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The Role Of Business Intelligence Applications In Addressing Obstacles To Decision Support Systems In Syrian Firms Operating In The Information Technology Sector

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ABSTRACT
This study aims to examine the impact of business intelligence applications on overcoming barriers to decision support systems in Syrian firms operating in the information technology sector. The research focuses on Syrian firms registered with the Gaziantep Chamber of Commerce (totaling 525) in the Information Technology (IT) sector. A sample of 223 Syrian firms was surveyed. The findings are based on this sample, allowing for generalizability. The study evaluates the levels of barriers to decision support systems and the use of business intelligence in the IT sector among Syrian firms, based on the research model and collected data. A positive relationship between BI systems and decision support systems (DSS) has been hypothesized. Consequently, it was assumed that there is a correlation between perceptions of BI and DSS, leading to the development of Hypothesis 6. It was found that there is no perceptual difference between BI factors and participants' gender, age, and tenure. Thus, it can be stated that BI is not influenced by gender, age, or tenure. However, a perceptual difference was identified between BI factors and participants' educational levels and job titles. Therefore, it can be concluded that BI is influenced by the educational levels and job titles of the participants.

Keywords: *Business Intelligence, Decision Support Systems, Information Technology Sector, Syrian Firms*

INTRODUCTION

In recent times, decision support systems (DSS) have become increasingly widespread, especially during the initial stages of decision-making. DSS are designed to assist decision-makers by providing easy access to both internal and external organizational data, enabling timely and efficient information retrieval that improves organizational ce and decision quality. Due to continuous advancements in information and communication technologies and the fast-paced nature of business environments, organizations are managing more data than ever. Advanced information technologies facilitate storage,processing, and transformation of data from diverse sources into actionable insights, enabling organizations to respond effectively to sudden changes. This has brought systems like BI to the forefront, as they allow managers to make accurate, timely, and strategic decisions (Keen, 1987). As BI encompasses a set of methods and processes aimed at developing a clear understanding of business dynamics for decision support, many organizations are investing significantly in BI systems to enhance managerial decision-making.BI applications are implemented across various sectors, including transportation, banking, retail, pharmaceuticals, and healthcare. These sectors are typically service-oriented, characterized by large volumes of data and complex data structures, making BI projects essential for handling and analyzing this data. Consequently, BI plays a crucial role as a supportive variable in addressing the limitations of DSS and in assisting decision-makers in identifying the most appropriate strategic options. Provided that DSS applications often extend across multiple branches of an organization, it is reasonable to assume that these systems are not immune to challenges in achieving their intended outcomes. Today's decision-making processes frequently encounter difficulties such as information overload, uncertainty in data quality, and resistance to change. Existing systems, which include employee data, financial records, service information, and supplier details, often fall short of providing comprehensive information, thereby limiting decision-makers' ability to exert control over decisions. DSS may face numerous challenges during implementation, such as dealing with new technology, fear of job loss, apprehension about the consequences of information, the perceived condemnation from upper management due to the scientific value of decisions, a lack of human resources skilled in decision-making methods, and a lack of understanding of human resources about DSS (Rouibah, 2002).

PREVIOUS STUDIES

Persson (2015) conducted a study titled "Challenges in Implementing Decision Support Systems", examining the obstacles consultants encounter when implementing DSS in organizations lacking prior internal knowledge. The study, grounded in qualitative research, revealed that users often lacked awareness of the possibilities offered by DSS, which posed a significant barrier to effective implementation. This qualitative approach allowed for an in-depth exploration of these challenges, offering insights into the complexities of DSS adoption in uninitiated organizations. Moreover, Yasin Özam and Erman Kokun (2016) conducted a study aimed at analyzing the level of BI usage among firms operating in Turkey. The researchers argued that for developing countries to maintain their positions in the global environment, it is crucial to place a high emphasis on innovation, enhance their scientific and technological capacities, and effectively utilize information and communication technologies. The primary goal of their study was to explain the level of BI usage among firms in Turkey. To achieve this, a theoretical framework was established through a literature review. An experimental study was conducted by surveying 161 firms, regardless of sector, and it was determined that a significant portion of the firms included in the study extensively used BI. This indicates that these firms have adapted to current technological innovations. Most firms preferred to use off-the-shelf BI systems, and it was observed that the information obtained through these systems was provided to employees at all levels, especially those who needed it most.In their article titled "A Study on the Examination of BI Usage Levels of Enterprises Operating in Turkey," Özcan and Coşkun (2016) provided a general assessment by determining the level of BI usage among businesses operating in Turkey. This study, which aimed to contribute to the existing literature in Turkey, empirically examined the usage of BI. Initially, a theoretical framework was established through a literature review, followed by the identification of goals and objectives. The literature on BI usage was then thoroughly analyzed. An empirical study was conducted in connection with the theoretical framework, utilizing primary data collected through surveys administered to businesses operating in various sectors in Turkey. It was observed that a high percentage of these businesses used BI, and some had plans to adopt it in the years to follow. This result indicates that the businesses included in the study are adapting to modern technological innovations.Hasibiya Desman and Erkan Ozan (2017) researched the awareness of DSS in small businesses. Their hypothesis was that the most crucial need for business managers when making decisions is accurate and timely information. To achieve this, they employed various tools to improve the success of the businesses. The purpose of their study was to identify the DSS that could be used in managerial decisions in small and medium-sized enterprises (SMEs) and to determine whether these enterprises use DSS and techniques in their decision-making processes. For this purpose, a survey was sent to 750 SMEs operating in the provinces of the Aegean region. A total of 184 responses were received, and 181 surveys were used in the analysis. Multiple correspondence analysis was used to determine whether DSS hardware and software were utilized in SMEs in the Aegean region. The analysis results indicated that organizations with a larger workforce, higher corporate turnover, and more established corporate structures were more likely to use DSS.

