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The Challenges of Data Accuracy in Business Analytics that Affect Managers' Decisions Making – Case Study of Saudi Arabia & Lebanon

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Abstract: *Digitization of information has made data an important factor in organizational decision making. Modern organizations are increasingly turning to data to generate data-driven decisions due to various advantages of relying on, such as quick decision making and accuracy of analysis. However, when the data relied upon is inaccurate, the repercussions for the organization are usually adverse. Considering the nature of data to influence processes and decisions throughout the organizational structure, it can be deduced that data inaccuracy is a serious threat to the effectiveness and profitability of a business. The aim of this study was to explore the challenges of data accuracy in business analytics that affect managers' decision making in organizations in Saudi Arabia and Lebanon. The study established that data accuracy is an important factor in the attainment of efficiency in an organization. The study identified some of the challenges associated with data inaccuracy in decision making as;wrong strategic decisions, waste of time and resources in data verification and reconciliation, and customer dissatisfaction.*

Keywords:*Data Accuracy, Business Analytics, Decision Making*

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I. Introduction

Access to data is an important component of good performance in a business. Data allows a business to anticipate and plan for the next step. Technological advancements have enabled modern businesses of all sizes to gather and store growing amounts of data. It is estimated by the International Data Corporation that 40 zettabytes (1 trillion gigabytes) of data will be produced by 2020 (Dragan & Metz, 2017). The growing amounts of data have led to data handling and storage problems, which can lead to the production of inaccurate data. The accuracy of data has a direct effect on the performance of an organization. In particular, data reliability isessential to good decision making in a business. The data that the business relies on to make decisions must not only be reliable or consistent but also accurate. Data accuracy refers to the correctness of data while reliability is a question of how consistent or up to date the data is (Dragan & Metz, 2017). Organizations usually rely on business analytics tools to make informed decisions on issues, such as financial planning, purchasing and supply decisions, budgeting, and predictive measures among others. Interconnections among the various modules of enterprise resource planning (ERP) systems mean that inaccurate data that is fed into one module can have adverse effects on the operations of other modules (Dragan & Metz, 2017). Business analytics, which involves analyzing and making sense of large amounts of data, is a process that is fully dependent on the underlying source of data. Therefore, when the data is inaccurate, the resultant outcomes from decisions based on the data may be negatively affected. This is because many managers make decisions based on the assumption that the data they are relying on is accurate or near perfect.

Around 1 % to 10 % of data in the databases of large organizations is inaccurate (Ge &Helfert, 2013). Increasing digitization of data makes organizations even more vulnerable to inaccurate data. The impact of poor information quality can be disastrous. For instance, inaccurate information has been linked to: wrong diagnosis in hospitals (Bjertnaes, Skudal, Iversen, Lindahl, 2013); fetal deaths in Wyoming, United States (Harrist, Busacker, &Kroelinger, 2017);andthe crash of Air France flight 447 in 2009 (O'Regan, 2013). Therefore, the quality of data is a key determinant of the quality of decisions made. Although the effect of data accuracy on decision making has been investigated previously, the previous studies have not explored the challenges of data accuracy that affect decision making. Investigating these challenges is valuable as the knowledge of such challenges is likely to foster ways of overcoming them. With this research gap in mind, the current study explored the challenges of data accuracy in business analytics that affect managers' decision making in organizations in Saudi Arabia and Lebanon. Decision makers in these countries are facing the challenge of poor data quality (Abumandil& Hassan, 2016). However, few studies have explored the effect of poor data quality on decision making in these countries or the wider Middle East and North Africa (MENA) region in general (Beersma, Greer, Dalenberg, & De Dreu, 2016; Abumandil& Hassan, 2016; Tamir et al., 2015). This study focused specifically on the effects of accuracy or correctness of data on decision making. The findings from the study are expected to provide practical insights to the use of data-driven decision making in Lebanon and Saudi Arabia.

