Assessing the Impact of Business Intelligence on Decision Support Environments in Enterprise Systems

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Abstract – This research paper aims at examining the effects of Business intelligence assessment on decision support systems of enterprise systems. The rationale for the study aims at understanding how BI capabilities affect decision making in organizations. The approach used in the paper included the analysis of prior works to build a strong research framework. Questionnaire was developed and mailed to IT Managers, Chief Information Officers and IT Project Managers of the Fortune 500 firms and received a total response rate of 41.90%, which was considered valid. To determine the key BI components and their relevance, an examination of the survey data was conducted with the help of factor analysis and hypothesis testing. Our results showed that the evaluation of BI capabilities plays a vital role in improving decision-support settings, as indicated by the Wald-Wolfowitz test and factor analysis. The study revealed six major factors that constitute 73.917% of the variation and are crucial to determine the intelligence levels of ES. These results highlight the importance of systematic BI assessment for enhancing organizational decision-making and lay the groundwork for creating better instruments to investigate and foster BI proficiency in ES.

Keywords – Business Intelligence, Knowledge, Knowledge Management, Business Analytics, Big Data, Decision Support Systems, Information Technology and Data Analysis Methodologies.

I. INTRODUCTION

Currently, information and knowledge are the essential assets of an organization [1]. The extensively document the privilege associated with the term “knowledge” and the resulting opportunities for occupational groups to safeguard their positions and obscure the intricacies of their skills. This is often achieved by asserting the authority of fields such as medicine, law, or other domains with complex bodies of knowledge. In observes that professionals in the modern knowledge-based companies are similarly drawn to the allure surrounding terms like knowledge and knowledge worker. The knowledge-intensive firms primarily function as systems of persuasion. In line with this argument, In propose that the increasing usage of these phrases may be seen as a language that normalizes a certain division of labor, diverting attention away from the significance of knowledge in all types of activities.

The term “Knowledge Management” (KM) is not coincidental, since the term “management” implies the need to oversee and control something. Following an exploration of the differentiation between explicit and tacit knowledge in 1966, The have formulated a series of management definitions, concepts, activities, stages, circulations, and procedures. These efforts aim to establish a framework for knowledge management, which serves as the methodology for managing and describing objects. In produced another definition of KM that has gained significant popularity and is regularly used. According to KM is defined as an effort to enhance knowledge within the firm. It is a natural outgrowth of a movement in the late 20th century to make organizational operations and management more effective for high quality and responsiveness to components in a rapidly-transformative global movement. The only true deficiency of this concept is that it is exclusively restricted to an organization's own information and knowledge assets [1]. The current concept of KM, including its early extension, encompasses the incorporation of pertinent information assets from any relevant source. It is important to consider the wide scope linked with KM when referring to it as a “discipline.” Both meanings exhibit a strong focus on organization and business matters. Historically, KM focused on the management of organizational knowledge. However, the notion of KM expanded rapidly beyond that.

Knowledge Management (KM) and Business Intelligence (BI) are two different fields that employ different approaches to making sense of information within organizations. Both ideas call for approaches to improve learning, decision making and understanding within organizations. The difference between BI and KM is based on the presumption that BI is the relationship between data, software-based logical tools, and technology, while KM is knowledge sharing of both the implicit and explicit knowledge [2]. Business Intelligence (BI) include the use of data warehousing technologies, decision support systems, Online Analytical Processing methods (OLAP), data mining, numerical studies, other business analytical tools. The evaluation involves the use of data analysis and information technology methodologies in order to understand the business environment, and the factors that are leading to the observed performance.