THEORETICAL BACKGROUND

Business intelligence

BI is a broad concept that combines IT and business technologies, applications, and tools to collect, integrate, automate, and evaluate data from various sources to improve decision-making (Lönnqvist & Pirttimäki, 2006; Presthus et al., 2012; Ranjan, 2008). BI encompasses both technological and managerial aspects, and several definitions focus on these different dimensions. Some of the most significant definitions of BI include:

1. Organized and Systematic Processes: BI is described as the organized and systematic processes used to obtain, analyze, and disseminate information to support operational and strategic decision-making (Hannula & Pirttimäki, 2003).

2. Supporting Business Strategy: BI is not only aimed at improving business decisions but also at supporting the implementation of a business's strategy through a set of concepts, methods, and processes (Olszak & Ziemba, 2003).These definitions highlight BI as a critical tool for enhancing both the tactical and strategic aspects of business operations, ensuring that organizations can make informed decisions that align with their overall goals.

BUSINESS INTELLIGENCE COMPONENTS

BI systems are designed to gather and integrate high-quality information from multiple sources, performing multidimensional analyses—such as clustering—to produce concise, meaningful reports that aid decision-making processes (Kronios & Yeoh, 2010). Although BI components may be categorized differently based on evolving technology, they typically include Online Analytical Processing (OLAP), data mining, data warehouses, and Extract, Transform, Load (ETL) tools (Olszak & Ziemba, 2003). Because of its ability to cover a wide range of technologies, BI serves different purposes: for some, it represents reporting and visualization, while for others, it is central to business performance management. These tools analyze data and generate insights, with reporting tools specifically designed to display detailed or summarized information for users who may not be data analysts (Azvine et al., 2005).Among these components, data warehouses are the core of all BI systems. Without a data warehouse, implementing and utilizing BI solutions is impossible. Therefore, data warehouses should be emphasized above all else. They serve as the central repository where data is stored, organized, and made accessible for analysis and reporting, making them the backbone of BI operations (Gile, 2006).

DATA WAREHOUSES

A data warehouse is the foundational element of BI that extracts business data from various operational systems transforms it into a consistent format and distributes it for analysis (Howson, 2008). It is a technology that collects and organizes data for analytical purposes, thereby providing management with access to business-related information and the ability to analyze this data (Reinschmidt & Francoise, 2000).According to a definition by Bill Inmon, the data warehouse is a collection of subject-oriented, integrated, time-variant, and non-volatile data (Ericsson, 2004). This means that the data warehouse is designed to focus on specific business areas, integrating data from multiple sources, retaining historical data for trend analysis, and maintaining stable data that does not change once entered into the system. This structure allows organizations to analyze historical data, uncover trends, and make informed decisions based on a comprehensive view of their operations (Evelson, 2007).

ONLINE ANALYTICAL PROCESSING (OLAP) ARCHITECTURES

OLAP is an approach that uses a specific architectural model in the application of a system methodology. There are several commonly used OLAP system architecture models, including MOLAP, ROLAP, and DOLAP (Mallach, 2000). Additionally, some systems are developed using the HOLAP model, each offering distinct features:

- MOLAP (Multidimensional OLAP): This model stores data in multidimensional databases, and is the traditional method used for implementing the OLAP approach. The architecture of the MOLAP model is based on a multidimensional cube structure. MOLAP uses a two-tier client/server architecture where the MOLAP server directly connects with the user at the presentation layer. One of the key features of MOLAP is its ability to perform data pre-calculation to store information in data cubes. These MOLAP data cubes contain potential answers to a wide range of queries that may be posed to the system. An example of a MOLAP server would be one that efficiently manages and processes multidimensional data for complex analytical queries.
- ROLAP (Relational OLAP): This model stores data in relational databases and performs multidimensional analysis via complex SQL queries. Unlike MOLAP, ROLAP doesn't pre-calculate and store data, allowing for more flexible and dynamic query processing. However, this flexibility can result in slower performance with larger datasets (Isik & Sidorova, 2011).
- DOLAP (Desktop OLAP): A lighter version of OLAP that is designed for smaller, localized databases, allowing for quick access and analysis directly on the desktop. DOLAP is typically used for more simplified and specific analytical tasks.
- HOLAP (Hybrid OLAP): This model combines elements of both MOLAP and ROLAP, providing a balance between performance and flexibility. HOLAP systems can store large volumes of detailed data in relational databases (like ROLAP) while also offering fast, pre-calculated summaries in multidimensional databases (like MOLAP).

