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An Assessment model for Intelligence Competencies of Accounting Information Systems

Mehdi Ghazanfari, Mostafa Jafari, Saeed Rouhani

Abstract— Accounting Information Systems (AIS) as computer-based systems that processes financial information and supports decision tasks have been implemented in most organizations but, but they still encounter a lack of Intelligence in their decision-making processes. Models and methods to evaluate and assess the Intelligence-level of Accounting Information Systems can be useful in deploying suitable business intelligence (BI) services. This paper discusses BI Assessment criteria, fundamental structure and factors used in the Assessment model. Factors and the proposed model can assess the intelligence of Accounting Information Systems to achieve enhanced decision support in organizations. The statistical analysis identified five factors of the Assessment model. This model helps organizations to design, buy and implement Accounting Information Systems for better decision support. The study also provides criteria to help organizations and software vendors implement AIS from decision support perspectives.

Index Terms— Business Intelligence; Decision Support; Accounting Information Systems; Assessment Model.

1 Introduction

Information and knowledge represent the fundamental wealth of an organization. Enterprises try to utilize this wealth to gain competitive advantage when making important decisions. Enterprise systems like Accounting Information Systems (AIS) converts and store the data. Therefore, it is important to integrate decision-support into the environment of these systems. Business intelligence (BI) can be embedded in these enterprise systems to obtain this competitive advantage.

Today, approaches using an individual system for decision-support, such as decision-support systems (DSS), have been replaced by a new, environmental approach. In the past, DSS were independent, separate systems in an organization (island systems). However, enterprise systems are now the foundation of an organization, and practitioners are designing BI as an umbrella concept to create a decision-support environment for management (Alter 2004). The increasing trend to use intelligent tools in business systems has increased the need for Intelligence Assessment of Accounting Information Systems (AIS).

There have been some limited efforts to assess BI, but they have always considered BI as a system that is isolated from the enterprise systems like AIS. Taking a global view, Lönnqvist and Pirttimäki (2006) have designed BI performance measures, but before their effort, the measurement and the evaluation in the BI field were restricted to proving the worth of BI investment, and the value of BI. Elbashir et al. (2008) have discussed measuring the effects of BI systems on the business process, and have presented effective methods of measurement. Lin et al. (2009) have also developed a performance evaluation model for BI systems using ANP, but they have also treated BI as a separate system.

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Organizations usually utilize functional and non-functional requirements to assess and select enterprise systems like AIS, so the consideration of their decision-support environment as a non-functional requirement, raises the following questions.

1. Which criteria are suitable and effective in the Intelligence assessment of Accounting Information Systems (AIS)?
2. What is the fundamental structure of these criteria?

This research was carried out to find answers to the above questions and to provide a model for efficient decision-support by evaluating systems and making BI an integral part of these systems. The rest of this paper is organized as follows. Section 2, describes brief literature about AIS. Section 3 is about attempts in previous studies to define Business intelligence (BI). A wide-ranging literature review about BI and decision-support criteria to assess systems is also summarized in Section 3. Research methodology and research stages are discussed in section 4. Section 5 discusses the design of the questionnaire, data collection, reliability analysis, factor extraction, and label-

- *Mehdi Ghazanfari is currently full professor in Iran University of Science and Technology, Tehran, Iran, E-mail: Mehdi@iust.ac.ir*
- *Mostafa Jafari is currently assistant professor in Iran University of Science and Technology, Tehran, Iran*
- *Saeed Rouhani is currently PhD Candidate in Iran University of Science and Technology, Tehran, Iran, E-mail: SRouhani@iust.ac.ir, Contact:+989122034980*

ling and assessment model. Finally, Section 6 concludes the research work, its findings and proposed future research.

2 Accounting Information Systems

An Accounting Information Systems (AIS) is defined as a computer-based system that processes financial information and supports decision tasks in the context of coordination and control of organizational activities. Extant accounting information systems research has evolved from the source disciplines of Computer science, organizational theory and cognitive psychology. An advantage of this evolution is a diverse and rich literature with the potential for exploring many different interrelationships among technical, organizational and individual aspects of judgment and decision performance. AIS research also spans from the macro to the micro aspects of the information system (Birnberg & Shields, 1989; Gelinas et al., 2005).