Business Intelligence (BI) mainly focuses on the exploitation of well-defined longitudinal and multidimensional data. In contrast, KM is defined as the effective management of both, tacit and explicit knowledge and the complex relations between them. There are several definitions of KM but one of the most comprehensive is that it is the process of implementing collaboration, structural behavioral science, content management and learning [2]. KM knowledges include the methods used to generate, store, retrieve, disseminate, and examine both unstructured and structured data and textual content. In their 2005 study examined the distinction among KM and BI determined that BI might be considered a KM subset. The record the ways in which ideas in knowledge management should be taken into account while comprehending and implementing BI. For instance, the utilization of BI analytics to operate and evaluate data often relies on the utilization of domain-specific expertise, the assessment of discoveries, the study of the viability of possible solutions in political or cultural settings, and the dissemination of knowledge to relevant groups [3]. This implies that while the analytics and data of BI are clear and specific, their implementation and usefulness frequently rely on implicit aspects that determine their significance and usefulness.

Which conducted a systematic analysis of published articles on the assessment and selection of software packages and Enterprise Systems (ES), it has been determined that there is no all-inclusive set of criteria for this evaluation. Previous studies have mostly neglected the examination of intelligence criteria and have failed to develop models for assessing these characteristics. Our ongoing research focuses on meeting these requirements in the domain of assessing the cognitive capabilities of corporate software and systems [3]. Organizations often analyze and choose enterprise schemes by assessing their non-functional and functional necessities. When considering decision-support requirements as non-functional, the queries below arise:

- RQ1. What are the primary components involved in the assessment of BI capabilities within enterprise systems, and how significant are these components to the overall BI assessment?
- RQ2. How does the assessment of BI capabilities influence the decision-support environments in organizations, and what are the measurable impacts on organizational decision-making processes?
- RQ3. What statistical methods and analytical frameworks are most effective in identifying and validating the key conditions that lead to the effectiveness of BI within enterprise systems?

The main aim of this research is to survey the effect of BI assessment on the decision-support environments within enterprise systems. By identifying and evaluating the primary components of BI capabilities, the study aims to determine their significance and impact on organizational decision-making processes. The research seeks to develop a comprehensive framework and utilize statistical methods to validate key factors that enhance BI effectiveness, ultimately providing insights and tools for organizations to improve their Decision-Support Systems (DSS). The rest of this paper is arranged as follows: Section II reviews previous literature works on BI on decision support environments in enterprise systems. Section III discusses the survey design, and data collection. Section IV discusses the findings obtained in this research, which integrates interviewees demographic profiles, hypothesis test, and extraction of factors. Section V concludes the research, and recommends future research directions.

II. RELATED WORKS

The defined Business Intelligence (BI) as an organization concept and tool that assists businesses in effectively managing and refining business information to facilitate informed decision-making. The phrase may be used to include the interconnected information and understanding of the company, including the business ecosystem, market circumstances, the organization, customers and competitors, and economic matters. The phrase may also be used to the holistic and methodical process via which businesses acquire, evaluate, and disseminate information to make choices regarding company operations. The objective of BI is to efficiently manage the allocation and use of resources and the flow of data within and around the company [4]. BI significantly enhances the intelligence and understanding of organizational management by effectively analyzing and interpreting data to uncover its underlying significance.

The argue that BI has consistently been a key focus for IT leaders over the last several years, and the market for BI software solutions continues to expand significantly, even in the face of difficult macro-economic circumstances. Recently, the rise of Business Analytics (BA) and the management of 'Big Data' have played a vital role in the continuous expansion of the BI software program. Although there were initial requests for study in BI, the broader academic study community has only slowly accepted the subject [4]. As of today, research on BI remains disjointed and scarce. Contemporary BI systems exhibit distinct differences from previous iterations of Decision Support Systems (DSS) in several aspects: Firstly, these processes usually include the methodical incorporation, consolidation, and administration of organized and unorganized data in data warehouses, which are becoming more and more capable of handling data in real-time. This allows for the development of novel fact-based decision support systems. Furthermore, modern BI systems are capable of handling vast and growing volumes of data, often referred to as 'Big Data'. These solutions may use exponentially improving processing capabilities, including in-memory technologies, which have opened up new possibilities for uncovering valuable insights, such as data mining. Furthermore, business intelligence solutions gain advantages from novel methods of data analysis and efficient dissemination of information (such as automated distribution to or self-service from ubiquitous computing devices).

