data and business intelligence and as a second purpose there can be the identification of the relationships among these constructs. The data collected for the study also essentially will provide data about the subject of the study that are evidences to show the existing relationships among big data and business intelligence and to provide necessary data to understand the research purposes.

Indeed, the aims of the research are that there is significance in the investigation on the relationships among big data, business intelligence and real time analysis because the contribution of this research in this field is in the way it is examined and analyzed. The research may be using variables that have never been examined before because the instrument that is developed in the form of the data analysis method and the precise questionnaire measures the variables better than others on the market. Also, this research is the next logical step in a continuous line of inquiry that solve an important subject about big data and business intelligence that is not yet made in this discipline. Thus, this study is important and valuable, it will create new knowledge with these new relationships among big data, business intelligence and real time analsyis.

The use of a case study in cross sector will be used. A case study is the collection of data from a real time environment and real context (Yin, 2006). The case is is divided into two parts in an agency of banking using information technologies and big data that knows business intelligence in every day life and the second is in micro-banking that uses big data and information technologies in the operations. This is the context of research that is rich of relevant data and information by which it is possible to make the findings.

The research questions are threefold with a focus on the big data, business intelligence and real time analysis. The research raises the following research questions:

– What are the characteristics of big data, business intelligence and real time analysis?
– What are the relationships among these three elements?
– How to overcome the gap among the links?
– What are the competences needed to relation big data and business intelligence?

There is the claim that business intelligence and real time analysis has around big data some kind of effects and impacts. It is possible to derive assumptions:

- Big data, rela time analysis and business intelligence has characteristics unique to each one of them
- There is a relationship among big data and business intelligence and real time analsyis. That is, the business intelligence and real time analysis have impacts and effects on the big data
- There are specific competences needed to deal with the relation among these three variable that are hidden or appear when there is interactions.

There is also the derivation of the null hypothesis and that is interesting because there is demand for big data and the consequences and effects are there nor not of business intelligence and rela time analysis:

- The three variables are exclusively independent and there is no relationship among them.

The paper is divided as follows. Next section presents the existing literature review with regards to the relationship among big data, and business intelligence and real time analysis, the third section presents the conceptual framework. Next sections show the results, discussions and conclusions.

2. LITERATURE REVIEW

2.1.1 Business intelligence and big data in relation

Much of earlier research of Ge (2018) emphasized that business decisions based on big data may also include various analytical activities, such as supporting big data discovery or analyzing customer satisfaction, customer journeys, supply chains, risk management, competitive intelligence, pricing, and pricing decisions. Now go into more detail: Modern big data analysis techniques can be applied to fresh, less organized data sources, and the resulting data can be used to inform better internal decisions. Customers who employ language that strongly suggests displeasure can be identified through analysis. The insurer can then take some action, such placing a call to find out what is making the customer unhappy.

Also, Paradza & Daramola (2021) introduced the idea that theories are essential to value realization because they establish the metrics for BV resulting from BI adoption. Therefore, gaining an awareness of the theories used in the literature to analyze corporate value is an useful first step in understanding the complexities of value generation. The many theories used in BV research come from many different fields of study, including strategic management, microeconomics, industrial-organizational, sociopolitical, organizational-behavioural, and business-strategy spectrums.

In sum, in the wake of the global financial crisis, the functions of digital technologies are becoming increasingly important in extending financial development into new industries. Cloud computing and big data management are not just technology trends; they also significantly and favorably affect how much money firms make. The use of cloud computing is growing quickly and may be the most exciting and anticipated technology in the age of globalization. Making wise decisions involves a strong capacity for learning that investigates historical status data as well as effective big data and cloud computing management (Ionescu & Andronie, 2021).

Big data security and privacy have emerged as a problem that prevents the company from using cloud services. Existing methods for protecting privacy have a number of flaws, including a complete reliance on third parties, a lack of data privacy and correct data analysis, and a lack of performance efficiency (Ramachandra et al. 2022). Organizations today have access to a vast amount of data for analysis purposes. In the twenty-first century, data is the key element of business, and the internet is already present on a sizable number of devices. The solutions should be investigated in light of this in order to manage and extract the knowledge-value pair from the datasets (Goar and Yadav, 2022). AI-powered information and Big Data (hereafter simply data) have quickly emerged as some of the most critical strategic resources in the global economy. Their value, however, is not (yet) formally recognized in financial statements, resulting in a growing disparity between book and market values and, as a result, limited decision usefulness of the underlying financial statements (Leitner-Hanetseder and Lehner, 2022).

2.2 Big data and real time analysis in relation

Certainly, businesses that use cloud computing and digital technologies have more options to specialize and have new business opportunities. In order to provide new financial services and work with other parties to compete in the financial sector businesses, the cloud has thus emerged as a significant technology. Big businesses all over the world are implementing contemporary big data management systems to assist decision-makers in making better decisions (Ionescu & Andronie, 2021). It seems reasonable to say that Big data management and cloud computing are emerging as new business trends as a result of globalization and the rise in consumer demand for high-quality good. Smart business people can quickly develop and introduce new goods, take advantage of emerging financial trends, and coordinate the work of accountants by using cloud computing services. Artificial intelligence, robots, and big data adoption will boost corporate profitability and the global economy, while big data can give firms a competitive edge over their rivals and propel investors toward the pinnacle of globalization (Ionescu & Andronie, 2021).

Interestingly, the corporation has made a number of changes during the course of its existence, which, when seen chronologically, paint a detailed picture of how it has both embraced the new opportunities presented by big data and tried to address the attendant organizational difficulties of ethics and governance. A technology infrastructure that enabled transactions at participating retailers to be tracked for the automatic provision of incentives was one of the most important earlier advances (Keren Naa & Owen, 2019). Besides, a system of innovation metrics is set up by leaders in order to quantify their progress in building an innovative culture. They actively look for ways to encourage interactions that foster cooperation, imagination, and creativity. Leaders were far more proactive than Strugglers when it came to pursuing innovation-related activities for the upcoming three to five years. Measure the return on innovation: As businesses devote more and more resources to fostering innovation, they look for new ways to determine the efficiency of those efforts (Marshall *et al.*, 2015).

In today's data-driven digital economy, organizations try to harness big data power to make better decisions. Big data analytics helps them not only identify new opportunities, but also extract knowledge and improve performance. Despite significant investment in big data analytics initiatives, the majority of organizations have failed to fully realize their potential (Pour et al. 2022). Big data is commonly defined as a massive volume of data that is constantly increasing in real time and is difficult to store, retrieve, and manage using traditional database techniques. Big data technologies are transforming traditional technology areas, and their effective use will necessitate new security models and security design methodologies to address new security challenges (Mishra, 2022). The telecommunications industry is the leader in big data trends because it has the most capable big data infrastructure. However, because of the high volume, velocity, and variety of big data characteristics, the adoption of big data in telecommunication services poses significant security and privacy challenges (Othman, 2022). Big data is distinguished by its large volume, diverse data, low value density, and rapid speed. It establishes our learning innovation, scientific and technological innovation, and management innovation by providing unique and brand-new thinking through technology. With the advent of the big data era, the modernization of government governance capacity has identified realistic big data needs, but there are still many specific directions that merit further investigation (Li, 2022).

2.2 Conceptual framework

In particular, the literature chapters present the rational for conducting research on the topic of big data, business intelligence and real time analysis. The following review of the literature represents the literature pertinent for this actual and current research on big data and business intelligence. The reference about business decisions using big data is included in this framework because it talks about the business analytics in relation to big data. There are many analytics that can be used because the data sources have large volume that is in the banking sector. Also, the customer interactions and segment names are used to show the customer opportunities and problems with a complex set to analyze the banking sector. Dong-Hui and Hyun-Jung (2018) are adding knowledge about the data problems used in large volumes to monitor the supply chain risks and commercial practices. At the same time, the authors add to the development of the study on the competitive intelligence in which big data is changing the approach by getting more detailed data for the strategic decisions and this relates to the research questions about the characteristics of big data and its relation to the other variables of business intelligence and real time analysis. Furthermore, analytics is applied with internal structured data into the big data algorithm. The business and technology organizations automate data analysis processes and use analytics for the business processes with big data structure for the analysis platform that supports external data and new data production systems are highly structured approaches with a long process with more flexible agile/scrum processes in which there is analytics and big data.

Following the methodological review about the project performance of manufacturing SMEs through BDA adoption, Mangla et *al.*, 2020 provide the current state of research in the subject through a survey about constraints and indications and the questionnaire is used to measure BDA adoption through the use of collected data analysis with significance value and confidence level in this analysis. There are the projects performance of SMEs and the constructs are with the items to correlate with each other freely to show the constructs of project knowledge and operational capabilities. And, this review is a significant contribution to the knowledge base about goodness of fit statistics and measured variables are following the project manager and others to show convergent validity and the CFA model leading to the path diagram and validation of latent constructs. The investigation on practical significance of the reported studies is very important. The politic is that this is a coherent argument about the dataset collected based on SEM analysis and the results in path analysis and that the BDA adoption is based on many hypotheses about project management, green purchasing, capabilities and performance of SMEs. This is a reference about the use of practical significance about the subject of BDA adoption and its influences and relationship with other variables in knowledge management, sustainability and project capabilities.

The advancement of data generation, processing, storing, and networking technologies has made data storage, capture, and sharing easier and less expensive than ever before, allowing organizations to handle massive volumes of data at high velocity and variety, dubbed "big data." When the associated challenges are properly addressed, big data offers numerous opportunities. Business intelligence (BI) is primarily concerned with converting raw data into usable, valuable, and actionable information for decision-making. It is categorized as a data-driven decision support system (Sirin and Karacan, 2017). Big data and big data analytics are widely regarded as a disruptive technology that will reshape business intelligence. While research has been dedicated to improving understanding of the impact of business intelligence and big data on organizational performance and decision-making in the majority of organizational theories (Alnoukari, 2020).

Organizations can benefit greatly from big data. It is simple to store large amounts of data, but it is more difficult to make sense of it. This is no small task when we're talking about terabytes and petabytes of data generated by social networking, sensors, financial transactions, mobile applications, and so much more. Business Intelligence (BI), on the other hand, a concept that has been around for decades, allows for easy interpretation of large volumes of data; identifying new insights and implementing effective strategies, thus assisting organizations in their long-term decision making and competitive market advantage (Atriwal, 2016). The business intelligence process analyzes data and uncovers insights so that managers, executives, and higher-level executives can make informed decisions. Business intelligence provides insight into past, present, and future business actions. Big data refers to large amounts of data that are growing exponentially over time. Data analytics examines massive amounts of data and provides some insights. The goal of big data analytics is to discover information such as hidden patterns, correlations, market performance, and customer preferences so that organizations can make business decisions (Kumar Mishra, 2022). Big data is one of the most misunderstood concepts in business today. The implications for big data analytics are not as simple as they appear, especially when it comes to so-called dark data from social media. Increases in data volume, velocity with which it is generated and captured, and the variety of formats in which it is delivered must all be considered (Kimble and Milolidakis, 2015).

Apart from this, the organization of the review is based on the use of understanding of the subject of review about big data, business intelligence and real time analysis and it provides a transition from one topic about the business intelligence and real time analysis to another about big data. The conceptual framework – Figure 1 – based on the literature review provides the various theories and practices about the subject of big data and business intelligences and the different synthesis in the literature review about big data provides a string of analysis and description to relate to each others about the subject of big data. There is a historical context presented in the literature about financial services sector that help to understand the subject about big data. It is possible to see in the literature also gaps analysis of the literature about banking sector.

Especially, there is also the difference among studies about innovation and technologies with the same theme about the innovation which fits the actual study. There is the Table I offering the references about the subjects with the description of the themes. The findings of the review also lead to divisions in the studies. There is practical significance in one of the literature reviews and inconsistent findings presentation. While the two references about the same theme is shown to present the difference in the studies. The research on this subjects reinforces the need for continued research on factors related to the research questions, especially questions about the characteristics of the relationship among the variables of business intelligence and real time analysis and big data. The theories used in the framework are related to big data, business intelligence and real time analysis. The conceptual framework suggests that big data, business intelligence and real time analysis have characteristics and relationships – Figure 1 and this can lead to the creation and prominent development of big data 4.0.

Neverthless, it should be noted that a previously neglected area of study which is the subject of big data and business intelligence and more precise research questions need to be asked about the nature of relationships among them. It is only now in this research that we consult these specific research questions and that research about this subject is found with a focus on big data in relation to business intelligence and real time analysis. Few studies examined factors related to the subject of big data and business intelligence and benefits are gained from business intelligence and real time analysis approaches. Next chapter presents the research method based on the questionnaire to investigate on the relationships among big data, business intelligence and real time analysis.

2.3 Research method

There is the possibility to combine both a quantitative and qualitative approaches and here it is qualitative primary and quantitative first. There is the collection of quantitative preliminary data from the questionnaire as a basis for collecting and interpreting the primary qualitative data. In nature, this type of research is a case study research. A very useful definition of the case study is provided by Yin (2014): "A case study is an empirical inquiry

Table I . The literature review with the themes.

Literature review	Description
Ge (2018)	Business decisions using big data
Dong-Hui & Hyun-Jung (2018)	Consumer products, big data and analytics
Paradza & Daramola (2021)	Business value and Business Intelligence
Mangla *et al.* (2020)	BDA adoption in the financial sector
Ionescu & Andronie (2021)	Cloud computing and big data
Keren Naa & Owen (2019) ; Marshall *et al.* (2015)	Innovation and big data
Persaud (2021)	Job order and big data

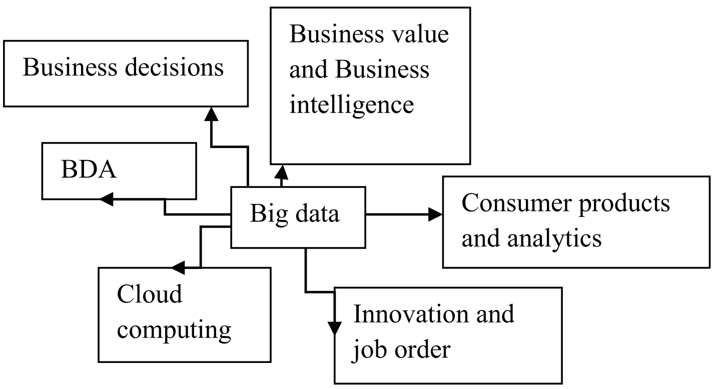

Figure 1. Conceptual framework about big data –Elements around big data.

that investigates a contemporary phenomenon in depth and within its real-life context, especially when the boundaries between phenomenon and context are not clear evident".

