Information Quality of Business Intelligence Systems: A Maturity-based Assessment

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Abstract

Background: The primary role of a Business Intelligence (BI) system is to provide information to decision-makers within an organization. Moreover, it is crucial to acknowledge that the quality of this information is of greatest significance. Several studies have extensively discussed the importance of information quality in information systems, including BI. However, there is relatively little discussion on the factors influencing 'Information quality".
Objective: This study aimed to address this literature gap by investigating the determinants of BI maturity that impacted information quality.
Methods: A maturity model comprising three dimensions was introduced, namely Data quality, BI infrastructure, and Data-driven culture. Data were collected from 84 companies and were analyzed using the SEM-PLS approach.
Results: The analysis showed that maturity had a highly positive influence on Information Quality, validating the relevance of the three proposed determinant factors.
Conclusion: This study suggested and strongly supported the importance and relevance of Data quality, BI infrastructure, and Data-driven culture as key dimensions of BI maturity. The robust statistical relationship between maturity and information quality showed the effectiveness of approaching the systems from a maturity perspective. This investigation paved the way for exploring additional dimensions that impact Information quality.

Keywords: BI infrastructure, BI maturity, Data-driven culture, Data quality, Information quality.

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I. INTRODUCTION

The field of information systems is in a constant state of evolution, comprising both professional and academic domains. With the constant influx of technological innovations and the growing prevalence of digital technology in organizations, big data are generated from various sources, both internal and external. This presents a significant challenge for business leaders, who invest varying amounts of time in analyzing this massive data [1]. Consequently, companies across diverse industries are increasingly skilled in utilizing Business Intelligence (BI) to exploit their data to obtain competitive advantages [2].

In this dynamic business landscape, where new competitors who could disrupt the industry are as prevalent as existing rivals, companies are actively exploring ways to be distinguished from others. Consequently, BI is regarded as a valuable tool for accomplishing this objective. This is because it incorporates the systematic process of obtaining, gathering, analyzing, interpreting, and using information to have an edge. To succeed in this context, any initiative needs to address two major challenges, namely integrating data from multiple sources into data warehouses (the infrastructure aspect) and adding value to this data through analysis and presentation in a usable format (the analytical aspect). According to Ahmad [3], many organizations opt for BI to obtain a competitive edge in the global market. The primary objective of this action is to use data to make decisions that improve and optimize revenue, driving widespread investment in solutions. BI is also viewed as a transformational tool for organizations, capable of introducing new business models and strategies at the enterprise level, fundamentally changing how companies compete in the marketplace [4].

The expectations for the proposed model are considerably high, making it a global priority [5]. In fact, it was valued at $20.5 billion in 2020 and is projected to reach $40.5 billion by 2026, with a compound annual growth

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rate (CAGR) of 12% for the period 2021-2026 [6]. The enthusiasm for BI is largely attributed to its potential and the benefits offered to organizations. Numerous "Success Stories" from organizations such as Continental Airlines, Harrah's, and Netflix influence the desire for other entities to replicate these experiences and leverage the model for improved profits and competitive advantages [7] -[12].

It is quite unfortunate that not all organizations are able to unlock value from their investments. In fact, more than 70% of projects fail, according to a study conducted by Ramesh and Ramakrishna [13]. Additionally, approximately 87% of data science projects fail to reach the deployment and production phase [14]. Project failures are a common issue faced by many companies. Several factors contribute to these failures, including inadequate planning, deficient project management, and unmet business requirements [15]. Another prevalent issue is the generation of inaccurate or irrelevant information by the systems [16]. Even when initiative progresses beyond the project phase and is deployed throughout a company, it will be considered a failure if it does not provide users with quality information that meets their needs.

Demonstrating the advantages of investing in BI systems presents a challenge, primarily due to the difficulty in quantifying the return on investment. This complexity arises because its impact is predominantly indirect and long-term [17]. Most metrics for assessing their business value, such as organizational performance or competitive advantage, do not adequately capture the immediate effects of these systems on the decision-making process. However, as a structured and systematic process for gathering, evaluating, and disseminating information for decision-making purposes [18], BI fundamentally aims to improve the speed and quality of information required for sound decision-making [19]. This implies that when evaluating the attainability of the system objectives, the standard of information quality assumes great significance.

BI systems have been recognized as a means to improve information quality within organizations. It is through the improvement of information quality that the systems can optimize decision-making processes [20]. Poor-quality information adversely impacts the decision-making process, diminishing the effectiveness of decisions or, in some cases, leading to erroneous choices. However, there is a paucity of investigation on how information quality is realized within the system [21]. Studies have addressed these challenges by formulating BI Maturity Models, which guide companies in maximizing the benefits of their BI initiatives. De Bruin argued that companies can cultivate strategic resources through these maturity models [22]. However, even with these models in place, many companies still struggle with realizing their full potential and encounter project setbacks [23]. While there is a substantial body of literature on the concept of "information quality," it is rarely explored in this context [24].

Companies are at a loss concerning how to enhance BI maturity and which dimensions to target in order to guarantee the success of their initiatives. Literature acknowledges the crucial role of information quality as the primary outcome of these systems and suggests maturity models as an avenue that can increase the chances of initiative success. However, it is surprising that there is scarcity of studies linking the concepts of "BI information quality" and "BI maturity. Current exploration on the quality of information in this context is limited, with one of the few examples being the study conducted by [25], which proposes and tests a model examining the relationship between system maturity and information quality. To bridge this gap in the literature, this study aims to provide and empirically test a model that investigates the determinants of BI maturity influencing the quality of information generated by such systems. In the study, the critical aspect of systems, namely information quality was addressed in order to describe the influence of maturity dimensions. Consequently, the following question was addressed, what is the impact of BI maturity on the quality of the information it produces?

The remaining sections of this essay are organized as follows. Initially, the foundational concepts of the proposed model and relevant literature are explored. Subsequently, the investigation plan is detailed, and a set of testable hypotheses is established. In the next section, the process through which the model was experimentally tested is outlined. The findings of the data analysis are also presented, and the last section consists of the findings and conclusions.