A literature analysis on the topic of Business Intelligence (BI) reveals a clear “division” between the technical and management perspectives, which may be categorized into two overarching patterns. Technologically, BI is a comprehensive classification of tools, software, solutions, and technologies that empower decision-makers to discover, gather, arrange, and retrieve a diverse array of information from various data sources [5]. In this particular context, the primary focus of BI is not on the procedural aspects, but rather on the technological infrastructure that enables the collection, storage, integration, examination, and extraction of organizational data. The expected outcome is the revelation of 'insights' that may be deeply ingrained in the data, provided there is an appropriate combination of data mining and data warehousing. The managerial approach views BI as a systematic procedure that associates information from both internal and external sources to produce vital data for effective decision-making [6]. It also emphasizes the advantages of implementing embedded transaction processing systems and enterprise utilizations to reap the benefits of BI. The main emphasis is on the organization and control of the procedure through which various information sources from a range of operational and transactional systems (both external and internal to the firm) may be combined and examined in a logical manner to facilitate the decision-making process.

Business Intelligence (BI), as described by Sun, Sun, and Strang, refers to the application of applications and technology in business management to collect, offer access to, and assess data and statistics about an association [7]. The role of BI is to assist management in making more informed business choices. The main aim of BI is to allow the organization of the extensive influx of business data inside and outside a company. This is achieved by first recognizing the information and then transforming it into concise and valuable managerial knowledge and intelligence. The BI work encompasses a range of themes and solves longstanding managerial issues [7]. It is a fundamental task within the realm of management tools, including the analysis of intricate corporate environments to facilitate improved decision-making. Organizations have gathered data about their rivals since the inception of capitalism. The true revolution lies in the endeavors to establish intelligence operations as a formal part of institutions. BI delivers company data in a prompt and readily comprehensible manner, allowing users to analyze and comprehend the significance of the information. This is achieved by methods such as discovery, analysis, and ad hoc querying. The research on business intelligence (BI) indicates that there are significant advantages to be gained from its use.

The argued that BI produces reports about inclinations in the company ecosystem and internal business issues. They clarified that reports might be generated in a systematic, Ad-hoc, or regular manner, according to a particular decision-making setting. Individuals in positions of authority at various levels within an organization use this information. The method yields both numerical and textual data. **Table 1** categorizes BI definitions according to three distinct methods: management, technical, and ES-facilitator.

Table 1. Key Definitions of BI

Definitions	**References**
A group of tools, procedures, structures, technologies, and strategies for storing, gathering, retrieving data	[1,2,3,4]
A group of programs, tools, and procedures for storing, gathering, retrieving, and analyzing data so that business users may make wise choices	[5,6,7,8]
A group of skills used to analyze historical data and provide answers to business concerns, including extract, OLAP, transact, load, reporting, and data warehousing.	[9,10,]
Data, strategy, procedures, technology, and analytics systems are all integrated to help in decision-making.	[11,12,]
Tools and procedures for accessing, examining, and analyzing BD in order to assist in decision-making	[13,14,]
Unified platform that unifies data so that it may be analyzed to support effective business choices	[15,16,]
Applications, systems, and procedures that provide data to support well-informed decision-making	[17,18,19]

The businesses need frameworks and methods to analyze and evaluate the BI skills and competences of their ES. This is necessary to gain a viable edge by making timely and informed choices. This study involves the identification of pertinent assessment criteria and the development of a methodology to assess enterprise system intelligence. In order to determine these criteria, we undertook a thorough examination of relevant literature up to 2024 [9]. The study included the identification, analysis, and classification of articles from conference proceedings, journals, textbooks, and PhD dissertations. In order to comprehensively explore the intelligence of a decision support and system, it was necessary to examine a diverse array of research from other disciplines, since several criteria are interconnected with these concepts.