II. Literature Review

The interest in the impact of data quality on decision making in an organization is not entirely new. However, the interest has grown in recent years due to the manner in which poor quality data has impacted on decision making and customer satisfaction. Dragan and Metz (2017) identified growing diversity and increasing volumes of data as the main causes of the increasing volumes of poor quality data in recent years. Research has demonstrated that the overall quality of a business decision or service is dependent on the quality of the data or information in use (Belhiah, Bounabat, &Achchab, 2015; Dragan & Metz, 2017; Wagaman, 2015). Decision making in most organizations is usually based on available business intelligence, which has proved to be a useful competitive differentiator. The accuracy of business intelligence, in turn, is dependent on the availability, completeness, consistency, precision, accuracy, and quality of customer data or information (Abumandil& Hassan, 2016).Studies have shown that decision makers, from teachers in the classrooms (Wagaman, 2015), to executives in the boardroom (Tamir et al., 2015) usually rely on data to make decisions. For teachers, decision making on the basis of data allows them to customize their lessons to meet the needs and specific learning targets of the learners (Wagaman, 2015).

The challenges of data accuracy in business analytics that affect managers' decision making is not a subject that has been explored widely, but the literature on the subject are growing. For instance, previous research has identified damage to brand reputation, drop in customer loyalty, and financial loss as some of the adverse effects of relying on inaccurate data (Dragan &Metz, 2017). Inaccurate data also wastes corporate resources spent correcting the data (Cai, 2015). Hamblin and Phoenix (2013), identified the following challenges associated with inaccurate data: wrong strategic decisions; waste of time and resources reconciling and verifying data to source; compromised audits; and poor forecasting of future trends. Dragan and Metz (2017), classified the effects of inaccurate data under two categories: indirect and direct costs. Indirect costs include: employee and customer dissatisfaction; duplication of data; poor planning of production; and focus on the wrong segments of the market. Direct costs include: delivery and payment errors; low efficiency; and delayed deliveries. The challenges associated with inaccurate data during decision making can occur at tactical, strategic, and/or operational levels (Hamblin & Phoenix, 2013). Within these levels, the constraints can be technical, behavioral, or organizational. Technical challenges are caused by the processes or systems used to gather, analyze, and interpret data while behavioral constraints are caused by the manner in which users apply the data to solve issues and enhance processes (Nutley et al., 2014). Organizational challenges, on the other hand, are caused by the organizational structure and processes that require the data. Studies have shown that enhancing the levels of data quality nurtures higher effectiveness, performance, and quality of the decision (Abumandil& Hassan, 2016).

There is widespread recognition that inaccurate data can lead to the wrong decisions (Beersma et al., 2016; Abumandil& Hassan, 2016). Inaccurate data, for instance, limits aorganization's capacity to identify and respond to priority needs at various levels (Nutley et al., 2014). Consequently, decision makers are forced into a cyclical process of verification in which they have to cross check data, adjust their actions or output, review areas of weakness, and then reassess to establish whether or notthe right decision and outcome have been achieved (Wagaman, 2015). This verification process takes time, which is the greatest challenge faced by decision makerswhen implementing decisions on the basis of data. Indeed, several studies have identified time as the biggest impediment to the effective implementation of data-based decision making (Henry & Lindsay, 2016; Wagaman, 2015).The perceived level of data accuracy can also affect the confidence levels of the decision makers and influence them not to implement data-informed decision making (Nutley et al., 2014).

Common causes of data inaccuracy include; typing errors, use of outdated data, use of data whose source is unknown, misspecification of attributes, and missing values (Grossmann &Rinderle, 2015). Other common sources of data errors include: errors in collection and recording of information; errors in the design of data collection, such as targeting the wrong group or asking the wrong questions; and loss of information in transit (Xu &Quaddus, 2013). Challenges in identifying appropriate metrics for rating data quality and the lack of data encapsulation standard have also been identified as causes of data inaccuracy (Dragan & Metz, 2017). Data inaccuracy can also be caused by misinterpretation when converting it from one form of presentation, such as metric, to another.