II. LITERATURE REVIEW

A. Theoretical background

An examination of the IS/BI literature [26]-[30] shows that technologies, in isolation, do not inherently provide benefits and advantages. However, they can synergize with existing organizational resources to ensure the success of investments. This necessitates an analysis from the vantage point of skills and capabilities. The concept of dynamic capabilities [31], [32] arises as the most suitable theoretical basis for scrutinizing BI's impact on information quality. Dynamic capabilities are defined as the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments [32], or the ability of an organization to deliberately create, extend, or modify its resource base [31]. The second definition shows the relevance of this approach to the study, as it revolves around the development of an organizational resource, specifically, quality information. Moreover, the literature also acknowledges that nurturing these capabilities is a challenging and time-consuming process, often extending over several years, necessitating continuous guidance

and evaluation for the success of corporate strategic initiatives based on BI. Maturity models describe the evolution of an entity over time [33], and this approach has proven to be valuable for evaluating various aspects of processes and organizations. It signifies a path toward a more structured and systematic approach to organizational management [34]. According to Rajteric [35], BI maturity models provide organizations with guidance to assess their current status and determine steps for advancement in this rapidly evolving field. Maturity models are characterized by a set of dimensions, known as "capability domains," which structure the field of interest [36].

B. *Conceptual model and hypotheses*

Based on the theories of maturity models and dynamic capabilities, a model is presented. This model suggests that the quality of information delivered by a BI system is dependent on its level of maturity. This maturity consists of three dimensions, namely source data quality, BI infrastructure, and Data-Driven Culture, as seen on Fig. 1.
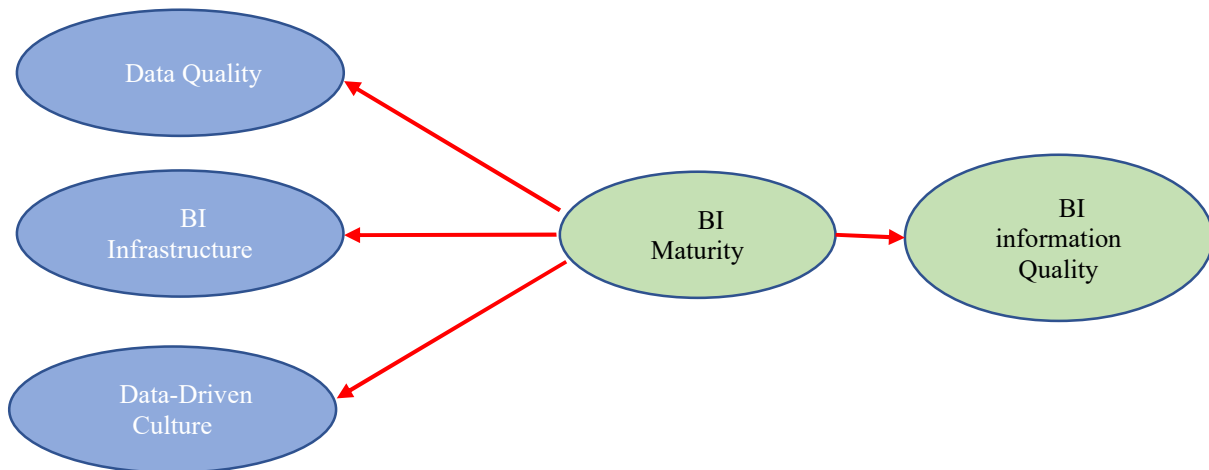

Fig. 1 Conceptual model on the impact of BI maturity on information quality

The model suggests that "BI maturity" serves as the explanatory variable for "information quality." The maturity is a second-order variable, determined by three first-order variables, namely, "Data quality," "BI Infrastructure," and "Data-driven Culture.".

Regardless of a company's size or the complexity of system implementation, data quality concerns are very significant. Without high-quality data, no system can provide relevant data for operations, financial reporting, or decision-making [37]. The concept of data quality applies to all types of systems, with particular relevance to BI due to their primary aim of improving decision-making. Data quality is considered high when it is appropriate for the specific use case [38], [39]. Wang and Strong [40] stated the increasing adoption of the concept of "fitness for purpose" in quality literature, showing the importance of considering the consumer's perspective on quality, as the determination of a product's suitability for its intended purpose rests with the customer. However, several definitions outline key attributes of data quality, such as completeness, validity, uniqueness, consistency, and accuracy.

The literature concerning information systems frequently confuses the concepts of "data" and "information," using them interchangeably [41]. In the study, a clear difference between data, which constitutes the inputs of BI systems, and information is established and it serves as the product and output of these systems. The approach of Strong et al. [42] was adopted, where data are regarded as raw, unprocessed facts. These data are subsequently organized, contextualized, and transformed into information, which can be utilized and analyzed by a data consumer, thereby leading to knowledge. This transformation process is referred to as the "data manufacturing system.

According to Watson and Wixom, the factor of data quality has received substantial attention from other studies, including the definition, the measurement of components, and significance [43]. The construction of a data warehouse primarily aims to furnish decision-makers with high-quality data [43]. As the quality of available data in the data warehouse improves, the system experiences enhanced benefits. According to Ait Touil and Jabraoui [44], most maturity models consider data quality as a fundamental dimension of BI. As a result, the following hypothesis is proposed:

H1a: Data quality influences the maturity of BI systems.

BI technological capabilities include technical platforms and shareable databases that ideally follow a well-defined technological architecture and data standards. Enterprise applications and services are built on this infrastructure, which comprises data, network, and processing infrastructures, including data warehouses, data marts, ETL processes, and more [45]. The technical ability to deliver the necessary information and analytical applications for leveraging the system is a crucial prerequisite for realizing business value. Some businesses excel in creating, deploying, operating, and maintaining the ideal technological environment to support data warehouses and BI, demonstrating a distinct advantage over others. Therefore, a fundamental BI capability includes establishing and continually developing the infrastructure, focused on the data warehouse's entire architectural style, in line with expressed needs [46].

In accordance with Popovic et al. [30], BI infrastructure presents the physical components of assets. However, the comprehensive definition provided by [47] was preferred. This is because the study characterizes IT infrastructure as the fundamental basis of the IT portfolio (technical and human assets) shared by the enterprise in the form of trusted services. For BI to thrive, effective governance that provides the necessary infrastructure, including hardware, software, human resources, and strategy, is considered indispensable [3].

The human aspect of the infrastructure is represented by a team, as they possess the technical expertise to craft new applications (such as reports, digital dashboards, and OLAP utilities), integrate data from diverse sources (including data warehouses, data marts, ETL engines, and procedures), and generally meet user expectations [48]. The infrastructure significantly influences the scope of opportunities available to companies in shaping their global business strategies [49]. Therefore, it is evident that any company with a weak BI infrastructure, whether on the technological or human front, is likely to encounter challenges in achieving its objectives. Consequently, the following hypothesis was proposed:

H1b: The maturity of BI systems is influenced by BI infrastructure.

