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Research Paper

Business Intelligence Technology in Research Organizations (Case Study of Academic Institutes in Tehran)

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Abstract

Business Intelligence (BI) covers the tasks of collecting, processing, and analyzing large volumes of data. This includes internal systems and external resources, utilizing advanced high-speed analytics and forecasting tools enabling organizations to achieve organizational goals in a timely manner affording immediate decision-making. The main purpose of BI is to help companies improve their performance in the turbulent environment of business and enhance their competitive advantage in this immense data age. Research organizations need integrated information technologies such as business intelligence, perhaps more so than commercial companies need, given the highly competitive environment and increasing progress of various disciplines. The development of such a system, like other organizational information systems, requires the adoption of technology by its users. Various models, including behavioral models, have identified the acceptance factors of information technologies. The purpose of this study is the Interpretive Structural Modeling of factors affecting the adoption of business intelligence technology in research organizations. ISM is a systematic and interpretive process as it is formed based on group judgment and is structured and complemented by common relationships, and finally, depicts the overall structure of several complex elements in a graph model. The sample used in this study was experts of academic research institutes in Tehran. According to the findings, 20 main acceptance factors were modeled in four levels based on interactions between the categories of individual, organizational, and technological criteria.

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Introduction

Most organizations today are realizing that information is the lifeblood of any digital economy. Besides, the key to success in the information age is to make decisions that are more consistent, better, and faster. Today, not only senior managers and executives but all researchers, scientists, and businessmen are forced to use information technologies. Proper use of information systems and intelligent systems provides valuable analysis for experts in various fields (Khorashadi Zadeh et al., 2017). Despite this widely accepted principle, some organizations have remained reluctant to invest in technologies that provide easy access to business decision-making information. It seems that the root cause of this skepticism is how organizations evaluate information technology investments such as investing in direct and valuable information. Valuable guidance information helps a buyer find the courage and confidence that a perfect return on investment has been made (Mohaghar et al., 2009; Niño et al., 2020). BI is one of the new systems enabling managers to integrate data sources, process huge amounts of data, extract information, and convert it into useful knowledge. In other words, the purpose of business intelligence is to deliver accurate and timely information to the managers and planners of an organization. As such, the system seeks to gather the large volume of data, analyze it, and then bring this desired intelligence to the organization to facilitate the decision-making process (Turban et al., 2010). Business intelligence can be perceived as a generic term that encompasses tools, architectures, databases, data warehouses, and algorithms that aim to integrate distributed data across different sources, then pursue the analysis with the extraction of knowledge from that data (Ain et al., 2019). Research organizations such as universities, R&D institutes, and science and technology centers have a fast-paced, knowledge-driven movement that reveals the need for robust, responsive, and flexible decision-making in these organizations as well as for various businesses and commercial companies (Akhmetov et al., 2019; Kabakchieva, 2015). Researchers and research executives, as well as senior and executive managers, need to have integrated information within their organization and business environment to find the ability to compete globally in special domains. Regarding this issue, the main purpose of the present study is first to identify the factors influencing the adoption of business intelligence technology in research organizations, and then to classify and relate these factors to each other. Thus, after reviewing the literature and considering behavioral models of technology acceptance, an interpretive structural modeling approach has been used that facilitates the understanding of variables and factors of the complex situation for researchers.