The comparative advantage of accounting researchers within the study of IT lies in their institutional accounting knowledge. Systems researchers can contribute insights into the development of systems utilizing technology, and the other sub-areas can contribute insights into the task characteristics in the environment. For instance, systems researchers have extensively investigated group decision support systems (GDSS), but they have only recently been considered in auditing. On the other hand, auditing research has extensively investigated the role of knowledge and expertise. The merging of the two sets of findings may be relevant to AIS design, training, and use.

As comparable term, Management accounting systems (MAS) also are formal systems that provide information from the internal and external environment to managers (Bouwens & Abernethy, 2000). They include reports, performance measurement systems, computerized information systems, such as executive information systems or management information systems, and also planning, budgeting, and forecasting processes required to prepare and review management accounting information.

Research on management accounting and integrated information systems (IIS) has evolved across a number of different research streams. Some research streams put heavier emphasis on the management accounting side, while other research streams put emphasis on the information systems side. Likewise, different research streams approach the topic from different perspectives (Anders Rom & Carsten Rohde, 2007).

A major stream of research within AIS research deals with the modeling of accounting information systems. Several modeling techniques stay alive within the information systems literature (e.g. entity-relationship diagrams, flowcharts and data flow diagrams). Whereas these modeling techniques can be used when modeling accounting information systems (Gelinas et al., 2005), But, the REA modeling technique is particular to the AIS domain. The REA model, which maps resources, events and agents, was first described by McCarthy (1979, 1982) and later developed by an exclusive group of researchers (David et al., 2002). Extensions to resources, events and agents include locations (Denna et al., 1993), tasks and commitments (Geerts and McCarthy, 2002).

An unshakable stream of research exists within the AIS literature that investigates behavioral issues in relation to accounting information systems (Sutton and Arnold, 2002). This stream of research investigates the impact of IT on individuals, organizations and society.

An example of behavioral AIS research is a study carried out by Arnold et al. (2004) on the use and effect of intelligent decision aids. The authors find that smart machines must be operated by smart people. If users are inexperienced, they will be negatively impacted by the system. Furthermore, they will not learn by experience. Abernethy and Vagnoni (2004) found that top management uses the newly implemented system for monitoring. Use of AIS is found to have a positive effect on cost consciousness, but the cost consciousness is hampered if people have informal power. In this context, power is an explanatory variable of AIS use.

3 *Business Intelligence*

Business Intelligence or BI is a grand, umbrella term introduced by Howard Dresner of the Gartner Group in 1989 to describe a set of concepts and methods to improve business decision-making by using fact-based computerized support systems (Nylund, 1999). The first scientific definition, by Ghoshal and Kim (1986) referred BI to a management philosophy and tool that helps organizations to manage and refine business information for the purpose of making effective decisions.

BI was considered to be an instrument of analysis, providing automated decision-making about business conditions, sales, customer demand, and product preference and so on. It uses huge-database (data-warehouse) analysis, as well as mathematical, statistical, artificial intelligence, data mining and on-line analysis processing (OLAP) (Berson and Smith, 1997). Eckerson (2005) understood that BI must be able to provide the following tools: production reporting tools, end-user query and reporting tools, OLAP, dashboard / screen tools, data mining tools and planning and modelling tools.

BI includes a set of concepts, methods, and processes to improve business decisions, which use information from multiple sources and apply past experience to develop an exact understanding of business dynamics (Maria, 2005). It integrates the analysis of data with decision-analysis tools to provide the right information to the right persons throughout the organization with the purpose of improving strategic and tactical decisions. A BI system is a data-driven DSS that primarily supports the querying of an historical database and the production of periodic summary reports (Power, 2008).

Lönnqvist and Pirttimäki (2006), stated that the term, BI, can be used when referring to the following concepts:

1. Related information and knowledge of the organization, which describe the business environment, the organization itself, the conditions of the market, customers and competitors, and economic issues;
2. Systemic and systematic processes by which organizations obtain, analyse, and distribute the information for making decisions about business operations.