  OLAP architectures are essential for supporting decision-making processes within organizations, allowing for fast and flexible access to data from multiple dimensions, enabling deeper insights and more informed strategic decisions.

DATA MINING

In the information age, where knowledge is believed to bring power and success, vast amounts of data can be collected thanks to advanced technologies such as computers and satellites. Initially, with the advent of computers and large digital storage tools, there was a reliance on the power of computers to help decipher this influx of information, leading to the collection and storage of all types of data. However, these large data collections, stored in different structures, quickly became overwhelming. This initial chaos led to the development of structured databases and Database Management Systems (DBMS) (Al Eid & Yavuz, 2022).Effective database management systems became crucial assets for managing large data sets and for efficiently retrieving specific information from a broad collection, especially when needed. Data mining, as a key component of BI, plays a crucial role in extracting valuable insights from this large data. Data mining involves discovering patterns, correlations, and anomalies within large data sets to predict outcomes and guide decision-making.

Extracting, Transforming, Loading

To create a multidimensional data warehouse, data from all previously described sources need to be extracted and brought into your BI environment. Given the diversity of source systems, connectivity is key here. After extraction, the data needs to be transformed. Transformation can mean a lot of things but includes all activities performed to fit the data into the multidimensional model that constitutes the data warehouse. Considering the significant difference between ER models and multidimensional models, transformations can become quite complex. When you add the extra work of cleaning and 'harmonizing' data from different systems, it is understandable why some authors describe ETL work as accounting for 70% of the IT side of a BI project. More often than not, a separate database or specific area in the data warehouse is allocated as storage for intermediate results of the required transformations. This area is commonly referred to as a staging area or workspace. After all transformation work, the prepared data can be loaded into the multidimensional model. Although this step is not as complex as the transformation part, great care must be taken as the data loaded into the data warehouse can be 'published' for end-users (Bălăceanu, 2007).

BUSINESS INTELLIGENCE CONSUMERS

When looking at the number of users within an organization, it is observed that 5% or less of the group are individuals who create or consciously use a BI system. Others are indirectly affected by the system (Biere, 2003). BI consumers can be classified as follows:

DECISION MAKERS

In business, there are decision-makers: managers, directors, general managers, etc. The amount of data they need is often different. For example, a general manager is more interested in summary reports that show the state of the business rather than detailed data. The lower the administrative level, the more detailed the data becomes. BI supports decision-makers by providing easy, understandable, and flexible applications, processing data as quickly as possible, and reporting visually.

INFORMATION TECHNOLOGY DEPARTMENT

Before the widespread adoption of BI, reporting, querying, and database management were the responsibilities of the IT department. The flexibility brought by BI allows managers to prepare their reports quickly and easily, thus lightening the load on the IT department. However, the role of this department in BI systems does not end there. As the unit responsible for creating and managing information systems, IT departments are involved in determining corporate needs when developing and implementing BI systems, selecting the most suitable BI tools, and working in collaboration with solution partners.

KNOWLEDGE WORKERS

Those referred to as knowledge workers do not make critical decisions that affect the entire project. They are concerned with decisions that keep daily operations running. To this end, it is necessary to understand which groups use a BI system the most and which groups need the most data. This group includes software developers, human resources, marketing, finance personnel, or individuals performing similar tasks (Utley, 2008). Knowledge workers generally deal with more detailed data than managers. Sometimes they also need to review historical data. However, they seek assistance from analysts for forecasts or trends related to the future.

ANALYSTS

Analysts are specialized knowledge workers. They make up about 2% of all users within the organization. They typically work closely with decision-makers. Regardless of their specific area of expertise, all analysts work to delve deeply into data to identify the causes of problems or future trends. They generally analyze data using statistical methods and use the results of their analysis for forecasting or setting business standards. For example, in a manufacturing or transportation business, it is important to predict potential costs related to fluctuations in oil prices. In such cases, data mining techniques and forecasting algorithms are often used to achieve results close to reality with minimal deviations.

Decision support systems (DSS) and the structure of decisions

A DSS is based on the scientific insights and designs created by professionals. Those who create these scientific insights and designs classify decisions into structured, semi-structured, and unstructured categories. They develop models appropriate to each category's characteristics and provide them to managers (Şahin, 2007).

Structured (Programmed) Decisions

Structured decisions are those made by lower-level management in organizations. They are repetitive, routine decisions with established rules and procedures, often automated, involving objects rather than people, and can be delegated to lower levels of the organization. These decisions do not need to be repeatedly processed as if they were new. Examples include inventory control, vehicle loading, and listing tasks (Laudon and Laudon, 2011; Akten, 2007).