Literature Review

The earliest known use of business intelligence appears to be in 'Cyclopaedia of Commercial and Business Anecdotes' by Richard Millar Devens (1865). Devens uses the term to describe the state-of-the-art business mind of banker Sir Henry Furnese detailing how he receives environmental information in order to act on that information and maximize profits before his competitors can (Devens, 2016:210). The term was later introduced as an umbrella term by Gartner and his researcher Howard Dresner in 1989 to describe a set of concepts and methodologies that enhance business decision-making through event-based systems. From this point of view, BI applications re-energize the strategy of an organization measuring the accuracy and success of company goals and objectives (Bazargani and Namazi, 2016). It is noteworthy that business intelligence is also recognized as part of competitive intelligence because many organizations choose to use business intelligence to gain organizational competitive advantage (Roodposhti and Mahmoodi, 2010; Ain et al., 2019) and the concept of intelligence is a sublime step in the maturation of expert systems and knowledge management processes (Nazari Farokhi et al., 2020). Business intelligence covers the tasks of collecting, processing, and analyzing large volumes of data from internal systems and external sources. It uses advanced analytics and predictive tools that help a company to make timely and immediate decisions and achieve predetermined goals (Gupta, 2003). Business intelligence is a place where data is refined and transformed for ready presentation to the main decision-maker (Gaol et al., 2020). The main purpose of business intelligence is to help a company improve its performance and enhance its competitive advantage in the marketplace. BI helps to make better decisions by assessing whether activities actually lead companies to their goals. Business executives need useful and relevant facts to make better decisions, but there is often a deep gap between the information needed by business executives and the enormous amount of data a business collects in its day-to-day operations. Businesses are filling in this gap by sufficient investment to develop and deploy BI systems in order to convert raw data into useful information and knowledge. The most effective thing about the BI system is that it allows executives and managers to process large volumes of data and deliver relevant sub-instances in a way that they can easily understand and analyze (D'Arconte, 2018). As the world is increasingly saturated with information and accelerating technology advances, BI-based decision-making and analysis are fundamentally affecting all organizations including universities and institutes (Mohaghar et al., 2009; Falakmasir et al., 2010). Business intelligence is a set of capabilities, technologies, tools, and solutions that provide help to managers affording them a better understanding of business situations using BI tools to provide perspectives on past, present, and future conditions (Sohofi and Kazemi, 2014). Business intelligence is the process of extracting, transforming, managing, and analyzing large volumes of data using mathematical models to make complex decisions. The key components of BI are data warehousing, data mining and a decision support system (Fitriana et al., 2011). The term ‘business intelligence’ can be used to refer to information and knowledge of the organization, which describes the business environment, the organization itself, and the market situation as well as the customers, competitors, and economic considerations. Systematic and organized processes of organizations are used to collect, analyze, and distribute information from internal and external sources for business decision-making (Lönnqvist and Pirttimäki, 2006). The purpose of business intelligence is to help control the sources and flow of business information that exists within and around the organization. Business intelligence, in this ‘information century’, is a great help to organizations by identifying and processing massive and diverse data converting it to pure knowledge and intelligence needed for management. BI provides business information in a timely and appropriate manner and provides the ability to reason and understand hidden meanings in business information (Azoff and Charlesworth, 2004). The main application of business intelligence is to help in the process of making decisions in the organization, so the use of structured and unstructured organizational systems data is the basis of BI in the organization. The literature on business intelligence has pointed out that it can be used more effectively in institutional organizations. Students, professors, and scholars can use intelligent data analysis tools to understand the industrial and commercial trends and move towards meeting future needs (Hindrayani et al., 2020). However, few organizations have metrics for measuring BI in their organizational systems (Cheng et al., 2020). The Business Intelligence system can be considered as an important technology to provide companies with all the necessary information they need (Bazaee and Karimian, 2018). Key parameters in business intelligence are needed to make high-quality decisions. These parameters include customers, competitors, partners, economic environment, and internal processes (Safarzadeh et al., 2010; Sabokro et al., 2018). BI architecture typically consists of three parts: Data warehouses, Online Analytical Processing (OLAP), and management dashboards. A data warehouse collects data from internal and external sources, OLAP processes data in real-time, and dashboards visualize the data, which is the part that the user sees from the system (Ahmad et al., 2020). Data storage is a repository for seamlessly storing data from different sources of information. In DWs, the current and historical data of an organization is stored in one place, and used to generate analytical reports for its managers. Generally, BI solution data is stored in a data warehouse, and the information in the subdivisions of the organization is stored in Data Marts. Using the ETL process, all raw data is collected from different information systems, integrated and refined, then stored in a central data warehouse. The schematic diagram of this process is shown in Figure 1.

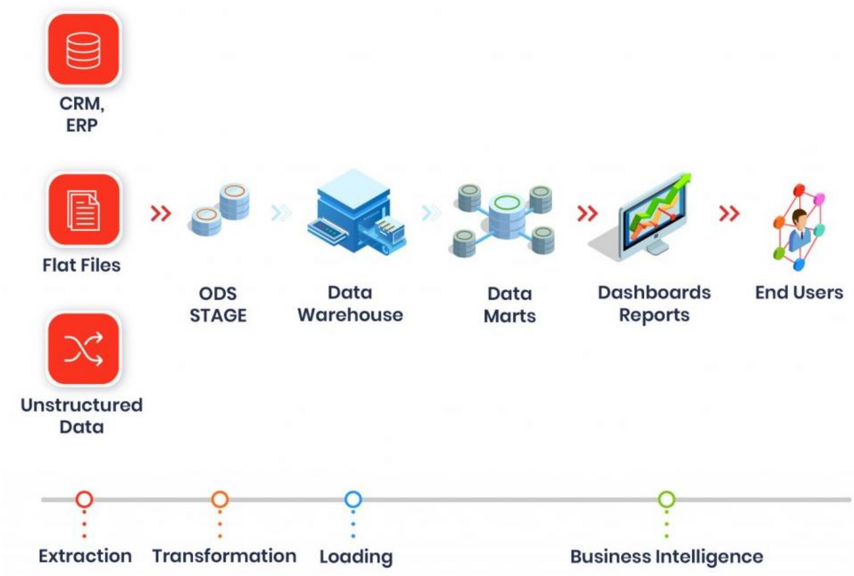

Figure 1.
ETL Architecture (Agrawal, 2019)

While the use of technology is a behavior that relates to a variety of contexts, the scope and results of studies in this area may vary. Technology acceptance behavior can be influenced by many individual factors such as age, gender, and socioeconomic status. Many theories and models explain the adoption and use of technology. The use of information technology has also become mobile due to the widespread release of smartphones, which has led to changes in social life, interpersonal relationships, businesses, and organizational behavior. Thus, the individual and social factors affecting the use of technology have been studied and interpreted by researchers from various disciplines (Tavallaei and Ahmadi, 2018). The most popular behavioral theories and models used to explain technology adoption are the

Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), and the Diffusion of Innovations Theory (DIT). The primary idea of the TRA is that attitude and norms are the defining factors of behavior. Attitudes include related beliefs and expectations of behavioral outcomes, and internal norms include beliefs related to popular assessment that is important to an acceptor (Fishbein and Ajzen, 1975). TPB, in addition to the mentioned variables, also includes the perceived control variable. Perceived control is beliefs regarding coping with behavioral problems (Ajzen, 1991). DIT describes some of the characteristics of innovations such as relative benefits, complexity, adaptability, experimentation capability and observability that determine technology adoption. From this perspective, technology adoption is divided into categories of initiator, primary acceptors, the majority of early acceptors, the majority of late acceptors, and backward acceptors in terms of personal specifications (Rogers, 2003). TOE and HOT-fit Models are among the other models of technology adoption. The TOE (Technology-Organization-Environment) model is used to understand the critical factors that influence the adoption of new technology or innovation in an organization. This framework encompasses a set of key acceptance factors that fall into the organizational, technological, and environmental categorization that integrate human and inhuman characteristics (Tornatzky and Fleischer, 1990). The HOT-fit (human-organization-technology fit) model considers net benefit besides human, organizational, and technical factors considering fit and effectiveness among the factors. It is worth noting that this model was born in studies of IT adoption (Yusof et al., 2008). One of the technology acceptance models used to study business intelligence is the Technology Acceptance Model. The TAM was introduced by Davis in 1989. This model, in the relevant literature, is one of the most widely used theories in predicting and explaining behavior in using information systems (Davis, 1989). TRA and TPB are the two basic theories of social psychology that led to the creation of TAM, which has been created as a compact, predictive, and powerful model for explaining and predicting behavior in decision-making and acceptance of the use of a particular technology (Lee et al., 2003). This model assumes that the use of a system is determined directly by the behavioral tendency to use it, which is influenced by individual attitude toward the use of the system and the benefits received from it. In addition, the ease of use of the system affects the attitude and benefits received (Davis et al., 1989). Many researchers have used and extended this model, in their research, to include the TAME project model (Jackson et al., 1997), and the TAM2 model (Venkatesh and Davis, 2000). The TAM3, presented by Venkatesh and Bala (2008) focusing on organizational perspective and management concerns, is well suited to accept systems such as business intelligence (Sönmez, 2018; Kohnke, et al., 2011).

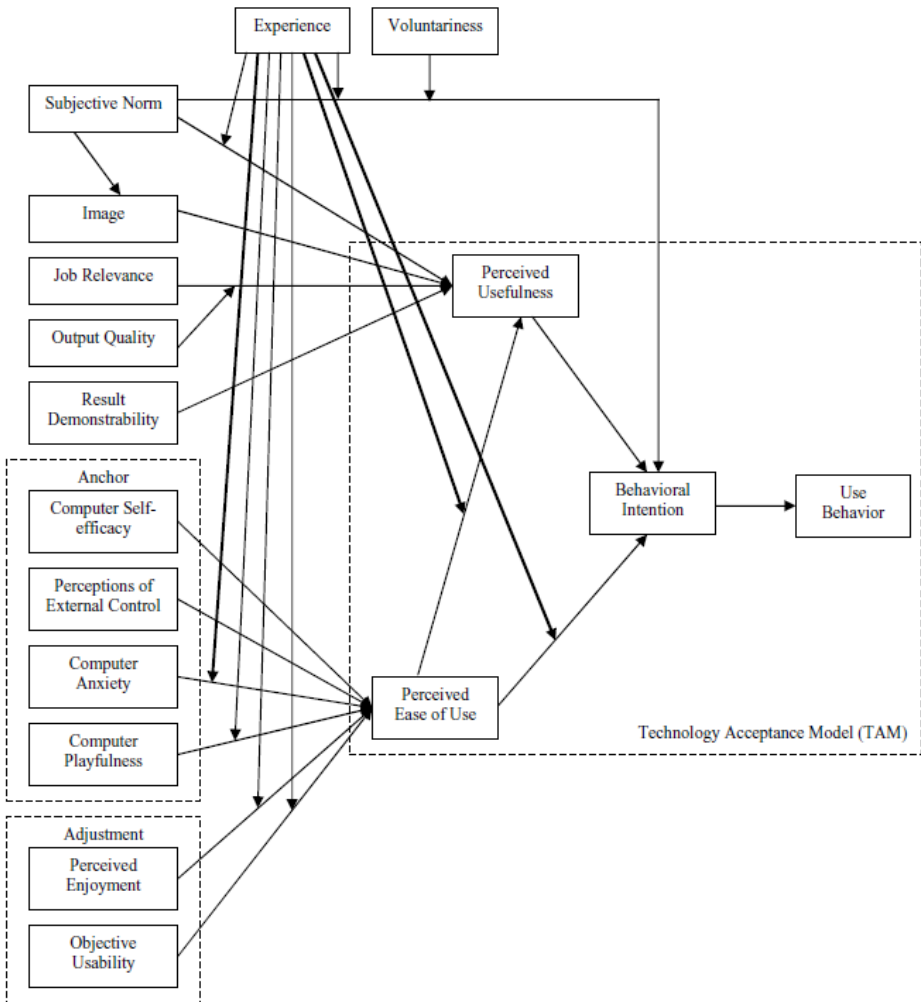

Figure 2.