Hence, the search included a wide range of sources including journals, Management, conference proceedings, textbooks, and PhD dissertations [8]. IT, computers, and IS are prevalent academic correlations in the field of BI research. To compile a thorough bibliography of the pertinent literature, we did searches in various online resources including the Web of Science, INFORM/ABI database, Science Direct, Sage, Emerald Fulltext, ACM Digital Library, JSTOR, ProQuest Digital Dissertations, and IEEE Xplore [8]. The literature search was conducted using the following keywords: 'decision support', 'BI capabilities', 'BI assessment criteria', 'decision-support criteria', 'BI assessment criteria', 'intelligent tools capabilities' and 'BI needs'. The discovered factors are presented in **Table 2** as BI assessment criteria.

Table 2. Evaluation Criteria for BI

ID	Elements of the criteria	Refences
001	Group sorting methodology and tools (Groupware)	[1]
002	Group decision-making	[2]
003	Flexible framework	[3]
004	Problem clustering	[4]
005	Optimization method	[5]
006	Learning method	[6]
007	Import information from other systems	[7]
008	Export reports to other systems	[8]
009	Simulation framework	[9]
010	Risks simulation	[10]
011	Financial analysis tools	[11]
012	Visual graphs	[12]
013	Summarization	[13]
014	Evolutionary prototyping framework	[14]
015	Dynamic framework prototyping	[15]
016	Forward and backward reasoning	[16]
017	Knowledge reasoning	[17]
018	Warnings and alarms	[18]
019	Recommender/Dashboard	[19]
020	Integration of experiments	[10]
021	Situational awareness model	[11]
022	Environmental sensitivity	[12]
023	Fuzzy decision-making	[13]
024	OLAP	[14]
025	Data mining method	[15]
026	Data warehouses	[2]
027	Web channels	[1]
028	Mobile channels	[3]
029	E-mail channels	[5]
030	Smart agent	[4]
031	Multi agent	[6]
032	MCDM tools	[7]
033	Stakeholders' satisfaction	[8]
034	Accuracy and reliability of analysis	[9]

III. METHODOLOGY

This research aims to examine the impact of BI assessment of ES on the decision-support business environments. The subsidiary study goals were to identify the primary components involved in the assessment of BI abilities and their respective significance. The study methodology used a literature review and previous studies together with current research conducted by the authors, to construct a research framework. Statistical techniques were employed, and the research process was structured according to the ten steps shown in **Fig 1**.

The first phase included doing a detailed review of the literature on the requirements and capabilities of business intelligence. This refers to the factors that determine the nature of a system's BI, as outlined in **Table 2**. For the second phase, a survey was created consisting of three primary sections [10]. The initial segment of the survey included inquiries on the attributes of the interviewers. The second segment of the study focused on inquiries regarding the level of BI competency, aiming to assess the significance of the assessment criteria. The third phase of the survey consisted of questions aimed at understanding the impact of BI assessment on the decision-support ecosystems within administrations. During the third phase, the survey information from the interviews were gathered. In order to verify the supposition, it was essential to establish the arithmetical circulation of the information acquired from the second section of the survey [11]. Afterwards, depending on information circulation, either parametric and non-parametric tests were conducted to validate the hypotheses. The primary objective of the fifth step was to validate the supposition established in phase two.

