Development of Model toward Predictive Analytics Use to Guide Tactical Non-Clinical Decision Making in Qatar Hospitals

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Abstract

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. Recently, predictive analytics have acquired a wide spread among organizations from different sectors and purposes of use such in education, in governmental organization, in supply chain, public transportation, IT service providers 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. This research studies the relationship between the use of predictive analytic systems and the tactical non-clinical decision-making performance in Qatar hospitals. The research model was developed on the basis of the unified theory of acceptance and use of technology (UTAUT) and the motivational framework for understanding information system use and decision performance. A Questionnaire has been developed to collect data through from various hospitals by focusing on information technology staff and managers, health information systems professionals and managers, administration staff and middle managers. The empirical findings will be published after analyzing the data and getting the results of the analysis

Key words: Predictive analytics, healthcare, tactical decision making, UTAUT, Motivational framework

1. Introduction

Qatar is one of the smallest and wealthiest countries of the world. It’s a fast growing and multicultural country including more than 80 nationalities. Healthcare in Qatar had face rapid and significant development in last years (Annekathryn Goodman, 2015). Moreover, the National E-Health and Data Management Strategy published in 2015 the vision statement was *“A world-class, sustainable, integrated and secure national E-Health ecosystem for the State of Qatar”*. Which show the envision of Qatar to be a leader in the world in the development and adoption of new innovative solutions. To achieve this many clinical information systems have been implemented and used such as The single electronic medical records have been implemented across all Hamad medical corporations (HMC) and primary health care center (PHCC), Population Health Systems to control the status of Qatari population health, Personal Health Account including services and solution to enable people accessing digitally the health system and manage their health data, Health Data Services including various systems and tools to analyze the big amount of digital health data in Qatar (PricewaterhouseCoopers (PwC), 2015)

However, there is a lack of research about the use of analytic systems especially predictive analytics in healthcare in Qatar. Thus, the present research attempt to minimize this literature gap by studying the relationship between the use of predictive analytic systems and the tactical non-clinical decision-making performance in Qatar hospitals. The research model was developed on the basis of the unified theory of acceptance and use of technology (UTAUT) and the motivational framework for understanding information system use and decision performance. This research provide insight about how predictive analytics can be used in healthcare especially for the tactical non-clinical decision-making in hospitals. The clinical applications of predictive analytics are significant and numerous, and the insight and knowledge acquired from the use and application of predictive analytics in health and medicine will change the healthcare to a preventive healthcare (Hana. Al, 2018). Thus, predictive analytics are implemented by healthcare organizations to manage data to discover hidden trends, relationships, and predictions which help in improving healthcare service and saving people lives (Hana. Al, 2018).

Researchers have addressed the use of predictive analytics from a technical point of view by developing predictive models that help in improving medical services and earlier detection of some diseases.

However, this research aims to develop a model toward predictive analytics systems use to guide the tactical non-clinical decision making in Qatar hospitals. This research can have implications for Qatar in general since there is a significant focus from the government in the development of healthcare sectors where they invest billions of dollars to make continuous improvements. Thus, this research can help decision makers in healthcare to take better and faster administrative decisions based on facts and with a clear view of the future trends.

1. 1 Background

Many hospitals are using the predictive analytics to help them in predicting and preventing diseases such as heart failures (Mohammad, Nabil et al, 2014), diabetes (Saravana et al, 2015), liver diseases (Tapas, and Subhendu, 2016) and others. Furthermore, they are intending to acquire benefits from predictive analytics such as having better revenues, predicting risks, making strategic corrections (Prasada, S.Hanumanth, 2014; Meryem et al, 2016), reducing costs (Mohammad et al, 2015), resource allocation and management, manage the hospitals staff and distribution of workforce (Noura Al Nuaimi, 2014), and taking better and faster decisions by managers (N. Ayyanathan et al, 2015; Yichuan et al, 2016; Gina, James S,2015). However, 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 (James ,2014; James ,2015), lack of input data for the predictive models (Samir.E et al, 2014; Raid et al, 2015; Riad Alharbey, 2016; Ali, Vandana P, Alex, 2012; Nawal N, Sreela, 2015), and the wrong use of predictive analytics (Michael, Sule, Dan, 2015; Prasada, S.Hanumanth, 2014).Those challenges and issues may constitute a barrier toward using the predictive analytics. Moreover, some studies have shown that the use and results of predictive analytics can be improved with the focus on the development of combination and integration of various models in a complex predictive model which increase accuracy and decrease the biased decisions(Alexey.V et al, 2016; Peter K, Kailash C, 2013; Mohammad et al, 2014), the improvement of data quality play an important role in the accuracy of models results (Yang et al, 2014). The integration predictive analytics with other organization systems and the right choice of the variables used in the model to get better quality in the resulted predictions (Prasada, S.Hanumanth, 2014).