In today's highly competitive business landscape, BI and Analytics (BI&A) have developed as fundamental cornerstones of decision-making. Decision-makers are increasingly driven to make well-informed choices, and BI has the capacity to improve the conventional decision-making process [50]. Irrespective of the terminology used, whether it is attitude, commitment, perspective, culture, mindset, or approach, numerous studies have emphasized the same essential need [9], [51], [52]. According to Davenport [9], adopting analytics at an enterprise-wide level incorporates a cultural shift, process changes, behavioral adjustments, and skill development for many employees. Instead of relying on subjective judgment and experience, Data-driven decision-making [53] represents an ideology that regards data as a strategic resource. To promote a culture oriented toward innovation, management needs to play an active role and give careful consideration to data management across all levels of decision-making.

The routine utilization and analysis of data in decision-making, often referred to as fact-based management, is a significant element of organizational culture [54]. A culture rooted in fact-based decision-making necessitates that decision-makers are open to embracing data-driven insights from their subordinates [9]. Additionally, they need to actively encourage the creation of a data-driven environment to support their subordinates in their problem-solving and decision-making [29], [55].

Numerous maturity models recognize the cultural aspect as an important dimension of BI maturity. For example, Williams and Williams' model, known as the "Enterprise Information Maturity Model" [45], considers a culture of data-driven decision-making as a critical component. Furthermore, in a comparative review conducted by [56], it was revealed that approximately half of the models examined include corporate decision-making culture as a dimension of maturity.

The sustained effectiveness of systems focuses largely on how willing and prepared users are to integrate the process into their decision-making processes [57]. Success or failure in the implementation of Information Systems (IS) projects is often attributed to the organizational culture [58]. In a business environment characterized by a data-driven decision-making culture, the measurement, testing, and evaluation of quantitative evidence during decision-making processes achieved widespread recognition. This kind of culture promotes the use of data and information to support work processes, conduct analysis, and apply advanced methodologies [59]. However, as noted by Lavalle et al., altering the decision-making approach from personal experience and intuition to factual data is a formidable challenge, particularly when the data contradicts long-standing beliefs [60]. The presence of such a culture within an organization is both a sign of robust system maturity and a catalyst for extensive BI utilization within the organization. Consequently, the following hypothesis was formulated:

H1c: BI system maturity is determined by the fact-based and data-driven culture.

The primary objective of BI is to empower users with access to high-quality information, such as information that caters to specific needs [52]. Hannula and Pirttimäki [61] describe that the chief benefit offered by the system is the provision of superior-quality information for decision-making.

According to Williams and Williams [62], to fully reap the rewards of projects, organizations should strive for a mature BI system. In addition, the systems are designed to bridge the gap between the volume and quality of data collected by organizations and the quantity and quality of information accessible to users at the tactical and strategic levels of business decision-making [25]. As a result, the following hypothesis was proposed:

H2: The maturity level of the BI system positively influences the quality of information provided.

III. METHODS

In testing the proposed model, a quantitative field study was conducted using a questionnaire. The survey targeted both private and public organizations in Morocco. In the absence of a database containing information about companies and organizations using BI, the focus was placed on middle and senior managers in decision-making roles to acquire data for the quantitative survey. To ensure a wide response rate, three distinct methods were utilized. The first method incorporated the utilization of a personal network of contacts. The second approach relied on an email list obtained from a prior ERP survey in Morocco, which comprised 625 contacts, of which only 156 met the specified criteria. The third approach made use of social networks, particularly Facebook and LinkedIn. In these platforms, outreach was directed towards professional groups, including entrepreneurs, economists, and managers. A message was disseminated outlining the survey's purpose and providing a link for easy access to the questionnaire across various devices (smartphones, tablets, PCs). Direct contact through private messages on LinkedIn was also made, targeting individuals who were often members of BI-related groups.

After the initial phase of emails and messages to individuals, follow-up phone calls, messages, and emails were conducted over the subsequent three weeks to augment the response rate. A total of 106 responses were gathered, with 22 being excluded due to incompleteness or the absence of a BI system in the respondent's organization. Among the 84 valid respondents, 84% comprised engineers or managers from business schools, with 12 holding a Ph.D. Table 1 shows an sample demographics profile of survey respondent. This demographic profile affirmed that the survey successfully reached the desired profiles.

TABLE 1
SAMPLE DEMOGRAPHICS

Description		Percentage (%)
Gender	Male	58
	Female	42
Education	BAC+3	2
	BAC+5/Engineer	84
	PhD	14
Hierarchical level	Top/upper	9
	Middle	89
	low	2
Activity	Finance and insurance	28.5
	ICT	15.4
	Industry	14.3
	Public sector	7.1
	Commerce	8.3
	other	26.4

The survey was designed to evaluate the model's elements and variables, as shown in Figure 1. Multiple-item measures were applied for each construct, drawn from existing studies in various literature. The origins of these items and the constructs they represented are comprehensively shown in Table 2. For example, data quality items were adapted from Wixom and Watson's study on data warehousing [63], while items concerning BI infrastructure were sourced from [3], [30]. Measurement items regarding the fact-based and data-driven analytical culture were taken from studies by [59], [64], [65], and the evaluation of information quality was in accordance with the study conducted by [3]. All these constructs were considered first-order constructs, except for BI maturity, which was conceptualized as a second-order construct using the repeated indicators technique.

The sample comprises various sectors within the Moroccan business landscape, although with varying levels of representation. The financial and insurance sector dominated, constituting 51% of the sample, a reflection of the sector's reliance on data and substantial investments in information and communication technologies [66]. The Information and Communication Technology (ICT) sector was the second most represented. Large companies and sizable SMEs made up almost three-quarters of the sample (72%). Respondents were primarily in top management (9%), senior management (76%), or middle management (13%).