Besides, the research method choice here is not to start with a quantitative approach as a primary method but to start with the qualitative primary and the research method choice is not to collect and interpret data with the basis of a quantitative approach. The choice of research method is the specific techniques used to collect data with respect to the research problem. There is not the use of interviews with individuals or groups to ascertain their perceptions. There is the use of surveys -questionnaire to assess opinions, perceptions and attitudes.

The methodology is typically divided into the following sections: – selection of participants which is the choice of the context of research and the unit of analysis – instrumentation-data collection and –data analysis. A more detailed description of each of these sections follows. The primary goal of this study is to test the research questions and instruments to measure the variables is utilized to this end. It might be also that it is necessary to select a sample of the population because inferences concerning a population are made based on the behavior of a sample. The sample needs to be representative, sufficiently large, and free of sampling error and bias. Since this is a qualitative research, the sample might be smaller, non random, and purposive as it is mentioned here. It is important to define the population in sufficient detail so that other researchers may determine how applicable the findings are to the study. That is, the elements as an outcome of the research on the sample from the population in the finance and banking sector about big data, business intelligence and real time analysis and from data collected here, it is possible to make generalization.

On the whole, the representative sample involves defining the population, identifying each member of the population and selecting individuals – the managers – for the sample. The target population of the study are all managers of the finance and banking sector company. This population includes only those leaders in the companies and the companies are used to determine the target population. The choice of method to select the sample is not a stratified random sampling or cluster sampling because there are no sub groups in the population or there is not the selection of groups. The sample are all equal managers in these companies that there is no comparison of the target population and no number of subgroups. Besides, the selection of the sample is based on the homogeneous sampling because there is the selection of very similar participants in experience and philosophy. This make data collection and analysis simpler. There are two ways of data collection which are the questionnaire sent by mail and the second method is an electronic mail or online questionnaire in which the sample respondents can answer on the web.

Talking about the data analysis, the content of the instrument the questionnaire is made. It is important to determine various points about the instrumentation –name of the instrument, the questionnaire – acronym, lets say Que- author of the instrument, elaboration of the researcher based on the content of the literature review and of course of the subject of research study – purpose of the instrument, the investigation on the elements of relationships and links among big data, business intelligence and real time analysis –number of items, which is the number of questions in the questionnaire which is around 25 questions for the completeness of the instrument – response format, which is the formation of the questions in the questionnaire that is Lickert, yes/no with comments but no open ended questions to facilitate the data analysis of the questions content.

Regarding this research, not only are there the use of questionnaire and documentation for the purpose of the research but also different methods for data collection can be used in case studies research. Multiple sources of evidence are highly advocated to be used in order to establish construct validity. Validity deals with the best available approximation to the truth or falsify of a given inference, proposition or conclusion. The content validity is the degree to which an instrument measures an intended content area. The validity refers to how well the instrument measures what it is supposed to be measuring. Along with, a measure is considered reliable if it would give us the same results over and over again. The goal of reliability is to minimize the errors and biases in a study. Reliability is the degree to which an instrument consistently measures whatever it is measuring.

On the other hand, the questionnaire consists in 25 questions which is 25 items that are divided into three parts. The first part of the questionnaire uses elements related to real time analysis, the second part uses factors for the description of the questions on the big data company, and the third one uses variables that has to do with business intelligence. There is the use of the software package SPSS for the analysis of data derived from the questionnaire. This choice of software usage is because others as NVIVO cannot provide statistical analysis of the responses of the structured questions in the form of lickert scale or yes/no questions. This qualitative primary quantitative base analysis is dedicated to the analysis of the closed-ended questions. For the comments, if the participants answer, this is a qualitative analysis in which every word and sentence of the comment is important. The analysis of the comments is through the use of NVIVO 12 of QSR international which is a software for qualitative thematical analysis. The research activities covered a one-month period from 25th april to 25th may 2022.

Importantly, in the questionnaire, there are many types of questions that are avoided as questions that put a strain on the intellect of the respondent, questions of a personal character and questions related to personal wealth ; this concerns ethics of the research. Thus, the questions of the questionnaire are focused and have specific aims to investigate on the relationships and links among big data, business intelligence and real time analysis. Successive questions to the opening questions in each part of the questionnaire are more precise and can be relatively more difficult because they are at the end of the parts of the questionnaire and even if the respondents do not answer the questions considerable information is already obtained.

3. RESULTS

3.1.1 The lickert scale model

While the authorization to output the findings using only the lickert scale entry of data is because this is considered as the alternative model that is followed here by the complete model. The lickert scale data is based on the assumption that the level of satisfaction that is the response scale with lickert scale shows the psychometric response scale. The level of satisfaction ranging from 1 that is very low satisfaction to high satisfaction that is very satisfied under the condition of lickert scale data. These responses and findings based

Récapitulatif de l'observation

	Observations					
	Valide		Manquant		Total	
	N	Pourcentage	N	Pourcentage	N	Pourcentage
$meanrealtime[a]	4	40,0%	6	60,0%	10	100,0%
$meanbigdata[a]	2	20,0%	8	80,0%	10	100,0%
$meanbusintl[a]	2	20,0%	8	80,0%	10	100,0%

a. Groupe de dichotomies mis en tableau à la valeur 1.

$meanrealtime fréquences

		Réponses		Pourcentage d'observations
		N	Pourcentage	
meanrealtime[a]	VAR00001	3	50,0%	75,0%
	VAR00003	1	16,7%	25,0%
	VAR00007	2	33,3%	50,0%
Total		6	100,0%	150,0%

a. Groupe de dichotomies mis en tableau à la valeur 1.

$meanbigdata fréquences

		Réponses		Pourcentage d'observations
		N	Pourcentage	
meanbigdata[a]	VAR00010	1	33,3%	50,0%
	VAR00013	1	33,3%	50,0%
	VAR00014	1	33,3%	50,0%
Total		3	100,0%	150,0%

a. Groupe de dichotomies mis en tableau à la valeur 1.

$meanbusintl fréquences

		Réponses		Pourcentage d'observations
		N	Pourcentage	
meanbusintl[a]	VAR00020	1	50,0%	50,0%
	VAR00026	1	50,0%	50,0%
Total		2	100,0%	100,0%

a. Groupe de dichotomies mis en tableau à la valeur 1.

Figure 2. The frequencies for the number of items.

on lickert are also a result from the very difficult data set. Because there are difficult questions there are also easy questions that related to the yes and no dataset existing with the lickert scale data. In comparison of the lickert scale model with the yes and no possible model there are also differences because from one hand related to the complexity of the variables and from the other hand the relationships among the variables. It is possible to see the start only of the analysis of yes/no questions model in appendix. Also, it is clear that the variables big data in relation to business intelligence and real time analysis have various findings whether in lickert scale model and complete model. Next are the necessary tables derived as an output from SPSS package of IBM to show the statistical findings for lickert scale model.

Neverthless, there is the focus first on the lickert scale model that has the objective of showing the data set findings with lickert scale data. For the type lickert scale model there are in each variable a set of six to eight items that can with lickert scale first show a rich data set that can be generally analyzed with descriptive statistics. The objectives of the items in general are supposed to bring good items analysis. In this case for each variable there are assumptions of the number of items to be output so there are in the findings enough items to analyze for all the variables – Figure 2. Thus, the rich data items for each variable is separately analyzed because there are various items in each variable and the frequencies from the tables show that there are again specifically enough items in each variable and that some items in each variable have a different

Statistiques de fiabilité

Alpha de Cronbach	Alpha de Cronbach basé sur des éléments standardisés	Nombre d'éléments
,603	,528	9

Figure 3. The reliability testing with cronbach alpha

Corrélations

		realtime	bigdata	busintel
realtime	Corrélation de Pearson	1	,531	,378
	Sig. (bilatérale)		,114	,281
	Somme des carrés et produits croisés	81,600	25,800	12,600
	Covariance	9,067	2,867	1,400
	N	10	10	10
bigdata	Corrélation de Pearson	,531	1	,646*
	Sig. (bilatérale)	,114		,044
	Somme des carrés et produits croisés	25,800	28,900	12,800
	Covariance	2,867	3,211	1,422
	N	10	10	10
busintel	Corrélation de Pearson	,378	,646*	1
	Sig. (bilatérale)	,281	,044	
	Somme des carrés et produits croisés	12,600	12,800	13,600
	Covariance	1,400	1,422	1,511
	N	10	10	10

*. La corrélation est significative au niveau 0.05 (bilatéral).

Figure 4. Pearson teast for correlation among the variables.

proportion of importance maybe because each data set is responsible for a specific meaning concerning big data, real time analysis and business intelligence.

Hence, there are many other measuremts as cronbach alpha coefficient that describes the reliability of the data set and its outputs and that can confirm that the lickert scale model is reliable. The level of satisfaction in this model is reliable because it is more than 0,5 and reaching 0,603 value – Figure 3. The reliability of the lickert model can lead to the observation that there is the possibility to use the model for general affairs of the subject so this model and its output can be presented in trust manner to shareholder and used to talk about big data and its relationship with real time analysis and business intelligence. It means it is an interesting subject of study that can provide many insights for overall performance and project management.

Moreover, there are also other measuremts to confirm the existence of validity of the data set and its output. The use of Pearson correlation is common in validity testing and to show that the level of satisfaction is low or high which means that the relationship among big data and real time analysis and business is low or high. Also the important when considering correlation of Pearson in the statistical testing and analysis is that in this case the degree of freedom is eight and that the output is greater than 21,95 hardly according to the two-test tailed table and not lower at a significance level of 0,005. In this table of correlations, it seems that surprisingly the strength of the linear relationship between each two variables is low also because the values are close to zero – Figure 4. This is possible because the objectives are the findings of relationships in this entire lickert scale model in which the big data must be in relation to real time analysis and business intelligence. The objectives are not for example to evaluate the relationship among real time analysis and business intelligence and this is going to be further developed in the analysis of the findings concerning the complete model. So the lickert scale model is valid because it concentrates on the development of the relationships more among the three variables than each two variables.

Finally, the intercepts of the model from the coefficients table show that if the intercept have high value and it is possible to compare them. It is noticed that the real time analysis with respect to big data is not really significant and that instead the business intelligence intercept is higher which says that there can be more obviously relationships among big data and business intelligence – Figure 5. Then, the significance of the low relationship between real time analysis and business intelligence is really serious and should be taken into consideration. This means there should be

Récapitulatif des modèles[b]

Modèle	Durbin-Watson
1	2,793[a]

a. Prédicteurs : (Constante), busintel, realtime

b. Variable dépendante : bigdata

Statistiques descriptives

	Moyenne	Ecart type	N
bigdata	9,1000	1,79196	10
realtime	9,2000	3,01109	10
busintel	11,2000	1,22927	10

Coefficients[a]

Modèle		Coefficients non standardisés		Coefficients standardisés			Intervalle de confiance à 95,0% pour B		Statistiques de colinéarité	
		B	Erreur standard	Bêta	t	Sig.	Borne inférieure	Borne supérieure	Tolérance	VIF
1	(Constante)	-1,207	4,334		-,278	,789	-11,455	9,042		
	realtime	,199	,170	,335	1,176	,278	-,202	,600	,857	1,167
	busintel	,756	,415	,519	1,821	,111	-,226	1,739	,857	1,167

a. Variable dépendante : bigdata

Figure 5. the intercpets for the variables in the lickert scale model.

improvement but there will be more discussion about this in the discussion section. Finally, there are also the mean of the three variables that are surprisingly close to maximum which shows that the discussion is about high satisfaction rather than low ones which means that big data is tremendous and especially when it is in relation and there is the continuous engineering of this relationship.

3.1.2 The complete model

Namely, let's talk now about the original model in which there are both the item in relation to lickert scale model and also yes and no items. Let's start with again correlation and describe the correlation of pearson that has a values one that is not close to 1 and the other is negative and not close to – 1 – Figure 6. Let's say that the model is only somehow valid because do not forget that there can be some interferences among the lickert scale data and the yes and no question. As a future research there is the discussion about the use of only lickert scale data responses scale in order to facilitate the analysis of the output and to achieve greater results with respect to the derivation of statistical regular output. The correlation of Pearson significance show that the correlation among big data and real time analysis is, whether high or low, not significant at all, as the two independent variables – the business intelligence and big data is significant.

Concerning the reliability, there are various measurements that can be used. For instance R = 0,525 (significant model at 52,5%) can be in this case somehow close to one which means that the model is somehow valid even though there is low correlation among some of the dependent variable and the independent variables. The table ANOVA-one factor for the analysis of variance demonstrates according to the significance of 0,323 that the value is somehow far from 1 which means that there is variance and that there is spread between items in the model – Figure 6. Also, with conbrach's alpha for reliability it should be less than one and here it is –0,087 which means that the model is really reliable. Finally, the correlation of Pearson is mostly for each correlation among the variables less than 21,95 which

Statistiques descriptives

	Moyenne	Ecart type	N
BigData	15,0000	1,41421	10
RealTime	15,9000	2,60128	10
BusIntlg	19,3000	1,49443	10

Corrélations

		BigData	RealTime	BusIntlg
Corrélation de Pearson	BigData	1,000	,453	,000
	RealTime	,453	1,000	-,506
	BusIntlg	,000	-,506	1,000
Sig. (unilatéral)	BigData	.	,094	,500
	RealTime	,094	.	,068
	BusIntlg	,500	,068	.
N	BigData	10	10	10
	RealTime	10	10	10
	BusIntlg	10	10	10

Récapitulatif des modèles[b]

Modèle	R	R-deux	R-deux ajusté	Erreur standard de l'estimation	Modifier les statistiques: Variation de R-deux	Variation de F	ddl1	ddl2	Sig. Variation de F	Durbin-Watson
1	,525[a]	,276	,069	1,36458	,276	1,333	2	7	,323	2,198

a. Prédicteurs : (Constante), BusIntlg, RealTime

b. Variable dépendante : BigData

ANOVA[a]

Modèle		Somme des carrés	ddl	Carré moyen	F	Sig.
1	Régression	4,965	2	2,483	1,333	,323[b]
	de Student	13,035	7	1,862		
	Total	18,000	9			

a. Variable dépendante : BigData

b. Prédicteurs : (Constante), BusIntlg, RealTime

Figure 6. Test of validity and reliability for the complete model.