Concerns over data accuracy have led to calls for increased awareness to afford decision makers with the knowledge required to review and analyze data (Wagaman, 2015). According to Nutley et al. (2014), for data to become a regular component of decision making at all organization levels, the essential personnel must possess the capabilities to review, interpret, analyze, and use the data.Indeed, if decision makers lack knowledge or understanding of how to review and interpret available data, then, regardless of whether the data is accurate or not, the decision maker is unlikely to make the best decision. Some of the measures of ensuring data accuracy include; edit checks, cross-checking of dependent values, and knowledge of source of data (Grossmann &Rinderle, 2015). Data accuracy can also be enhanced through use of technology and verification of data with similar data from other evidence sources before making decisions (Wagaman, 2015). Other measures of enhancing data accuracy include; use of internal regulation procedures, removal of redundant data from the organization's data store, introduction of monitoring or control mechanisms to monitor errors, implementation of data accuracy processes, and data standardization (Naicker &Jairam-Owthar, 2017).

In a nutshell, this section has shown that high quality data enhances the quality and effectiveness of decisions made by managers in an organization. Based on these findings, this study seeks to answer the following questions:

I: Does data accuracy lead to high quality decisions?
II. Does data accuracy contribute to decision-making effectiveness?
III: Is data-driven decision-making dependent on the size of an organization?

III. Methodology

The data for this research was collected via a survey questionnaire. The survey questionnaire was piloted among 6 individuals to test its validity, relevance, reliability, and whether it was understood by respondents. A Cronbach Alpha test of reliability was conducted on four questions from the data collected from the pilot study. The results of this test are shown in table 1.

Table 1: Reliability Statistics

Cronbach's Alpha	Number of Items
0.92	4

The Cronbach value of 0.92 shows that the questionnaire was reliable as a Cronbach value greater than 0.6 which is interpreted to mean the questionnaire is internally consistent (Ray, 2016). A few questions were redesigned after the pilot study before the questionnaire was distributed. After the piloting, an online survey questionnaire was created on the online survey site, kwiksurveys.com and Google Docs, for the purpose of data collection. The links to the online questionnaire was shared with purposively sampled respondents via email and social media applications. The questionnaire had a total of 31 questions, which were a mixture of open-ended, close-ended, and Likert scale questions. The study targeted respondents from Saudi Arabia and Lebanon with each of these countries producing a total of 300 valid responses each.The respondents were from diverse economic sectors including; the manufacturing/production and retail, education, telecommunication, hospitality, construction, consultancy, healthcare, and entertainment among others. The responses to the questionnaires were statistically analyzed and interpreted using SPSS to establish patterns, relations, and trends. Descriptive statistics and cross tabulations were used to express the study results.

IV. Results

Descriptive Statistics

The demographicdistributionof the respondents is shown in Table 2. The respondents were split equally at 300 each between Lebanon and Saudi Arabia. Majority of the respondents were male (56.17%)and between the age of 25-35 (49 %). In terms of education, most of the respondents were BA-BS holders (50.5%). Additionally, most of the respondents (63 %) worked in organizations with more than 250 employees. This basically implies that most of the respondents worked in large organizations while (8.83%) worked in micro-sized enterprises (less than 10 employees),those working in small-sized enterprises were 13.33 % while 14.83 % worked in medium-sized enterprises.

Table 2: Respondents' Demographics

Value		Frequency	%
Gender	Male	337	56.17
	Female	263	43.83
Country of Residence	Lebanon	300	50
	Saudi Arabia	300	50
Age Group	18-24	43	7.17
	25-35	294	49.00
	36-45	210	35.00
	46	53	8.83
Education Background	BA	303	50.50
	MBA-MSc	221	36.83
	PhD	74	12.33
Number of Employees	Less than 10	53	8.83
	10 to 50	80	13.33
	51 to 250	89	14.83
	More than 250	378	63.00
Amount of time BA has been used in organization	Less than 1 year	162	27.00
	1 year	95	15.83
	1-5 years	166	27.67
	More than 5 years	177	29.50

Many of the respondents worked in organizations that used Business Analytics (BA). However, only 29.50 % of the respondents worked in organizations that had used business analytics for more than five years. Most of the respondents (73.17 %)reported that their employers applied checks on collected data. Only a mere 6 % of the respondents indicated that they were not aware of the source of the data they relied on for decision making. Additionally, a majority of the respondents (92.67 %) indicated that their employer kept a duplicate of data. 94.17 % of the respondents felt that inaccurate data affected decision making while 77.67 % reported that reliance on inaccurate data had caused them to suffer loss. 80.83 % of the respondents reported that their organization based its decisions on data. Most organizations generate data every month (46.67 %)and sourced their data directly (86.50 %).