TABLE 2
THE MODEL CONSTRUCTS AND INDICATORS

Construct	Items	References
Data quality	**Data1**: Users now have more accurate data with BI than they did with source systems **Data2**: Today's users have access to more comprehensive data than is available from source systems. **Data3**: Users now have access to more accurate data compared with source systems **Data4**: The system has improved data consistency for users (or applications) compared with source systems.	Wixom & Watson [63]
BI infrastructure	**Eq1**: BI team maintains the system satisfactorily **Eq2**: The team has the technical knowledge and skills to meet the requirements of the system. **Eq3**: The team has the ability to lead the system design and development process. **Inf1**: The BI infrastructure is well synchronized with the organization's databases and with external sources. **Inf2**: The infrastructure is accessible to users **Inf3**: The infrastructure meets the organization's technological needs **Inf4**: The infrastructure enables development of easy-to-use, intuitive tools **Inf5**: The systems are flexible enough to meet your organization's current and future needs. **Inf6**: BI infrastructure enables rapid response to system usage	Fink et al [30], Ahmad [3]
Data-Driven Culture	**Cult1**: Decisions that are based on data rather than intuition **Cult2**: We are prepared to abandon our intuition when the data contradicts our views. **Cult3**: Company encourages the search for data/information to inform decision-making. **Cult4**: Company shows respect for the measurement and evaluation of evidence in decision-making. **Cult5**: Company encourages decision-making processes that include quantitative/digital analysis.	Gupta & George [64], Mikalef et al [65], Kulkarni & Robles-Flores [59],
Information Quality	**QI1**: The systems produce accurate and correct information **QI2**: The systems always provide the information needed. **QI3**: Information from the systems is complete and adequate. **QI4**: Information from the systems is always up-to-date. **QI5**: The systems produce information in a presentable format that is easy to understand and interpret. **QI7**: Information from the systems is secure and free from threats **QI8**: The information provided systems is of the highest integrity and trustworthiness. **QI9**: The systems produce relevant information that meets business needs.	Ahmad [3]

IV. RESULTS

The assessment of reliability and validity for the items was shown in Table 3. All items revealed an outer loading exceeding the 0.7 threshold [67], with the exception of item IQ6, which had an outer loading of 0.549 and was subsequently excluded. However, the removal of this item resulted in a decrease in Composite reliability, Cronbach's Alpha, and the coefficient of determination (R^2) for the Information Quality construct. This showed that items QI8 and QI9 were retained as long as their loadings exceeded 0.5 [68], ensuring the model's reliability. Both Cronbach's Alpha and Composite reliability showed highly satisfactory values exceeding 0.7 [69].

The Average Variance Extracted (AVE), which signified the proportion of variance in the items explained by their associated construct, consistently showed values above 0.5 [70], demonstrating robust convergent validity. To assess discriminant validity, the criteria proposed by [70] were applied. The process was achieved by comparing each construct's AVE to the squared inter-construct correlations, serving as an indicator of shared variance within the construct and with all other reflexively measured constructs in the structural model. The shared variance among constructs did not surpass their respective AVE values. Table 3 showed that the square root of the AVE (values in gray cells) exceeded those in the cells below and to the left, affirming sound discriminant validity.

The reliability and validity assessment of the second-order construct, "BI maturity," solely followed the guidelines provided by Sarstedt et al. [71]. This approach incorporated the allocation of all indicators from lower-order components to the higher-order component, using the repeated indicators technique [71]. However, the statistics generated by SmartPLS were inapplicable for the second-order construct because the software failed to recognize it, causing the result to be treated as every other variable. This led to distorted validity and reliability metrics, necessitating manual computation following the formulas outlined by Sarstedt et al.. The results affirmed the resilience of the second-order construct, "BI maturity". The values found for the different criteria of the second-order construct "BI maturity", therefore, indicate good reliability and validity.

Composite reliability = **0.811**
Cronbach's Alpha = **0.801**
Average Variance Extracted (AVE)= **0.588**

TABLE 3
SUMMARY OF RELIABILITY AND VALIDITY ASSESSMENT CRITERIA.

ITEM	Outer loading	Alpha	CR	AVE	Data Quality	BI Infra	D.D culture	Quality Information
Data1	0,853							
Data2	0,912	0.896	0.924	0.754	0,868*			
Data3	0,838							
Data4	0,868							
Eq1	0,748							
Eq2	0,791							
Eq3	0,829							
Inf1	0,752							
Inf2	0,863	0.934	0.939	0.633	0,690	0,796		
Inf3	0,765							
Inf4	0,733							
Inf5	0,858							
Inf6	0,810							
Cult1	0,850							
Cult2	0,772							
Cult3	0,746	0.877	0.905	0.655	0,411	0,434	0,809	
Cult4	0,837							
Cult5	0,838							
QI1	0,670							
QI2	0,737							
QI3	0,780							
QI4	0,827							
QI5	0,782	0.879	0.899	0.529	0,690	0,503	0,537	0,727
QI7	0,759							
QI8	0,596							
QI9	0,638							

*The values in the gray cells represent the square root of the AVE
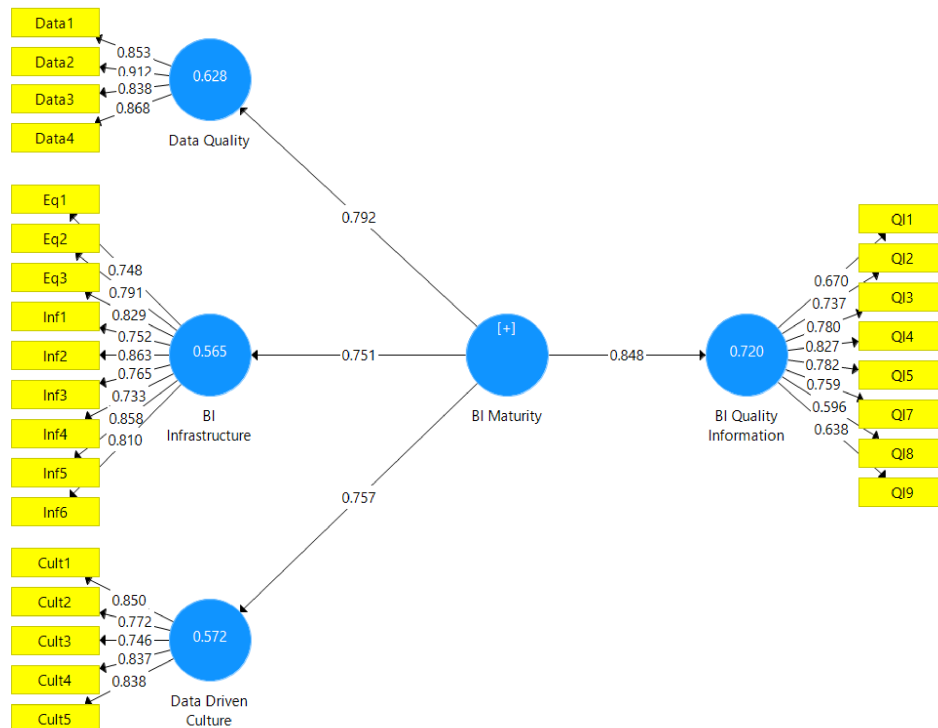
Fig. 2 Structural model results