Corrélations

		RealTime	BigData	BusIntlg
RealTime	Corrélation de Pearson	1	,453	-,506
	Sig. (bilatérale)		,189	,136
	N	10	10	10
BigData	Corrélation de Pearson	,453	1	,000
	Sig. (bilatérale)	,189		1,000
	N	10	10	10
BusIntlg	Corrélation de Pearson	-,506	,000	1
	Sig. (bilatérale)	,136	1,000	
	N	10	10	10

Figure 7. The correlations in the complete model.

means that there is no correlation among many items which just like confirm the fact that when integrating licker scale with yeas and no items model data there could be some interferences for the typologies of values – Figure 7. As a future research, there is the possibility of transforming the yes and no questions items into better lickert as it is mentioned in the lickert scale model.

Altogether, with this analysis of the findings there is the possibility to see how a model and another can lead to the occurrence of non correlation because of the level of satisfaction and yes and no questions that are more general will not lead to a complete model. However, there are also comments in the questionnaire omme is possible to see also the effect and impact of big data and real time analysis and business intelligence. In next section, it is mentioned how it is possible to use the comments of the respondents in order to show the reliability and validity of the model. Finally, the questionnaire also included the mandatory response to comments to each question of the questionnaire. There is the possibility to analyze directly the comment with regards to the conceptual framework because this is a qualitative analysis that need coding and thematical analysis to show the results and analysis. In the next section there is the focus on the comments to derive a new conceptual framework.

4. DISCUSSION

4.1 The development of the conceptual framework

The important point from these omment sis that they allow the derivation of new variable or new parameters that are involved and can be in the life of big data. It is possible to see new emerging variables that are really presented that show there are relationships among big data and various other variables than the ones present in the sub section about the conceptual framework. Here there is the possible integration of new variables and parameters about real time analysis and business intelligence in the Big data model with the organization of the new variables in each different important parameters that are the business intelligence big data and real time analysis. Here is a table with the new variables and the newly derived conceptual framework – Table II.

There is the possibility to see the integration of various new variables or parameters that by themselves have relationships and lead to relationshisps. The model consists in the big data in relation to real time analysis and business intelligence. Each one of them now includes new variables and parameters that lead to the definition of the relation of big data with these. The old conceptual framework has less than a dozen of the variables now in hand and that provide more sense and more meaning to the new model of big data company. In addition to the three parts of the variables there are also the possibility now to see relationships that based on inside of the main variables that are leading to the enrichment of each part of the variables –Table II.

4.2 The development of the characteristics and relationships:

According to the research questions, the aim is to find the characteristic and the relation and the competences for the links among big

Table II. The new variables from the questionnaire results.

Actual variables	Real time analysis	Big data	Business Intelligence
New variables	big data acquisition and the big data processing capabilities. Analysis of big data in relation to the information and communication technologies. Supply chain and the revenue model the value chain relation to the costs development the technologies for the development of the big data analysis in relation to the investment chain opportunities in relation to the customers interactions the optimization of products prices in relation to the application of data analysis : the analytical value of big data and clients privacy	decision making in relation to business analysis the characteristics of supply chain in relation to transaction data analysis and management data distribution and data collection	business intelligence and business value data sources, storage and collection value creation in relation to the use of generated information the business processes and the big data projects the big data creation and collection with regards to its multiple sources the customer value and digital technologies profitability in relation to business value the factors that influence data analysis in relation to the partners the efficient decision making and continuous growth value chain in relation to business processes and service the big data environment and the customers products the relation between business decisions and competitive intelligence

Big data

Business Inteligence

Real time analysis

Figure 8. The words clouds for big data, real time analysis and business intelligence.

data and real time analysis and business intelligence. The judgement that the derived new variables are valid is that these variables show the needed parameters. For instance, each variable in the table show the needed parameter for the research question. The following words clouds show the most common important variables in each of big data, real time analysis and business intelligence and lead to the development of the characteristics of the variables – Figure 8:

– The characteristics of big data are that the transactions influence decisions management and makes better analysis, and the relation analyzes data quality, chain business, day specific characteristics and technological supplier distribution.
– The characteristics of business intelligence are that information from customers bring business value and data that is big making analysis and collection of sources empowered by competitive intelligence.
– The characteristics of real time analysis are that customer analysis and value chain make possible data that is big and product cost with company development.

The following word tree show the relation big data has from one side with real time analysis and from the other side business intelligence:

The complex relationship big data has either with business intelligence or with real time analysis is vast and enriched with parameters. Here are some of the relationships and their natures between big data and business intelligence derived from the word tree in which this latter empowers big data – Figure 9:

– To improve planning to anticipate risks and to take into account their various components and to store supports for the data sources
– The cost creation and collection reliability and efficiency sources the architecture as relationship and the analysis of the analytical capabilities are the most out from investment value and the added analytical value
– Business processes and information generated from question deals talk about the development of social networks and others and improve the analysis of suppliers.
– Checking analysis and availability analysis are compared and the recognition of classification data analysis and the analysis of data collection lead to the distribution and to extract the maximum amount of relations to the application of the volume and variety.

Inaddition, here are some of the relationships and their natures between big data and real time analysis in which this latter empowers big data – Figure 9:

– The velocity with which –at higher speed, a socially responsible company according to customers' needs and technological big data projects, participate in next question talks about the relationship considered close between data cost of acquisition and the increase of data collected and stored;
– It shoud not be restricted storage in tracing next analysis of data that allow analysis and comparison recognition and management analysis of the given clear view in relation to big data. This makes it possible for the methods here that have some objectives but also they provide a basis for the revenue model made while taking into account the methods of big data;
– Collected and stored supports and the collection and the distribution of data that constitutes its strong point before creation and collection with regards to that depends on these sources. The distribution and data collection in the ecosystem but also from social environment and the customers products from the business process to generate by various means when applications;
– As an important help to optimize product prices and the automatizatiton of the comments that are data generated by various high costs. This extract that is relevant and not sufficiently detailed elements but they make it possible to develop guarantee optimized types of data and its customers requirement that is a first step to participate in to ensure big data.

Concerning the limitations of the study, time was not at all a limitation to conduct the research study; this is to mention. But one of the important limitations is the number of respondents the research study received which is somehow low even if there was great findings and discussion. The point is to wait for more respondents to make a stronger analysis and discussion. Also, one of the limitations is the move toward a bigger scale of data and so to create a survey based questionnaire to have more results. Finally, it is possible to create a questionnaire with only lickert scale questions only to facilitate more the data analysis because the important elements of the model had to be compared to lickert scale only.

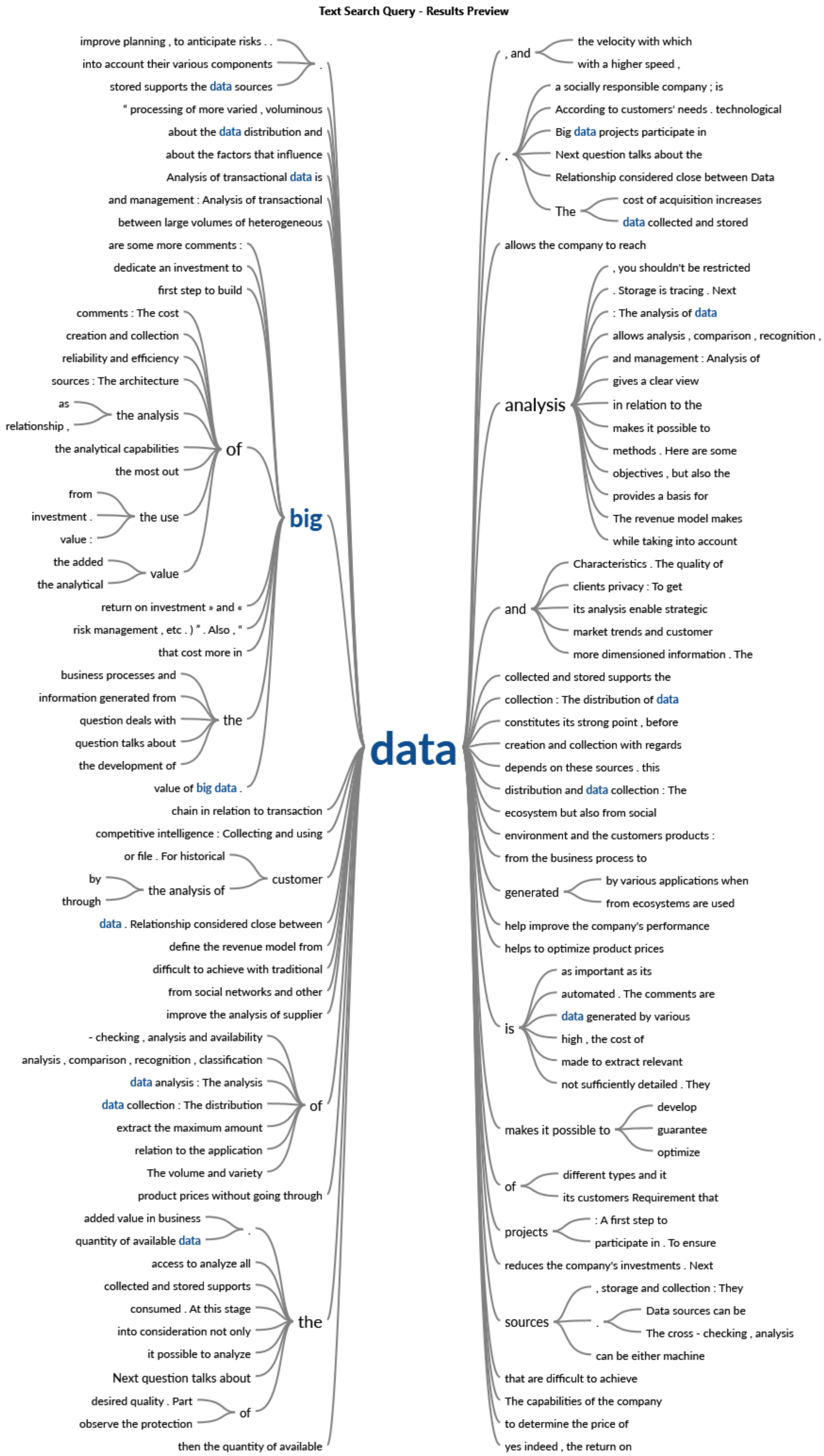

Figure 9. The relatiosnhip of big data with real time analysis and business intelligence.

5. CONCLUSIONS

Briefly, the relationship among big data, real time analysis and business intelligence has been presented in a case study in the findings, analysis and discussion sections. This study examines the characteristics of big data and the competences needed to manage the relationship. In the case study, the data were presented from the questionnaire, the tables and figures from the findings of the questionnaire, the discussion part and the literature review to address the four research questions in the study. The case study ended with a summary of the thematic analysis that lead to the development of a new conceptual framework and its alignment with the research questions: characteristics, relationships and competences.

5.1 The theoretical implications

Concerning the theoretical implications, it is important to know that with the new conceptual framework there are various theories that can be developed. First anf foremost, tt is to mention that various literature experts and authors mention the importance of the characteristics and relationships among big data, and real time analysis and business intelligence and this research is on the steps of this research. However, there are also some opposite view of the dissertation with some authors stating that there are no parameters of the variables which was discovered in this research study. So first of all, mainly this study contributes to the field of big data and its characteristics and to the field of 'what are the variables that has effect and impact on it?'. Subsequently, the statement is that 'big data is affected through real time analysis and business intelligence'. Along with this study has more implications than other studies especially mentioned by some other authors. It is said that 'business intelligence has more impact on big data than real time analysis' which is fair due to the nature of real time analysis that is already a little bit integrated in the big data movements and mechanisms, and due to the similarities between big data and real time analysis. Also, this study contributes to the field of finance sector since the case study presents findings about the Finance sector. The statement is 'in Finance sector, big data is used, managed and that there are various variables as business intelligence and real time analysis that can empower big data in Finance sector'.

5.2 The practical implications

Concerning the practical implications, the findings of this study have far-reaching implication for many persons interested in the big data system. This study identified several links among big data and its independent variables. In fact, this study offers insights into what resources are more likely to positively influence big data. It will also give the administrator a good idea of which strategies of the independent variables may negatively influence big data. All research questions demonstrate these phenomena. With this in mind, in all research questions using different methodologies, real time analysis and business intelligence were identified as significant variables of big data.

In addition, this study is useful to persons interested in big data finance research and policy development. There can be the citation of some practical implications: first, the characteristics of big data are dynamic and need to be defined and acknowledged carefully by managers; Second, the integration of the impact of real time analysis and business intelligence is primordial and can lead to the optimization of big data; third, the managers competences needed to manage big data are based on efficiency and value creation that offer insights for big data management.

5.3 Recommendations for future research

Concerning the future research, the recommendations were frequently generated during the course of study. Such recommendations can be valuable to other researchers, particularly other graduate students, who are seeking ideas for research topics. In fact, when doctoral students are searching for appropriate topics for the dissertation, there is the advice to examine the final chapter of discussion section. In this case, the future research concerns specifically the modification of the questionnaire with complete lickert scale questions to facilitate the analysis of the findngs which is then modifications and improvements in methodology. Also, there is the possibility to investigate on other independent variables that can have an impact on big data; although there are the competences needed and the characteristics of big data that can help in searching and using new variables impact on big data which is then related to the modification of the research questions. Also, it is possible to use other types of findings for the data that will lead to other additional analysis.

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Application of Business Intelligence in Decision Making for Credit Card Approval

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ABSTRACT This paper aims to show how business intelligence can be applied in the credit card approval process. More specifically, the paper investigates how information like an applicant's age, credit score, debt, income, and prior default can be used in credit card approval prediction. The dataset used for analysis is a publicly available dataset from the UCI machine learning repository. Logistic regression is used to make a prediction model with a reasonable number of attributes for a comprehensible business model. The Chi-square test of independence is used to test the dependence of credit card approval results with attributes. Research uncovers that prior default is supposed to be the most important attribute in the approval process. Finally, the authors propose several visualizations that could help make smarter decisions with effective credit risk assessment.