A literature review around the theme of BI shows ‘‘division” between technical and managerial view points, tracing two broad patterns. The managerial approach sees BI as a process in which data, gathered from inside and outside the enterprise and are integrated in order to generate information relevant to the decision-making process. The role of BI here is to create an informational environment in which operational data gathered from transactional processing systems (TPS) and external sources can be analysed, in order to extract ‘‘strategic” business knowledge to support the unstructured decisions of management.

The technical approach considers BI as a set of tools that support the process described above. The focus is not on the process itself, but on the technologies, algorithms and tools that allow the saving, recovery, manipulation and analysis of data and information (Petrini and Pozzebon, 2008).

However, in the overall view, there are two important issues. First, the core of BI is the gathering, analysis and distribution of information. Second, the objective of BI is to support the strategic decision-making process.

By strategic decisions, we mean decisions related to implementation and Assessment of organizational vision, mission, goals, and objectives, which are supposed to have medium- to long-term impact on the organization, as opposed to operational decisions, which are day-to-day in nature and more related to execution (Petrini and Pozzebon, 2008).

4 RESEARCH METHODOLOGY

Based on literature review, the points discussed above, the authors’ recent researches on BI and applying some statistical methods, the research structure of this study has been developed on seven stages as shown in Figure 1. In this way, at first stage a literature review was done on business intelligence specifications or criteria that a system should have to cover BI definitions. These criteria listed in Table 1.

TABLE 1
BI ASSESSMENT CRITERIA

Criteria ID	Criteria Name	Related Studies
C1	**Group sorting tools & methodology (Groupware)**	Shim et al. (2002), Reich and Kapeliuk (2005), Damart et al. (2007), Marinoni et al. (2009)
C2	**Group decision-making**	Eom (1999), Evers (2008), Yu et al. (2009)
C3	**Flexible models**	Reich and Kapeliuk (2005), Zack (2007), Lin et al. (2009)
C4	**Problem clustering**	Reich and Kapeliuk (2005), Loebbecke and Huyskens (2007), Lamptey et al. (2008)
C5	**Optimization technique**	Lee and Park (2005), Nie et al. (2008), Shang et al. (2008), Azadivar et al. (2009), Delorme et al. (2009)
C6	**Learning technique**	Power and Sharda (2007), Ranjan (2008), Li et al. (2009), Zhan et al. (2009)
C7	**Import data from other systems**	Ozbayrak and Bell (2003), Alter (2004), Shang et al. (2008), Quinn (2009)
C8	**Export reports to other systems**	Ozbayrak and Bell (2003), Shi et al. (2007), Shang et al. (2008)
C9	**Simulation models**	Power and Sharda (2007), Shang et al. (2008), Quinn (2009), Zhan et al. (2009)
C10	**Risk simulation**	Evers (2008), Galasso and Thierry (2008)
C11	**Financial analyses tools**	Santhanam and Guimaraes (1995), Raggad (1997), Gao and Xu (2009)
C12	**Visual graphs**	Noori and Salimi (2005), Kwon et al. (2007), Power and Sharda (2007), Li et al. (2008), Azadivar et al. (2009)
C13	**Summarization**	Bolloju et al. (2002), Hemsley-Brown (2005), Power and Sharda (2007), Power (2008)
C14	**Evolutionary prototyping model**	Fazlolahi and Vahidov (2001), Bolloju et al. (2002), Gao and Xu (2009), Zhang et al. (2009)
C15	**Dynamic model prototyping**	Koutsoukis et al. (2000), Bolloju et al. (2002), Goul and Corral (2007), González et al. (2008), Pitty et al. (2008)
C16	**Backward & forward reasoning**	Gottschalk (2006), Evers (2008), Zhang et al. (2009)
C17	**Knowledge reasoning**	O¨ zbayrak and Bell (2003), Plessis and Toit (2006), Evers (2008)
C18	**Alarms & warnings**	Power (2008), Ross et al. (2008), Zhang et al. (2009)
C19	**Dashboard/Recommender**	Nemati et al. (2002), Hedgebeth (2007), Bose (2009)
C20	**Combination of experiments**	Courtney (2001), Nemati et al. (2002), Gottschalk (2006), Gonnet et al. (2007), Ross et al. (2008), Hewett et al. (2009)
C21	**Situation awareness modelling**	Raggad (1997), Plessis and Toit (2006), Feng et al. (2009)
C22	**Environmental awareness**	Phillips-Wren et al. (2004), Koo et al. (2008), Güngör Sen et al. (2008)
C23	**Fuzzy decision-making**	Metaxiotis et al. (2003), Zack (2007), Makropoulos et al. (2008), Wadhwa et al. (2009), Yu et al. (2009)