On the other hand decision making in organization in general and in healthcare especially face many challenges such as making the decision on the right time, analysis of value for money, stakeholder involvement (Akyürek, Sawalha, Ide, 2015). Moreover, all the decision makers in hospitals such as managers have a considerable responsibility to use appropriately and manage the available resources, reducing costs, and providing a high quality of healthcare services. Furthermore, as a focus on tactical decision making one of the challenges facing the managers in tactical decision making is the difficulty to access and get the right information at the right time, a lot of important information is missing due to the existence of various information systems with different abilities and its separated and decentralized. Thus, there is a need to enhance the information management process in healthcare and better integrated information systems are required to support the middle managers in the tactical decision making (Elina. Ket al, 2013). However, previous research has shown thatthe use of data and analytic tools is one of the main factors that lead to have better decisions based on evidence. (Akyürek, Sawalha, Ide, 2015). Furthermore, one of the main reasons to use the information technology systems in the healthcare is to assist the decision-making process to make it more effective and efficient by reducing the time to access to the information (Elina. K et al, 2013). And, the usage of specific models for decision making and decision supporting tool have positive impact on decisions making process(Çağdaş, Raya, Sina, 2015).

Gaps in this research are that most of the current research in predictive analytics is focusing only on the technical side for medical challenges in hospitals by developing models to predict medical and health issues such as heart disease, diabetes, etc… There is lack of research frameworks and models, and lack of focus on the importance of using predictive analytics to assist in the management and administration of hospitals and their role to improve the tactical non-clinical decision making such as resource management (Saravana.K et al, 2015; Tapas, and Subhendu, 2016; Raid et al, 2015; Kenney et al, 2014; Muhammad. K et al, 2015). Therefore, the aim of this research is to overcome the weaknesses which will be developed in a model that shows predictive analytics use in management, tactical non-clinical decision making in hospitals through the unified theory of acceptance and use of technology (UTAUT) and the motivational framework for understanding information system use and decision performance.

1.2 Problem Statement

Recently, predictive analytics have acquired a wide spread among organizations from different sectors and purposes of use such in education (Abdul Rauf, Hajira, 2016), in governmental organizations (Adam et al, 2015), in supply chain (N. Ayyanathan, A. Kannammal, 2015), public transportation (Fangzhou et al, 2016), IT service providers (Aly, Guang-Jie, Michael, 2015) 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 (Hana. Al, 2018).

So far, most of the focus was in developed countries such as USA, UK, Canada, and Australia.However, this research will focus to investigate and discover the correlation between the use of predictive analytics and the tactical non-clinical decision making in hospitals which was neglected by previous studies who focus on technical side only of predictive analytics and its use for medical purposes. The problem statement of this research can be divided into three main parts. The first part regarding the lack of focus and models of using predictive analytics for managerial and administrative purposes with focusing only on technical issues and medical use of predictive analytics. The second part is concerning the lack of studies investigating how the use of predictive analytics can guide and assist the administrative decision making in hospitals such as budget decisions, resource allocation decision, staff recruitment decisions, staff training and development decisions, scheduling decisions, and technology acquisition decisions. The third part is regarding the lack of models studying the correlation between the use of predictive analytics and the tactical non-clinical decision-making performance in hospitals.

1.3 Research Questions

Based on the problem mentioned above the main question that this research will try to answer is: What is the relationship between the use of predictive analytics and the tactical non-clinical decision-making performance in healthcare? To answer this main question, three sub questions will be answered:

1. What are the factors affecting the use of predictive analytics and the factors affecting the tactical non-clinical decision-making performance in healthcare?
2. What is the relationship between the use of predictive analytics and tactical non-clinical decision-making performance in healthcare?
3. How can a model of predictive analytics use to guide tactical non-clinical decision-making performance be developed?