Cross Tabulations

Several tabulations were conducted in this study to identify the relationship between various variables. 71.67 % of the respondents from Saudi Arabia reported that their organizations had a professional BA technology in place compared to 59.67 % of the respondents in Lebanon. This difference can be linked to the differences in development between the two countries, with Saudi Arabia being more developed than Lebanon.

Table 3: Cross Tabulations

No of Employees	Are There Edit Checks?		Are Dependent Values Crosschecked?		Is decision-making at your organization data driven?		Have you suffered loss caused by data inaccuracy?	
	No	Yes	No	Yes	No	Yes	No	Yes
Less than 10	17 (2.83%)	36 (6.00%)	20 (3.33%)	33 (5.50%)	36 (6%)	17 (2.83%)	22 (3.67%)	31 (5.17)%
10 to 50	25 (4.17%)	55 (9.17%)	58 (9.67%)	22 (3.67%)	18 (3%)	62 (10.33%)	17 (2.83%)	63 (10.50%)
51 to 250	17 (2.83%)	72 (12.00%)	46 (7.67%)	43 (7.17%)	12 (2%)	77 (12.83%)	7 (1.17%)	82 (13.67%)
More than 250	102.00 (17.00%)	276 (46.00%)	134 (22.33%)	244 (40.67%)	49 (8.17%)	329 (54.83%)	88 (14.67%)	290 (48.33%)

As shown in table 3, the likelihood that anorganization would edit check its data grew with the number of employees (6% for organizations with less than 10 employees; 9.17% for organizations with 10 to 50 employees; 12% for organizations with 51-250 employees; and 46% for organizations with more than 250 employees). Table 3 shows that organizations with more employees are more likely to cross-check their data, except fororganizations with less than 10 employees, where managers in most cases are the owners and prefer to cross-check their data themselves. The direct correlation between number of employeesand crosschecking of data can be explained on the basis that organizations with more employees are more likely to spare some human resources to verify data than those with fewer employees. Other than, the organizations with less than 10 employees (micro-sized enterprises), most SMEs and large organizations based their decisions on data as shown in table 3. The respondents' data also shows that large organizations (with more than 250 employees) afford greater significance to data when making decisions as most of these types of organizations (31 %) reported that they based more than 50 % of their decisions on data as shown in table 4.

Table 4: Cross tabulation: No of employees vs. quantification of data driven decision making

No of employees	Quantification of data driven decision making		
	0 – 30 %	30 – 50%	More than 50%
Less than 10	36 (6%)	9 (1.5%)	29 (4.83%)
10 to 50	13 (2.17%)	38 (6.33%)	26 (4.33%)
51 to 250	12 (2%)	51 (8.5%)	8 (1.33%)
More than 250	37 (6.17%)	155 (25.83%)	186 (31%)

Micro-sized enterprises and SMEs experienced more cases of data inaccuracy than large organizations as seen in table 3. For large organizations, typing errors was the most common form of data inaccuracy. Additional results of cross-tabulations show that the amount of time business analytics was used in an organization does not appear to affect the manner in which BA is applied in the organization. However, no linear relationship was identified between the number of employees and the presence of a professional BA in an organization.

V. Discussion and Conclusion

Data quality has been identified as a key success factor for organizations (Naicker &Jairam-Owthar, 2017). The quality of data is adjudged based on; accuracy, consistency, timelessness, completeness, and uniqueness (Xu &Quaddus, 2013). Increasing digitization of data has made organizations vulnerable to the adverse effects of relying on incomplete or inaccurate data, particularly considering the fact that many business processes are increasingly being automated. This study was conducted with the purpose of examining the challenges of data accuracy in business analytics that affect managers' decision making in firms in Saudi Arabia and Lebanon. The study sought to answer the following questions:

1. Does data accuracy lead to high quality decisions?
2. Does data accuracy contribute to decision-making effectiveness?
3. Is data-driven decision-making dependent on the size of an organization?

