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Development of Model toward Successful Predictive Analytics Use for the Organizational-Decision Making in Hospitals

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Abstract The umbrella that covers predictive analytics systems is called business intelligence (BI) systems which are set of technologies, architecture, tools, processes and best practices to extract insight and useful information from structured and unstructured data about the current business performance of the organization and to report about historical trends to take better decisions and improve the organization performance. Thus, Healthcare predictive systems are analytic systems which aim to minimize the future medical cost and help to provide in hospital a high level of healthcare and preventive healthcare due to the early detection of risks and possibility to take better actions and decisions. This paper is about developing a model toward successful predictive analytics use for organizational decision making. Furthermore, this research show that most of the previous research was focusing only on the use of predictive analytics for technical purpose and medical decision making while neglecting its use for the organizational decision making in hospitals.

Keywords: *predictive analytics, organizational decision making, healthcare*

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1. Introduction

1.1. Background

Many healthcare organizations are using the predictive analytics to assist them in predicting and preventing diseases such as heart failures [1], diabetes [2], liver diseases [3] and others. Furthermore, they are intending to acquire benefits from predictive analytics such as having better revenues, predicting risks, making strategic corrections [4,5], reducing costs [6], resource allocation and management, manage the hospitals staff and distribution of workforce [7], and taking better and faster decisions by managers [8,9,10].

Furthermore, the use of predictive analytics in healthcare is facing many issues and challenges such as data quality, low return on investment, did not know how to benefit from the predictive analytics outcomes [11,12], lack of input data for the predictive models [13,14,15,16,17], and the wrong use of predictive analytics [4,18].

1.2. Problem Statement

Recently, predictive analytics have acquired a wide spread among organizations from different sectors and purposes of use such in education [19], in governmental organizations [20], in supply chain [8], public transportation [21], IT service providers [22] and others to improve services, minimize costs, reduce time, retaining customers, and wining a business advantage. In healthcare sector organizations have start using predictive analytics to discover trends, patterns and predictions that help in improving the healthcare services. Even so, these efforts in healthcare sector still immature in comparison to the use of predictive analytics and its success in other sectors [23].

The problem statement of this research can be divided into two main parts. The first part is concerning the lack of studies investigating the success of predictive analytics use. The second part is regarding the lack of models studying the effect of successful use of predictive analytics for the improvement of organizational decision making in hospitals.

1.3. Research Questions

Based on the problem mentioned above the main question that this research will try to answer is: What are the factors affecting the successful use of predictive analytics for organizational decision making in healthcare organization? To answer this main question, three sub questions will be answered:

1. What is the predictive analytics success?
2. What is the basis of predictive analytics use for organizational decision-making in healthcare organizations?
3. How can a model of predictive analytics successful use for organizational decision making in healthcare organization be developed?

1.4. Research Objectives

This research aims to develop a model for the successful use of predictive analytics systems for organizational decision making in hospitals and to investigate the valid of the theories expectation confirmation theory and DeLone and McLean IS success model for the successful use f predictive analytics and its effect on the organizational decision making in hospitals. The specific objectives of this study are identified in the following points:

1. To identify predictive analytics success
2. To determine the basis of predictive analytics, use for organizational decision making in healthcare organizations
3. To develop a model of predictive analytics successful use for organizational decision making in healthcare organization

2. Literature Review

2.1. Introduction to Predictive Analytics Systems

To introduce what is predictive analytics we need to know where it comes from. Thus, firstly the umbrella that covers those systems is called business intelligence (BI). In this research the business intelligence systems are defined as set of technologies, architecture, tools, processes and best practices to extract insight and useful information from structured and unstructured data about the current business performance of the organization and to report about historical trends to take better decisions and improve the organization performance. Thus, Data mining is part of Business intelligence functionalities as defined by Gartner who described BI as a software platform delivering 14 capabilities divided into three groups of functionalities including integration, information delivery and analysis functionality which contain the data mining and predictive modeling. While data mining is considered as the automated process to detect the unknown patterns in the structured data of the organization [24,25]. Another research [6] describes data mining as the process to collect, filter, prepare, analyze and store data that will be used to create useful knowledge and supporting the data analytics and predictive modelling. In fact, data analytics is divided into four types as follow:

- The descriptive analytics: which describe the current situation and answer the question what is happening now?
- The diagnostic analytics: which answer the question why this is happening?
- The predictive analytics: which answer the question what will happen in the future?

The prescriptive analytics: which answer the question what is the right choice or solution?