TABLE 4
HYPOTHESES TEST RESULTS

Ref	Hypothesis	β	p-value	Supported
H1a	The maturity of the BI system is determined by the quality of the data.	0.792	0,000	Yes
H1b	The maturity of the system is determined by the BI infrastructure.	0.751	0,000	Yes
H1c	The maturity of the system is determined by the data-driven culture.	0.757	0,000	Yes
H2	The level of maturity of the system positively influences the quality of the information provided.	0.848	0,000	Yes

The structural model was evaluated using SmartPLS 3.0, based on the recommendations of Hair et al. [68]. The significance levels of the model's relationships were determined through a Bootstrapping procedure, with 5000 iterations. The results confirmed that all paths in the model were statistically significant at the 0.001 threshold. Fig. 2 showed the final model, presenting path coefficients (β) on the arrows and the coefficient of determination (R^2) within the circles.

Table 4 showed the findings relating to the model's hypotheses. The hypotheses related to the dimensions of maturity demonstrated outstanding confidence levels, with p-values falling below 0.001. The hypothesis concerning the relationship between BI maturity and information quality also showed high significance. These results were consistent with the path coefficients of the maturity dimensions, all of which exceeded 0.751. The central hypothesis of the model, asserting that the maturity level of the system positively influenced the quality of information provided had strong support, with a coefficient β=0.848.

The R^2 values contained within the circles in Fig. 2 showed the extent to which independent variables in the structural equations explained the variance in dependent variables. According to the figure above, the model interpreted approximately 72% of the variance in "BI information quality. This substantial explanatory power surpassed the 75% threshold [67], [72], and "BI maturity" effectively clarified at least 56.5% of its first-order variables, signifying the robustness of these Key Factors of Success (KFSs).

V. DISCUSSION

Based on the hypotheses of this study, an organization's internal resources and BI competencies exerted an influence on its maturity. The findings indicated that greater BI maturity within an organization correlated with higher quality information and knowledge derived, thereby elevating the probability of user utilization. The findings corroborated the operationalization of BI as a second-order construct. This study identified three dimensions of system maturity, namely data quality (H1a), BI infrastructure (H1b), and data-driven analytical culture (H1c).

Data quality, recognized as a critical success factor for BI maturity [44], [73], received substantial support from the proposed model. This was consistent with the observation by Skyrius et al. that "attention to data quality was insufficient because systems based on data suffering from poor quality are not trusted by users [28], [37].

Davenport and Harris asserted that deploying a BI infrastructure was crucial for organizations seeking to integrate analytics as a core component of their strategy [9]. The results strongly substantiated H1b, and were in line with prior studies by [3], [30], [51], [74].

The cultivation of a data-driven culture, emphasizing the use of testing and measurement for informed decision-making backed by quantitative data rather than intuition [57], [75], arose as a crucial dimension of BI maturity in the study results. It should be acknowledged that a data-driven culture significantly influenced the success or failure of IS implementation projects [58]. However, fostering such a culture demanded substantial effort, particularly from top management. According to Davenport and Bean, "A significant and persistent problem was the slowness with which established companies moved towards a data-driven culture" [76].

The empirical results firmly supported the hypotheses related to the dimensions of BI maturity (H1a through H1c) and validated the theoretical framework proposed by [77]. This framework comprehensively covered BI capabilities across four domains, namely Governance (Data Quality), Culture (Data-Driven), People, and Technology (BI Infrastructure).

As hypothesized in the study, the findings showed the highly positive influence of maturity levels on the quality of information and knowledge derived from the systems. This outcome was consistent with a previous study by [25], demonstrating that a higher level of system maturity improved information quality. Essentially, the maturity significantly contributed to improved information quality, as stated by Lönnqvist and Pirttimäki, who proposed that the primary benefit of system was "better information quality for decision-making" [18]. Building upon the study conducted by Shen et al. [78], which stated the positive impact of BI maturity on information quality (β= 0.575), the exploration reinforced this relationship, revealing a substantial positive impact with a β of 0.848 on information quality.

The results affirmed the idea that the development of BI-related resources and skills, the capabilities defined as maturity dimensions in the model, contributed significantly to maturity within organizations, thereby providing the information necessary for strategic decision-making. In line with [3], it could be concluded that BI was one of the most important technologies and tools for facilitating knowledge generation in businesses.

The empirical findings of this study provided strong support for the proposed theoretical model, indicating the relevance and significance of the suggested dimensions of system maturity. Few studies explored maturity as a determinant of information quality, similar to [25], and such studies were even more scarce in the context of developing countries, such as Morocco. This investigation filled an important gap in the literature regarding BI systems maturity and its impact on information quality. The robust statistical relationship between maturity and information quality revealed in this study showed the significance of adopting a maturity perspective to comprehend the performance of these systems [45], [52].

A significant theoretical contribution of this study was the proposal of an innovative conceptual model elucidating the link between BI Maturity and information quality, bridging a practical and professionally dominant field with the theoretical foundations of information systems. This contribution addressed a gap in the literature on maturity models, which often lacked strong theoretical underpinnings [24].

The result of this study provided valuable insights for organizations that are already engaged in, or planning to initiate, BI initiatives. Specifically, it described the critical factors and variables influencing BI's contribution to improving decision-making through better information quality. The model identified BI capabilities that were most likely to improve information quality. The exploration showed the internal corporate resources and competencies that determine maturity. Factors, including high-quality data, adequate technical infrastructure, a skilled team, and a data-driven analytical culture were all crucial resources for BI maturity.

VI. CONCLUSIONS

In conclusion, despite BI having been a long-standing priority for information systems investments and promising market forecasts, it was surprising to observe high failure rates in its initiatives. This issue revealed the need to assess the contributions and benefits of these systems. One way to comprehend the impact was to evaluate the primary output, which was information. Improving the quality of information was a key objective for BI systems to promote decision-making. Although the aspect of information systems had extensively explored information quality, it remained understudied in the context of BI, especially concerning its determinants. This study made two significant contributions, first, it addressed this gap by identifying BI resources and capabilities that enhanced information quality. Second, it applied maturity approach to achieve the desired results. When compared to previous studies that focused on two dimensions of maturity, the current exploration introduced three capabilities, including source data quality, BI infrastructure, and data-driven culture, all in line with those stated by Cosik et al.