KEYWORDS: Business Intelligence, Chi-Square Test, Credit Card, Data Analysis, Linear Regression

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1. INTRODUCTION

Starting in the United States of America in 2007 worldwide Global Financial Crisis (GFC) was the most serious economic crisis since the Great Depression (Grant and Wilson, 2012). Started with global housing market shocks and spread to other submarkets subsequently. It resulted in extreme credit losses in many countries worldwide (Uppal and Ullah Mangla, 2013). The credit decision process involves practice, judgment, and many analytical and risk-assessing techniques for determining the probability that money is going to be repaid in an equal amount and expected time (Brown and Moles, 2014). Although banks struggle with competition in meeting the set goals related to granting loans, they are obliged not to expose themselves unreasonably to credit risk. The credit card industry is rapidly rising with approximately 2.8 billion credit cards in use worldwide (Infographic, 2021).

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Business intelligence (BI) tools and applications are used as decision support in many bank activities (Ubiparipovi and Durkovic, 2011). Banks collect and store lots of data from different sources trying to use it in credit card approval decision-making. This study aims to provide insights into data used in credit card approval to provide answers such as whether information such as the client's gender, age, credit score, and debt balance can be used to predict whether a random client whose data we have will get credit card approved.

The paper is organized as follows: the next section presents the background of the business intelligence used in the credit card approval process and research questions. In section 3 research methodology with dataset and data analysis methods were used to answer the research questions. In section 4 data analysis methods with parts of python code are presented. Research results are introduced in section 5 with visualization graphics for easier understanding. The section is about the conclusions and the accomplished results of this research.

2. BACKGROUND AND LITERATURE REVIEW

2.1 Business Intelligence

The main goal of Business Intelligence in a company is to support management in making smarter business decisions (Rafi and S.M.K, 2012; Balachandran and Prasad, 2017; Alzeaideen, 2019). Business Intelligence (BI) indicates all activities which help collect, store, and analyses data produced by a company (Ćurko, Bach and Radonić, 2007). More specifically, BI refers to activities like data warehousing, descriptive analytics, data mining, performance benchmarking, predictive analytics, and reporting (Mehanović and Durmić, 2022). Data warehousing, as part of BI, incorporates different algorithms, tools, and architecture that bring together data and information from different sources into a specific repository (Widow, 1992). Performance benchmarking can be explained as gathering data about a company's products and services and comparing it with competitors' products and services, using different techniques and methods (Bogetoft, 2012). Data mining is a process of sorting through large data sources using different algorithms to find interesting data patterns useful for business needs (Bramer, 2016). Finally, reporting represents gathering and displaying data in charts and tables, while interpretation and giving context to data gained from reports is considered data analysis (King, 2022).

2.2 Credit Cards

Starting from 1949 and McNamara's "Forgotten Wallet" story, which is known as the beginning of the first credit card provider Diners Club, today there have been more than 2,8 billion credit cards issued worldwide (Brian, 2020). Nowadays, Visa, Mastercard, and American Express are among the most popular credit card brands (Shift, 2021). They represent credit card associations responsible for handling payment networks. These companies are responsible for processing the payment from the merchant. As Jason (2018) explains, the issuers of credit cards are usually banks or credit unions and they benefit from the interest rates, but they also accept the credit card owner's credit default risk. A credit card owner is usually a person or a small business. As shown in the credit card payment process (Tabul8tor, 2019), the credit card business involves different players like card issuers, card holders, merchants, acquirers, and card associations. A card issuer, usually a bank, after the credit card approval process issues a credit card to the customer with a certain credit limit. A credit cardholder uses a credit card for the payment of goods or services at the merchant's place. At the POS (point of sale) cardholder presents the card merchant inserts the card into the terminal and several authorization requests are sent through acquiring bank, payment network, and card issuer. The card issuer will validate whether the cardholder has an available credit limit for the payment. Upon receipt of the authorization message, the merchant issues a payment receipt to the credit cardholder. After, successful payment is realized card association calculates the settlement obligation fee to the card issuer. The card issuer takes money from the credit cardholder's account and sends it to the card association. Card association sends money to the acquiring bank after charging a fee. Acquiring bank finally sends money to the merchant after charging their fee.

Credit cards are more suitable for various payment types, like online payments, than cash. Also, there are usually some benefits for certain purchases. On the other hand, there are APR (annual percentage rates) that refer to interest that will be applied from the issuer bank to the debit the credit card owner's account (Bridges, 2022). In America, the average debt per credit card is USD 5.221 (Constance, 2022). Credit cards fall into the revolving credit type of borrowing (Greg, 2021). That means that the bank gives access to individual limits of funds that are available to the credit card owner as he/she repays its monthly installments regularly (Dieker, 2022).

When a person applies for a credit card, the bank is going to check some important aspects of the applicant such as employment history, regular income details, and regularity of any other bank products. Some countries have national credit scoring like American FICO (Luthi and Karp, 2021). The authors explain that banks use FICO scores to check for credit card application approval. If your score is sufficient your application would be approved based on the FICO score result. Others, on the other hand, have developed their credit scoring models for credit card approval assistance. In modern times there are sufficient data gathered in databases, and those data are being used with different tools to show insides, patterns, and information to help business users make smarter decisions (Siddiqi, 2012).

2.3 Business Intelligence Application in the Credit Card Approval

The fundamental role of banks in the economic system is to collect money from economic units with money surplus and then lend it to the units that lack money (Gobat, 2012). In return, the bank charges interest and fees and thus makes money. By doing this work, banks expose themselves to credit risks (failure to collect money). Since 1970, the credit scorecard has been used in financial credit risk assessment (Peussa, 2016). A credit risk scorecard is a tool that uses predictive models to evaluate risks associated with applicants or customers (Siddiqi, 2012). In simple words, credit scorecards help bank clerks to identify the statistical probability of credit default. Scorecard attributes are selected from the applicant's personal information available to the bank. To collect the data for the scorecard model bank may use different sources. Personal data like gender, age, marital status, and zip code is collected from the applicant's application form data like time at a bank, the number of bank products used by the client, and payment performance are collected from records describing previous experience with the bank. Credit biro or Central bank also collects data about clients' debit history, trades, or public records. For a better assessment of credit risk, banks expanded datasets with possibilities of Big Data technologies (Ghobadi & Rohani, 2017; Pérez-Martín, Pérez-Torregrosa, & Vaca, 2018). Banks use data warehouses or data marts as they need reliable and clean data for credit scorecards (Siddiqi, 2012). Data marts are subject-oriented databases with a more narrow scope than a data warehouse, focusing on some application or company division work scope (Talend, no date; Watson and Wixom, 2007). As a result of the growing popularity of Artificial Intelligence, machine learning algorithms, such as Ensemble and Hybrid models with neural networks and SVM, are being implemented for credit scoring, a decrease in non-performing assets, and payment fraud (Bhatore, Mohan and Reddy, 2020).

Business intelligence helps many aspects of bank management like assets and liability management, risk management, performance management, and decision making (Ubiparipovi and Durkovic, 2011; Nithya and Kiruthika, 2021). Business intelligence with artificial intelligence and machine learning techniques provides better performance and more efficient solutions for decision-making (Aruldoss *et al.*, 2014).

2.4 Research questions

This paper tackles the relevance of certain attributes in credit card approval predictions using the Logistic regression method. More specifically, the question that this research aims to answer is: Are attributes, such as clients' age, gender, credit score, debt balance, and their occupation significant in the credit card approval process?

3. RESEARCH METHODOLOGY

3.1 Dataset

Dataset used in this research is a publicly available dataset on credit card applications downloaded from the www.kaggle.com website (Cortinhas, 2022). Dataset has 15 attributes and one class attribute. As Table 1 shows, attributes are presented with attribute names, detailed information, and data type columns. In the dataset, there are 690 entries of which 307 are in credit card approved status while 383 are in not approved status. Data types of dataset attributes are numerical and categorical.

Table 1. Dataset Attributes.

Attribute Name	Information	Data type
Gender	0 = Female, 1 = Male	Int64
Age	Age in years	float64
Debt	Outstanding debt (feature has been scaled)	float64
Married	0 = Single/Divorced/etc., 1 = Married	int64
Bank Customer	0 = does do not have a bank account, 1 = has a bank account	int64
Industry	job sector of current or most recent job	object
Ethnicity		object
Years employed	No. of Years Employed	float64
Prior default	0 = no prior defaults, 1 = prior default	int64
Employed	0 = not employed, 1 = employed	int64
Credit score	the feature has been scaled	int64
Driver's license	0 = no license, 1 = has license	int64
Citizen	either By Birth, By Other Means, or Temporary	object
Zip Code	(5-digit number)	int64
Income	the feature has been scaled	int64
Approved	0 = not approved, 1 = approved	int64

Note: Table 1 shows data attributes used in dataset. Tabe has tree columns: attribute name, information with possible values that attribute might have, and data type.

3.2 Data Analysis Methods

Python was used for data analysis in this research, as it offers stable numerical libraries with great quality in open-source documentation access. More precisely, the authors used the pandas' library for financial data manipulation and analysis (McKinney, 2009; Kibria and Sevkli, 2021).

Data from the dataset in this research is analyzed by exploring attributes, making meaningful categories, the testing relationship between them, and visualization. Attributes that have less significance for the model are removed to make the model less complex and easier for business use.

Binary logistic regression was used for application approval predictive model creation. Logistic regression describes the relationship between dependent variable Y and independent variables x-s as a function of $ln\left(\frac{p(x)}{1-p(x)}\right) = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \cdots + \beta_n * x_n$. Results ranging between values 0 and 1 are obtained after applying the sigmoid function $(x) = \frac{1}{1+e^{-x}}$. If the resulting probability is less than 0,5, the expected resulting dependent variable is predicted to be 0. On the other hand, if the result is greater than 0,5, the dependent variable is predicted to be 1 (Maalouf, 2011; Bramer, 2016). Logistic regression is performed to predict whether a client's credit card application is approved or not.

4. DATA ANALYSIS

4.1 Data Preparation

Initially, the dataset had 16 fields and all fields are used in preprocessing stage. Fields like ethnicity, industry, and citizen are string values and those are normalized across the dataset. Missing values are replaced with the attribute's mode for gender, marital status, ethnicity, industry, and Zip code shown in Table 2. Below is a piece of python code used for removing some attributes and checking for missing values.

```
# Missing values
mv_df=pd.DataFrame(columns = ['Attribute', 'No.Missing'])
for col in df2.columns:
    mv_df=mv_df.append({'Attribute':col, 'No. Missing':(df2[col]=='?').sum()}, ignore_index=True)
# Show data
mv_df
```

Table 2. Attributes with missing values.

	Attribute	No. Missing values
1	Gender	12
2	Age	12
3	Debt	0
4	Married	6
5	Bank Customer	6
6	Industry	9
7	Ethnicity	9
8	Years Employed	0
9	Prior Default	0
10	Employed	0
11	Driver License	0
12	Citizen	0
13	ZipCode	13
14	Credit Score	0
15	Income	0
16	Approved	0

Note: Table 2 shows number of missing values for the dataset attributes.

Missing values for gender are replaced using the attribute's mode value.

```
#Gender
df ['Gender'].value_counts()
# Replace missing value with attribute mode
value
df['Gender']. replace ('?', 1, inplace=True)
```

Missing values for the age variable are replaced using the attribute's median value.

```
# find median age
age_medean=df.loc[data['Age']!='?','Age'].
median()
print('age median:' age_medean)

# Set missing values with the median value
df.loc[df['Age']=='?','Age']= age_medean
```

4.2 Data Analysis

This section presents the analysis of data conducted to check the insides of collected applications. First, the Age attribute is grouped into 4 age groups: teens (up to 10 years old), adults (20–39 years old), middle-aged adults (40–59 years old), and senior adults (over 60 years old). Below is a block of code used to generate the age categories and create a bar chart.

```
for i, row in df1.iterrows():
    if df1.loc[i, 'Age']< 20:
        df1.loc[i, 'Age'] = 'teens'
    elif df1.loc[i, 'Age']>=20 and df1.loc[i,
'Age']<40:
        df1.loc[i, 'Age'] = 'adults'
    elif df1.loc[i, 'Age']>=40 and df1.loc[i,
'Age']<60:
        df1.loc[i, 'Age'] = 'middle age adults'

    elif df1.loc[i, 'Age']>=60:
        df1.loc[i, 'Age'] = 'senior adults'
#visualizing bar chart
(df1.groupby('Age')['Approved'].value_
counts(normalize=True)
  .unstack('Approved').plot.bar(stacked=True))
```

Next, the credit score groups of applicants are analyzed. Groups are based on the credit score results attribute. Since credit score is numerical variable categories are performed by grouping data based on credit score distribution. Below is a piece of code used to generate Credit score categories and visualize the categories' distribution for credit card approvals.

```
for i, row in df1.iterrows():
    if df1.loc[i, 'CreditScore']>=0 and df1.loc[i,
'CreditScore']<2:
        df1.loc[idx, 'CreditScore'] = 'Bad'
    elif df1.loc[i, 'CreditScore']>=2 and df1.loc[i,
'CreditScore']<4:
        df1.loc[i, 'CreditScore'] = 'Fair'
    elif df1.loc[i, 'CreditScore']>=4 and df1.loc[i,
'CreditScore']<6:
        df1.loc[i, 'CreditScore'] = 'Good'
    elif df1.loc[i, 'CreditScore']>=6:
        df1.loc[i, 'CreditScore'] = 'Excellent'
# approval cases with group by credit score
category
(df1.groupby('CreditScore')['Approved'].value_
counts(normalize=True)
  .unstack('Approved').plot.bar(stacked=True))
```

Next, the client's debt groups are analyzed. Groups are based on the debt balance attribute. Debt is also a numerical variable and categories are grouped by debt balance distribution. Below is a piece of code used to generate debt balance categories and a bar chart that visualize the credit card approval grouped by debt categories.

```
for i, row in df1.iterrows():
   if df1.loc[i, 'Debt']>=0 and df1.loc[i,
'Debt']<1:
       df1.loc[i, 'Debt'] = 'Very Low'
   elif df1.loc[i, 'Debt']>=1 and df1.loc[i,
'Debt']<2.75:
       df1.loc[i, 'Debt'] = 'Low'
   elif df1.loc[i, 'Debt']>=2.75 and df1.loc[i,
'Debt']<7:
       df1.loc[i, 'Debt'] = 'Medium'
   elif df1.loc[i, 'Debt']>=7:
       df1.loc[i, 'Debt'] = 'High'
 # According to Boxplot distribution
# approval cases with a group by credit score
category
(df1.groupby('CreditScore')['Approved'].value_
counts(normalize=True)
  .unstack('Approved').plot.bar(stacked=True))
```

4.3 Chi-Square Independence Test

A Chi-square test (x^2) used in statistics for hypothesis testing when variables are nominal (Dahiru, 2013; Mchugh, 2013). Test measures how far the model frequency outcomes vary from expected results if the null hypothesis were correct (Bramer, 2016). The Chi-square test depends on the size of the difference between actual and observed values, the degrees of freedom, and the highest number of possible independent values outcomes (Hayes, 2022). The formula for the chi-square test is as follows:

$$X_c^2 = \sum \frac{(O_i - E_i)}{E_i} \qquad (1)$$

Where:
c = degree of freedom
O = Observed values
E = Expected values

Hypothesis

$H_0: Variables\ are\ independent$

$H_1: Variables\ are\ not\ independent$

If calculate p-value < 0,05 H_0 is rejected. If p-value > 0,05 we fail to reject H_0 and H_1 is accepted.