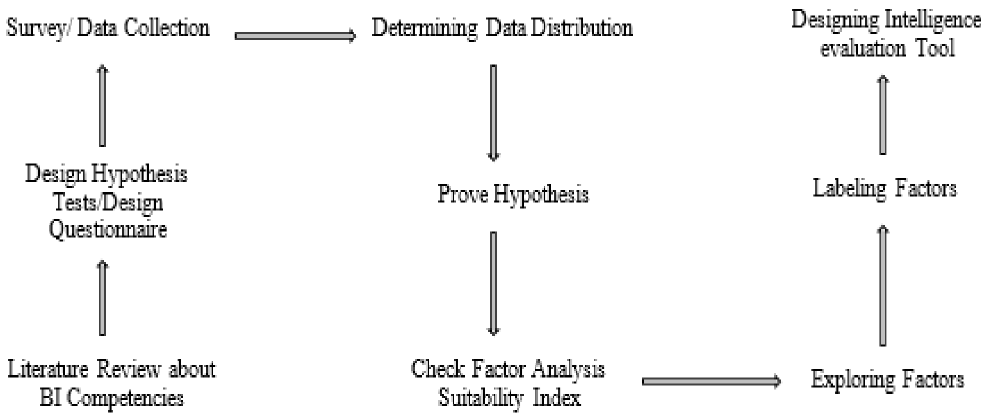

Fig 1. Research Stages and Structure

The seventh and sixth phases of the study model use “factor analysis” to extract and identify the assessment criteria that impact BI. Factor analysis is a term used to refer to a group of statistical procedures that are used to identify the fundamental structure inside a matrix of data [12]. Through the use of factor analysis, we first discerned the distinct components within the edifice and then assessed the degree to which every constant was accounted for by every factor. After identifying these characteristics and providing clarification for every variable, the data was then summarized and reduced. The component analysis condensed the data by identifying underlying factors that explained the data using a fewer number of ideas compared to the original individual variables. The process included assessing the validity of the gathered data, doing factor analysis, and assigning names to the identified components, each of which were distinct stages.

Lastly, labeling helped to clarify the most significant elements and their impact. Subsequently, a sophisticated tool was developed using the acquired understanding of the connections between business intelligence abilities and the key determinants of intelligence stages in enterprise schemes. This innovative tool may assist a company in analyzing and assessing the cognitive capabilities of its ES.

Survey Design

A survey was organized and designed into three distinct components. At the start of the questionnaire, we collected information pertaining to the fundamental properties of the respondents [13]. In the second segment, a total of 34 questions were posed to assess their views, focusing on the significance of the BI assessment criteria outlined in **Table 2**. The advancement of a Likert (or Likert-type) scale is based on the study goal. Occasionally, the objective of the study is to gain insight into the views or viewpoints of entrants on a certain 'latent' variable (the phenomena of interest). The latent variable is signified by many established items in the survey. These created objects are designed to each focus on a distinct aspect of the event being studied and collectively assess the whole phenomenon. During our study, the scores of all questions in the survey are summed to create a complex score, which effectively evaluates a single feature in its whole. The term used to refer to this instrument is Likert scale [14]. The selected feedback was assessed using a “Likert Scale”, which included the following options: disagree, agree, strongly agree, strongly disagree, very strongly agree, or no opinion. Put simply, the second section of the survey assesses participants' views on the significance of each business intelligence capability inside the enterprise system. After the completion of the first 34 questions, a single question (*Y*) was included in the third phase of the survey to assess the impact of BI assessment on the DSS inside their respective businesses.

Y. *Does the assessment of BI for ES play a crucial role in the DSS inside the firm?*

Data Collection

The study primarily focused on stakeholders inside firms that were actively engaged in decision-making processes and had a strong understanding of BI and Information Technology (IT) technologies [15]. Hence, the primary focus of the sample was on IT Managers, CIOs (Chief Information Officers), and IT Project Managers, who play a crucial role in IT initiatives. The data-collection strategy used in this study was oriented on a straightforward random assortment of targets from Fortune 500 businesses, as described.

IV. RESULTS AND DISCUSSION

Data Collection

The study focused on CIOs, IT Project Managers, and IT Managers. A total of 420 surveys were sent, and 185 were received, amounting to a 44% return rate. Out of the surveys that were returned, 26 were partial and thus not considered. This means that the number of legitimate questionnaires was 176, which accounts for 41.90% of the overall number that were sent out.

Interviewees Demographic Profiles

The survey has provided an outline of the demographic properties of the respondents, which may be seen in **Table 3**. The findings indicate that the majority of participants (87.5%) are male and come from a variety of public and commercial organizations [16]. The majority of the respondents (88.7%) possess at least a BS (Bachelor of Science) degree, as seen in **Table 3**. Regarding decision-making approaches, most respondents use a combination of unstructured and semi-structured decision-making methods in their professional endeavors. Additionally, **Table 3** displays the participants' level of seniority. It is evident that 20.4% of individuals possess more than fifteen years of seniority, while 43.2% have fewer than ten years of seniority, and 36.4% have a seniority ranging from 10 to 15 years.