While this study was consistent with previous theoretical work that described the importance of BI maturity for Information Quality, it was essential to acknowledge its limitations. One primary limitation was the selection of BI maturity dimensions. Professional models offered numerous potential dimensions, but for practical reasons, a subset was chosen. Methodologically, the sample size was limited, implying that results had to be interpreted cautiously. Despite these constraints, it was worth acknowledging that all paths in the structural model were statistically significant.

The study on BI maturity and its relationship with the capabilities was relatively unexplored. Future explorations could expand the model by incorporating additional dimensions to enrich the understanding of maturity. Another avenue for future investigation included introducing moderating variables that might influence the relationship between maturity and Information Quality.

Informed Consent: Informed Consent was obtained, and a detailed explanation was presented in the Methods section.

Animal Subjects: There were no animal subjects.

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REFERENCES

[1] C. S. Reddy, R. S. Sangam, and B. Srinivasa Rao, "A Survey on business intelligence tools for marketing, financial, and transportation services," in *Smart Intelligent Computing and Applications*, S. C. Satapathy, V. Bhateja, and S. Das, Eds., in Smart Innovation, Systems and Technologies, vol. 105. Singapore: Springer Singapore, 2019, pp. 495–504. doi: 10.1007/978-981-13-1927-3_53.

[2] T. Ermakova, J. Blume, B. Fabian, E. Fomenko, M. Berlin, and M. Hauswirth, "Beyond the hype: why do data-driven projects fail?," in *the Hawaii International Conference on System Sciences*, 2021. doi: 10.24251/HICSS.2021.619.

[3] A. Ahmad, "Business intelligence for sustainable competitive advantage," in *Advances in Business Marketing and Purchasing*, Emerald Group Publishing Limited, 2015, pp. 3–220. doi: 10.1108/S1069-096420150000022014.

[4] L. Rao-Graham, M. L. McNaughton, and G. Mansingh, *Business intelligence for small and medium-sized enterprises: an agile roadmap toward business sustainability*, 1st ed. Auerbach Publications, 2019. doi: 10.1201/9780429316371.

[5] P. R. Clavier, H. H. Lotriet, and J. J. van Loggerenberg, "Business intelligence challenges in the context of goods- and service-dominant logic," in *2012 45th Hawaii International Conference on System Sciences*, Maui, HI, USA: IEEE, Jan. 2012, pp. 4138–4147. doi: 10.1109/HICSS.2012.138.

[6] I. Mordor, "Part de marché de la Business Intelligence, taille (2022-27) | Croissance de l'industrie." https://www.mordorintelligence.com/fr/industry-reports/global-business-intelligence-bi-vendors-market-industry (accessed Jun. 06, 2023).

[7] R. A. Lehman, H. J. Watson, B. H. Wixom, and J. A. Hoffer, "Continental airlines flies high with real-time business intelligence," *MIS Quarterly Executive*, vol. 3, no. 4, p. 30, 2008.

[8] B. H. Wixom, H. J. Watson, A. M. Reynolds, and J. A. Hoffer, "Continental airlines continues to soar with business intelligence," *Information Systems Management*, vol. 25, no. 2, pp. 102–112, 2008, doi: 10.1080/10580530801941496.

[9] T. H. Davenport and J. G. Harris, "Competing on Analytics," *Harvard Business Review*, Jan. 01, 2006. Accessed: Aug. 15, 2021. [Online]. Available: https://hbr.org/2006/01/competing-on-analytics

[10] G. Loveman, "data-mining-at-harrah.pdf," *Harvard Business Review*, p. 5, May 2003.

[11] R. SHARDA, D. DURSUN, and E. TURBAN, *Business intelligence and analytics: systems for decision support*, Tenth edition. Boston: Pearson, 2015.

[12] J. S. Valacich and C. Schneider, *Information systems today _ managing in the digital world*, SEVENTH EDITION. New Jersey: Pearson Education, 2016.

[13] B. Ramesh and A. Ramakrishna, "Unified business intelligence ecosystem: a project management approach to address business intelligence challenges," in *2018 Portland International Conference on Management of Engineering and Technology (PICMET)*, Honolulu, HI: IEEE, Aug. 2018, pp. 1–10. doi: 10.23919/PICMET.2018.8481744.

[14] VentureBeat, "Why do 87% of data science projects never make it into production?," *VentureBeat*, Jul. 19, 2019. https://venturebeat.com/ai/why-do-87-of-data-science-projects-never-make-it-into-production/ (accessed Mar. 12, 2023).

[15] J. Pereira, M. Basto, and A. Ferreira-da-Silva, "Comparative Analysis between Statistical and Artificial Intelligence Models in Business Failure Prediction," *JMS*, vol. 4, no. 1, p. p114, Feb. 2014, doi: 10.5539/jms.v4n1p114.

[16] M. R. Arizmendi and L. Stapleton, "Failure Factors in the Control of Large-Scale Business Intelligence Systems Development Projects," *IFAC-PapersOnLine*, vol. 52, no. 25, pp. 579–584, 2019, doi: 10.1016/j.ifacol.2019.12.609.

[17] J. Jaklič, P. Coelho, and A. Popovič, "Information Quality Improvement as a Measure of Business Intelligence System Benefits," *WSEAS Transactions on Business and Economics*, vol. 6, Sep. 2009.

[18] A. Lönnqvist and V. Pirttimäki, "The measurement of business intelligence," *Information Systems Management*, vol. 23, no. 1, p. 9, 2006.

[19] S. Negash and P. Gray, "Business intelligence," in *Ninth Americas Conference on Information Systems*, 2003, p. 10.

[20] M. Kowalczyk and P. Buxmann, "Investigating business intelligence and analytics from a decision process perspective: a structured literature review".

[21] A. Popovič, P. S. Coelho, and J. Jaklič, "Absorption of information provided by business intelligence systems-the effect of information quality on the use of information in business processes," in *Proceedings of the 12th International Conference on Enterprise Information Systems*, Funchal, Madeira, Portugal: SciTePress-Science and and Technology Publications, 2010, pp. 176–181. doi: 10.5220/0002890901760181.