1.4 Research Objectives

This research aims to develop a model toward predictive analytics systems use to guide the tactical non-clinical decision-making performance in Qatar hospitals. The specific objectives of this study are identified in the following points:

- To identify the factors affecting the use of predictive analytics and the factors affecting the tactical non-clinical decision-making performance in healthcare.
- To determine the relationship between the use of predictive analytics and tactical non-clinical decision-making performance in healthcare.
- To develop a model of predictive analytics usage to guide the tactical non-clinical decision-making performance in hospitals.

2. Literature review

2.1 review of predictive analytics systems

Predictive analytics in general are used to detect the relationships and patterns in data to look forward, to predict the future, and discover the reason(Sunil. T, H.M.W, Yosef. D, 2018) by analyzing the past and taking better preventive decisions(Hoda et al, 2016).For the predictive analytics process it pass by five phases, the identification of the problem, the collection and preparation of the data, analysis of the data and the development of the model, the deployment, observation and control of the predictive model (Kosemani, Shaun, Pavol, 2016). Moreover, (Michael, Sule, and Dan, 2015) 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. Predictive analytics are considered by(Hoda, Stephen, Steven, Nilmini, 2016) 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 (Prasada, S.Hanumanth, 2014) 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 (Prasada, S.Hanumanth, 2014) (Meryem et al, 2016). 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 usages of predictive analytics 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.(Yichuan et al, 2016) 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.

A research conducted to analyze types of analytics used in the healthcare literature has shown that the most analytics used are descriptive, predictive, and prescriptive. Moreover, most of the articles applied the analytics for the decision making in healthcare. The highest application area of predictive analytics was for the clinical decision support as shown in the figure below followed by a high percentage of its use in the healthcare administration such as for reducing costs, improving quality, and resource allocation (Md S.I et al, 2018).

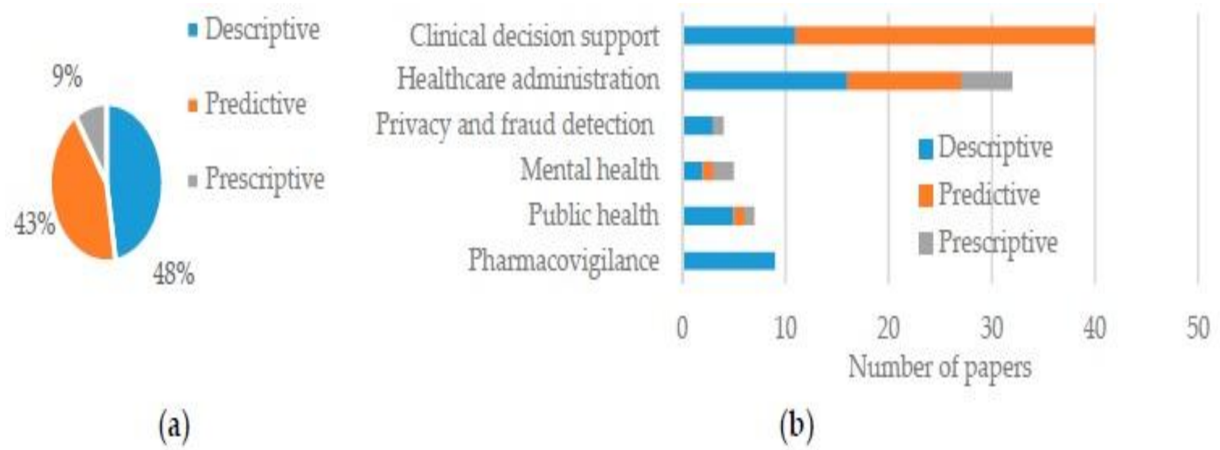

Figure 2: types of analytics used in healthcare, (a) percentage of analytics types, (b) analytics by application area (Md S.I et al, 2018)

The usage of predictive analytics in healthcare was mainly for the clinical decision support and its used in the healthcare administration such as for reducing costs, improving quality, and resource allocation. The table below show some of researches conducted on the use of predictive analytics to overcome many healthcare challenges.