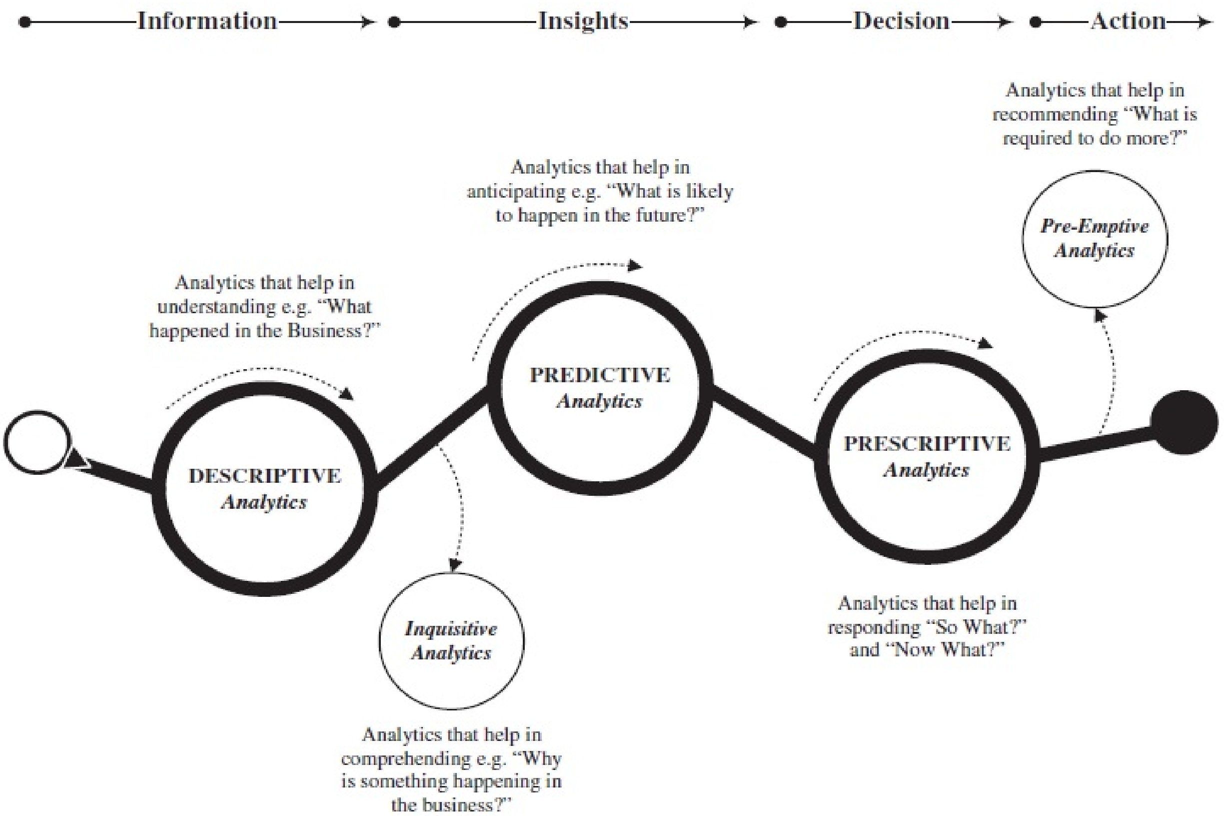

Figure 1. Classification of analytical methods [26]

Thus, Predictive analytics in general are used to detect the relationships and patterns in data to look forward and to predict the future by analyzing the past and taking better preventive decisions [27]. While, as shown in the Figure 1 above the classification of analytical methods start by the descriptive analytics which look backward and deliver information that help in understanding what happened in the organization. Thus, business intelligence (BI) is considered as descriptive analytics and it had proven its efficiency in enhancing the quality and process of decision making [28]. Whereas, predictive analytics is a higher level than descriptive analytics due to its capability to create insight to know what can happen in the future which help decision makers to make fact based decisions. Based on that, we can consider that predictive analytics have been developed to optimize the level of analytics and results of BI which are the precedent and preparatory stage for predictive analytics that can analyses the information delivered by BI to create insight and make future predictions and better decisions.

Moreover, Michael, Sule, and Dan, [18] define predictive analytics as technologies and methods that allow organization to detect orientations and patterns in data, developing models, and testing a huge number of variables. The predictive analytics are used by organizations to achieve their desired goals and increase their profits. Also, the research reports show that its estimated to have a grow in the predictive analytics market from $1.70 billion in 2013 to $5.24 billion in 2018 with CAGR rate of 25.2%. Predictive analytics are considered by Hoda, Stephen, Steven, Nilmini, [27] as a prediction of the future by analyzing the past performance and studying the historical data to uncover the relationships and patterns in these data. While [4] add that the predictive analytics help organizations' in predicting risk, tendency, and in attaining better revenues by enhancing their key metrics and making strategic corrections and this is by making accurate predictions from structured and unstructured information. Those predictions are done based on models. Thus, predictive models are creating during the predictive modelling process to discover the patterns between dependent variables and explanatory variables and predicting an outcome [4,5].

Indeed, predictive analytics will be defined in this research as the analysis of past performance, structured and unstructured data by using predictive models, to discover new patterns and information to learn, to predict the future and make better and preventive decisions.