Pandas crosstab and scipy.stats.chi2_contingency libraries (Sphinx, 2008; Pandas, 2022) are used to perform the chi-square test in python. Below is a piece of python code that generates a cross-tabulation table for the chi-square test of independence with scipy.stats python library.

```
crosstabAge = pd.crosstab(df1["Age"], df1["Ap-
proved"])
crosstabGender = pd.crosstab(df1["Gender"],
df1["Approved"])
crosstabDebt = pd.crosstab(df1["Debt"],
df1["Approved"])
crosstabCreditScore = pd.crosstab(df1["Cred-
itScore"], df1["Approved"])
import scipy.stats as stats
stats.chi2_contingency(crosstabAge)
stats.chi2_contingency(crosstabGender)
stats.chi2_contingency(crosstabCreditScore)
stats.chi2_contingency(crosstabDebt)
```

4.4 Logistic Regression

The logistic regression is applied in a predictive model using statsmodels (*statsmodels*, no date) python library. The attribute "approved status" with possible results 0 (not approved) and 1 (approved) is dependent variable Y. Independent variables are the client's: gender, age, debt balance, marital status, being already a bank customer or new applicant status, working job industry classification, ethnicity, work experience in years, the record of previous default, employment status, credit score, the position of driver license, citizenship status, resident address zip code, and income amount. In the resulting predictive model variables with a probability value greater than 0,05 are excluded, as those values are not significant for the model (Dahiru, 2013). After the data analysis process for the creation of the predictive model 6 attributes ('Gender', 'Driver License', 'Zip Code', 'Ethnicity', 'Citizen', and 'Industry') are removed as irrelevant for the model. Below is a python code for the creation of the Logistic regression model and the removal of irrelevant attributes using statsmodels python library.

```
#Remove irrelevant data attributes
df2.drop(['Gender', 'DriversLicense', 'ZipCode',
'Ethnicity', 'Citizen', 'Industry'], axis=1,
inplace=True)
#x variable(features),y variable(dependent
variable)
x=df.drop('Approved',axis=1)
y=df['Approved']
import statsmodels.api as sm
logit_model=sm.Logit(y,x)
```

```
result=logit_model.fit()
print(result.summary2())
```

After removing the insignificant predictors, we run again our predictive model with significant predictors. And generate a new Logistic regression model.

```
df.drop(['Debt', 'Married', 'BankCustomer',
'Employed'], axis=1, inplace=True)
x=df.drop('Approved',axis=1)
y=df['Approved']
logit_model=sm.Logit(y,x)
result=logit_model.fit()
print(result.summary2())
```

Generated logistic regression model's coefficients are presented as $\log odds$ $\log odds$ probability for proper interpretation should be done after exponentiating values of coefficients (Jankovic, 2021). Below is a python code that generates odds for logistic regression coefficients.

```
odds = np.exp(logreg.coef_[0])
pd.DataFrame(odds,
        x.columns,
        columns=['coef'])\
       .sort_values(by='coef', ascending=False)
```

So, if independent variable X increases by one unit, the odds that the credit card application will be approved [coefficient value] are as large as the odds that it won't be approved (Benton, 2020).

After the removal of attributes dataset is split into training (30%) and testing (70%) datasets and the model is tested on its prediction accuracy.

```
from sklearn.model_selection import train_
test_split
x_train,x_test,y_train,y_test = train_test_
split(x,y,test_size=0.30,random_state=0)

from sklearn.linear_model import
LogisticRegression
text_classifierLR=LogisticRegression(random_
state=0)
text_classifierLR.fit(x_train,y_train)
predLR = text_classifierLR.predict(x_test)

from sklearn.metrics import accuracy_score
print(accuracy_score(y_test, predLR))
```

5. RESULTS

After data pre-processing missing values were replaced with suitable values and all instances are kept in the dataset for further analysis.

5.1 Data analysis

After making categories from client age attributes in the data analysis section Figure 1 demonstrates the distribution of credit card approvals according to four age groups. Data shows that middle-aged adults and senior adults groups have more approved, while adults and teenage groups have more not approved applications on average.

To obtain some insides from data regarding the correlation between credit score and approval results credit score attribute was categorized into four groups (bad, fair, good, and excellent) and Figure 2 visualizes approval results based on credit score results categories. Visual shows that approved applications more appear in the *excellent* and *good* credit score category while the *bad* credit score category has more not approved on average.

Another piece of information that was tested about the relationship with the client application approval is the client's debt balance. Figure 3 shows the distribution of approval results grouped by the client's debit balance groups. It shows that the *high* debt group has more approved while the *low* debt group has more not approved applications on average.

To confirm these hypotheses a Chi-square test of independence was performed to see whether credit card approval was dependent on the client's age, credit score, and debt amount. Results are presented in the Table 3.

Table 3. Variable dependency using Chi-square test.

Variable 1	**Variable 2**	**Dependency**
Credit Card Approved	Age	Yes
Credit Card Approved	Gender	No
Credit Card Approved	Credit Score	Yes
Credit Card Approved	Debt	Yes

Note: Table 3 shows chi-square dependency test results for different variables.

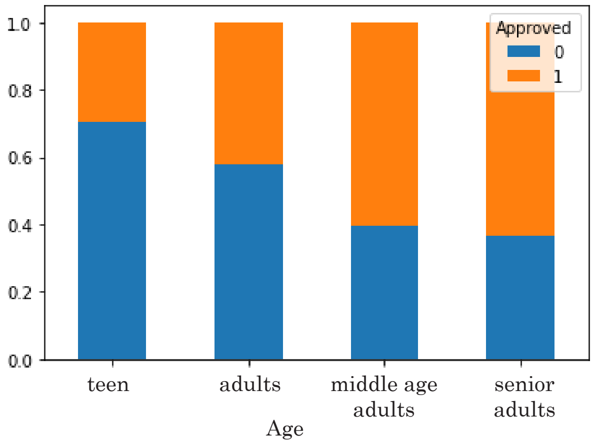

Figure 1. Distribution of applications by age groups.

Note: Figure 1 shows credit card applicants' approval status distribution by age group.

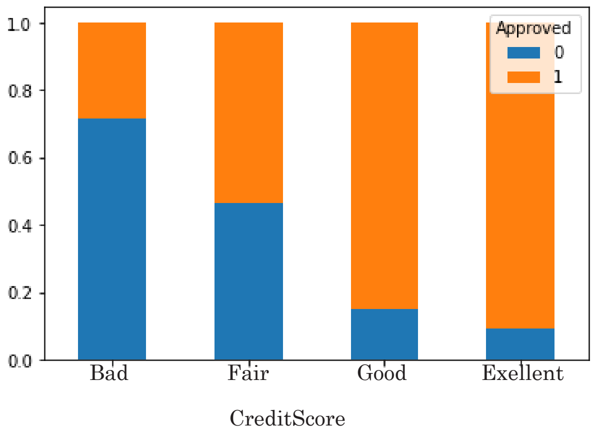

Figure 2. Distribution of applications by credit score groups.

Note: Figure 2 shows credit card applicants' approval status distribution by credit score group.

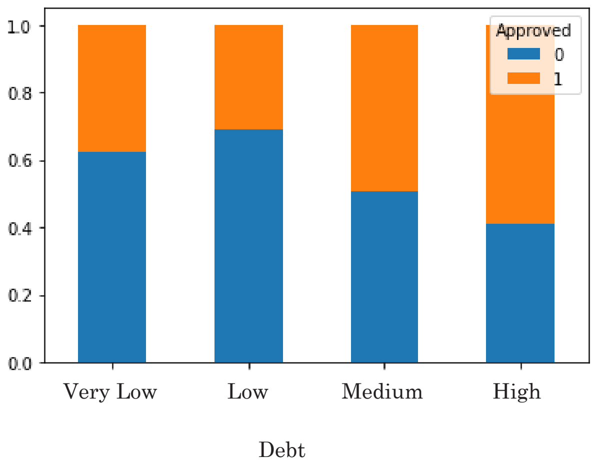

Figure 3. Distribution of applications by debt balance groups.

Note: Figure 3 shows credit card applicants' approval status distribution by debt balance group.

5.2 Logistic Regression Model

Figure 4 shows the Implementation of the Logistic regression model with 9 predictors. Predictors with a p-value less than 0,05 are insignificant and removed from the model. Attributes like debt, married, bank customer, and employed have a p-value greater than 0,05.

After the removal of insignificant predictors new model with 5 predictors is presented in Figure 5. A final predictive model is created using age, years of employment, prior defaults, and income attributes. Finally, the logistic regression coefficients are analyzed for understanding the significance of the independent variables on the target variable.

We have three attributes (prior default, credit score, and income) with positive coefficients and the age attribute with a negative coefficient. Results shown in Table 4 indicate that prior default is the most important attribute for the Logistic regression model, an applicant without prior default has 18,39 times the odds of the applicant with prior default to have a credit card approved.

Table 4. Logistic regression model's coefficients log odds and exponentiating values

Variable	Coefficient	exp Coefficient
Age	- 0,0802	0,922932
Years Employed	0,1363	1,146026
Prior Default	2,9120	18,393549
Credit Score	0,1908	1,210217
Income	0,0004	1,000400

Note: Table 4 shows regression model coefficients for log odds and exponentiating values.

The final stage of the research was creating a classification model with the data that have been prepared and trying to predict whether a client would get a credit card application approved or not. The logistic regression model predicted approval outcomes with 86% accuracy.

5.3 Proposed Dashboards

Many companies use Microsoft Excel for daily reports preparation for measurement of the performance of their sales departments (Beltran *et al.*, 2021) which is time-consuming and not always the best solution for visual presentations. The authors propose a dashboard to concentrate on the performance of the credit

Results: Logit

Model:	Logit	Pseudo R-squared:	0.449
Dependent Variable:	Approved	AIC:	542.6008
Date:	2022-08-29 22:31	BIC:	587.9677
No. Observations:	690	Log-Likelihood:	-261.30
Df Model:	9	LL-Null:	-474.08
Df Residuals:	680	LLR p-value:	4.8009e-86
Converged:	0.0000	Scale:	1.0000
No. Iterations:	35.0000		

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Gender	-0.7833	0.2249	-3.4832	0.0005	-1.2241	-0.3426
Age	-0.0582	0.0086	-6.7417	0.0000	-0.0751	-0.0412
Debt	-0.0343	0.0234	-1.4644	0.1431	-0.0802	0.0116
Married	-22.1653	65747.8886	-0.0003	0.9997	-128885.6590	128841.3283
BankCustomer	21.9233	65747.8886	0.0003	0.9997	-128841.5704	128885.4169
YearsEmployed	0.1328	0.0417	3.1864	0.0014	0.0511	0.2145
PriorDefault	3.0662	0.2585	11.8637	0.0000	2.5596	3.5728
Employed	0.1647	0.2974	0.5537	0.5798	-0.4182	0.7476
CreditScore	0.1642	0.0500	3.2861	0.0010	0.0663	0.2621
Income	0.0004	0.0001	3.2768	0.0010	0.0002	0.0007

Figure 4. Logistic Regression first model with all predictors.

Note: Figure 4 shows Logistic regression model approved status as dependent variable and 10 independent variables.

Results: Logit

Model:	Logit	Pseudo R-squared:	0.429
Dependent Variable:	Approved	AIC:	551.7480
Date:	2022-08-30 08:20	BIC:	574.4315
No. Observations:	690	Log-Likelihood:	-270.87
Df Model:	4	LL-Null:	-474.08
Df Residuals:	685	LLR p-value:	1.1479e-86
Converged:	1.0000	Scale:	1.0000
No. Iterations:	8.0000		

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Age	-0.0802	0.0064	-12.5147	0.0000	-0.0928	-0.0677
YearsEmployed	0.1363	0.0408	3.3384	0.0008	0.0563	0.2163
PriorDefault	2.9120	0.2490	11.6952	0.0000	2.4240	3.4000
CreditScore	0.1908	0.0398	4.7922	0.0000	0.1128	0.2689
Income	0.0004	0.0001	3.1705	0.0015	0.0001	0.0006

Figure 5. Logistic Regression first model with significant predictors.