USAGE PURPOSE	COMMENTS	REFERENCE
predicting future hospital visits and hospital costs to enhance the clinical decision making	This research has highlighted the significant role that predictive analytics can play to make enhanced administrative decisions and reducing costs. Moreover, two methods were proposed to predict the number of future visits for a patient to the hospital and the total future charges for each patient and based on those two methods an assessment of patients' risk level will be predicted and identification of patients with high risk to better provide health care services and treatment.	(Archana. C, 2017)
Predicting chronic kidney diseases	In this research the right choice of the classification algorithm used has result a low error rate and prove a good performance in term of time and accuracy of predictions. Moreover, this research emphasizes on the importance of using predictive analytics to have a preventive health care and to help in decision making.	(Basma. B et al, 2016)

Early detection of liver disease and testing the accuracy of different classifications algorithms	The results of this research emphasis on the necessity to choose the right variables, models, and algorithms when using predictive analytics in order to get accurate predictions	(Tapas, and Subhendu, 2016)
Complex model to support decision making in treatment of acute coronary syndrome, and predicting the risk, and unwanted events such as clinical death	This research strength for better usage of predictive analytics to use a combination and integration of various models in a complex predictive model which increase accuracy of predictions and decrease the biased decisions	(Alexey V et al, 2016)
To predict the Chronic obstructive pulmonary disease (COPD) aggravation risks before it happens to prevent it	The limitation of this research is the use of a limited number of data which decrease the accuracy and correctness of results. Thus, data availability affects the usage and results of predictive analytics	(Riad Alharbey, 2016).
Developing predictive models to define the factors affecting the death anxiety.	The predictive 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	(Muhammad. K et al, 2015)
predicting types of diabetes diffuse, complications, and identifying possible treatment	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	(Saravana.K et al, 2015)
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	The system needs 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	(Raid et al, 2015)
to predict the need to transfer a stroke-in-patients to the intensive care unit	This research had a contradictor results with many other researches 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	(Nawal N, Sreela, 2015)
predicting number of hospitalization days by using data of health insurance claims	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	(Yang et al, 2014).
Predicting mortality rates in the intensive care units	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.	(Yun, Hui, 2014).
To predict the readmission of patients with heart failure based on a multiple model	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 researches in predictive analytics in healthcare	(Mohammad et al, 2014)
Developing a parallel predictive modeling (PARAMO) based on HER to make the process of health data simple and	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	(Kenney et al,2014)

faster	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.	
Predicting risk of readmission for patients with congestive heart failure	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.	(Samir.E, Mingyuan, Bruce.E, Kensaku, 2014)
To predict diabetes patients' conditions and improving decision making	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.	(Ravi.S, Pranitha, Ankur, Ritesh, 2014)
Predicting readmission of patients with (pneumonia, acute myocardial infarction, or chronic obstructive pulmonary, and heart failure disease.	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 enough to efficiently identify and differentiate between the preventable and non-preventable readmissions	(Issac, Saeede, Kai, 2014) (Elizabeth et al, 2013)
Predicting 30-day-readmission risk of congestive heart failure patients	In this research they have use multi-algorithm which lead to the satisfactory results of the research with high accuracy.	(Kiyana et al, 2013)
Multiple predictive model to predict the physiological status of patients	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	(Peter K, Kailash C, 2013)
To predict the hospital length of stay (PHLOS) andto recognize which patients require fast and early interventions or normal interference to prevent any complication that may lead to length of stay	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.	(Ali, Vandana P, Alex, 2012)

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

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, 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 enough and accurate which require more research with more descriptive attributes to enhance the accuracy of the results (Noura Al Nuaimi, 2014).

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 and this was emphasized by (Archana. C, 2017) who highlighted in his research that "*One fourth of all healthcare budget expenses go towards administrative costs. This is a proof that, there is a room for significant improvement to cut down costs and improve operational efficiency. Recent advances in healthcare analytics however, have helped make better administrative decisions improving efficient and cutting down on overhead* "(Archana. C, 2017). And explained the significant role that predictive analytics can play to make enhanced administrative decisions and reducing costs.

2.3 Tactical decision making

In healthcare the decision making is complex, thus all the decision makers in hospitals such as managers have a considerable responsibility to use appropriately and manage the available resources, reducing costs, and providing a high quality of healthcare services. Furthermore, managers take decisions based on collected information which must be with high quality to be able to make and implement right and successful decisions. Some factors can be taken into consideration during decision making such as the decision maker characteristics, the nature and context of the decision, the availability of the information needed for making a decision, financial and economic factors, and the governmental regulations and politics. Moreover, the use of data and analytic tools, advanced personal skills and the convenient organizational climate lead to have better decisions based on evidence. (Akyürek, Sawalha, Ide, 2015). (Çağdaş, Raya, Sina, 2015) 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, 2015) 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 was the most cited factor to influence the decision making. Actually, (John. B.K.., 2015) 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.., 2015) 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 (John. B.K.., 2015).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 enough 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 tactical decisions based on the meaningful information presented by the analytic systems.