TAM3 Model for Information Systems including BI (Venkatesh and Bala, 2008)

Many types of research have been published in reputable international sources in the field of BI, its functions in various fields of management, and its acceptance as new information technology. The description of some of these cases has been considered in the previous section. The table below (Table 1) represents a number of new articles published in this field.

Table1.
Summary of Several Studies Related to the BI Acceptance and Adoption

No.	Source	Location	Including a Case Study	Description
1	Niño et al., 2020	Colombia	Universidad de la costa	Designing a BI model to achieve institutional goals in the university and establish a system of data governance
2	Cheng et al., 2020	China	Chinese Companies	Investigating the correlation between BI and agility, speed of organizational reactions
3	Ain et al., 2019	International	None	A review of the thematic literature of BI with a focus on acceptance and adoption subject
4	Sönmez, 2018	Turkey	Capital market companies	Development of the TAM3 model for BI systems with its application approach in CRM
5	Verma et al., 2018	India	Big data analytics specialists	Study of information technologies acceptance in the big data ecosystem
6	D'Arcont, 2018	Italy	Small for-profit Corporations	Develop the role of BI in improving performance and studying the requirements for using it in small businesses
7	Fang et al., 2018	Malaysia	None	Feasibility study of accepting mobile BI and explaining its role in improving decision making
8	Bach et al., 2017	International	USA companies	Development of the TAM model for BI systems with its application approach in project management

No.	Source	Location	Including a Case Study	Description
9	Bach et al., 2016	International	None	Study of BI acceptance through the TAM
10	Grubliešič and Jaklič, 2015	International	None	Explain the differences between Business Intelligence and other management information systems and examine the organizational factors of BI technology acceptance
11	Yoon et al., 2014	United States	None	In-depth study of individual BI acceptance key factors and providing a comprehensive model and list of them

As much as business intelligence at its operational level is a technological solution and originates from data and computer science, its application in manager decision-making, especially its organizational acceptance, is a soft humane-related issue. The use of interpretive structural modeling, which is a soft approach to operational research, is another aspect of the present research innovation.

Method

Interpretive Structural Modeling (ISM) is a reliable procedure used to recognize relationships between specific concepts that identify a problem or issue. This approach has been increasingly utilized by researchers to express the interrelationships between the various elements related to the subject (Attri et al., 2013). ISM is defined as a process that aims to help people better understand what they believe and what they do not know. The most primary application of ISM is in organizational matters. The added information through this process is zero and its value is structural. The ISM process converts obscure mental systems into well-defined models (Sage, 1977). ISM begins with identifying variables related to a problem or issue and then continues with a group problem-solving procedure. Subsequently, a relevant content-dependent relationship is selected. The Structural Self-Interaction Matrix is created based on a two by two comparison deciding the conceptual relationship on each variable. The next step is to convert the SSIM to the Reachability Matrix and assure that it is transitive. When Transitivity is approved, a Conical Matrix is obtained, then the elements are segmented and a structural model called ISM is extracted (Agarwal et al., 2006). ISM is interpretive as group judgment decides whether and how different elements are related. It is structural as it is based on common relationships and a general system that is derived from several complex elements. It is also a modeling method as a result specific relationships and general structure are depicted in a graph model. ISM enables order and direction to the relationships between the various elements of a system (Dewangana et al., 2015). It is primarily intended as a group learning process, but can also be used by individuals. ISM can be used at high-level abstraction, such as strategic and long-term planning. It can also be used at a more realistic level to understand and redesign the details of problem-related or activity-related structures such as process design, product design, re-engineering, complex technical problems, financial decisions, manpower issues, competitive analysis, and e-commerce (Hasan et al., 2007; Agi and Nishant, 2017; Ahmad et al., 2019).

Findings

In many sources (e.g. Attri et al., 2013 and Jayant and Azhar, 2014) the prerequisite for entering the ISM process is the summation of factors and components related to complex or decision situations that are made using a systematic review or group problem-solving method. The present study uses both approaches. In this way, after reviewing the relevant literature, a set of acceptance factors is extracted and then presented to the academic experts in research institutes for final judgment. For this purpose, a focus group has been used. In addition, to determine the type of relationships between the variables in the next step, evaluations of the experts have been used in the form of these meetings. Focus groups are one of the key methods of qualitative exploration in the social sciences (Barbour and Kitzinger, 1999) and are used to achieve various goals in various fields of research. Therefore, depending on the objectives, they are defined in different ways. Focus group research is a method for collecting data that involves individuals in an informal group discussion (or several discussions) on a specific topic or set of topics (Wilkinson, 2004). Researchers in the social and behavioral sciences usually form focus groups to collect data from experts at the same time. Focus groups provide the right conditions for many people to participate in research to discuss perceptions, ideas, beliefs, and thoughts (Krueger and Casey, 2000). The choice of participants in a focus group is very important. Typically, participants are selected based on their experience with the research topic. Burgess (1996) suggests purposive sampling; relying on the judgment of researchers. Since participants in the focus group are not selected by random sampling, the success of the group depends on the dynamics between individuals within the group. Well-designed focus groups consist of six to twelve participants (Baumgartner et al., 2002). The number of participants should be large enough to provide a variety of information and de-emphasize members being uncomfortable with sharing their ideas, beliefs, and experiences.