Table 3. Demographic Characteristics of the Interviewed Individuals

	Descriptions	No. interviewees	Percentage	Cumulative percentages
Gender	Male	152	86.5	86.5
	Female	125	100	
	Total	277	100	
Type of organization	Governmental	101	58.1	58
	Private	75	42.1	100
	Total	176	100	
Educational degree	Lower than BS	21	12.2	12.4
	BS	82	47.1	57.5
	MS	73	40.7	100
	Total	175	100	
Type of decision	Structured	15	8	7
	Semi-structured	55	30.3	40.2
	Unstructured	100	61.7	100
	Total	170	100	
Seniority	Less than 5 years	7	4.2	4
	5 to 10 years	61	39.1	41.2
	10 to 15 years	65	36.3	79.6
	15 to 20 years	25	14.3	93.8
	Above 20 years	11	6.1	100
	Total	169	100	

Hypothesis Test

To attain the primary goal of the study, the results must substantiate the hypothesis. As stated before, the poll concluded with a question that proposed a hypothesis:

*H1***.** *Assessing the BI of enterprise systems is crucial for establishing a DSS inside a company.*

Kolmogorov-Smirnov (KS) test is a widely used statistical method for determining the distribution of data. KS test is used to compare the observed cumulative circulation purpose of a variable with a predetermined theoretical circulation, like exponential, normal, Poisson, or uniform [17]. The KS test may be used to analyze one-dimensional data samples that are continuous and not grouped into bins. It presupposes that a collection of data points may be readily transformed into a Cumulative Distribution Function (CDF). The test employs the largest absolute disparity among two cumulative distribution functions. The KS test is employed to compare dataset $F(x)$ with an identifiable CDF $P(x)$ as shown in Eq. (1).

$$D_{KS} = \max|F(x) - P(x)| \tag{1}$$

The data is defined as the comparison of two samples using their CDF, $F(x)$ and $G(x)$ as shown in Eq. (2).

$$D_{KS} = \max\ |\mathrm{F(x)} - \mathrm{G(x)}| \tag{2}$$

Expanding the KS statistic to higher dimensions is a significant problem. In a 1D space, the statistic is unaffected by the direction in which the data is ordered since the probability of a value being more than x is equal to 1 minus the probability of it being less than x. In a space with d dimensions, there are $2d - 1$ distinct methods for creating a cumulative distribution function.

Based on our test findings, the p-value for all queries were below 0.05, indicating that their distribution was not normal. Since the Y variable's statistical distribution is similarly non-normal, it is necessary to employ a numerical non-parametric test to establish $H1$ [18]. To assess the difference among the 'disagree' and 'agree' scores, a Wald-Wolfowitz (WW) test was used. The technique was devised in 1940 by the Romanian mathematician Wald and the Polish mathematician Wolfowitz. It utilizes the runs approach to determine the similarity between two sets of data. This test relies on the replication of population differences in situations when there are two samples. Additionally, the WW sequenced numbers test may be used for analyzing angular data as well. When doing the WW runs test, the null hypothesis is evaluated, which states that the distribution features of the two continuous populations are similar. As per Daniel, the alternative and null hypotheses may be stated as:

H0. The null hypothesis states that the X's and Y's are derived from two distributions that are identical.