Moreover, as a focus on tactical decision making (Elina. K et al, 2013) have defined decisions in tactical management as the decisions to handle the medium- term (Misni, F. and Lee, L.S, 2017) and short-term schedules, plans, budgets. Furthermore, they assign the business objectives, procedures and policies for the subunits of the healthcare organization. Additionally, tactical decision-making help in resource management and allocation and controlling the performance of the subunits in the organization comprising the departments, divisions, process teams, project teams and others. The tactical decision makers are usually the middle managers who use information from different resources to make their decisions. (Elina. K et al, 2013) have divided the tactical decisions in healthcare into two categories:

- Process decisions: it need information concerning the work management
- Resource decisions: it need information concerning the material and human resources.

Although, one of the challenges facing the managers in tactical decision making is the difficult to access and get the right information at the right time, a lot of important information is missing due to the existence of various information systems with different abilities and its separated and decentralized. Thus, there is a need to enhance the information management process in healthcare and better integrated information systems are required to support the middle managers in the tactical decision making. Moreover, there is no enough training for the systems users, thus healthcare organisations need staff and manager who are more able to use and get efficient results from the systems to enhance the hospitals performance, improving the quality of healthcare and reducing costs (Elina. K et al, 2013).

3. Research theories

3.1 The unified theory of acceptance and use of technology (utaut)

Understanding the information technology use is one of the most important areas in information system research and there have been many theoretical models developed from theories in sociology and psychology that were used to explain the acceptance and usage of technology (Viswanath.V, James Y. L. T, 2012). The Unified Theory of Acceptance and Use of Technology (UTAUT) model was formulated with four basic determinants of intention and actual usage in organizational context and up to four moderators of key relationships after reviewing eight models of technology use (the theory of reasoned action (TRA), the technology acceptance model (TAM/TAM2), the motivational model (MM), the theory of planned behavior (TPB), the model of PC utilization (MPCU), the innovation diffusion theory (IDT), the social cognitive theory (SCT), and model combining the technology acceptance model and the theory of planned behavior (C-TAM-TPB)) (Viswanath Venkatesh, M. G,.., 2003). In fact, UTAUT model has been widely used and applied to the study of technologies in organizational and non-organizational settings (Viswanath.V, James Y. L. T, 2012) and is one the most popular models due to its validation by various empirical studies as a precise model to predict the information technology acceptance and usage. Moreover, the UTAUT model has proved its effectiveness to predict user behavior and explaining a wide proportion of difference in IT usage by different applications in various research such as E- health technology, ERP systems, E-government, E-learning, Internet banking (Isaac, O et al.,2018).

In UTAUT model there are three direct determinants of intention to use which are the performance expectancy, the effort expectancy, and the social influence. Furthermore, there are two direct determinants of usage behavior which are the facilitating conditions and the intention to use. Moreover, the four moderators of key relationships are the experience, voluntariness, gender, and age. Thus, in UTAUT model four constructs play an important role as direct determinants of user acceptance and usage behavior:

Performance expectancy: is defined as *"as the degree to which an individual believes that using the system will help him or her to attain gains in job performance,* this construct is the strongest one to predict the intention of usage. However, the relationship between the performance expectancy and intention is moderated by gender and age.

Effort expectancy: is defined as *"the degree of ease associated with the use of the system",* the relationship between the effort expectancy and intention is moderated by gender, age, and experience.

Social influence: is defined as *"the degree to which an individual perceives that important others believe he or she should use the new system".* the relationship between the social influence and intention is moderated by gender, age, voluntariness and experience.

Facilitating conditions: aredefined as *"the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system".* However, when the performance and effort expectancy constructs are present. Facilitating condition will not have a significant influence on behavioral intention. In the other hand, facilitating conditions have direct influence on usage and is moderated by age and experience.