There were eight participants in this study; four professors of research centers in the field of IT management and four student researchers in academic institutes of public universities in Tehran who are familiar with the subject of research. The number of samples has been supplemented to the point of theoretical saturation and the type of sampling was purposive. The meetings were held at the Faculty of Management and the type of questions included the factors of BI acceptance in research organizations. After approval and summarization of the experts in focus group meetings, the factors and indicators of BI acceptance in research organizations concerning theoretical literature and research background are show in table 2.

Table 2.

Indicators and Factors Affecting BI Acceptance

No.	Indicators	Factors	Source
1	Individual (Acceptor)	Individual Characteristics (Age, Experience, Gender, Education, etc.)	[Venketash et al., 2003] [Grubliešič and Jaklič, 2015] [Ain et al., 2019]
2		Perceived Usefulness of BI	[Bach et al., 2016] [Fang et al., 2018]
3		Perceived Ease of Use	[Bach et al., 2017] [Fang et al., 2018]
4		Behavioral Intention of BI Use	[Bach et al., 2016] [Sönmez, 2018]
5		Computer Playfulness and Enjoyment	[Venkatesh and Bala, 2008] [Sönmez, 2018]
6		Computer Avoidance and Anxiety	[Venkatesh and Bala, 2008] [Sönmez, 2018]
7	Information Technology System	Data/ Information Quality	[Bouchana and Idrissi, 2015] [Bach et al., 2016]
8		IT Project Management (PM Maturity)	[Bach et al., 2016] [Bach et al., 2017]
9		Organizational Information Systems Quality	[Zhao et al., 2012] [Ain et al., 2019]
10		Display Results Capability	[Jaklič et al., 2018]
11		BI System Maturity	[Skyrius et al., 2016]
12		System Compatibility	[Yoon et al., 2014] [Jaklič et al., 2018]

No.	Indicators	Factors	Source
13	Organization Specifications	Technology-Based Strategy	[Bach et al., 2016] [Ain et al., 2019]
14		Change Management	[Bach et al., 2016] [Bach et al., 2017]
15		Knowledge Sharing	[Al-Zayyat et al., 2010] [Bach et al., 2017]
16		Senior Management Support and Commitment	[Yoon et al., 2014] [Puklavec et al., 2017]
17		Organizational Culture	[Grublješič and Jaklič, 2015] [Puklavec et al., 2017]
18		Company Size	[Zhao et al., 2012]
19		Learning Environment	[Yoon et al., 2014]
20		Competitive Pressure	[Boonsiritomachai et al., 2016]

SSIM consists of comparing BI acceptance factors using four modes of conceptual relationships. This matrix has been completed according to the opinion of IT management experts and specialists. To determine and finalize the relationships between the factors, the focus group method has been used (as described in Section 5.1). At this stage, the relationships between the factors influencing the BI acceptance, in the form of pair comparison and using the concept of "lead to" have been analyzed. In the first row and first column of this matrix, the factors are listed in order. The modes and symbols used in this conceptual relationship are:

- V: The variable ‘i’ leads to ‘j’
- X: Shows the two-way effect
- A: The variable ‘j’ leads to ‘i’
- O: Shows there is no relationship between ‘i’ and ‘j’ (Ahmad et al., 2019)

By conducting focus group meetings, the SSIM matrix of BI acceptance factors was adjusted according to the above rules. The Reachability Matrix is obtained by converting the SSIM into a two-value matrix (0 and 1). After converting all the rows, the result is called the initial reachability matrix.

According to the following rules, the initial reachability matrix can be obtained (Faisal et al., 2006):

- If the entry (i, j) in the SSIM takes the symbol V, the peer entry in the matrix is 1 and its symmetric entry (j, i) is 0.
- If the entry (i, j) in the SSIM is denoted by the symbol A, the similar entry in the matrix is 0 and its symmetric entry (j, i) is 1.
- If the entry (i, j) in the SSIM takes the symbol X, the corresponding entry in the matrix is 1 and its symmetric entry (j, i) is 1.
- If the entry (i, j) in the SSIM is denoted by the symbol O, the peer entry in the matrix is 0, and its symmetric entry (j, i) is also 0.
- If i = j, the corresponding entry in the matrix is 1 (Agi and Nishant, 2017).