2.2. The Use of Predictive Analytics System in Healthcare

Healthcare predictive systems are analytic systems which aim to minimize the future medical cost and help to provide in hospital a high level of healthcare and preventive healthcare due to the early detection of risks and possibility to take better actions and decisions. In fact, those predictions are based on the historical patients' data including detailed information about the patient, his medical history and diagnoses. For instance, in one of hospitals in Texas due to predictive analytics the hospital could save more than half million dollars by implementing a predictive system that predict any complications of heart failure patients to prevent it. Thus, the predictive analytics use models which suggest algorithms to help in the medical treatment and disease detection; or it can be used beside the electronic health records systems [6]. Yichuan, LeeAnn, Terry, [9] highlight also that predictive analytics has been extensively used in healthcare to reduce preventable readmissions rates, to allow faster and better decision making by managers, and contribute in preventive healthcare. Moreover, it assists healthcare organizations to evaluate the situation of their current services, determining the best clinical practices, reduce healthcare costs, and understand the future trends in healthcare.

Predictive analytics systems and models have been used in healthcare in various ways and many researches have been conducted on the use of predictive models to overcome many healthcare challenges. The table below show some of researches conducted.

Table 1. Review of previous research of predictive analytics use in healthcare

PURPOSE	ALGORITHMS AND TOOLS	COMMENTS	REFERENCE
Predicting 30-da- readmission risk of congestive heart failure patients	Multiple classification algorithm: - Logistic regression - Random forest • Hadoop • Hive • Casandra • Mahout	In this research they have use multi-algorithm which lead to the satisfactory results of the research with high accuracy.	[29]
Predicting readmission of patients with (pneumonia, acute myocardial infarction, or chronic obstructive pulmonary, and heart failure disease.	- Tree based classification	This study had weaknesses such as the use of homogeneous data which lack of diversity, and the data was only from administrative data which make the predictions inaccurate and this was proved by research before that administrative data is not sufficient to efficiently identify and differentiate between the preventable and non-preventable readmissions	[30,31]
Predicting risk of readmission for patients with congestive heart failure	- classifier, features, discretization algorithm • Weka • KEEL	In this research they have use the operational data to make predictions, which might be incomplete. Moreover, the accuracy was acceptable but the data number was small and lack of diversity which decrease the validity and accuracy of results.	[13]

PURPOSE	ALGORITHMS AND TOOLS	COMMENTS	REFERENCE
predicting types of diabetes diffuse, complications, and identifying possible treatment	• Hadoop • Map Reduce • HDFS	The system developed in this research target to detect earlier diabetes which will cure diabetes patients and decrease the costs of the treatment but the efficiency of this research can be affected by depending solely in Hadoop as a tool especially that it does not give the query functionality and it run slower than other database management systems	[2]
To predict diabetes patients' conditions and improving decision making	- Classifiers: Multilayer perception and Baes network • WEKA • Root means squared error • Area under ROC	The results of this research were not satisfactory regarding the prediction of wellness where the accuracy was low, but the results for predicting diabetes occurrence was higher and more accurate.	[32]
Early detection of liver disease and testing the accuracy of different classifications algorithms	Classification algorithms: decision trees J48, artificial neural network, Zero R, Naïve bayes, VFI. • WEKA	The results of this research have shown that for higher accuracy in the predicting results multilayer perceptron algorithm must be used While in the other hand the lower accuracy is resulted from the use of Naïve Bayes.	[3]
Complex model to support decision making in treatment of acute coronary syndrome, and predicting the risk, and unwanted events such as clinical death	- outcome prediction, simple classifier and states-based prediction	This research strength is the use of combination and integration of various models in a complex predictive model which increase accuracy and decrease the biased decisions	[33]
Predict the disease risk in short term for the patients of heart failure in the tele-health environment. The goal of this system is to improve the decision making and minimizing the cost and time for patients	- recommendation algorithm used based on time series data analysis	The system need to be improved to reduce more the workload of patients and more tests. And experiments on larger number of patients might be made to ensure of the accuracy and ability of the system	[14]
To predict the Chronic obstructive pulmonary disease (COPD) aggravation risks before it happens to prevent it	- Multi-layer neural network - Backpropagation algorithm	The limitation of this research is the use of a limited number of data which decrease the accuracy and correctness of results	[15]
Multiple predictive model to predict the physiological status of patients	Four neural network algorithms: - Probabilistic Neural Network - Support Vector Machine - Multi-layer - Levenberg-Marquardt (LM)	This research has integrated four different algorithms to take benefit of the strength of each one in addition to their combination with multiple schemas which increase the accuracy of prediction results	[34]
To predict the hospital length of stay (PHLOS) and to recognize which patients require fast and early interventions or normal interference to prevent any complication that may lead to length of stay	- Clustering algorithms: K-means clustering - Classification algorithms: SVM (support vector machine), Bayesian Network, JRIP, J48;	The results of this research show that the use of clustering algorithms with classification algorithms lead to have results with higher accuracy but the results of this research were approved only by one expert of emergency medicine thus the results of the research need to be tested and validated to be approved.	[16]
predicting number of hospitalization days by using data of health insurance claims	- bagged regression decision tree • MATALAB	this kind of research help hospital to provide better quality of care, lower the costs and well allocation of hospital resources, but the use of more detailed information about patient medical history will lead to higher accuracy in the prediction especially with the incompleteness and low data quality and missing values in the insurance especially the clinical data such as the codes of diagnoses	[35]
to predict the need to transfer a stroke-in-patients to the intensive care unit	- Artificial neural network(ANN), - Logistic regression (LR), - Support vector machine(SVM), - Decision tree (DT)	This research had a contradictor results with many other research by finding that the artificial neural network algorithm has less accuracy in comparison with other tested algorithms in this research. But to approve this result there is a need to make the test with larger and diverse amount of data	[17]
Predicting mortality rates in the intensive care units	- Multi-layer neural network - Cross validation, - K-fold, - Random sampling	The results were positive and this kind of research encourage the healthcare organizations to use the predictive models to enhance the quality of healthcare and services provided to patients.	[36]
To predict the readmission of patients with heart failure based on a multiple model	- feature selection algorithms - K-means clustering algorithm - Classification algorithms: the random forest and 10-fold cross validation technique	In this research also, there is a confirmation through the results that the multiple model lead to higher and better predictive results which is consensus with the results of many other research in predictive analytics in healthcare	[1]