[22] T. de Bruin, M. Rosemann, and R. Freeze, "Understanding the main phases of developing a maturity assessment model," p. 11, 2005.

[23] N. Ain, G. Vaia, W. H. DeLone, and M. Waheed, "Two decades of research on business intelligence system adoption, utilization and success – A systematic literature review," *Decision Support Systems*, vol. 125, p. 113113, Oct. 2019, doi: 10.1016/j.dss.2019.113113.

[24] A. Ait Touil and S. Jabraoui, "Les modèles de maturité de la business intelligence Analyse comparative.," *Revue Marocaine de la Prospective en Sciences de Gestion*, vol. 2022, no. 4, p. 16, May 2022.

[25] A. Popovič, P. S. Coelho, C. de Campoilde, and J. Jakli, "The impact of business intelligence system maturity on information quality," *Information Research*, vol. 14, no. 4, p. 26, 2009.

[26] C. Soh and M. L. Markus, "How it creates business value: a process theory synthesis," in *Proceedings of the Sixteenth International Conference on Information Systems*, Amsterdam, The Netherlands, 1995, pp. 29–41.

[27] N. Melville, K. Kraemer, and V. Gurbaxani, "Information technology and organizational performance: an integrative model of it business value," *MIS Quarterly*, vol. 28, no. 2, pp. 283–322, 2004, doi: 10.2307/25148636.

[28] R. Skyrius, G. Kazakevičienė, and V. Bujauskas, "From management information systems to business intelligence: the development of management information needs," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 2, no. 3, Art. no. 3, 2013, doi: 10.9781/ijimai.2013.234.

[29] V.-H. Trieu, "Getting value from business intelligence systems: a review and research agenda," *Decision Support Systems*, vol. 93, pp. 111–124, 2017, doi: 10.1016/j.dss.2016.09.019.

[30] L. Fink, N. Yogev, and A. Even, "Business intelligence and organizational learning: an empirical investigation of value creation processes," *Information & Management*, vol. 54, no. 1, Art. no. 1, 2017, doi: 10.1016/j.im.2016.03.009.

[31] D. J. Teece, "Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance," *Strategic Management Journal*, vol. 28, no. 13, Art. no. 13, 2007, doi: 10.1002/smj.640.

[32] D. J. Teece, G. Pisano, and A. Shuen, "Dynamic capabilities and strategic management," *Strategic Management Journal*, vol. 18, no. 7, Art. no. 7, 1997, doi: 10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z.

[33] G. Klimko, "Knowledge management and maturity models: Building common understanding," in *Second European conference on knowledge management*, in Second European Conference on Knowledge Management. Slovenia: Academic Conferences Limited, 2001, pp. 269–278.

[34] D. Proença and J. Borbinha, "Maturity models for information systems - a state of the art," *Procedia Computer Science*, vol. 100, pp. 1042–1049, 2016, doi: 10.1016/j.procs.2016.09.279.

[35] I. H. Rajteric, "Overview of business intelligence maturity models," *Management*, vol. 15, no. 1, pp. 47–67, 2010.

[36] G. Lahrmann and F. Marx, "Systematization of maturity model extensions," in *Global Perspectives on Design Science Research*, R. Winter, J. L. Zhao, and S. Aier, Eds., in Lecture Notes in Computer Science, vol. 6105. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 522–525. doi: 10.1007/978-3-642-13335-0_36.

[37] H. Xu, "ERP implementation satisfaction-a data quality approach," *Journal of Technology Research*, vol. 8, p. 17, 2019.

[38] C. Batini and M. Scannapieco, "Data and information quality: dimensions, principles and techniques," in Data-Centric Systems and Applications. Cham: Springer International Publishing, 2016. doi: 10.1007/978-3-319-24106-7.

[39] Y. Lin and A. K. M. Hadi, "Evaluation of information quality in business intelligence as a key success factor for using decision support system," p. 95, 2011.

[40] R. Y. Wang and D. M. Strong, "Beyond accuracy: what data quality means to data consumers," *Journal of Management Information Systems*, vol. 12, no. 4, pp. 5–33, 1996.

[41] L. Marshall and R. De la Harpe, "Decision making in the context of business intelligence and data quality," *S. Afr. j. inf. manag.*, vol. 11, no. 2, 2009, doi: 10.4102/sajim.v11i2.404.

[42] D. M. Strong, Y. W. Lee, and R. Y. Wang, "Data quality in context," *Commun. ACM*, vol. 40, no. 5, pp. 103–110, 1997, doi: 10.1145/253769.253804.

[43] H. Watson, T. Ariyachandra, and R. J. Matyska, "Data warehousing stages of growth," *Information Systems Management*, vol. 18, no. 3, pp. 42–50, 2001, doi: 10.1201/1078/43196.18.3.20010601/31289.6.

[44] G. Lahrmann, F. Marx, R. Winter, and F. Wortmann, "Business intelligence maturity: development and evaluation of a theoretical model," *th Hawaii International Conference on System Sciences*, p. 11, 2011.

[45] S. Williams and N. Williams, *The Profit Impact of Business Intelligence*, Updated and rev.[New ed.]. in The Morgan Kaufmann series in interactive technologies. Amsterdam ; Boston: Elsevier/Morgan Kaufmann Publishers, 2008.

[46] M. Alsqour, M. Owoc, and K. Matouk, "A survey of data warehouse architectures-preliminary results," in *Federated Conference on Computer Science and Information Systems (FedCSIS)*, Poland, 2012.

[47] Piccoli and Ives, "Review: IT-dependent strategic initiatives and sustained competitive advantage: A Review and Synthesis of the Literature," *MIS Quarterly*, vol. 29, no. 4, p. 747, 2005, doi: 10.2307/25148708.

[48] Chen, Chiang, and Storey, "Business intelligence and analytics: from big data to big impact," *MIS Quarterly*, vol. 36, no. 4, p. 1165, 2012, doi: 10.2307/41703503.

[49] A. Bharadwaj, V. Sambamurthy, and R. Zmud, "IT capabilities: Theoretical perspectives and empirical operationalization," in *Proceedings of the 19th International Conference on Information Systems*, Helsinki, Finland, 1998, pp. 378–385. doi: 10.1145/352925.352962.

[50] N. Elgendy and A. Elragal, "Big data analytics in support of the decision making process," *Procedia Computer Science*, vol. 100, pp. 1071–1084, 2016, doi: 10.1016/j.procs.2016.09.251.