This study has established that data-driven decision making is common in most organizations regardless of size. This means that potential inaccuracy of the data relied upon by a firm during decision making is likely to have serious negative effects on the organization. This study has identified typing errors as the most common form of data inaccuracy. These types of errors are more common in large organizations, perhaps due to the greater amount of data that employees in large organizations have to deal with. This study has also shown that the quality of data determines the quality of decisions. This validates previous studies in this area, which have demonstrated that managers make more effective decisions when data is accurate and consistently presented (Belhiah, Bounabat, &Achchab, 2015; Dragan & Metz, 2017; Wagaman, 2015). The accuracy of data determines the time taken to reach a decision and the quality of that decision. When data is erroneous, the predictions deduced from that data are likely to be wrong. The consequence of this is likely to be poor performance or financial loss for the firm.

The role of data in decision making in recent years has been enhanced further by the proliferation of the internet and other forms of information technologies. Indeed, in the increasingly automated business environment, the quality of data is now considered as the main determinant of the general quality of a business decision or process (Belhiah, Bounabat, &Achchab, 2015). The current study has shown that poor quality data generates wrong information, which results in ineffective business processes. This finding agrees with previous research in the area (Panahy, Sidi, Affendey, &Jabar, 2014). It implies that information can only be utilized effectively if it is drawn from accurate data.

The current study has also shown that use of data-driven decision making is not dependent on the size of an organization. Indeed, even micro-sized enterprises are increasingly relying on data-driven decisions. This demonstrates the growing significance of data in decision making, particularly as a tool of gaining competitive advantage. Data-driven decision making has been linked to better service delivery in line with the strategy of an organization (Todorova &Hoeben, 2016). The smaller organizations, in particular, have great potential to benefit from data-driven decision making. Unlike large organizations, which have multiple levels of management that complicate the process of obtaining data for decision making, smaller enterprises have fewer bureaucracies and are more likely to experience higher effectiveness of data-driven decisions. Additionally, the amount of data that decision makers in small organizations need to analyze and synthesize before making decisions is not as large as in large organizations. This means that it is relatively easier for decision makers in smaller organizations to trace their data to the source when in doubt. Most of the respondents in this study reported that they knew the sources of the data they relied upon for decision making. Previous studies have shown that accessibility is the main determinant of the type of data source used by an organization (Huie, 2014). Therefore, firms avoid relying on data that they cannot access or verify.

In recognition of the growing importance of data, some firms have established business units that are focused primarily on data management and dedicated efforts to the enhancement of data accuracy. Most respondents in the current study listed lack of time, proliferation of low quality data collection technology, untrained or unqualified employees for data entry, and lack of awareness about the importance of data as some of the challenges that cause data inaccuracy. Previous research has also shown that the size of a business is an influential factor on whether an organization adopts BA, which influences the accuracy of data due to size-related factors, such as management structure and access to information and finances (Choughri& Soubjaki, 2017). Based on findings from this study and previous studies, the accuracy of data can be enhanced in several ways including; knowing the data source, edit checks in the data entry program, cross-checking of dependent values, duplication of data, employee training, frequent generation of data, control or monitoring of data entries, and increased awareness about the value of data. These methods ensure that information is complete and consistent thereby leading to higher-quality decisions.

References

[1]. Abumandil, M.S.S. & Hassan, S. (2016). Information quality and decision-making effectiveness: A study of banks in Palestine. International Review of Management and Marketing, 6(S7), 127-132.

[2]. Beersma, B., Greer, L.L., Dalenberg, S., & De Dreu, C.K. (2016). Need for structure as asset and liability in dynamic team decision-making. Group Dynamics: Theory, Research, and Practice, 20(1), 16-33.

[3]. Belhiah, M., Bounabat, B., &Achchab, S. (2015). The impact of data accuracy on user-perceived business service's quality. The Institute of Electrical and Electronics Engineers, Inc. (IEEE) Conference Proceedings, 1-4.