PURPOSE	ALGORITHMS AND TOOLS	COMMENTS	REFERENCE
Developing a parallel predictive modeling (PARAMO) based on HER to make the process of health data simple and faster	- Classification algorithm: Random Forest, Naïve Bayes, K-nearest Neighbor, Logistic regression • Map Reduce	This platform has been to allow the independent tasks to work in parallel in a cluster computing environment. the results of the research have shown an important improvement of speed of research workflow and reutilization of health information compared to standard approaches of running sequentially. The weakness in this research is their focus on the scalability of PARAMO and the have forget the quality and accuracy of predictions. Moreover, the development of predictive models based on EHR data have improve its success during its application on several targets disease.	[37]
Developing predictive models to define the factors affecting the death anxiety.	support vector machine (SVM) K- neural network, Naïve- Bayes	the models were tested on the HER nursing system and it results a high accuracy prediction which can contribute to minimize the healthcare costs and improving the quality of care and services	[38]

Indeed, from the table above we can see that the previous research in predictive analytics use in healthcare sector was focusing mainly in technical perspective and in the development of algorithms and models to help to overcome clinical challenges; chronic diseases; and enhancing clinical decisions. Those researches have shown that there is a consensus that the use of multiple models or the integration of various algorithms together can help significantly in improving the accuracy of predictions. And, the right choice of the algorithm and of the data to be used is also very important to get efficient results with high accuracy. Moreover, the integration of predictive analytics with other hospital systems improve the results of predictions. Although, data quality and availability still a challenge in predictive analytics application where many studies show the issue of lack of data and it's not available to be able to test and train the predictive models developed. In addition to problems in data quality such as the incomplete data. Moreover, in some cases the Unavailability of right data for the right model to get right predictions affect the quality of results. However, despite those challenges, predictive analytics had proven its ability to bring many benefits to healthcare by its use in solving medical problems such as reducing costs, High quality of healthcare, better services, better resource management and allocation, better clinical decisions, saving people lives, and preventing diseases.

In addition to researches focusing on clinical application of predictive analytics a research was handling the costs and resource planning of healthcare sector. Thus, it focuses on demand prediction to know the places that need the healthcare services and include it in the future plans which will organize the demand and supply of healthcare services. While, the aim is to develop a model to predict the demand for healthcare services in Emirate especially Abu Dhabi. This is by combining four predictive models which are known by its high accuracy results K Nearest Neighbor (KNN), Naïve Bayes (NB) algorithm, Support Vector Machine (SVM), and C4.5 algorithms which are an extension of ID3 of decision tree algorithm. The tool of analysis used is WEKA due to its great ability to process the used models. The results of this research show a high demand on some places for the healthcare services but this result is not sufficient and accurate which require more research with more descriptive attributes to enhance the accuracy of the results [7].

Indeed, this research give the ability to ministry of health, and hospitals managers to be able to coordinate together firstly to know more about the prioritization list of places that need more healthcare services, secondly, they can allocate the needed resources to be able to deliver those services. In addition, they can use it to distribute and manage hospitals staff depending on the priority of places with high need of healthcare services. Thus, in this context predictive analytics help managers in making right decisions about the resources allocation and management including the right distribution of workforce among hospitals to ensure the delivery of high quality of healthcare and services.