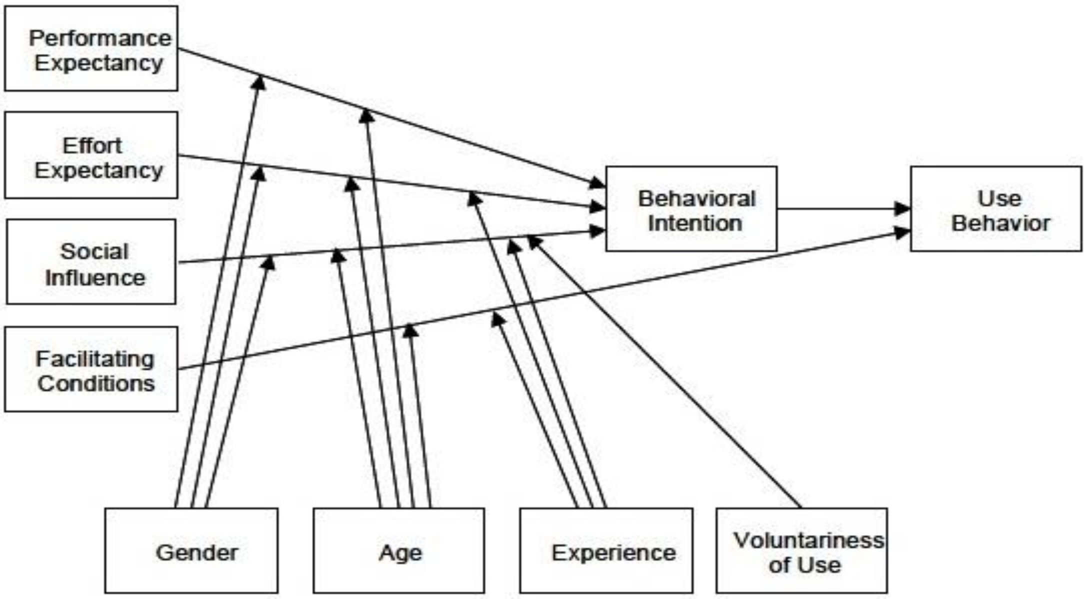

Figure 3: The Unified Theory of Acceptance and Use of Technology (UTAUT) (Viswanath Venkatesh, M. G,.., 2003)

3.4 review of the motivational framework for understanding information system use and decision performance

One of the main objectives of designing and using information systems is to provide useful information for decision making and increasing the decision quality. However, the information technology adoption and use in organizations still one of the main concerns of research in information systems and despite the important research that have been conducted to study the IS use and decision performance much still unknown about variables that provide valuable insight into information technology use and decision performance. Thus, (Siew H. Chan, 2005) developed the motivational framework for understanding IS use and decision performance with focus on the important role of motivation factor in explaining the information system (IS) use and decision performance. The framework was developed based on a review of motivation, systems, decision performance, information processing, and auditing literatures (Siew H. Chan, 2005).