At the Second stage, a questionnaire was designed with two main parts: first section of the questionnaire consisted of some questions the characteristics of the interviewees. The content of second section was based on business intelligence specifications which were asked as the important evolution criteria.

At the third and forth stage, the survey is run to collect data from interviewees; and based on the collected data; the reliability analysis can be performed. Reliability analysis allows you to study the properties of questionnaire and the items that make them up. The reliability analysis procedure calculates a number of commonly used measures of scale reliability and also provides information about the relationships between individual items in the measurement scale (Hair et al., 1998).

The fifth and sixth stages of research framework are based on “factor analysis” and are concentrated on extraction and identification of the BI Assessment criteria affecting the intelligence of AIS. Factor analysis is also known as a generic name given to a class of multivariate statistical methods whose primary purpose is to define the underlying structure in a data matrix. With factor analysis, the researcher can first identify the separate factors of the structure and then determine the extent to which each variable is explained by each factor. Once these factors and the explanation of each variable are determined, the two primary uses for factor analysis-summarization and data reduction-can be achieved. In summarizing the data, factor analysis derives underlying factors that, when interpreted and understood, describe the data in a much smaller number of concepts than the original individual variables (Hair et al., 1998). Evaluating the suitability of collected data, performing factor analysis and naming the extracted factors are different steps.

5 DISCUSSION

A questionnaire was designed and structured in three sections. Information related to the basic profile of the interviewees was requested at the beginning of the questionnaire.

In the second part, there were 23 questions designed to

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measure their attitude, based on the BI Assessment Criteria listed in Table 2. The selected response was evaluated by a "Likert Scale" (Likert, 1974) and the responses could be: very strongly disagree, strongly disagree, disagree, no opinion, agree, strongly agree or very strongly agree. In other words, the second part of questionnaire measures their opinions the importance of each BI specification in terms of the intelligence Assessment Criteria of AIS.

The main targets of the sampling were accounting managers who are involved in systems efforts and decision-making.

5.1 Reliability analysis

With reliability analysis, you can get an overall index of the repeatability or internal consistency of the measurement scale as a whole, and you can identify problem items that should be excluded from the scale. The Cronbach's α is a model of internal consistency, based on the average inter-item correlation. The Cronbach's α (Likert, 1974) calculated from the 34 variables of this research was 0.941 (94 percent), which showed high reliability for designed measurement scale.

5.2 Data collection

The research targets were accounting managers who were involved in systems efforts and decision-making in organizations. The number of questionnaires sent out was 210 and the number returned was 176, which showed a return rate of 83 per cent.

5.3 Demographic profiles of interviewees

The demographic profile of interviewees who participate in the survey has been summarized in Table 2. The results show that most of the members (87.5 per cent) are male. Most of the interviewees (88.7 per cent) have a Bachelor of Science (BS) or a higher degree, as shown in Table 2.