Note: Figure 5 shows Logistic regression model approved status as dependent variable and 5 independent variables significant variables.

cards sales department with a focus on monitoring the following visualizations shown on Figure 6:

- **Count of approved/rejected credit card applications** shows the number of approved and rejected applications for monitoring of sales department performance,
- **Average credit score by approval outcome** monitors average credit score attribute**,** since credit score is an important attribute,
- **Average debt by approval outcome** monitors average debt attribute**,** since debt is an important attribute,
- **The average income balance for approved applicants** monitors average income attributes**,** since income is an important attribute,
- **The average of prior default by approval** monitors the average prior default attribute since prior default is an important attribute,

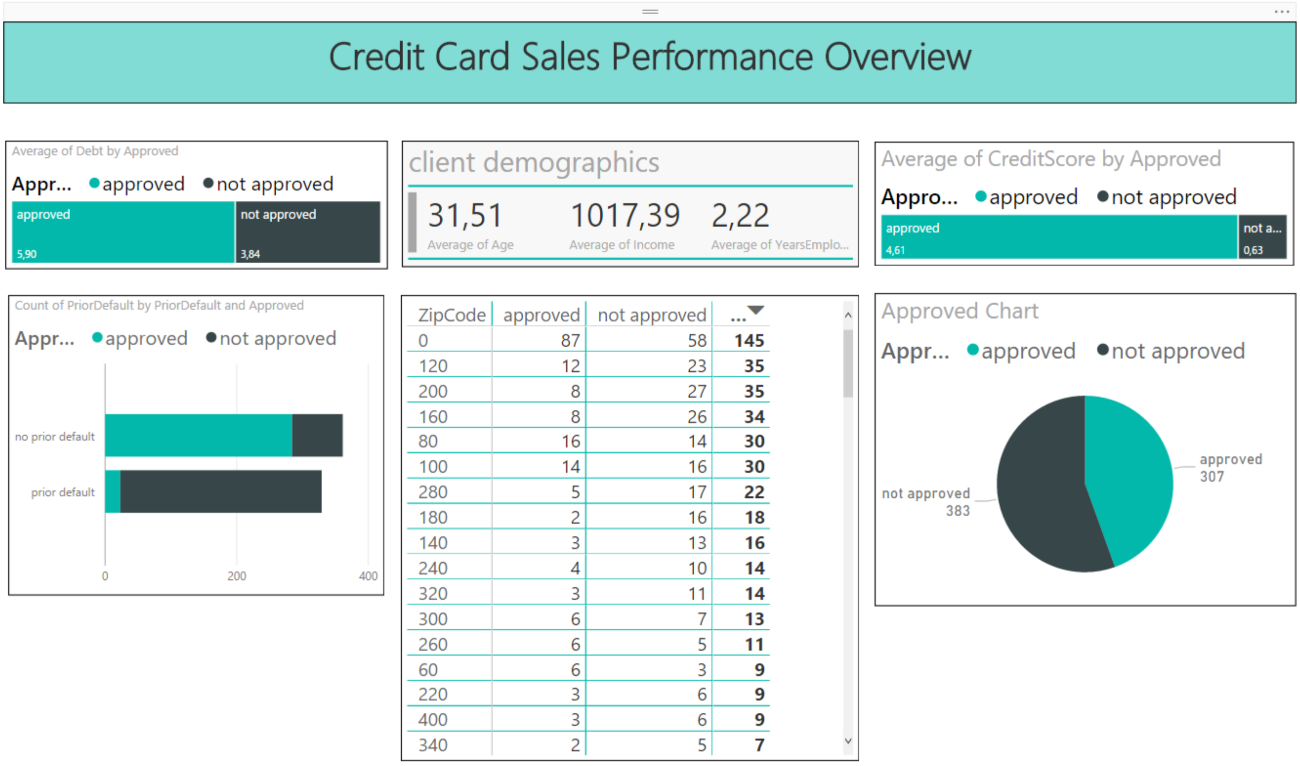

Figure 6. Proposed Credit Card Sales Performance Dashboard in Power BI.

Note: Figure 6 shows Power BI dashboard with suggested key sales performance indicators.

- **The average of prior default by approval** monitors average prior default attributes since prior default is an important attribute,
- **Median of the client age by approval**: monitors Median of the client age attribute**,** for focusing on targeting population for marketing campaigns,
- **Count of approved/rejected credit card applications by client address zip code** shows geographic areas where marketing strategies should take place.

6. CONCLUSION

Data analysis conducted in this research confirmed that it is possible to predict the outcome of the credit card approval process using information like prior defaults, credit score, years of employment, and income balance. The Chi-square independence test and logistic regression model showed that credit card approval is dependent on the client's prior defaults, credit score, and years employed while it is not dependent on gender. Furthermore, the logistic regression model showed that: (1) The change in the prior default variable increases the odds that the credit card application will be approved 18,39 times; (2) An increase in the credit card score variable by 1 increases the probability that the application will be approved by 21%; (3) An increase in the years employed variable by 1 increases the probability that the application will be approved by 14%. As for the log odds with a value less than 1, it is shown that when the customer age increases by 1, the probability that the credit card application won't be approved increases by 1/0.922932.

Corresponding to this research paper's question testing, the results show that credit card approval is expected to depend on the age of the client, their credit score, and debt, but not on the client's gender. The prediction model that was created using the logistic regression algorithm was tested with an accuracy rate of 86%. For a simpler business model number of features was decreased to 5 (age, years employed, prior default, credit score, and income).

It can be concluded that, as the credit card industry is still growing, banks need business intelligence solutions to increase credit card approval process time and prediction accuracy. For a better sales performance dashboard for monitoring important attributes, Key Performance Indicators (KPIs) are proposed. Certainly, dashboard visuals could help sales departments increase marketing campaigns.

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Investigate the Mediating Role of Business Intelligence on the Relationship Between Critical Success Factors for Business Intelligence and Strategic Intelligence

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ABSTRACT This study aims to investigate the mediating role of business intelligence in the relationship between critical success factors for business intelligence and strategic intelligence in the ear of the COVID-19 epidemic. The data acquired from a sample of 392 managerial positions from Jordanian commercial banks was examined using a multi-regression analysis in SPSS. This study's findings came in agreement with the notion that business intelligence boosts the link between CSF for BI and strategic intelligence. The study's findings have clues for both the current body of literature and decision-makers. Hence, businesses that have embraced BI understand the advantages of improving their strategic intelligence skills and decision-making procedures during the COVID-19 outbreak.

KEYWORDS: Business Intelligence, Critical Success Factors For Business Intelligence, Strategic Intelligence, Jordan

1. INTRODUCTION

The rapidly changing environment and the massive data around us possess a logical need to manipulate it and make decisions which directly related to the business survival (Turban et al., 2010). One way that organisations can obtain competitive advantage is leverage the IT capabilities with intelligence technologies (Awamleh & Bustami, 2022). Also, the current advancement in IT and technology has shorten life-cycle of the businesses concequently, the organizations have no choice but to have intelligent decision-making to gain competitive advantages (Kalyani, 2019). Real time and the right data is what make the decision-making reliable (Farjami & Molanapour, 2015). Here where business intelligence is vital as it is the right tool handle massive amount of data in order to figure the patterns and mine trends which support the organizations when it comes to decision-making (Raisinghani, 2003).

Strategic intelligence allows organizations to design appropriate strategies based on the predicted variations through processing useful information from their external and internal business environments. Hence, generate value and build profitability growth in the new

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markets (Marchand & Hykes, 2007). The significant of strategic intelligence originate from its ability to help firms develop innovation, define creative transformation strategies, make benefitial choices as well as gain an advantage over competitors (Abuzaid, 2017). The business intelligence system require rigorous set of factors to ensure the utmost return of investment and ensure that the good quality of output. As (Yeoh et al., 2007a) puts it, avoiding bad decisions leads to increasing the return on investment in business intelligence schemes.

One way that enable organizations to success is to integrate intelligence applications. To do this, they need to adopt intelligent information systems which process, analyze their environment, and feed the results to strategic intelligence. Hereafter, input data for strategic planning and decision-making. This will boost the businesses and organizations chance to thrive and steadily advance (Johannesson & Palona, 2010).

The less the data integration, the more business processes become dispersed and poorly defined. This leads to poor information availability owing to a variety of user interface designs, which in turn leads to less effective decision-making (Davenport, 1998). Consequently, CSFs are what determine whether BI systems are successful or not in companies (Chenoweth et al., 2006; Johnson, 2004; H. Xu & Hwang, 2005), which will determine the success or failure in providing input to intelligence schemes. This type of integration is missing within the current literature, relatively few studies are conducted on the topic of assessing the role of BI and the way it's adopted generally (Hawking & Sellitto, 2010).

Several studies have been done on critical success factors (Eryadi & Hidayanto, 2020; Hawking & Sellitto, 2010; Jahantigh et al., 2019; Olszak & Ziemba, 2012; Pellissier & Kruger, 2013; Pham et al., 2016; Yeoh & Popovič, 2016). Another stream of literature on Business intelligence (Alatiqi, 2022; Alnoukari & Hanano, 2017; Al-Okaily et al., 2022; Awawdeh et al., 2022; Binzafrah & Taleedi, 2022; Fatima & Linnes, 2019; GhalichKhani & Hakkak, 2016; Heang & Mohan, 2017; Kalyani, 2019; Paulino, 2022; Pirttimäki et al., 2006; Raisinghani, 2003; Smith & Crossland, 2008; Turban et al., 2010) and strategic intelligence (Abuzaid, 2017; Alnoukari & Hanano, 2017; Esmaeili, 2014; Marchand & Hykes, 2007), there is non about the integration between these concepts. The current study proposed a conceptual framework to study the integration between CSFBI, BI, and SI in Jordanian banks.

Jordan is a stable country with IT-enabled infrastructure and the right talent to deal with an intelligent system. Jordanian banks are operating in a digital domain and produce a massive amount of data. Consequently, they're profoundly invested in business intelligence to aid in handling their data (Al-Okaily et al., 2022). A fair share of studies about the intelligent system has been conducted in Jordan which proves the suitability of this study's context (Abuzaid, 2017; Al-Daouri & Atrach, 2020; Alkharabsheh & Al-Sarayreh, 2022; Al-Okaily et al., 2022; Alomian & Alsawalhah, 2019; Alzeaideen, 2019; Hamour, 2021; Jaradat et al., 2022; Malkawi, 2018; Rahahleh & Omoush, 2020; Shannak & Obeidat, 2012).

The rest of the current paper is organized as follows: Present the review of the body of literature first, followed by the research's technique. Afterward, the analysis and findings discussion are provided. Lastly, the study's outcomes with the research's practical and theoretical consequences are presented.

2. LITERATURE REVIEW

2.1 Theoretical framework

2.1.1 CSFBI

Several definitions of CSFs may be found in the literature. CSFs are described by (Yeoh et al., 2007a) as crucial areas where success is required for the business to develop, ensuring beneficial competitive performance for the firm. In other words, if the outcomes of these extents are inadequate, the company's endeavors for the specified duration would be, indeed, futile (Pham et al., 2016). CSFs are described as criteria that an organization or project must fulfill in order to achieve its objectives. The CSFBI are components of business intelligence that impact the effective adoption of business intelligence solutions in organizations.

Several studies have looked into CSFs for deploying BI systems as a standalone idea in a specific setting (Kfouri & Skyrius, 2016; Olszak & Ziemba, 2012; Pellissier & Kruger, 2013; Pham et al., 2016). Various dissemination studies, such as the one done by (Yeoh, 2011) focused on other aspects of implementation, such as the role of CSFs in BI system deployment. Additionally, (Yoon et al., 2017) found that incentive to learn the BI application affected individual intention, and another study (Yeoh & Koronios, 2010) looked at organizational determinants. Numerous empirical studies on CSFBI have been conducted (Dawson & van Belle, 2013; Hawking & Sellitto, 2010; Olbrich & Poppelbuß, 2012; Yeoh et al., 2007b; Yeoh & Koronios, 2010). According to these studies, the most essential CSFs are dedicated "top management support, source system data quality, and user participation".

2.1.2 Business Intelligence

Business intelligence is labeled as transforming data into useful information and knowledge using mathematical models and analytical methodologies in order to improve and aid strategic planning. In other words, it is using applications and procedures to manipulate data to aid decision-making (Davenport, 1998; Wixom & Watson, 2010). Along with current technology advancements, BI is in high demand because of its ability to meet the expectations of customers (Nithya & Kiruthika, 2020).

The literature defines three perspectives on BI use and success: an organizational perspective that represents organizational objectives, strategies, and plans; an information systems (IS) perspective that represents IT infrastructure and user interface; and a users' perspective that includes human resource capabilities (Ul-Ain et al., 2019). A fourth approach, the macro-environmental perspective, which covers the external environment such as market impacts, is being debated (Lautenbach et al., 2017). However, because the macro-environment is undefinable, it is uncapturable and will be excluded from this research. For this study, three viewpoints of (Salisu et al., 2021) will be considered to build the study's instrument.

The present literature stream has mostly concentrated on the organizational and information technology perspectives, as opposed to the user viewpoint, which has received less attention but offers greater projections for future study (Ul-Ain et al., 2019). Furthermore, there is a scarcity of research that thoroughly covers organizational IS and user viewpoints. There is a tendency in the bulk of articles from 2000 to 2019, where the attention is split between BI success and BI use and adoption. However, success is dependent on users' consistent usage of BI systems (Ul-Ain et al., 2019).

As for the theory that backed BI, the UTAUT has incorporated aspects such as social influence, which influences behavioral intention. Furthermore, it identified enabling factors as a factor influencing behavioral intention to identify whether an existing organizational and technological infrastructure to employ technology existed (Venkatesh et al., 2003). Several earlier investigations employed UTAUT to explain BI (Hou, 2014; Kester & Preko, 2015).

2.1.3 Strategic Intelligence

Strategic intelligence is defined as the act of gathering and interpreting data from the environment in order to formulate an organization's strategy (Kuosa, 2011). Organizational standards, financial and tax activities, political and economic breadth, and human resource classifications are all part of strategic intelligence. Strategic intelligence, in other words, investigates and analyses an organization's whole social, political, and economic activities. When analyzing strategic intelligence, numerous variables must be considered, including "the strategic vision, human and social resources, and the organization's economic and political concerns" (Gabber, 2007).

Strategic intelligence, in particular, depends on an organization's strategic planning framework and strategic decision-making. An additional definition of strategic intelligence views it as a widely related concept to organizational intelligence, organizational strategies, organizational strategic resources, and strategic management (Richard, 2007). Academics agree that "strategic intelligence" is a broad and multifaceted concept with no definite or certain definition (Maccoby (2011); Coccia (2010); Tessaleno (2010)). Rendering to books, articles, and research outlines, the effective factors of strategic intelligence are "human resource intelligence, organizational process intelligence, information intelligence, financial resource intelligence, technological intelligence, competitors intelligence, and customers intelligence" (Karl Weick, 2001) (Kruger, 2010).