H1. The populations of X and Y are statistically distinct from each other Eq. (3) is used to compute WW sequenced numbers tested with big data.

$$Z = \frac{R - \left(\frac{2n_1n_2}{n_1+n_2} + 1\right)}{\sqrt{\frac{2n_1n_2(2n_1n_2 - n_1 - n_2)}{(n_1+n_2)^2(n_1+n_2-1)}}} \tag{3}$$

where R represents the quantity of runs. When considering the large sample method, the test statistic is computed using a specific formula. This calculated test statistic is then compared to values derived from the standard normal table at a predetermined level of implication. If Z is less than or equal to the table values, H0 (null hypothesis) is dismissed at the given significance level (α). In states that Eq. (3) is applicable when the sample sizes are unequal and either n_1 or n_2 is more than 20, or when the sample sizes are equal and either n_1 or n_2 is greater than 100.

Table 4. Results of the WW Test for Alternative Hypothesis (H1)

Queries	Clusters	N	No. runs	Z	Asymp. Significance
Y	1	16	2	-12.99	0.0001
	2	160			

Cluster 1 comprises responses indicating a high level of disagreement, including "very strongly disagree," "strongly disagree," and "disagree." Cluster 2, on the other hand, comprises responses indicating a high level of agreement, including "agree," "strongly agree," and "very strongly agree."

The WW test merges and arranges the data from both clusters. If the chosen clusters are drawn from the same population, they have to be distributed arbitrarily during the positioning and provide several iterations. A significant level below 0.05 states that there is a variance among the two clusters, which is also seen in **Table 4**. Considering a substantial level below 0.05 in the findings of the WW test, and achieving agreement on the main issue (Y), it is crucial to assess the BI of enterprise schemes in order to establish a decision-support environment inside an organization. Thus, it can be said that a company must assess the business intelligence conditions of its systems, as this assessment may enhance their decision-support ecosystem [19]. Consequently, based on the outcome of this hypothesis test, it may be inferred that firms should assess their systems using BI standards.

Factor Analysis

Factor analysis is an approach primarily used to examine the intricate and multifaceted interactions that researchers meet. Factor analysis is a numerical technique that may be employed to analyze the fundamental patterns or interactions among a large number of constants. It helps assess whether the data can be reduced into a smaller set of components or factors. Factor rotation is a crucial method for understanding factors. Factor rotation is performed to facilitate the understanding of findings from Exploratory Factor Analysis (EFA) by identifying several significant factor loadings for each component. The significant loadings are referred to as salient factor loadings. When determining the salient factor loadings, it is important to take into account the sampling variance. This is because a high factor loading in the present sample may not necessarily be a significant factor loading in another sample. The standard error of a factor loading may represent the variance in sampling. Jennrich first computed the standard errors for rotational factor correlations and factor loadings. Howard emphasized the significance of standard errors in EFA studies. In a comprehensive evaluation of the EFA model indicates a three-factor model. However, one of the components does not exhibit any statistically significant loadings.

The phrase rotation refers to the action or process of turning or spinning anything around a central axis. More precisely, the reference axes of the components are rotated about the source until they reach a different location. The un-rotated factor solutions extract factors based on their relative significance. The first component typically has a comprehensive influence, with almost every variable displaying a strong correlation, and it explains the greatest proportion of variability. The second and following components are determined by the remaining portions of alteration. The primary outcome of revolving the matrix is majorly for variance reallocation from initial components to subsequent ones in order to get a more streamlined and conceptually significant factor pattern. An example of a basic revolution is an orthogonal alternation, where the axes are kept at a 90° angle. Prior to commencing the component analysis, the Kaiser-Meyer-Olkin (KMO) test was used to assess the Bartlett's x^2test of sphericity, and the suitability of the sample was utilized to evaluate even if the partial correlation of the constants is modest. KMO process is simple, but needs a lot of computer recourses. The inverse computation of the observed correlation matrix (R^{-1}) is necessary to generate the anti-image correlation matrix in Eq. (4).

$$Q = \left[(diagR^{-1})^{-1/2}\right]R^{-1}\left[(diagR^{-1})^{-1/2}\right] \tag{4}$$