TABLE 2
DEMOGRAPHIC PROFILES OF INTERVIEWEES

	Description	Number of interviewees	Percent
Gender	Male	154	87.5
	Female	22	12.5
	Sum	176	100
Educational degree	Under BS	20	11.4
	BS	83	47.2
	MS or higher education	73	41.5
	Sum	176	100
Seniority	Less than 5 years	7	4
	5 to less than 10 years	69	39.2
	10 to less than 15 years	64	36.4
	15 to less than 20 years	25	14.2
	20 years and above	11	6.2
	Sum	176	100

On the subject of decision-type, the majority of interviewees make semi-structured and unstructured decisions in their work. Table 2 also shows the seniority of the participants. As can be seen, 20.4 per cent have over 15 years of seniority, 36.4 per cent have 10-15 years, and 43.2 per cent have less than 10 years seniority.

5.4 Factor Extaction and Labeling

Factor analysis can be utilized to examine the underlying patterns or relationships for a large number of variables and to determine whether the information can be condensed or summarized in a smaller set of factors or components (Hair et al., 1998).

An important tool in interpreting factors is factor rotation. The term rotation means exactly what it implies. Specifically, the reference axes of the factors are turned about the origin until some other position has been reached. The un-rotated factor solutions extract factors in the order of their importance. The first factor tends to be a general factor with almost every variable loading significantly, and it accounts for the largest amount of variance. The second and subsequent factors are then based on the residual amount of variance. The ultimate effect of rotating the factor matrix is to redistribute the variance from earlier factors to later ones to achieve a simpler, theoretically more meaningful factor pattern. The simplest case of rotation is an orthogonal rotation, in which the axes are maintained at 900 (Hair et al., 1998).

In order to determine whether the partial correlation of the variables is small, the Kaiser-Meyer-Olkin was used to measure of sampling adequacy (Kaiser, 1958) and Bartlett's χ^2 test of Sphericity (Bartlett, 1950) before starting the factor analysis. The result was a KMO of 0.963 and Bartlett test p-value less than 0.05, which showed good correlation. The factor analysis method is "principle component analysis" in this research, which was developed by Hotteling (1935). The condition for selecting factors was based on the principle proposed by Kaiser (1958):

TABLE 3
ROTATED FACTOR ANALYSIS RESULTS

		Rotation Sums of Squared Loadings	
Factor	Initial Eigen values	Percentage of Variance	Cumulative percentage
1	16.114	21.366	21.366
2	3.173	18.366	39.732
3	1.850	14.836	54.568
4	1.457	8.755	63.324
5	1.348	6.025	69.349

Eigen value larger than one, and an absolute value of factor loading greater than 0.5. The 23 variables were grouped into five factors. The results can be seen in Table 3. Five factors had an Eigen value greater than one and the interpretation variable was 69.349 percent. The factors were rotated according to Varimax rotation method.

To indicate the meaning of the factors, they have been given short labels indicating their content. “Analytical Decision-support”, “Providing Integration with Environmental and Experimental Information”, “Optimization Model”, “Reasoning” and finally, “Enhanced Decision-making Tools” are the names which have been assigned to the extracted factors.

6 Conclusion

Enterprise systems like Accounting Information Systems (AIS) converts and store the data. Therefore, it is important to integrate decision-support into the environment of these systems. Business intelligence (BI) can be embedded in these enterprise systems to obtain competitive advantage.

This research confirmed the necessity to assess the Intelligence of Accounting Information Systems and demonstrated that this assessment can advance a decision-support environment. From a wide-ranging literature review, 23 criteria for BI assessment were gathered and embedded in the second part of the research. The interviewees selected the more important criteria from these 23 variables by assigning ranks to them. The research then applied factor analysis to extract the five factors for evaluation. These factors were ““Analytical Decision-support”, “Providing Integration with Environmental and Experimental Information”, “Optimization Model”, “Reasoning” and finally, “Enhanced Decision-making Tools”. The authors believe that after this research, organizations can make better decisions for designing, selecting, evaluating and buying Accounting Information Systems, using criteria that help them to create a better decision-support environment in their work systems. Of course, further research is needed. One area is the design of expert systems (tools) to compare vendors’ products. The other is the application these criteria and factors in a Multy Criteria Decision Making framework to select and rank AIS, financial and banking systems based on BI specification. The complex relationship between decision-making satisfaction of managers, and these factors should also be addressed in future research.

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