2.3. Decision Making

Helen, Paul and Douglas, [39] found in the use of computerized decision support systems (CDS) an opportunity for hospitals to solve their problems and to increase and encourage the adoption of CDS in hospitals by learning from the previous experiences in different disciplines where the decision support design has features such as the customizing interfaces for specific users and roles, effective presentation of data, generating multiple scenarios, allowing for contingent adaptations, facilitate collaboration. Moreover (Helen W Wu., 2012) emphasize on the importance of organizational culture and training in the success of CDS implementation and found that the best style of decision making is by combining the two approaches of decision making which are rational analytic and naturalistic -intuitive styles. The rational- analytic style is based on data and models to make decisions its usefulness is in the synthesize of big amounts of information and reducing bias on the other hand naturalistic-intuitive decisions are made based on human experience.

Çağdaş, Raya, Sina, [40] argue that decision making in health care can be considered complicated as it has two sides a clinical and a nonclinical one, in addition the decision must take into consideration multiple factors such as patient treatment and cost, thus the pressure of decision making is high on the healthcare managers due to the necessity to make budgetary and operational decisions and improving operational efficiency and eliminating unimportant costs and maintain the quality of healthcare provided to patient high. Çağdaş, Raya, Sina, [40] highlight the factors that affect the decision-making process in healthcare organizations which are the knowledge based decision making, informative decision making, training, organizational factor, the usage of specific models for decision making and decision supporting tool have positive impact on decisions making process, in addition to the decision maker capabilities, financial resources, The timelines of decisions, the delegation of decisions, and shared decision making factors. Although, knowledge and evidence informed decision making (EBDM) was the most cited factor to influence the decision making

John, Immaculate, Hojops, Vincent, [41] study how different management practices such as decision making, process, communication, structure and management style can affect the hospitals performance in the context of Uganda healthcare and lead to better service delivery and effectiveness in the organizational context. Actually, John. B.K.., [41] consider that the decision making can be improved by enhancing the structure of the organization and hospital board size play role in its ability to make important decisions, and minimizing the technical complexities. Moreover, the decision making is affected by the regulatory pressure. While, the hospital performance has been defined in term of costs, bed occupancy, rate of mortality, salary rates, growth, accreditation, and resource acquisition. John. B.K.., [41] show that more the decision making is better this will lead to improve quality of outcomes and in turn will affect positively and improve hospital performance.

In fact, the healthcare sector faces more challenges than any other sector such as ensuring the patient access to services and keeping a high quality of healthcare. Although, the results at the end of research had shown that the prime factor affecting hospital performance among management practices and have the highest effect is the communication and in the other hand the lower effect is decision making which was explained by the fact that its supported by the structure. Moreover, the key decisions do not come from the hospital board rather from the ministry and district authorities. However, for effective management in hospitals this demand an efficient usage of funds, and expert governing structures [41].

Indeed, making the right decision clinical or administrative at the right time is not an easy task especially in healthcare due to the complexity of structure, processes, and the role of external authorities such as government and ministry. Thus, taking decisions based on experience and intuitive of decision makers is not sufficient especially with the need to have rapid and effective decisions in hospitals for this decision makers can use the analysis results of analytic systems to take operational and strategic decisions based on the meaningful information presented by the analytic systems.

3. Research Theories

3.1. Review of Delone and Mclean IS Success Model

Information system success was clearly defined as a dependent variable in the model developed in 1992 by W.H. DeLone, E.R. McLean, [42] who measured the success of an information system based on six main interdependent categories which are the system quality, information quality, use, user satisfaction, individual impact and organizational impact as shown in Figure 2 [42].

In this model system quality is categorized as taking place on the technical level and is concerned with the input in the system while information quality is semantic. The rest of categories is to assess the effectiveness of the system [43]. After 10 years DeLone and McLean presented an updated model based in the changes of information systems role and management. The figure below shows the updated model which contain 6 categories. Quality have 3 main dimensions in the model which are the information quality, service quality and system quality where each dimension is measured separately from the other [44].

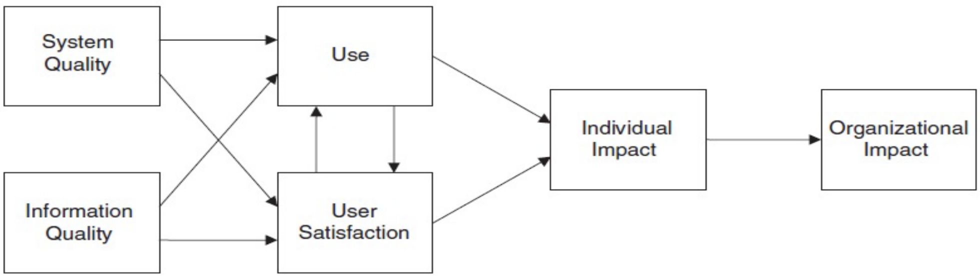

Figure 2. DeLone and McLean IS success model [42]