Semi-structured (Semi-Programmed) Decisions

Semi-structured or semi-programmed decisions are those made by middle-level managers in firms. They are a blend of structured and unstructured decision types. The problem has a clear answer based on an accepted procedure for only part of the issue. For example, this could involve obtaining a report from regional authorities to answer why orders have declined over the last six months at a distribution center. However, this decision type may also include additional steps, such as interviewing employees and gathering information from external sources about regional economic conditions and sales trends, rather than relying solely on the report (Laudon and Laudon, 2011).

Unstructured decisions (non-structural or non-programmed decisions)

Unstructured (or non-structured) decisions, unlike structured ones, are innovative and non-routine, lack clear decision rules, involve a high degree of uncertainty, and cannot be delegated to lower levels. Although they may involve tangible assets, they primarily concern people and require judgment from top-level managers. Examples of unstructured decisions include opening a new branch, increasing capital, pursuing company mergers, launching a new product, making personnel appointments, and replacing existing technology (Akten, 2007).

RESEARCH METHODOLOGY

Research design

This study is based on both descriptive and analytical approaches. Descriptive studies lay the groundwork for analytical studies and help in formulating hypotheses. The research employs a descriptive approach, which involves examining the phenomenon as it is in reality. In the analytical section, field data will be collected through surveys, and results will be analyzed using statistical methods such as measures of central tendency, distribution, and proportions. The data analysis and table generation will be conducted using IBM's SPSS.

Sampling and representation

Making generalizations about a population is possible based on data obtained from a sample, a probability-based practice. Generally, increasing the sample size reduces the likelihood of errors in these generalizations. Therefore, a sample size should be chosen to ensure representativeness of the population, while also considering factors like cost, time, and data analysis constraints. Additionally, population size is a fundamental determinant of the sample size. In this study, the goal was to gather sufficient data from businesses exhibiting the variable characteristics outlined in the conceptual model to support meaningful generalization of findings. The research population includes 223 Syrian firms in the IT sector registered with the Gaziantep Chamber of Commerce, and employees with varying demographic characteristics were included. Information about the participants' genders is presented in Table 4.1, as generated by SPSS.

Table 4.1. *Distribution of Participants by Gender*

Demographic Characteristics (Gender)	Gender	Total
	Male	Female
Frequency	213	10
Percentage	95%	5%

Looking at the results of the table referring to the analysis of responses by gender in the research sample, it is observed that the percentage of males in the IT sector is 95%, while females make up 5%. The reasons behind this statistic could be that the information and communication technology sector require more technical knowledge and skills, is a more information-intensive sector, and due to the increasing globalization in electronics, knowledgeable and conscious personnel need to continually improve their expertise. The information regarding the ages of the participants is presented in Table 4.2 below, as generated by SPSS.

Table 4.2. *Distribution of Participants by Age*

Demographic Characteristics (AGE)	AGE	Total
30 years and below	31-40 years	41-50 years
Frequency	112	100
Percentage	50%	44%

When we look at the data in the table above, which refers to the analysis of the study variables by age, it is found that 112 participants belong to the age group of 30 years and below. The frequency percentage of the 31-40 age group is determined to be 44%. The number of individuals in the 51 years and above group is shown to be 2. The information regarding the educational status of the participants is presented in Table 4.3 below, as generated by SPSS.

Table 4.3. *Distribution of Participants by Educational Status*

Educational Level	Educational Level	Total
High School	Vocational School	University
Frequency	71	72
Percentage	31%	33%

In the previous table showing the distribution of the research sample by educational level, it is evident that the participants who responded most frequently to the survey were those with a Vocational School, High School, and Master's Degree education.The areas of application for DSS and BI in Turkish and Syrian firms operating in the field of IT can be found in table 4.4, as generated by SPSS.

Table 4.4. *Areas of Application for Business Intelligence and Decision Support Systems*

Application Areas of Decision Support Systems and Business Intelligence	Frequency	Percentage	Rank
Report Preparation	168	0.16	4
Data Analysis	170	0.16	3
Decision Making	125	0.12	5

Continuous Improvement	100	0.09	6
Business Monitoring	99	0.09	7
Management Tasks	175	0.16	2
Performance Measurement	200	0.20	1

\After analyzing the results in table 4.4, it was found that Syrian firms in the IT sector primarily utilize BI applications and DSS for performance measurement, management tasks, data analysis, and reporting. Detailed information about The following table, table 4.5., details the frequency, percentages and ranks of the different departments of the studied IT firms that use BI applications and DSS systems.

Table 4.5. *Departments Using Business Intelligence Applications and Decision Support Systems*

Departments Using Decision Support Systems and Business Intelligence	Frequency	Percentage	Rank
Marketing	200	14.81	2
Information and Communication Technology	198	14.66	3
Human Resources	210	15.55	1
Foreign Trade	154	11.40	6
Statistics	167	12.37	5
Monitoring and Evaluation	125	9.25	7
Projects	186	13.77	4
General Services	110	8.14	8

The table above shows the departments in Syrian firms operating in the IT sector in Gaziantep that use BI applications and DSS. After analyzing the data, it was found that Syrian firms in the IT sector primarily utilize BI applications in the Human Resources department, followed by the Marketing department. Additionally, it was observed that BI applications are also used in project management, as well as in the Monitoring and Evaluation department and other various departments.The following table, table 4.6., details the frequency, percentages and ranks of the different DSSs and BI tools used in the Syrian IT firms that were studied.