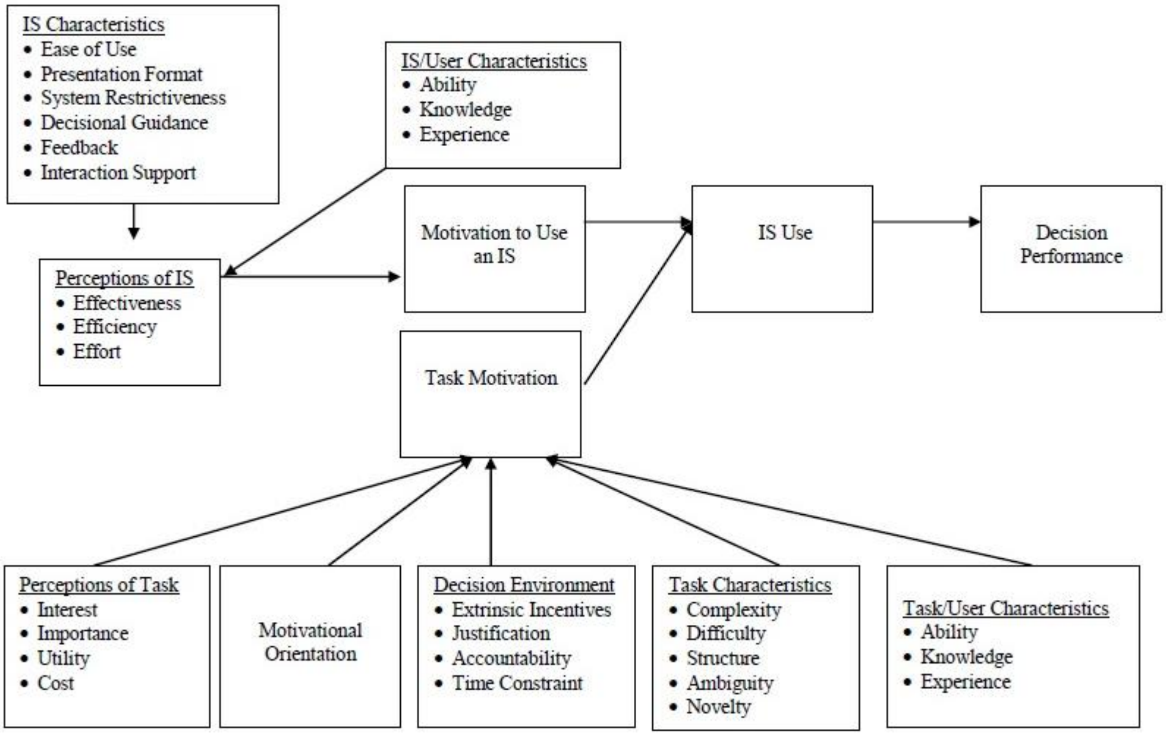

Figure 4: motivational framework for understanding IS use and decision performance (Siew H. Chan, 2005)

The constructs of the framework are (Siew H. Chan, 2005):

IS characteristics: it includes ease of use ("*IS use is expected to occur if users perceive the IS to be easy to use and that using it enhances their performance and productivity*", "*The perceived ease of use construct has been proposed and used extensively as a surrogate measure for the ease of use characteristic*", "*Favorable perceived ease of use is a significant determinant of initial acceptance of an IS and is essential for adoption and continued usage of the IS*"), presentation format("*Presentation of a problem can be modified based on the assumption that information is correctly processed when it is presented in a form that evokes appropriate mental procedures*"), system restrictiveness ("*it refer to the degree to which the IS limits the options available to the users*"), decisional guidance ("*refers to the IS assisting the users to select and use its features during the decision-making process*"), feedback, and interaction support.

Perceptions of the IS: it includes effectiveness, efficiency, and effort. This construct affects significantly the motivation to use the IS. Thus, the framework proposes a positive relationship between perceptions of the IS and the motivation to use the IS. Thus, when the IS is perceived to be more effective, efficient, or less effortful this will increase the motivation to use the IS.

IS/User characteristics: "*The users" ability, knowledge, and experience in use of an IS are predicted to moderate the relationship between IS characteristics and user perceptions of the IS*"

Task Motivation: is considered as a key construct in the framework and has an important influence on motivation to use information system. The framework suggest that the task motivation can be influenced by five factors which are the user perception of the task, user's motivational orientation, decision environment, task characteristics, and task/user characteristics.

Motivation to use an IS: information systems usage can be affected by the characteristics of the information system in addition to the needs, goals, and values of the users. (Siew H. Chan, 2005) theorize that "*motivation to use an IS is high when the IS is perceived to be high in interest, importance or utility, or opportunity cost of using the IS is low. Motivation to use an IS is expected to be low when the IS is perceived to be low in interest, importance or utility, or the cost of using the IS is high.*"

IS use: Many theories have been used previously to predict and explain the user acceptance of information technology such as theory of reasoned action and technology acceptance model. Moreover, the theories suggest that users would use IS if they perceive benefits related with such usage.

Decision performance: few valid measures of the quality of decision performance currently exist in the IS literature and this could be due to the difficulty to measure and assess the quality of a decision until after certain period of time (Siew H. Chan, 2005).Individual-level decision performance measures include objective outcomes, better understanding of the decision problem, or user perception of the system usefulness (Siew H. Chan and Qian Song, 2010).

Based on the motivational framework developed by (Siew H. Chan, 2005), a research has been conducted by (Siew H. Chan and Qian Song, 2010) to study how the characteristics of decision support systems (DSS) interact with the characteristics of a task to affect the DSS use and decision performance. The key constructs in the motivational framework are task motivation, user perception of DSS, motivation to use DSS, DSS use, and decision performance. This framework highlights the important role of motivation factor in explaining the DSS use and decision performance. Previous models such as TAM and UTAUT did not clearly explain the relationship and connection between the system use and the decision performance. However, (Siew H. Chan, 2005) did not suppose that the use of DSS will obligatory result with positive outcome this is the reason of adding the decision performance as construct in the motivational framework. Thus, the motivational framework developed by (Siew H. Chan, 2005) provides a base to understand the DSS use and decision performance. Furthermore, DSS are made to be used to get more fast and accurate decisions but in fact potential users do not always take advantage of DSS to support their decision making and this had raised the need to understand how to encourage the use of DSS (S.H. Chan, et al., 2017). Moreover, its important to focus in measuring the actual usage than the intention to use because reported low correlations between intention and system use suggest that intention may not appropriately represent the actual use. (S.H. Chan, et al., 2017) developed an experimental DSS to control the DSS performance feedback and response time, measuring the task motivation and DSS motivation, tracking the DSS usage, and getting the important information for evaluating decision performance through combined analysis. The results of the experiment have suggested that DSS use can be a mediator in the relationship between the decision performance and the DSS motivation. Furthermore, DSS motivation is affected positively by the task motivation, more positive DSS performance feedback, and fast DSS response time.