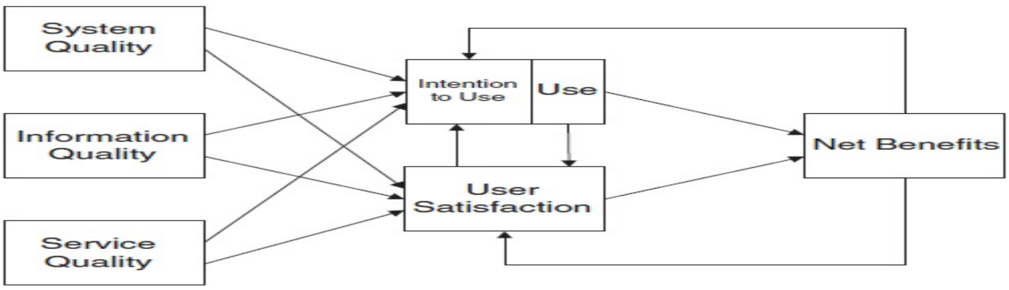

Figure 3. Updated DeLone and McLean IS success model [44]

This model is considered as one of the most famous and used models for the measurement of IS success in different industries such as e-commerce, e-learning [45], e-government [46], and healthcare information systems [46,47,48,49].

The main categories of the model are defined as [50]:

- System quality: is the system general performance as seen by users. The main and useful measurement features of an information system such as flexibility, ease of use, reliability, ease of learning, and response time.
- Information quality: the useful features of the system outputs such as accuracy, completeness, usability, conciseness, and timeliness.
- Service quality: the quality of assistance that the users of the system get from the information support personnel and IT assistant personnel such as accuracy, technical competence, and responsiveness.
- Use: the level and way of using the capabilities of the information system by the employees and customers such as the purpose of usage, the frequency, and the nature of use. Therefore, system use is a suitable measure of success in many cases and is an important variable to understand the information system success.
- User satisfaction: the degree of satisfaction of users with their interaction with an information system [47]
- Net impacts (net benefits): the range to which information systems are participating or not to the success of individuals, groups, organizations, industries, and nations. For instance, improving the productivity, improving the decision making, increase the profits and sales, and economic development.

3.2. Review of Expectation Confirmation Theory

The expectation confirmation theory (ECT) or also called expectation disconfirmation theory (EDT) was initially developed by Oliver (1980) based on studies on consumer behavior where the customer satisfaction is specified by the confirmation/disconfirmation of expectation. Thus, it is a theory used in the post adoption of systems to assess the users' satisfaction and continuance intention by measuring the expectations and perceived performance levels. The expectations are the beliefs about what is intended and expected to happen in the future. Whereas performance is the resulted efficiency and effectiveness after completing a task. Those two factors affect level of satisfaction. This model suppose that the consumer satisfaction come from a process of five steps starting by having a primary expectation before purchase, then accepting the service or product, after the use and consumption of the product or service an understanding of the performance will be formed. Later, this understanding is compared with the primary expectations, then the consumers will decide their satisfaction or dissatisfaction based on the level of disconfirmation/confirmation. At the end if customers are not satisfied with service or product the will not use it again in contrary if they are satisfied [51,52]. Figure 4 shows the model of expectation confirmation/disconfirmation theory.

EDT/ ECT have been widely used in marketing to study the consumer satisfaction of different services and products. However, researchers in information systems have also begun to use this theory to understand and explain the satisfaction of information technology users. Thus, in this context this theory describe how technology satisfaction is formulated as users form primary technology expectations, the use of the technology, and make a comparison between the primary expectations and the technology performance [53].

3.3. Research Model

Predictive analytics can be defined as the analysis of past performance, structured and unstructured data by using predictive models, to discover new patterns and information to learn, to predict the future and make better and preventive decisions. Thus, organizations use predictive analytics to be able to make strategic business decisions based on facts, patterns and accurate future trends predicted with these systems with lower costs. In healthcare sector organizations have start using predictive analytics to discover trends, patterns and predictions that help in improving the healthcare services. Even so, these efforts in healthcare sector still immature in comparison to the use of predictive analytics and its success in other sectors [20]. Moreover, there is a lack of studies investigating the success of predictive analytics use. In addition to lack of models studying the effect of successful use of predictive analytics for the improvement of organizational decision making in hospitals. Therefore, this research will focus on determining the factors affecting the successful use of predictive analytics for organizational decision making in hospitals by using two theories which are the updated DeLone and McLean IS success model and the expectation confirmation theory (ECT). The research model is shown in Figure 5.