Table 4.6. *Business Intelligence and Decision Support Systems Tools*

Decision Support Systems and Business Intelligence Tools	Frequency	Percentage	Rank
Qlik Sense	69	6.73	6
Microsoft BI	200	19.50	2
Power BI	220	21.46	1
SAS BI	188	18.34	3
Looker	155	15.12	4
IBM Cognos Analytics	68	6.63	7
Google Analytics	99	9.65	5
Oracle NetSuite	12	1.17	8
HubSpot	8	0.78	9
Pentaho	6	0.58	10

The table above shows the distribution of the most widely used BI and decision support system tools in Syrian firms operating in the IT sector in Gaziantep. After analyzing the table data, it was found that the most commonly used BI tools among Syrian firms in the IT sector are Power BI, Microsoft BI, SAS BI, Looker, and Google Analytics. Additionally, it was observed that other tools are also utilized for BI applications.

RELIABILITY OF THE DATA COLLECTION INSTRUMENT

The ranges for the alpha coefficient and the corresponding reliability levels of the scales are presented below:

- If $0.00 \leq \alpha < 0.40$, the scale is not reliable.
- If $0.40 \leq \alpha < 0.60$, the scale has low reliability.
- If $0.60 \leq \alpha < 0.80$, the scale has considerable reliability.
- If $0.80 \leq \alpha < 1.00$, the scale has a high degree of reliability (RTÜK, 2012).

In this research, Cronbach's alpha coefficient was used to evaluate the reliability (internal consistency) of the scales included in the questionnaire. Table 4.7 provides a summary of the Cronbach's alpha coefficients of the scales used in the analysis of the data and provides an overview of the structure of each scale.

Table 4.7. *Reliability Coefficients of the Scales*

Scale	Measurement Range	Number of Items	Cronbach's Alpha Coefficient
Business Intelligence	5-point scale (1–5)	36	0.92
Decision Support Systems	5-point scale (1–5)	24	0.86

As seen in Table 4.7, all the scales used in this study have a high level of reliability (internal consistency). The reliability coefficients of the scales range between 0.86 and 0.92. These results indicate that the scales used are highly reliable. Reliability was also measured in the dimensions of wisdom and BI. In the case of DSS, factor analysis was used to reveal the dimensions of the variable. Therefore, reliability will be measured in the DSS section. Table 4.8 presents the correlation coefficients for the dimensions of the Business Intelligence scale.

Table 4.8. *Business Intelligence Correlation Coefficients*

Relationship Between Business Intelligence and Its Dimensions	Correlation Coefficient
Satisfaction Dimension	0.512**
Data Types Dimension	0.593**
Data Reliability Dimension	0.835**
Quality of Data Sources Dimension	0.761**
User Access Dimension	0.740**
Flexibility Dimension	0.402**

Not: N=500, p<0.001

As seen in Table 4.8, the correlation coefficients for the total dimensions of the Business Intelligence scale range between 0.40 and 0.83.

PERCEPTION OF BUSINESS INTELLIGENCE

To assess participants' evaluations of items on the Business Intelligence Scale, a five-point Likert scale was utilized, as shown in Table 4.9. In this scale, a score of 1 corresponds to "strongly disagree," while a score of 5 represents "strongly agree." The Business Intelligence Scale, developed by Işık et al. (2011), comprises 36 items distributed across six distinct dimensions. Table 4.9 presents the mean and standard deviation values for the Satisfaction Dimension of the scale, based on the perceptions of employees from Turkish and Syrian IT firms.

Table 4.9. *Evaluations Related to the Satisfaction Dimension*

Relationship Between Business Intelligence and Its Dimensions	N	Mean	Std. Dev.
Satisfaction Dimension	223	3.64	0.99
Data Types Dimension	223	3.47	0.91
Data Reliability Dimension	223	2.94	0.95
Quality of Data Sources Dimension	223	2.51	1.32
User Access Dimension	223	3.58	0.95
Flexibility Dimension	223	3.87	0.66

Before performing the factor analysis, the mutual correlation level between the variables and their suitability for factor analysis were assessed using the Kaiser-Meyer-Olkin (KMO) test (Ang et al., 2000; Bülbül, 2003; Aleid & Yavuz, 2022). The results are shown in Table 4.10.

Table 4.10. *Kaiser-Meyer-Olkin (KMO) Values of the Scales*

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,871
Bartlett's Test of Sphericity	Approx. Chi-Square	3649,558
	Sig.	,000

KMO values below 0.50 are considered unacceptable, while KMO values close to 1 are regarded as excellent (Ang et al., 2000: 57). As shown in Table 4.10, all the KMO values of the main scales in the study are greater than 0.50. The high values indicate that the variables can be subjected to factor analysis. The factor analysis results for each scale used in the study are detailed under the relevant headings.