The term "diag R^{-1}" refers to a diagonal matrix that is created by setting all non-diagonal members of the inverse correlation matrix to zero. The KMO test value is calculated using Eq. (5);

$$K = \frac{trace(R^2)-p}{trace(R^2)+trace(Q^2)-2p} \tag{5}$$

or equivalently using Eq. (6),

$$K = \frac{\sum_i \sum_i r_{ii}^2}{\sum_i \sum_{i^*} r_{ii}^2 + \sum_i \sum_{i^*} q_{ii}^2} \quad (i \neq i^*) \tag{6}$$

After calculating the KMO value, it is necessary to compare it following a certain criterion. In a calculated KMO value of .60 or above suggests that the observed variables have at least one common factor. In other words, if $K \geq .60$, there is enough proof to support the presence of a shared factor. However, the value of 0.60 is arbitrary and without clear reason. Initially suggested that the minimum requirement for factorability should be set at .50, since a KMO value at this level would indicate $\sum_i \sum_{i'} r_{ii'}^2 = \sum_i \sum_{i'} q_{ii^2}^2$. The calculates a statistic that follows a chi-square circulation with k^{-1} DoF (Degree of Freedom). This estimate holds when the k random sample has been taken from different typical populations, as explained. Bartlett's statistic is specifically developed to assess whether the variances across several groups are equal or not. It tests against the alternative hypothesis that the alterations are uneven for at least two groups. The test data is $\chi_0^2 = 2.3026\frac{q}{c}$ and computed using Eq. (7), (8), and (9).

$$q = (N-k)log_{10}S_p^2 - \sum_{i-1}^{k}(n_i - 1)log_{10}S_i^2 \tag{7}$$

$$c = 1 + \frac{1}{3(k-1)}\left(\sum_{i=1}^{k}(n_i - 1)^{-1} - (N-k)^{-1}\right) \tag{8}$$

$$S_p^2 = \frac{\sum_{i=1}^{k}(n_i - 1)S_i^2}{N-k} \tag{9}$$

Table 5. Rotational Factor Analysis Results

Factors	**Eigen value**	**Rotation summation of S^2**		
		Net loadings	Variance percentages	Cumulative percentages
1	16.10	7.27	21.36	21.36
2	3.16	6.25	18.36	39.72
3	1.86	5.03	14.83	54.56
4	1.46	2.98	8.76	63.32
5	1.35	2.05	6.03	69.35
6	1.19	1.55	4.57	73.92

where n_i is the i^{th} category's sampling size and 2.3026 is an integer. The result was a KMO measurement of 0.925 and a Bartlett test z-value < 0.05, showing a significant correlation. S_i^2 is the variance of the sample of the i^{th} category, N is the overall sample size $\left(N = \sum_{i=1}^{k} n_i\right)$, k is the number of categories, and S_p^2 is the combined variance (weighting by DoF). In this study, the factor analysis approach used is known as "principal component analysis." The criteria for choosing factors were determined and are as follows: an eigenvalue higher than one and a factor loading with an absolute value more than 0.5. There was a total of 34 variables that were categorized into six components. The outcomes of this categorization may be displayed in **Table 5**. There were six components with an Eigen value larger than one, and the interpretable variables accounted for approximately 74%. The aspects went through rotation using the Varimax rotation procedure.

V. CONCLUSION AND FUTURE SCOPE

The findings of this research emphasize the significance of a regular evaluation of Business Intelligence (BI) competencies in enterprise systems to improve decision-support contexts. Conducted through literature review, survey and advanced statistical analysis, the study established six factors that affect BI concerning organizational decision making. The fact that both factor analysis as well as hypothesis testing points to the fact that the importance of BI components such as data quality, integration, analytical capabilities, user access and decision support tools cannot be overemphasized. These components together explain a good proportion of the variation in BI effectiveness, thus underlining the importance of these components in enhancing decision making in enterprises. The study offers a theoretical model and clear guidelines for organizations to structure and evaluate the advancement of their BI solutions, thus improving the decision-making contexts and organizational performance. The further development of these tools is a great asset in an endeavor to bring BI to the next level in such organizations.

CRediT Author Statement

The author reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author declares that they have no conflicts of interest.

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Competing Interests

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