The primary reachability matrix, which was set based on the SSIM matrix, can be seen in the Appendices (Appendix 1). Once the initial reachability matrix has been formed, its internal transitivity must be established. Thus, if 'i' and 'j' are correlated and 'j' and 'k' are correlated, then 'i' and 'k' must be correlated. In this step, the secondary relations are controlled. By identifying secondary relationships, the modified (final) reachability matrix is obtained. The column of influence power is derived from the sum of the rows, and the dependency row is obtained from the columnar sum of the factors (Agarwal et al., 2006). The final reachability matrix of BI acceptance factors, which is obtained from applying the transitivity rules to the primary reachability matrix, can be seen in Appendix 2. In order to determine the relationships and leveling of the factors affecting the BI acceptance, it is necessary to extract the set of outputs (Access) and inputs (Prerequisites) for each factor from the reachability matrix. The set of outputs includes the factor itself and the factors that it affects. The set of inputs includes the factor itself and the factors that are affected by them. Then, the set of mutual relations of each of the factors is determined; that is, the factors that are repeated in the two sets. These factors are then leveled based on the resulting sets. Typically, factors that have the equal output set and mutual set of relationships form a high level of hierarchy; therefore, high-level factors will not be the source of any other factor. When a high level is defined, it is separated from other factors. Then, through a similar process, the next levels are identified (Dewangana et al., 2015).

Table 3.
Level Partitions of BI Acceptance Factors

Factors	Output Set	Input Set	Mutual Set	Level
1. Individual Characteristics	All except 16, 18 and 20	All except 6	All except 6, 16, 18 and 20	II
2. Perceived Usefulness of BI	All except 16 and 18	All except 6	All except 6, 16 and 18	II
3. Perceived Ease of Use	All except 16, 18 and 20	All except 6	All except 6, 16, 18 and 20	II
4. Behavioral Intention of BI Use	All except 16, 18 and 20	All Factors	All except 16, 18 and 20	I
5. Computer Playfulness and Enjoyment	All except 16, 18 and 20	All Factors	All except 16, 18 and 20	I
6. Computer Avoidance and Anxiety	4, 5, 6, 8, 9, 11, 14, 15, 17 and 19	All Factors	4, 5, 6, 8, 9, 11, 14, 15, 17 and 19	I
7. Data/ Information Quality	All except 18	All except 6	All except 6 and 18	II
8. IT Project Management (PM Maturity)	All except 18	All Factors	All except 18	I

Factors	Output Set	Input Set	Mutual Set	Level
9. Organizational ISs Quality	All except 18	All Factors	All except 18	I
10. Display Results Capability	All except 18	All except 6	All except 6 and 18	II
11. BI System Maturity	All Factors	All Factors	All Factors	I
12. System Compatibility	All except 16 and 18	All except 6	All except 6, 16 and 18	II
13. Technology-Based Strategy	All except 16 and 18	All except 6	All except 6, 16 and 18	II
14. Change Management	All except 16 and 18	All Factors	All except 16 and 18	I
15. Knowledge Sharing	All except 18	All Factors	All except 18	I
16. Senior Management Support and Commitment	All except 18	7, 8, 9, 10, 11, 15, 16, 18, 19 and 20	7, 8, 9, 10, 11, 15, 16, 19 and 20	III
17. Organizational Culture	All except 16 and 18	All Factors	All except 16 and 18	I
18. Company Size	All Factors	11, 18 and 20	11, 18 and 20	IV
19. Learning Environment	All except 18	All Factors	All except 18	I
20. Competitive Pressure	All Factors	All except 1, 3, 4, 5, 6	All except 1, 3, 4, 5, 6	III

To draw the diagram, the factors are first sorted from top to bottom according to their level, due to the priority obtained in the previous step. Then, using the reachability matrix and based on the levels, the structural model is illustrated by nodes and arrows. If there is a relationship from ‘i’ to ‘j’, it is identified by an arrow from ‘i’ to ‘j’ (Thakkar et al., 2007). Figure 3 shows the final model. In this model, all the connections between the factors (except for the relationship of each factor with itself) are displayed.