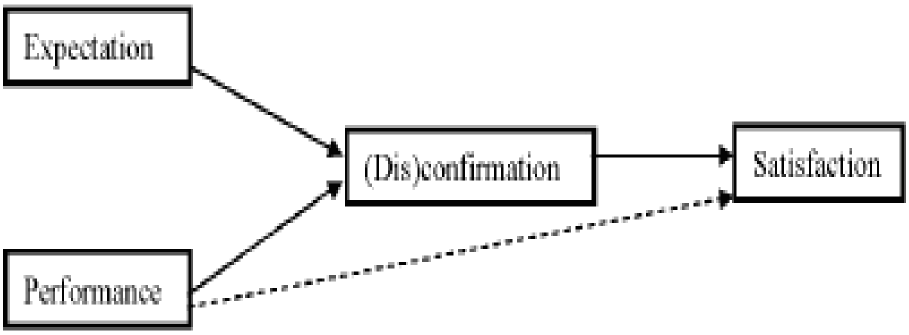

Figure 4. model of expectation confirmation theory [54]

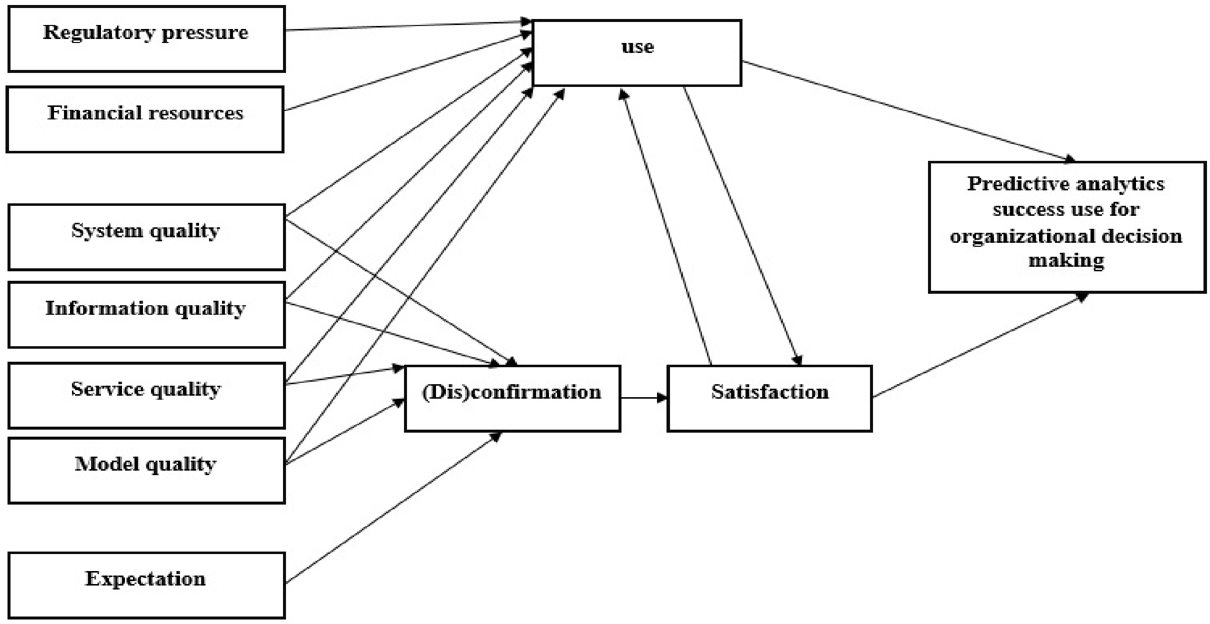

Figure 5. Research model describing the main variables for the successful use of predictive analytics for organizational decision making in hospitals

3.3.1. Overview of the Model

The research model of this study has been developed based on two theories which are firstly the DeLone and McLean IS success model to measure the success of predictive analytics based on the interrelated categories of the model. The second theory is the expectation confirmation theory (ECT) for the use of predictive analytics systems for organizational decision making and to understand and explain the satisfaction of its users. In addition to those theories additional variables have been added to the model based on the literature review and previous models which are: the regulatory pressure [41], financial resources [40], and model quality [1,11,29,34,54].

3.3.2. Description of The Hypotheses

3.3.2.1. Use

Can be defined as the level and way of using the predictive analytic systems by the employees and managers in hospitals such as the purpose of usage, the frequency, and the nature of use. Therefore, system use is a suitable measure of success in many cases and is an important variable to understand the predictive analytic system success:

- Regulatory pressure: it plays a significant role in the decision making in the hospitals. Moreover, it affects the purpose and natures of usage of the predictive analytic systems in healthcare.
- Financial resources: It affect the managers and responsible decision making in healthcare and the use of predictive analytic systems
- System quality: is the predictive analytic system general performance as seen by users. The main and useful measurement features of predictive analytic system are flexibility, ease of use, reliability, ease of learning, and response time. Moreover. The predictive analytic system quality is affected by many factors such as the communication between team members, integration with other systems, and decision maker capabilities.
- Information quality: is the useful features of the predictive analytic system outputs such as accuracy, completeness, usability, conciseness, and timeliness which affect the predictive analytic system usage.
- Service quality: the quality of assistance that the users of the predictive analytic system get from the information support personnel and IT assistant personnel such as accuracy, technical competence, and responsiveness.
- Model quality: It affect significantly the usage of predictive analytic systems and is affected by some factors such as the lack of input data, the variables choice, data quality, and the team skills.
- Satisfaction: the degree of satisfaction of users with their use of predictive analytic systems in healthcare management and when the perceived performance surpasses expectations, users will be satisfied.