Table 4.11. Factor Analysis Results of the Decision Support Systems Component

Item		Component					
		1	2	3	4	5	6
KDS20	The degree of technology diffusion	0.74					
KDS19	Poor attitude towards quality improvement.	0.72					
KDS23	Organizational dependency on technology.	0.65					
KDS17	Lack of proper planning.	0.65					
KDS24	Absence of technical support.	0.64					

KDS21	General competition in the industry.	0.54					
KDS18	Lack of understanding of potential benefits.	0.54					
KDS4	Lack of training and education.	0.52					
KDS7	Communication barrier between end-user and developer.		0.67				
KDS3	Lack of resource allocation from upper management.		0.63				
KDS1	Lack of management support.		0.62				
KDS2	Lack of attention from top management.		0.60				
KDS9	Rapid technological advancements.			0.68			
KDS8	Security issues.			0.67			
KDS16	Cost implications.				0.81		
KDS6	Lack of skills and knowledge on how to apply technology.				0.60		
KDS12	Interaction between technology and organization.				0.55		
KDS5	Inappropriate change management approach.				0.41		
KDS10	Mismatch of systems with system requirements.					0.76	
KDS11	Inadequate technology alignment.					0.71	
KDS13	Organizational size.					0.39	
KDS22	Compliance with standards.						0.66
KDS15	External relations (electronic data interchange).						0.62
KDS14	Organizational culture.						0.50
Initial Eigenvalues		6,190	2,698	1,389	1,272	1,152	1,046
Explained Variance (%)		25,790	11,242	5,789	5,301	4,799	4,359

According to the results of the factor analysis with Varimax rotation, the Decision Support Systems Scale was divided into six new dimensions. The eigenvalues of these newly formed dimensions are greater than 1. The items explain 57.28% of the total variance, and all factor loadings of the items are greater than 0.30. It was concluded that the dimensions of the newly formed scale in the context of the Decision Support Systems Scale can be renamed based on literature information. The factor analysis results obtained for the Decision Support Systems Scale formed a structure consistent with the literature, so the classifications in the first part of the study were used for renaming the factors. The factors in the scale were named as follows, in line with the literature: Factor 1 - Technical and Technological Barriers, Factor 2 - Decision Environment-Related Barriers, Factor 3 - Security Barriers, Factor 4 - Resistance to Change, Factor 5 - Organizational Barriers, and Factor 6 - Internal and External Barriers. As a result, the scales were reorganized according to the factor analyses conducted in the context of structural validity. All scales have an eigenvalue greater than 1, and the factor loadings range from 0.26 to 0.58. These findings indicate that the scales in the survey have good structural validity.

Additionally, the Cronbach's Alpha coefficients of the newly formed scales were calculated, and it was observed that the new scales possess internal consistency.

Hypotheses related to the conceptual model

One of the objectives of this study is to examine whether there is a relationship between the perceptions of BI and DSS among Syrian firms operating in the field of IT. In this context, the relationship between the scales of Wisdom Management, BI, and DSS perceptions was calculated using the Pearson correlation coefficient (Table 4.13).

Table 4.13. *Perception Matrix of Wisdom Management, Business Intelligence, and Decision Support Systems*

	Business Intelligence	Decision Support Systems
Business Intelligence	1	.219**
		.001
	223	223
Decision Support Systems	.219**	1
	.001	
	223	223

As seen in the correlation matrix in Table 4.14, there is a low positive correlation (0.219) between BI and DSS among Syrian firms operating in the field of IT. In this context, the hypotheses suggesting a positive relationship between the perceptions of BI and DSS have been accepted.

Hypotheses related to demographic variables

The study investigated whether participants' perceptions of DSS and BI measurements in Syrian IT firms differ by gender. Instead of evaluating each item separately, judgments were made based on the general factor structures. The results are shown in Table 4.14 below.

Table 4.14. *Evaluation of Business Intelligence and Decision Support Systems by Gender*

Gender	N	Mean	Std. Dev.	T-Test	P
Decision Support Systems					
Male	213	3.53	0.53	0.787	0.432
Female	10	3.39	0.59	0.721	0.488
Business Intelligence					
Male	213	3.18	0.69	-0.946	0.345
Female	10	3.39	0.66	-0.987	0.347

When examining Table 4.14, it is observed that there is no statistically significant difference between the groups formed by gender in Syrian firms in the IT sector, according to the T-test. Moreover, there is no significant difference in any of the BI and DSS concerning gender. These results do not support Hypothesis 1, which posits, "There is a difference in the perceptions of BI and DSS according to the participants' gender."The study also investigated whether participants' perceptions of DSS and BI measurements in Syrian IT firms differ by age. Instead of evaluating each item separately, judgments were made based on the general factor structures. The results are shown in Table 4.15 below.