Prior studies on strategic intelligence have primarily focused on the process (information collecting, analysis, and distribution) and have been less concerned with its components. Hosseini et al. (2012) provided a methodology for evaluating strategic intelligence in businesses using IT, whereas Kuosa (2011) focused on the usage of strategic intelligence in businesses. Coyne and Bell researched the importance of strategic intelligence in estimating organized offenses and crimes (2011). Companies, on the other hand, must have strategic advantages, transferrable experiences, changing phases inside the company, and information collection in order to construct a strategic intelligence system. Sigismund (1979).

Strategic intelligence has been studied in a model that echoes most of Kaplan and Norton's balanced and privileged card. This model's aspects include prediction, supervision, patterning, motivation, and empowerment Maccoby (2011). Strategic intelligence is also looked at from a strategic planning angle. In cooperation with Aboee Ardakani and Abasi, Andrew (1985) proposed an integrated technique for information-age changes based on the protection framework. Another research by Rezaiean and Lashkar looked at strategic decision-making as the dependent variable (2010).

2.2 "Hypothesis Development and Theoretical Linkages"

2.2.1 CSFSBI and Business Intelligence

Several studies have looked into CSFs while deploying BI systems, including Olszak and Ziemba (2012), Kfouri (2016), Dawson and Van Belle (2013), and Pham et al. (2016), Eryadi and Hidayanto 2020. Based on the conclusions of the preceding research, the success of BI systems may be secured by properly analyzing and focusing on the aspects that may affect the BI system's performance. Understanding the CSFs helps BI stakeholders to alter their resources, efforts, and focus on the areas most likely to support the BI system's successful implementation (Yeoh & Koronios, 2010).

Researchers have discovered some common characteristics that are crucial to the success of BI programs. The term "Critical Success Factors" refers to a wide range of influences, including "top management support, market dynamics, data quality of source systems, and BI technology utilisation" (Adamala & Cidrin2011). Considerable empirical research on CSFs in BI have been conducted and they consistently revealed that user engagement, source system data quality, and committed top management support were the most critical CSFs (Yeoh et al. 2007; Hawking & Sellitto 2010; Yeoh & Koronios 2010; Olbrich et al. 2012; Presthus et al. 2012).

Implementing BI systems is a complex process that involves the usage of proper infrastructure and a convince amount of resources over time, rather than just acquiring the application or tool (Yeoh and Koronios, 2010). It is critical to identify the CSFs in the process of managing and implementing IT, particularly in the case of business intelligence. The project will achieve its objectives if certain specified events occur that are critical to its success and negative impacts are kept to a minimal. These elements include, "among others, managerial difficulties, changing needs and objectives, organisational and personnel challenges, team issues, project planning and scheduling, data quality, and security". As a result, the following possibilities are proposed:

H1: CSF for BI has a positive association with Business Intelligence during the COVID-19.

2.2.2 Business Intelligence and Strategic Intelligence

"Business intelligence, competitive intelligence, and knowledge management" that are embedded within strategic intelligence, considered enablers of transforming the collective data and intellectual properties into one structured and intelligent body of information that support decision-making processes as well as strategic planning and management Pellissier and Kruger (2013). (MouhibAlnoukaria and Abdellatif Hananoa 2017) have made an attempt to broaden the research in the BI and strategic intelligence domains by defining the linkages between business intelligence and strategic management. It has also shed light on business intelligence's significance in corporate performance management and strategic intelligence. As a result, the second hypothesis might be stated as follows:

H2: Business intelligence has a positive association with strategic intelligence during the COVID-19 Pandemic.

2.2.3 CSF for BI and Strategic intelligence

Pellissier and Kruger investigated the long-term insurance industry empirically (2013). They concentrated on a subset of business intelligence known as strategic intelligence applications. Their study revealed a lack of awareness as well as ineffective use of cognitive capacities. They advocated utilizing strategic intelligence framework to steer intelligence operations in order to manage complexity and gain the utmost benefits of strategic intelligence, which increased innovation, competitive advantage, and decision-making. All potential relationships between CSF for BI and strategic Intelligence elements are evaluated while developing the first hypothesis:

H3: CSF for BI has a positive association with strategic intelligence during the COVID-19 Pandemic.

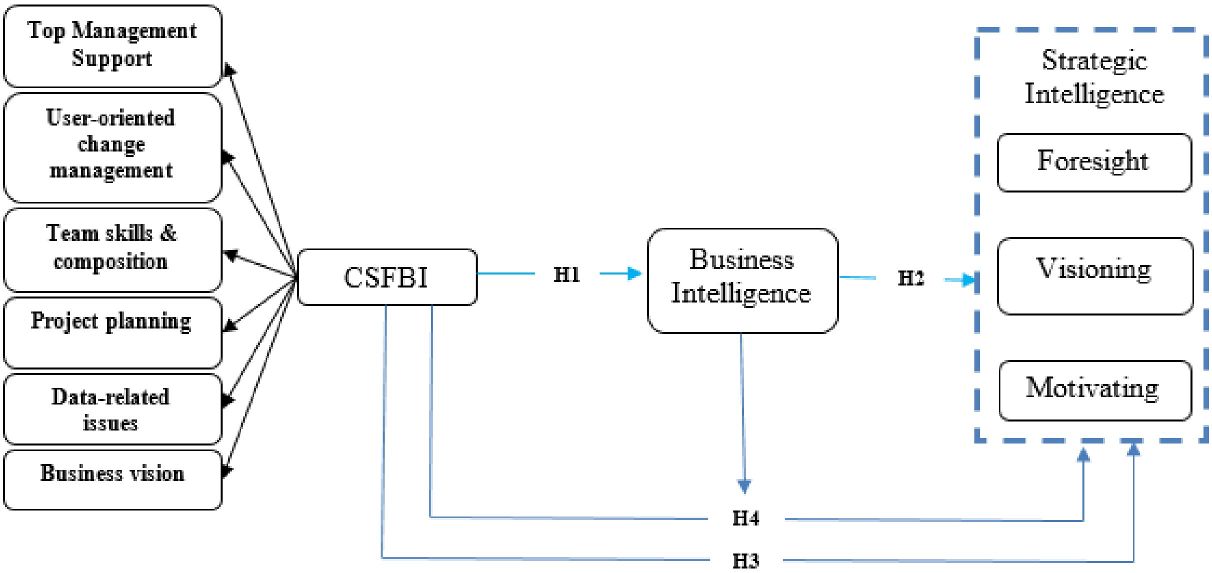


Figure 1. Research model during the COVID-19 Pandemic.

2.2.4 Hypothesis Scenery

This study's theoretical framework depicts a hypothetical sort of link between CSFBI and strategic intelligence, as well as the mediating function of BI. It is based on the existing level of knowledge in the literature and attempts to contribute to it by filling a gap with an explanation of the linkages between the study's parts and how it would aid businesses during the coronavirus outbreak.

3. METHODOLOGY

3.1 Study Participants

The people of the study consists of 13 commercial banks in Jordan while the sample consists of 392 managerial positions from commercial banks in Jordan. The "random method" method was used by a sample of administrative employees in commercial banks in Jordan.

Banks	Position	Frequency	Percentage (%)
"Arab Bank"	"Managerial Employee"	35	8.93
"The Housing Bank For Trade And Finance"	"Managerial Employee"	31	7.91
"Bank Of Jordan"	"Managerial Employee"	29	7.40
"Capital Bank Of Jordan"	"Managerial Employee"	28	7.14
"Jordan Ahli Bank"	"Managerial Employee"	32	8.16
"Cairo Amman Bank"	"Managerial Employee"	29	7.40
"Bank Al Etihad"	"Managerial Employee"	33	8.42
"Jordan Commercial Bank"	"Managerial Employee"	28	7.14
"Arab Jordan Investment Bank"	"Managerial Employee"	29	7.40
"Arab Banking Corporation /(Jordan)"	"Managerial Employee"	31	7.91
"Jordan Kuwait Bank"	"Managerial Employee"	30	7.65
"Invest Bank"	"Managerial Employee"	29	7.40
"Societe Generale De Banque – Jordanie"	"Managerial Employee"	28	7.14
Total	"Managerial Employee"	**392**	**100**

3.2 Measures

The questionnaire was developed based on recent studies, namely (Abuzaid, 2017; Paulino, 2022; Adjie Eryadi & Nizar Hidayanto, 2020; Yeoh & Popovič, 2016). Hence, it adds up to more valid and reliable device to collect the data. The following is the current study's tool in detail.

3.2.1 CSFBI

This research looks at six CSFBI dimensions: "top management support, user-oriented change management, team skills and composition, project planning, data-related difficulties, and business vision". Many studies have backed it, the most relevant of which are (Adjie Eryadi & Nizar Hidayanto, 2020; Yeoh & Popovi, 2016). As a result, The first section, was designed with questions that can be answered on a 7-point Likert scale taking "1" as strongly disagree and "7" as strongly agree.

3.2.2 Business Intelligence

The five questions used to assess business intelligence were backed by several studies, the most recent of which are (Paulino, 2022). The scale questions forlulated based on 5-point Likert with "1" indicating severe disagreement and "5" indicating strong agreement.

3.2.3 Strategic Intelligence

In terms of strategic intelligence, three dimensions were evaluated, which were labeled as (Foresight, Visioning, and Motivating) and have been verified by various previous studies, the most notable of which are (Abuzaid, 2017). As a result, a 5-point Likert scale was utilized, with "1" indicating severe disagreement and "5" indicating strong agreement.

3.3 Design

The nature of this study is a descriptive and analytical study based on comparing previous studies and developing a new idea in the social sciences. The questionnaire method is then used to collect data from the target population to generate valuable results that might enrich the previous literature with a contribution to the knowledge. The random probability sample of the participants was used to get the most accurate results in this study (Sekaran & Bougie, 2016). During, the pilot phase, data has obtained from 33 administrative staff samples in commercial banks in Jordan to ensure that the questionnaire is understood thoroughly by this study's sample.

3.4 Statistical analysis

There were 392 questionnaires completed and were ready for analysis. The researchers utilized "SPSS 25 software" to analyze data and calculate. Where demographic variables were used and several tests were conducted that confirm reliability, validity, normal distribution, and averages. Upon ensuring the integrity of the study data, the study questions were examined using multiple regression to answer the questions and verify the degree of influence in the study question. Finally, the mediating role testing was conducted via "PROCESS Macro version 3.5 software by Andrew F. Hayes" using SPSS to measure the direct and indirect effect among the study variables.

3.5 Results

3.5.1 "Summary statistics and internal validity of bivariate correlations"

The results of the internal validity among the variables of the study showed that there is no linear correlation between the variables because the correlation of the variable with itself is higher than any other variable (Sekaran & Bougie, 2016; Hair et al., 2014). The statistical significance was $p < .01$ & $p < .05$, which indicates the independence of the data and its non-interference. In addition, there is no weakness in the relationship between the variables, and there is no similarity in the data because the values range from 0.20 to 0.90, which confirmed the integrity of the data and the non-overlap of the variables, which made the study achieve the highest level of validity.

3.5.2 Tests of Reliability, Normality, Multicollinearity, Descriptive statistics

The reliability test shows that for CSFBI number of items is 15 and reliability is ($\alpha = 0.96$), for Business Intelligence number of items are 5 and reliability is ($\alpha = 0.86$), and strategic Intelligence's number of items is 15 with reliability ($\alpha = 0.94$). collectively, the overall percentage of all variables' number of items is 35 and reliability is ($\alpha = 0.97$). These figures show where the reliability ratio exceeded 70% for all elements of the study, which proved a high degree of reliability for the study variables (Hair et al., 2014). The normality test illustrated that the variables in the study are between ±2.58, which proves all the study variables have been distributed naturally (Hair et al., 2014). According to (Sekaran & Bougie, 2016), the test of multicollinearity statistics clarified VIF test should be "VIF = < 5" which indicates VIF test has been proven that it did not suffer from any problem with multicollinearity.

The effect of the study questions was measured using a descriptive analysis to response of the managerial employees in 13 commercial banks in Jordan, and It concluded that the respondents responded with a high degree in the all variables of the study is between 5.35 and 4.46. As for the Standard Deviation, it is between 1.42 and 1.04 according to 7 points Likert scale which indicates high arithmetic for CSFBI dimensions, while for business intelligence is 3.90, and the Standard Deviation is 0.68 according to 5 points Likert scale which indicates the high arithmetic of business intelligence. Finally, The descriptive mean for strategic intelligence is between 3.95 and 3.60, and the Standard Deviation is between 0.84 and 0.71 according to 5 points Likert scale which indicates the high arithmetic of strategic intelligence dimensions. These results came from the perspective of the respondents to the study questions.

Table 1. Summary statistics of the internal validity of bivariate correlations.

Variable	TMS	UOCM	TSC	PP	DRI	BV	SIF	SIV	SIM	**BI**	**CSFBI**	**SI**
TMS	1.00											
UOCM	.831**	1.00										
TSC	.738**	.762**	1.00									
PP	.673**	.663**	.814**	1.00								
DRI	.593**	.595**	.686**	.732**	1.00							
BV	.528**	.557**	.622**	.664**	.744**	1.00						
SIF	.596**	.578**	.706**	.690**	.706**	.696**	1.00					
SIV	.585**	.544**	.649**	.596**	.520**	.478**	.624**	1.00				
SIM	.543**	.546**	.612**	.549**	.503**	.455**	.568**	.697**	**1.00**			
BI (M)	**.523****	**.541****	**.591****	**.576****	**.548****	**.486****	**.637****	**.633****	**.813****	**1.00**		
CSFBI (IV)	**.836****	**.845****	**.931****	**.902****	**.834****	**.770****	**.772****	**.665****	**.631****	**.638****	**1.00**	
SI (DV)	**.664****	**.642****	**.759****	**.709****	**.671****	**.634****	**.856****	**.890****	**.856****	**.795****	**.799****	**1.00**

** "Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed), N = 402".

CSFBI = critical success factors for business intelligence: TMS = Top Management Support, UO = User-oriented change management, TSC = Team skills & composition, PP = Project planning, DRI = Data-related issues, BV = Business vision; BI = Business Intelligence; SI = Strategic Intelligence: F = Foresight, V = Visioning, M = Motivating.

Table 2. Tests of Reliability, Normality, Multicollinearity, and Descriptive statistics.