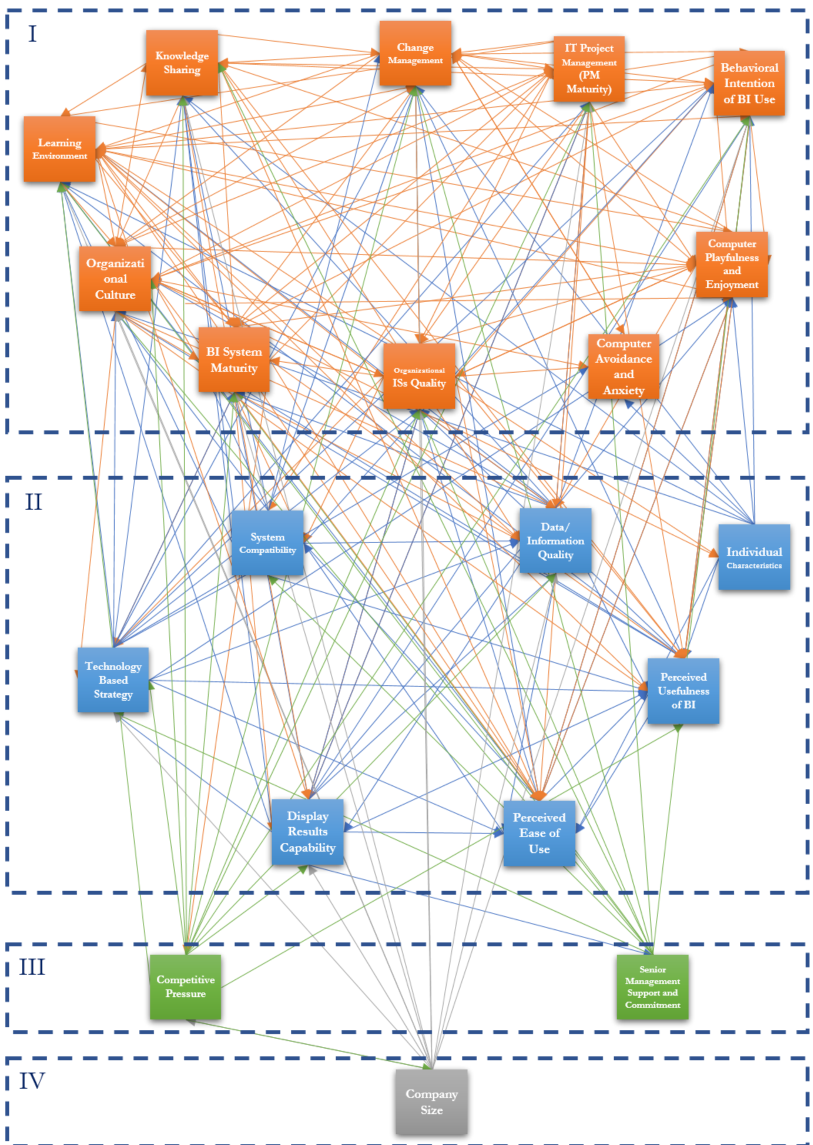

Figure 3.

Interpretive Structural Model of Factors Affecting BI Acceptance

Factor clustering can be seen in Figure 4.