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Table *Error! No text of specified style in document.***.15.** *Evaluation of Business Intelligence and Decision Support Systems by Age*

Age Groups		N	Mean	Std. Dev.	F-Test	P
	Total	277	3.04	0.63		
Decision Support Systems	30 years and under	112	3.49	0.53	.786	0.50
	31-40 years	100	3.54	0.54		
	41-50 years	9	3.74	0.56		
	51 years and over	2	3.29	0.12		
	Total	223	3.52	0.54		
Business Intelligence	30 years and under	112	3.12	0.70	1.038	0.37
	31-40 years	100	3.27	0.68		
	41-50 years	9	3.17	0.72		
	51 years and over	2	2.83	0.79		
	Total	223	3.19	0.69		

When examining Table 4.15, an ANOVA (F) test was conducted among Syrian firms in the IT sector, revealing statistically significant differences by age. However, no significant differences were found in other variables concerning age, particularly in BI and DSS. These results support Hypothesis 2, which posits, "There are differences in perceptions of BI and DSS according to participants' age."The study also investigated whether participants' perceptions of DSS and BI measurements in Syrian IT firms differ by educational level. Instead of evaluating each item separately, judgments were made based on the general factor structures. The results are shown in Table 4.16 below.

Table *Error! No text of specified style in document.***.16.** *Evaluation of Business Intelligence and Decision Support Systems by Educational Levels*

Education Level		N	Mean	Std. Dev.	F-Test	P
Decision Support Systems	High School	71	3.62	0.49	3.180	0.02
	Associate Degree	72	3.40	0.52		
	Bachelor's Degree	25	3.69	0.56		
	Master's Degree	55	3.48	0.57		
	Total	223	3.52	0.54		
	High School	71	3.45	0.71	5.299	0.002

Business Intelligence	Associate Degree	72	3.03	0.67
	Bachelor's Degree	25	3.15	0.68
	Master's Degree	55	3.09	0.61
	Total	223	3.19	0.69

When examining Table 4.16, an ANOVA (F) test was conducted among Syrian IT firms, revealing statistically significant differences based on education level. It was found that the p-value for BI and DSS dimensions is less than 0.05. These results support Hypothesis 3, which posits, "There are differences in perceptions of BI and DSS according to participants' educational levels."The study also investigated whether participants' perceptions of DSS and BI measurements in Syrian IT firms differ by job title. Instead of evaluating each item separately, judgments were made based on the overall factor structures. The results are shown in Table 4.17 below.

Table *Error! No text of specified style in document.*.**17.** *Evaluation of Business Intelligence and Decision Support Systems by Job Titles*

Job Title		N	Mean.	Std. Dev.	F-Test	P
Decision Support Systems	Staff	129	3.56	0.59	1.155	.328
	Department Head	39	3.55	0.43		
	Assistant Manager	46	3.39	0.47		
	General Manager	9	3.57	0.33		
	Total	223	3.52	0.54		
Business Intelligence	Staff	129	3.29	0.70	3.907	.010
	Department Head	39	3.21	0.70		
	Assistant Manager	46	2.89	0.61		
	General Manager	9	3.25	0.54		
	Total	223	3.19	0.69		

When examining Table 4.17, an ANOVA (F) test was conducted among Syrian firms in the IT sector, revealing statistically significant differences based on job titles. It was found that the p-value for BI is less than 0.05. Therefore, it can be stated that there are significant differences in perceptions of wisdom and BI depending on the job title in Syrian firms operating in the IT sector.

The study also investigated whether participants' perceptions of DSS and BI measurements in Syrian IT firms differ by years of work experience. Instead of evaluating each item separately, judgments were made based on the general factor structures. The results are shown in Table 4.18 below.

Table *Error! No text of specified style in document.*.**18.** *Evaluation of Business Intelligence and Decision Support Systems by Years of Work Experience*

Years of Experience		N	Mean	Std. Dev.	F-Test	P
Decision Support Systems	5 years or less	123	3,50	0,54	.333	0.717
	6-10 years	78	3,56	0,49		
	11-15 years	22	3,53	0,66		
	Total	223	3,52	0,54		
Business Intelligence	5 years or less	123	3,25	0,69	1.117	0.329
	6-10 years	78	3,14	0,70		
	11-15 years	22	3,05	0,64		
	Total	223	3,19	0,69		

When examining Table 4.18, an ANOVA (F) test was conducted among two groups of firms—Turkish and Syrian—working in the IT sector, and it was found that there are statistically significant differences based on years of work experience. From the above table, it is evident that in Turkish firms, there are fundamental differences in DSS due to varying work experience durations.

Summary of the Study's Objectives and Theoretical Foundations

The primary objective of this research is to explore the relationship between BI and DSS and how a decision-maker can address the limitations of DSS through the application of BI. As is well known, organizations continue to exist as phenomena designed to achieve specific objectives. In today's context, the pressures created by globalization determine the survival conditions of organizations and align these conditions with the quality of information. In fact, in many sectors, competition has become increasingly dependent on modern technologies such as BI applications, decision support, and information sharing, which rapidly generate information that is difficult to protect. BI helps organizations meet their information processing needs by facilitating organizational information processing capacity (Gray and Negash, 2003). It does so by combining data collection, data storage, and information management with analytical tools, enabling decision-makers to convert complex information into effective decisions (Eckerson, 2007).