[51] H. J. Watson and B. H. Wixom, "The current state of business intelligence," *Computer*, vol. 40, no. 9, pp. 96–99, 2007, doi: 10.1109/MC.2007.331.

[52] B. Wixom and H. Watson, "The BI-Based organization," *International Journal of Business Intelligence Research*, vol. 1, no. 1, pp. 13–28, Jan. 2010, doi: 10.4018/jbir.2010071702.

[53] A. McAfee and E. Brynjolfsson, "Big data: the management revolution," *Harvard Business Review*, no. October 2012, Oct. 01, 2012. Accessed: Jun. 20, 2019. [Online]. Available: https://hbr.org/2012/10/big-data-the-management-revolution

[54] J. Pfeffer and R. I. Sutton, "Evidence-based management," *harvard business review*, 2006.

[55] R. Cosic, G. Shanks, and S. Maynard, "Towards a business analytics capability maturity model," p. 11, 2012.

[56] A. Thamir and B. Theodoulidis, "Business intelligence maturity models: information management perspective," in *Information and Software Technologies*, T. Skersys, R. Butleris, and R. Butkiene, Eds., in Communications in Computer and Information Science, vol. 403. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 198–221. doi: 10.1007/978-3-642-41947-8_18.

[57] T. Grublješič and J. Jaklič, "Conceptualization of the business intelligence extended use model," *Journal of Computer Information Systems*, vol. 55, no. 3, pp. 72–82, 2015, doi: 10.1080/08874417.2015.11645774.

[58] A. Popovič, "If we implement it, will they come? User resistance in post-acceptance usage behaviour within a business intelligence systems context," *Economic Research-Ekonomska Istraživanja*, vol. 30, no. 1, pp. 911–921, 2017, doi: 10.1080/1331677X.2017.1311232.

[59] U. Kulkarni, J. Robles-Flores, Universidad ESAN, A. Popovič, and University of Ljubljana, "Business Intelligence Capability: The Effect of Top Management and the Mediating Roles of User Participation and Analytical Decision Making Orientation," *Journal of the Association for Information Systems*, vol. 18, no. 7, Art. no. 7, 2017, doi: 10.17705/1jais.00462.

[60] S. Lavalle, E. Lesser, R. Shockley, M. S. Hopkins, and N. Kruschwitz, "How the smartest organizations are embedding analytics to transform information into insight and then action. Findings and recommendations from the first annual New Intelligent Enterprise Global Executive study.," *MIT Sloan Management Review*, vol. 52, no. 2, Art. no. 2, 2011.

[61] M. Hannula and V. Pirttimaki, "Business intelligence empirical study on the top 50 Finnish companies," *Journal of American Academy of Business*, vol. 2, no. 2, p. 7, 2003.

[62] S. Williams and N. Williams, "Assessing BI Readiness: The Key to BI ROI," p. 12, 2004.

[63] B. H. Wixom and H. J. Watson, "An Empirical Investigation of the Factors Affecting Data Warehousing Success," *MIS Quarterly*, vol. 25, no. 1, p. 17, 2001, doi: 10.2307/3250957.

[64] M. Gupta and J. F. George, "Toward the development of a big data analytics capability," *Information & Management*, vol. 53, no. 8, Art. no. 8, 2016, doi: 10.1016/j.im.2016.07.004.

[65] P. Mikalef, M. Boura, G. Lekakos, and J. Krogstie, "Big data analytics and firm performance: findings from a mixed-method approach," *Journal of Business Research*, vol. 98, pp. 261–276, 2019, doi: 10.1016/j.jbusres.2019.01.044.

[66] R. BILLOT, C. BOTHOREL, and P. LENCA, "Introduction to big data and its applications in insurance," in *Big data for insurance companies*, Hoboken, NJ: ISTE Ltd/John Wiley and Sons Inc, 2017, pp. 1–25.

[67] J. F. Hair, G. T. Hult, C. M. Ringle, and M. Sarstedt, *A primer on partial least squares structural equation modeling (PLS-SEM)*, Second edition. California,USA: SAGE Publications, Inc., 2017.

[68] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *EBR*, vol. 31, no. 1, pp. 2–24, 2019, doi: 10.1108/EBR-11-2018-0203.

[69] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate data analysis*, 7th ed. New Jersey USA: Prentice Hall PTR, 2009.

[70] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, p. 39, 1981, doi: 10.2307/3151312.

[71] M. Sarstedt, J. F. Hair, J.-H. Cheah, J.-M. Becker, and C. M. Ringle, "How to specify, estimate, and validate higher-order constructs in PLS-SEM," *Australasian Marketing Journal*, vol. 27, no. 3, pp. 197–211, 2019, doi: 10.1016/j.ausmj.2019.05.003.

[72] J. Henseler, C. M. Ringle, and R. R. Sinkovics, "The use of partial least squares path modeling in international marketing," in *Advances in International Marketing*, R. R. Sinkovics and P. N. Ghauri, Eds., Emerald Group Publishing Limited, 2009, pp. 277–319. doi: 10.1108/S1474-7979(2009)0000020014.

[73] W. Yeoh and A. Koronios, "Critical success factors for business intelligence systems," *Journal of Computer Information Systems*, p. 12, 2010.

[74] H. Watson, C. Fuller, and T. Ariyachandra, "Data warehouse governance: best practices at blue cross and blue shield of North Carolina," *Decision Support Systems*, vol. 38, pp. 435–450, 2004, doi: 10.1016/j.dss.2003.06.001.

[75] T. Davenport, "The right way to use business analytics," *CIO*, Oct. 01, 2005. https://www.cio.com/article/2448414/the-right-way-to-use-business-analytics.html (accessed Aug. 15, 2021).

[76] T. H. Davenport and R. Bean, "Big companies are embracing analytics, but most still don't have a data-driven culture," p. 4, 2018.

[77] R. Cosic, G. Shanks, and S. B. Maynard, "A business analytics capability framework," *AJIS*, vol. 19, 2015, doi: 10.3127/ajis.v19i0.1150.

[78] C.-C. Shen, R.-E. Chang, C. J. Hsu, and I.-C. Chang, "How business intelligence maturity enabling hospital agility," *Telematics and Informatics*, vol. 34, no. 1, pp. 450–456, 2017, doi: 10.1016/j.tele.2016.06.009.

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