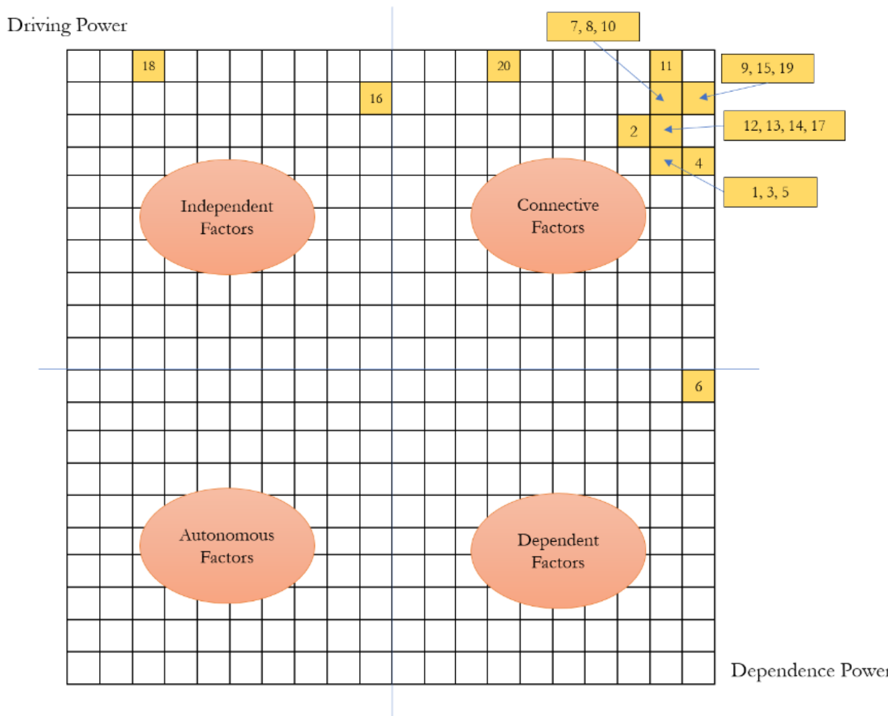

Figure 4.
Clustering of Factors

Conclusion

In this study, according to the steps of interpretive structural modeling, the factors affecting the acceptance of business intelligence (BI) in research organizations were analyzed at four levels. At the highest level (orange in Fig. 3) with the most affectivity, there are 10 different individual, technological, and organizational factors. In the second level (blue in Fig. 3), there are seven factors. In the third level (green in Fig. 3), two and, finally, in the fourth level (gray in Fig. 3) with the most effectivity being only one factor. The reverse pyramidal structure of the model indicates a complex network and extensive interconnection between factors that have been simplified to the utmost in the methodological stages. The results of MICMAC analysis show that most of the factors influencing the acceptance of business intelligence technology have a high degree of dependence and driving power, and therefore, are in the connection area. In this area, any change in the factors causes a change in other factors. This means that managers, researchers, and all stakeholders in the field of information technology management should heed the fact that attention to all individual, technological, and organizational factors are equally necessary for research organizations. Due to the complex interaction of factors, focusing on one or some specific factors will be an unfavorable strategy for developing business intelligence; however, more strategies that are inclusive will increase the likelihood of BI adoption in such institutes. Factors such as "senior management support and commitment" and "company size" were identified as influential factors with low dependence and high influence. This means that in research organizations, the support of top executives plays an important role in BI technology adoption, so managers and other decision-makers must begin to play their role in the adoption process. In addition, company size is another factor that has high-driving power. The larger a research organization is in the greater complexity of its system, information, and environment, the better its understanding of business intelligence. "Computer avoidance and anxiety" alone are among the most dependent factors, indicating high dependence and low-driving power. In research organizations, computer avoidance depends on several factors, while having limited effect on other technology adoption factors. The fact that none of the factors are in the Autonomy area is indicative of the broad connection between the factors in the socio-technical situation; in other words, there is no factor that can be considered separate from the system. According to Niño et al. (2020), the BI governance is studied in the operational, process, communication, and strategic layers, while according to the findings of the present study, individual, systemic, and organizational factors should be studied separately. The research model of Owusu et al. (2017) is designed based on the TOE framework, which divides the BI adoption factors into three categories: Technological, organizational, and environmental. Given that the study of Owusu et al. (2017) has used structural equation modeling, a large number of its confirmed results are similar to the findings of this study. The study of Sujitparapitaya et al. (2012) is limited to a brief description of some of the factors of BI acceptance (only 10) and a survey on their importance. The interpretive and structural view of the present study covers all the factors of this and other research. Some BI acceptance studies in research organizations such as Ta'a et al. (2006) focus only on the technological aspects of the subject, which makes their findings describe only a segment of a socio-technical system. In contrast, the study of both technological and social factors in the findings of the present study is significant. It is recommended to researchers in the fields of information technology management and business intelligence, in order to apply and expand the acceptance of this technology, that they pay similar attention to individual, organizational, and technological factors. It is also recommended that research centers begin to take advantage of this technology and develop the acceptance of it given the immense BI benefits.

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Appendices

Appendix 1. Primary Reachability Matrix of BI acceptance factors

i / j	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Individual Characteristics	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	0	1	0	1	0
2. Perceived Usefulness of BI	0	1	1	1	1	0	0	0	1	0	1	0	0	1	0	0	1	0	1	0
3. Perceived Ease of Use	0	1	1	1	1	0	0	0	1	0	0	1	0	1	0	0	1	0	1	0
4. Behavioral Intention of BI Use	0	1	1	1	1	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0
5. Computer Playfulness and Enjoyment	0	1	1	1	1	0	1	0	1	0	0	0	0	1	1	0	1	0	1	0
6. Computer Avoidance and Anxiety	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
7. Data/ Information Quality	0	1	1	1	0	0	1	1	1	1	1	0	0	0	1	0	1	0	1	0
8. IT Project Management (PM Maturity)	0	1	1	1	1	0	1	1	1	1	1	1	0	1	1	0	1	0	1	0
9. Organizational ISs Quality	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0
10. Display Results Capability	0	1	1	1	1	0	1	1	1	1	1	0	1	0	1	1	0	0	1	0
11. BI System Maturity	0	1	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	1	1
12. System Compatibility	0	1	1	1	0	0	1	0	0	0	1	1	0	1	1	0	1	0	1	0
13. Technology-Based Strategy	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	1	0	1	0
14. Change Management	0	0	0	1	1	1	0	1	1	0	1	0	0	1	1	0	1	0	1	0
15. Knowledge Sharing	0	1	1	1	0	0	1	0	0	1	1	0	0	1	1	0	1	0	1	0
16. Senior Management Support and Commitment	0	0	0	1	0	0	0	1	1	0	1	1	1	1	1	1	1	0	1	0
17. Organizational Culture	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	0	1	0	1	0
18. Company Size	0	0	0	1	0	0	1	1	1	1	1	0	1	1	1	0	1	1	1	1
19. Learning Environment	1	1	1	1	1	0	1	0	0	1	1	0	0	1	1	0	1	0	1	0
20. Competitive Pressure	0	1	0	1	0	0	1	1	1	1	1	0	1	1	1	0	1	1	1	1

Appendix 2. Primary Reachability Matrix of BI acceptance factors

i / j	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Influence Power
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	17
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	18
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	17
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	17
5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	17
6	0	0	0	1	1	1	0	1	1	0	1	0	0	1	1	0	1	0	1	0	10
7	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	19
8	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	19
9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	19
10	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	19
11	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	20
12	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	18
13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	18
14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	18
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	19
16	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	19
17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	18
18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	20
19	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	19
20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	20
Dependency	19	18	19	20	19	20	19	19	20	19	19	19	19	19	20	10	19	3	20	14	