[4]. Bjertnaes, O., Skudal, K.E., Iversen, H.H., & Lindahl, A.K. (2013). The patient-reported incident in hospital instrument (PRIH-I): Assessments of data quality, test-retest reliability and hospital-level reliability. BMJ Quality & Safety, 22(9), 743-748.

[5]. Cai, L. & Zhu, Y. (2015). The challenges of data quality and data quality assessment in the big data era. Data Science Journal, 14, pp. 2-12.

[6]. Choughri, R & Soubjaki, M. (2017). The Future of Business Analytics for SMEs in MENA Region. IOSR Journal of Business and Management (IOSR-JBM). 19. 86-92.

[7]. Dragan, M.A. & Metz, D. (2017). Analysis and improvement of data quality: Improvement of data quality for business purposes. Review of Economic Studies and Research Virgil Madgearu, 10(2), 43-55.

[8]. Ge, M. &Helfert, M. (2013). Impact of information quality on supply chain decisions. The Journal of Computer Information Systems, 53(4), 59-67.

[9]. Grossmann, W. &Rinderle-Ma, S. (2015). Fundamentals of business intelligence. New York: Springer.

[10]. Hamblin, D.J. & Phoenix, D.A. (2013). A model for managing data assurance in higher education. Journal of higher education Policy and Management 34(4), 421-435.

[11]. Harrist, A.V., Busacker, A., &Kroelinger, C.D. (2017). Evaluation of the completeness, data, quality, and timeliness of fetal mortality surveillance in Wyoming, 2006-2013. Maternal and Child Health Journal, 21(9), 1808-1813.

[12]. Henry, D. & Lindsay, G. (2016). Empowering stakeholders through data-driven decision making. Quarterly Practice Connections, 1(4), 6-8.

[13]. Huie, C.P. (2014). Perceptions of business intelligence professionals about factors related to business intelligence input in decision making. (Doctoral dissertation). Retrieved from ProQuest Dissertations and Theses. (3614934)

[14]. Naicker, V. &Jairam-Owthar, D. (2017). The linkage of information quality to an executive decision support framework for the financial service sector of a developing economy. South African Journal of Information Management 19(1), a781.

[15]. Nutley, T., Gnassou, L., Traore, M., Bosso, A.E., & Mullen, S. (2014). Moving data off the shelf and into action: An intervention to improve data-informed decision making in Cote d'Ivoire. Global Health Action 7(25035), 1-10.

[16]. O'Regan, M. (2013, March 16). Flight disaster captain had just one hour's sleep. Irish Independent.

[17]. Panahy, P.H.S., Sidi, F., Affendey, L.S., &Jabar, M.A. (2014).The impact of data quality dimensions on business process improvement. The Institute of Electrical and Electronics Engineers, Inc. (IEEE) Conference Proceedings, 70-73.

[18]. Ray, N. (Ed.). (2016). Business infrastructure for sustainability in developing economies. New Delhi: IGI Global.

[19]. Tamir, M., Bigman, Y.E., Rhodes, E., Salerno, J., & Schreier, J. (2015). An expectancy-value model of emotion regulation: Implications for motivation, emotional experience, and decision making. Emotion, 15(1), 90.

[20]. Todorova, N. &Hoeben, K. (2016). From data to decisions: A case study of capability assessment in a health organization. The European Conference on Information Systems Management, 185-194.

[21]. Wagaman, R.M. (2015). Understanding the private school: How do private school teachers understand and describe data-driven decision making?(Doctoral dissertation). Retrieved from ProQuest Dissertations and Theses. (3700924)

[22]. Xu, J. &Quaddus, M. (2013). Managing information systems: Ten essential topics. Paris: Atlantis Press.

1Radwan Choughri. "The Challenges of Data Accuracy in Business Analytics that affect managers' decisions making – Case Study of Saudi Arabia & Lebanon." IOSR Journal of Business and Management (IOSR-JBM) , vol. 20, no. 01, 2018, pp. 13-18.