H1: There is a significant relationship between regulatory pressure and use

H2: There is a significant relationship between financial resources and use

H3: There is a significant relationship between system quality and use

H4: There is a significant relationship between information quality and use

H5: There is a significant relationship between service quality and use

H6: There is a significant relationship between model quality and use

H7: There is a significant relationship between satisfaction and use

3.3.2.2. Confirmation

Confirmation is the evaluation of perceived performance, according to one or more dimensions of quality standards which are in this study system quality, information quality, service quality, and model quality. Confirmation can have a positive result, that usually consequence in satisfaction, or a negative outcome, that usually consequence in dissatisfaction or with a zero-effect result (Oliver 1980).

H8: There is a significant relationship between system quality and (dis)confirmation

H9: There is a significant relationship between information quality and (dis)confirmation

H10: There is a significant relationship between service quality and (dis)confirmation

H11: There is a significant relationship between model quality and (dis)confirmation

H12: There is a significant relationship between expectation and (dis)confirmation

3.3.2.3. Satisfaction

Satisfaction is the degree of satisfaction of users with their use of predictive analytic systems in healthcare management and when the perceived performance surpasses expectations, users will be satisfied.

H13: There is a significant relationship between (dis)confirmation and satisfaction

H14: There is a significant relationship between use and satisfaction

3.3.2.4. Predictive analytics success use for organizational decision making

Predictive analytics success use for organizational decision making is the dependent variable and output of this study which is affected by the usage of the system and users' satisfaction.

H15: There is a significant relationship between use and predictive analytics success use for organizational decision making

H16: There is a significant relationship between satisfaction and predictive analytics success use for organizational decision making

4. Conclusion

The table below conclude the main benefits and challenges facing the predictive analytics:

PA BENEFITS	REFERENCES	PA CHALLENGES	REFERENCES
-predictive analytics help organizations' in predicting risk, tendency, -in attaining better revenues by enhancing their key metrics -making strategic corrections by making accurate predictions from structured and unstructured information	[4,5]	-data quality - Ethical and legal issues - How to communicate the outcome -some organizations still did not get an important or the desired return on investment from predictive analytics projects	[11,12]
-getting meaningful business information -allow to have better revenues and outcomes in organizations	[11,12]		
-taking better decisions	[8]		
-to minimize the future medical cost -help to provide in hospital a high level of healthcare and preventive healthcare due to the early detection of risks -possibility to take better actions and decisions	[6]		
-to allow faster and better decision making by managers -contribute in preventive healthcare -it assists healthcare organizations to evaluate the situation of their current services, - determining the best clinical practices, - reduce healthcare costs -understand the future trends in healthcare	[9]		
To decrease costs	[2]		
minimize the healthcare costs and improving the quality of care and services	[38]		
resource allocation and management, manage hospitals staff , distribution of workforce	[7]		
- save and reduce many financial expenditures -to take better decision	[10]		

The second table below conclude what are the main weaknesses in previous predictive analytics research and how it can be improved.

WAYS FOR BETTER USE OF PA	WEAKNESSES IN PREVIOUS PA RESEARCH
- use of multi-algorithm which lead to results of with high accuracy [29]	-the use of homogeneous data which lack of diversity, and the choice of wrong data which is not suitable to solve a specific problem [30,31,35].
the use of combination and integration of various models in a complex predictive model which increase accuracy and decrease the biased decisions [1,34,55].	-The lack of input data to test and train model, lack of diversity and wrong choice of the right data to tests the model [13]
- data quality play an important role in the accuracy of models results [35].	- the wrong choice of tools [2]
-integration of PA with other organisatio sstems increase its benefits	- the right choice of the algorithm play a significant role in the results and level of accuracy [3]
- the right choice of the variables used in the model to get better quality in the resulted predictions [4]	- amount of data available for testing model is limited and small which decrease the accuracy and efficiency of results [14,15,16,17]
	some cases the focus is only in the tactical and short-term decision without investigating the use of predictive analytics to improve and make strategic decisions [4]
	the current use of predictive analytics models still divided and fragmented into parts for each business unit [18]

5. Future Work

Empirical study based on survey and interviews will be conducted with IT managers, hospital mangers and IT staff in hospitals to study the variables affecting the successful use of predictive analytics and how it plays a role in the improvement of organizational decision making.

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