In the literature of DSS, experts propose various approaches or methodologies for designing and developing DSS. However, there is no consensus on which methodology yields the best results for creating different types of DSS. If managers and DSS analysts understand various methods, they can make better and more informed choices when building or purchasing a specific Decision Support System. Developing a DSS is often very costly. Therefore, it is essential to explore alternative design and development approaches. It is desirable to select an approach that increases the likelihood of DSS being used and achieving its objectives. It is important to remember that DSS is designed and developed to help people make better and more effective decisions than they could without computer assistance. Creating any type of DSS is challenging because people differ significantly in terms of personalities, knowledge, abilities, preferences, jobs they hold, and decisions they need to make. Additionally, DSS often must meet a variety of requirements. These diverse requirements have led to the design and development of a wide range of DSS capabilities and systems.

FINDINGS AND DISCUSSION

The hypotheses of the research were formulated to address the questions posed in alignment with the study's objectives and theoretical framework, as discussed in previous sections. These hypotheses were tested using appropriate methodologies.

Table 5 below summarizes the hypotheses of the study, the methods used for analysis, and whether the hypotheses were accepted or rejected. The results are then evaluated in detail.

Table 5. *Summary of the Study Hypotheses*

Hypothesis	Method of Analysis	Result	Explanation
Hypothesis 1: There is no difference in the perception of business intelligence based on the gender of the participants.	ANOVA Test	Rejected	It was found that gender has no impact on participants' perception of business intelligence.
Hypothesis 2: There is no difference in the perception of business intelligence based on the age of the participants.	ANOVA Test	Rejected	It was found that age has no impact on participants' perception of business intelligence.
Hypothesis 3: There is no difference in the perception of business intelligence based on the educational level of the participants.	ANOVA Test	Accepted	It was found that educational levels have an impact on participants' perception of business intelligence.
Hypothesis 4: There is no difference in the perception of business intelligence based on the participants' job titles.	ANOVA Test	Accepted	It was found that job titles have an impact on participants' perception of business intelligence.
Hypothesis 5: There is no difference in the perception of business intelligence based on the participants' years of experience.	ANOVA Test	Rejected	It was found that years of experience have no impact on participants' perception of business intelligence.
Hypothesis 6: There is a positive effect of business intelligence perception on decision support systems perception.	Regression Analysis	Accepted	It was found that the perception of business intelligence positively impacts the perception of decision support systems.

The results obtained in the previous chapter, along with the analysis results of the hypotheses presented in the table above, are evaluated as follows:As previously mentioned, the study's hypotheses explored the differences in responses regarding participants' perceptions of BI and discussed the relationship between BI systems and DSS.

Hypotheses 1, 2, and 5 assessed whether there was a perceptual difference between the demographic characteristics of the participants and BI factors. It was found that there is no perceptual difference between gender, age, and years of experience of the participants and the BI factors. Therefore, it can be stated that BI is not influenced by factors such as gender, age, and years of experience. However, Hypotheses 3 and 4 identified a perceptual impact between educational levels, job titles, and BI factors. It can e concluded that BI is affected by the educational levels and job titles of the participants.When examining Tables 4.16 and 4.17, differences in the BI variable were identified based on educational levels and job titles among IT Syrian firms. BI systems collect all data generated within and outside the organization, store it in a centralized data warehouse, analyze it using various technologies (such as data mining, OLAP...), and extract relevant information. These systems not only extract information but also deliver it quickly to all users who need it, using visually powerful and easy-to-use tools. In addition to providing real-time status, they have the ability to make future predictions and highlight current issues using alert technologies. With all these features, BI is a significant competitive factor and, most importantly, offers substantial advantages in the decision-making process.Today, BI systems are employed by organizations across various industries and sectors, and BI has gained significant popularity since the first decade of the 21st century (Harison, 2012; Nguyen et al., 2018). Accordingly, a positive relationship between BI systems and DSS has been hypothesized. Therefore, a relationship between the perceptions of BI and DSS has been accepted, leading to the development of Hypothesis 6.

RECOMMENDATIONS

Based on the insights gained from the literature review and research findings, it can be concluded that while the implementation of Decision Support Systems (DSS) is challenging, it is not impossible.It is crucial to enable employees to approach situations with a more appropriate, accurate, objective, clear, and in-depth perspective.In the increasingly widespread adoption of Business Intelligence (BI) applications today, the ability to integrate Microsoft Office tools plays a significant role in the acceptance of BI within enterprises. When the power of business intelligence is combined with applications like Microsoft Excel, which users have been accustomed to for years, both the benefits derived from Excel increase and the users' adaptation to the system becomes easier. Since Microsoft Office support is already present in many businesses, it is advisable to make the necessary adjustments to these tools in line with the new BI systems as quickly as possible. Additionally, BI tools should keep the user engaged and encourage the generation of new questions.It is important for BI designers to not only conduct various studies in this field but also to develop different solutions tailored to the cognitive styles and personality types of end users.Finally, a decision support system should assist decision-makers at every level, support both individual and collective decision-making in semi-structured decisions, provide simulation and analysis tools for interaction with the general data terminal, and be equipped with adequate features. Flexibility in coordinating different management methods should also be ensured.

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