Variables	TMS	UOCM	TSC	PP	DRI	BV	SIF	SIV	SIM	**BI**	**CSF**	**SI**	Total
N. of item	2	2	4	3	2	2	5	5	5	**5**	**15**	**15**	35
Alpha (α)	.88	.89	.92	.81	.87	.80	.94	.89	.86	**.86**	**.96**	**.94**	.97
Skewness	-1.22-	-1.21-	-.98-	-.68-	-.95-	-.71-	-.87-	-.75-	-1.04-	**-.98-**	**-.96-**	**-.94-**	Er = .12
Kurtosis	1.83	1.70	.72	.30	.47	.53	.91	.92	2.07	**2.34**	**1.16**	**1.91**	Er = .25
VIF	2.87	3.65	2.54	2.74	3.14	2.73	2.76	1.21	2.45	**4.60**	**3.64**	**3.43**	VIF < 5
Tolerance	.37	.35	.29	.37	.32	.37	.37	.83	.41	**.22**	**.28**	**.38**	T < 1.00
Mean	5.35	5.33	4.97	4.76	5.03	4.46	3.63	3.60	3.95	**3.90**	**4.97**	**3.73**	HL
SD	1.22	1.22	1.31	1.24	1.42	1.04	.84	.78	.71	**.68**	**1.09**	**.67**	HL

Alpha (α) > = 70; Skewness & Kurtosis = ±2.58; VIF = < 5; Mean & SD = High level (HL).

CSFBI = critical success factors for business intelligence: TMS = Top Management Support, UO = User-oriented change management, TSC = Team skills & composition, PP = Project planning, DRI = Data-related issues, BV = Business vision; BI = Business Intelligence; SI = Strategic Intelligence: F = Foresight, V = Visioning, M = Motivating.

3.5.3 Linear regression analysis

Based on the previous study's conclusions, which indicated the data's validity, reliability, and trustworthiness, as well as confirmed the data's normal distribution and arithmetic averages. These findings showed that multilinear regression could be utilized to validate and correct the study's assumptions and concerns.

Model[1] CSFBI's positive effect on business intelligence.

R square for "CSFBI" comfirmed that the value is "0.41" from business intelligence. Also, the acceptable value for D.W should be 2.5 < = D.W > = 1.5, consequently for this study, hence there isn't auto-correlation in the study items. F-test is "267.71" which guaranteed the overall variables in the model are positively effect significantly at p-value = < 0.01. Whereas, the t-test is "16.36" shows the items in the study variables are positively effect at p = < 0.01. Furthermore, CSFBI (ß = 0.64) indicates that CSFBI is strictly correlated to business intelligence, when CSFBI grows by one mark business intelligence will grow accordingly to ß (Kumawhichi & Yadav, 2018).

Model[2] Business intelligence positively affects strategic intelligence.

R square for "business intelligence" confirmed that the value is "0.63" from strategic intelligence. Also, the acceptable value for D.W should be 2.5 < = D.W > = 1.5, consequently for this study, hence there isn't auto-correlation in the study items. F-test is "670.94" guaranteed the overall variables in the model are positively effect significantly at p-value = < 0.01. Whereas, the t-test "25.90" shows the items in the study variables are positively effect at p = < 0.01. Furthermore, Business intelligence (ß = 0.80) indicates that Business intelligence is strictly correlated to strategic intelligence. When Business intelligence grows by one mark strategic intelligence will grow accordingly to ß (Kumari & Yadav, 2018).

Model[3] CSFBI positively affects strategic intelligence.

R square for CSFBI is "0.64" from strategic intelligence. Also, the acceptable value for D.W should be 2.5 < = D.W > = 1.5, consequently for this study, hence there isn't auto-correlation in the study items. F-test is "688.36" guaranteed the overall variables in the model are positively effect significantly at p-value = < 0.01. Whereas, the t-test value is "26.24" shows the items in the study variables are positively effect at p = < 0.01. Furthermore, CSFBI (ß = 0.80) indicates that CSFBI is strictly correlated to strategic intelligence. When CSFBI grows by one mark strategic intelligence will grow accordingly to ß (Kumari & Yadav, 2018).

3.5.4 PROCESS Micro v3.5

This test was presented to estimate the time period between the variables of the study for the ability to identify the direct and indirect relationship, which contributes to the improvement and development of the research to reveal the defect in the previous literature and to develop a new contribution in the field of the studied research.

Model[4] Business intelligence is a partial mediation (complementary) between CSFBI and strategic intelligence.

CSFBI has a positive effect on strategic intelligence (b = 0.30, t = 15.77, p < 0.001). Furthermore, LLCI is between 0.27 and 0.34 so it's significant due to the absence of zero numbers between them (Hayes, 2015). Similarly, Business intelligence has a positive effect on strategic intelligence (b = 0.48, t = 15.44, p < 0.001). As LLCI is between 0.42 and 0.54, it confirms the significance level due to the absence of zero numbers between them (Hayes, 2015). The values for the direct and indirect effect is as the equation: Indirect effect = a (0.40) * b (0.48) = 0.19; Direct effect = 0.30; Total effect = Indirect effect + Direct effect: 0.30 + 0.19 = 0.49. Hence,

Table 3. Linear regression analysis.

Model	variables	R Square	D.W	β	F	t	Sig.	Decision
Model[1]	CSFBI → BI	0.41	2.12	0.64	267.71	16.36	0.00**	Accepted
Model[2]	BI → SI	0.63	1.94	0.80	670.94	25.90	0.00**	Accepted
Model[3]	CSFBI → SI	0.64	1.97	0.80	688.36	26.24	0.00**	Accepted

Regression is significant at p ≤ 0.01; * Regression is significant at p ≤ 0.05.

CSFBI = critical success factors for business intelligence; BI = Business Intelligence; SI = Strategic Intelligence.

the mediating variable positively affects IV and DV due to BootLLCI being between 0.14 and 0.24 as there are no zero numbers between them, therefore, it's significant at $p < 0.001$ (Hayes, 2015).

Is it a full or partial effect?

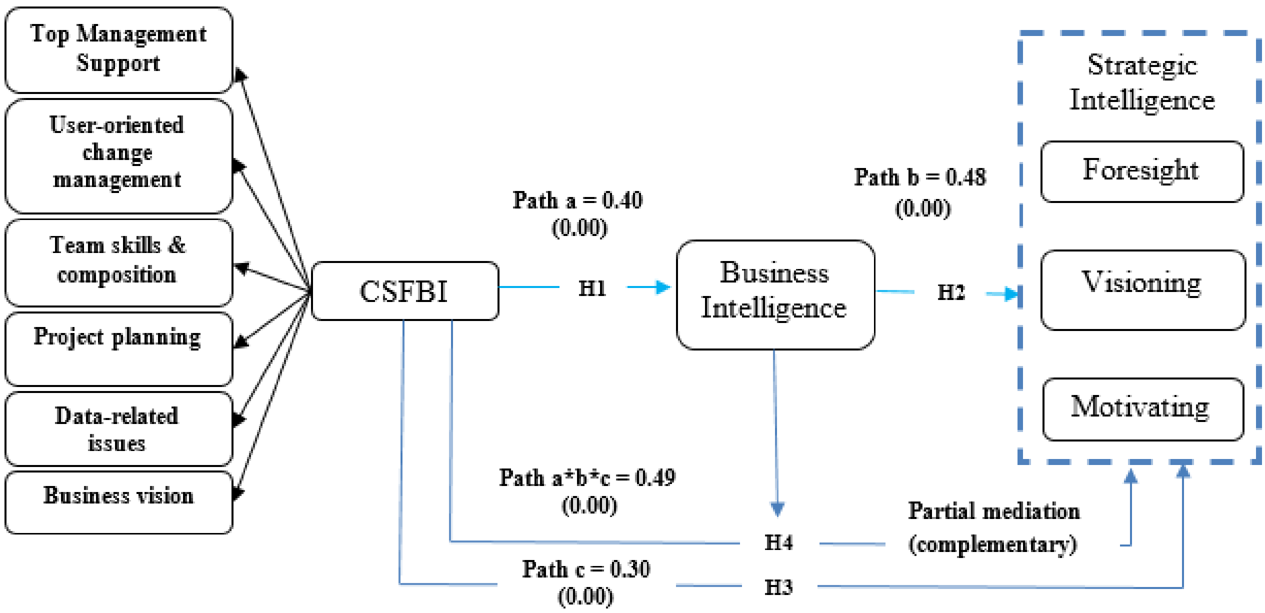
As for the partial mediation, the direct effect and indirect effect are significant at $p < 0.001$. Hence, (a*b*c) have complementary effects (Hayes, 2015).

The results proved that CSFBI has a positive effect on strategic intelligence, where the degree of influence reached 30%, which indicates a good effect between IV and DV. Moreover, business intelligence as a mediator intervenes between CSFBI and strategic intelligence, it increases the proportion of the relationship by 19% so that the total effect becomes 49% which strengthens the relationship to increase the influence, consequently playing a role in enhancing the indirect influence on a partial degree that called complementary competition and not less significance at the full effect because it is more common, indicating the discovery of additional mediators, which improves the quality of the relationship and shows new contributions that might enrich future studies with knowledge, reduce risks, and increase the odds of progress and success.

Table 4. Mediation analysis summary of BI between CSFBI & SI.

Relationship	Total Effect	Direct Effect	Indirect Effect	Confidence Interval		t-statistics	Conclusion
Model4				**Lower Bound**	**Upper Bound**		
CSF → BI → SI	0.49	0.30	0.19	**0.14**	**0.24**	**26.24**	**Partial Mediation**
Sig.	(0.00)	(0.01)	(0.00)				

** Level of confidence for all confidence intervals in output:95.0000.



The structure model illustrates the direct and indirect effects that "business intelligence is a partial (complementary) mediation between CSFBI and strategic intelligence"

NB.
Indicates direct effect (path c)
Indicates indirect effects (path a*b*c)

Figure 2. The illustration structural model of the direct and indirect effects between the study variables:

CSFBI = critical success factors for business intelligence; BI = Business Intelligence; SI = Strategic Intelligence.

4. DISCUSSION

Companies gain competitive advantages by incorporating intelligence technologies with IT capabilities (Awamleh & Bustami, 2022). Furthermore, technological advancement has made business life-cycle rather shorter than before. Hereafter, the organizations must have efficient and smart decision-making to gain a competitive advantage (Kalyani, 2019). Decision-making is not effective without real-time data for the right cause (Farjami & Molanapour, 2015). Previous research on the integration of CSF for BI, BI, and strategic intelligence is lacking. Specifically, the function of BI as a bridge builder between CSF for BI and Strategic Intelligence during the COVID-19 Pandemic. As a result, the current study offered a paradigm that shed light on the BI's mediating function in the interaction between CSF for BI and strategic intelligence in Jordan's financial industry.

The findings of this study demonstrated that CSF for BI is connected with strategic intelligence during the COVID-19 Pandemic. It also gave insight into the BI's mediating role in the link between CSFBI and strategic intelligence. On the one hand, as stated by (Yeoh & Popovi, 2016), CSF for BI leads to BI. The previous study has demonstrated that CSF for BI has been studied in a variety of contexts (Kfouri & Skyrius, 2016; Pellissier & Kruger, 2013; Pham et al., 2016). This research adds to the body of knowledge by giving empirical evidence of CSFBI, BI, and SI in Jordan. The mediating function of BI improves the association, which is consistent with the findings of another study done in Jordan (Awawdeh et al., 2022). Similar research (Esmaeili, 2014) that employed various variables but reached similar conclusions in different situations supports CSFBI and its favorable influence on strategic intelligence through the mediating function of business intelligence.

4.1 Academic and Practical Implications

Separate research on CSFBI, Business Intelligence, and strategic intelligence may be found in the literature. However, the integration of the three principles is lacking, particularly in emerging markets such as Jordan. The goal of this study is to present a paradigm for explaining the integration of intelligent systems and the impact these systems may have on each other as well as on businesses, particularly during the COVID-19 Pandemic's economic collapse. This study's academic implication is that more studies and research similar to it should be conducted in various industries and markets, primarily in developed economies, to investigate intellectual and cultural perspectives as well as differences between businesses and other countries during the COVID-19 Pandemic. Second, this work provides a well-established and dependable model for explaining how the CSFBI influences strategic intelligence via BI mediation effects. Third, this study demonstrated that CSFBI improves strategic intelligence. Furthermore, corporate intelligence has a good mediation impact. Fourth, this research illuminated the integration of intelligent systems in businesses.

In terms of practical applications, this study discovered that CSFBI and BI assist firms in improving their strategic intelligence by increasing the integration of intelligent systems. As a result, businesses may make greater use of existing data to assist strategic intelligence and decision-making. On the other hand, ensuring that the significant investment in BI is used to benefit the businesses. The findings of this study motivate managers to integrate intelligent systems in order to leverage decision-making intelligence and inform strategic intelligence. Furthermore, managers may utilize BI to improve the usage of accessible data in businesses and integrate CSFBI with BI to achieve a beneficial outcome for the organization's intelligence system. Managers may employ integrated intelligence systems to better use data to adapt to external environment elements and strategic planning, especially during the COVID-19 pandemic, with the help of the study's findings.

4.2 Limitations

The applicability of this study to a certain sector, area, and city will have an impact on the findings' generalizability. Furthermore, this evidence was prevalent throughout the COVID-19 pandemic, limiting the generalizability of the study's findings. The findings, however, can still add to the body of knowledge by demonstrating how BI mediates the association between CSFBI and strategic intelligence. A solid model that quantifies the connections between CSFBI, business intelligence, and strategic intelligence should be provided as well.

4.3 Future Research

The outcomes of the study motivate academics to use the notion in a range of circumstances, such as new markets, industries, and cultural backgrounds. Because the literature on intelligent systems appears to be lacking in integration, there are possibilities to do research that can fill this void. In this case, the research model would be an assistant. The model would also be useful in cross-cultural or cross-sector inquiries.

5. CONCLUSION

This study investigated the association between CSFBI and strategic intelligence using BI as a bridge. The investigation was conducted on a sample of Jordanian banks during the COVID-19 pandemic. The collected data was examined and hypotheses were evaluated using SPSS's multi-regression analysis and descriptive statistics. The findings of the study indicated that the factors had a significant influence. BI has proved its ability to serve as a link between CSFBI and strategic intelligence. This study's model and findings add to the body of current literature and will guide future research by providing an integrated model that encompasses some of the intelligent systems in organizations. Companies must ensure that the significant investment in BI-related applications has borne fruit, and this study gives a means of doing so.

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