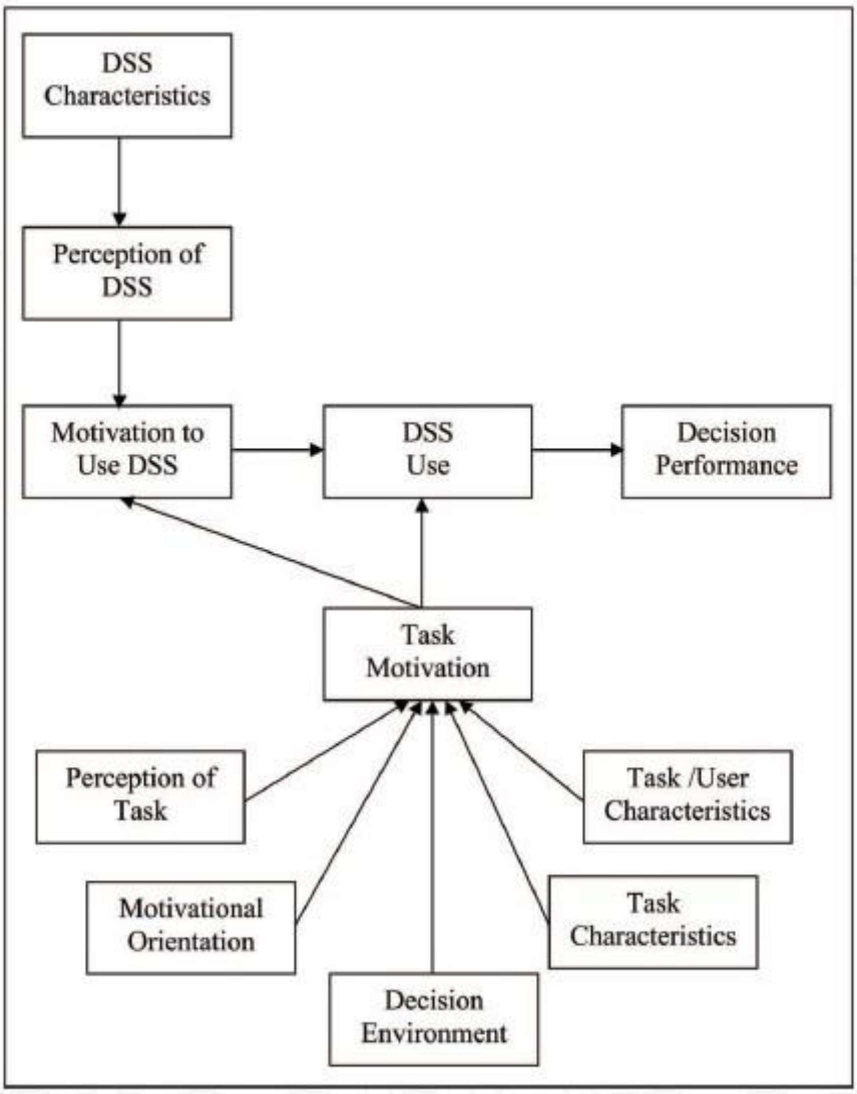

Figure 5: Motivational framework for understanding decision support system use and decision performance (Siew H. Chan and Qian Song, 2010)

4. 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 makebusiness 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 (Hana. Al, 2018). Moreover, there is a lack of focus and models of using predictive analytics for administrative purposes with focusing only on technical issues and medical use of predictive analytics. Therefore, this research will focus to determine the factors affecting use of predictive analytics and the factors affecting the tactical non-clinical decision-making performance in hospitals and to define the relationship between the actual usage of predictive analytics and the tactical non-clinical decision-making performance by using two theories which are the unified theory of acceptance and use of technology (UTAUT) and the motivational framework for understanding information system use and decision performance. The research model is shown in the figure below

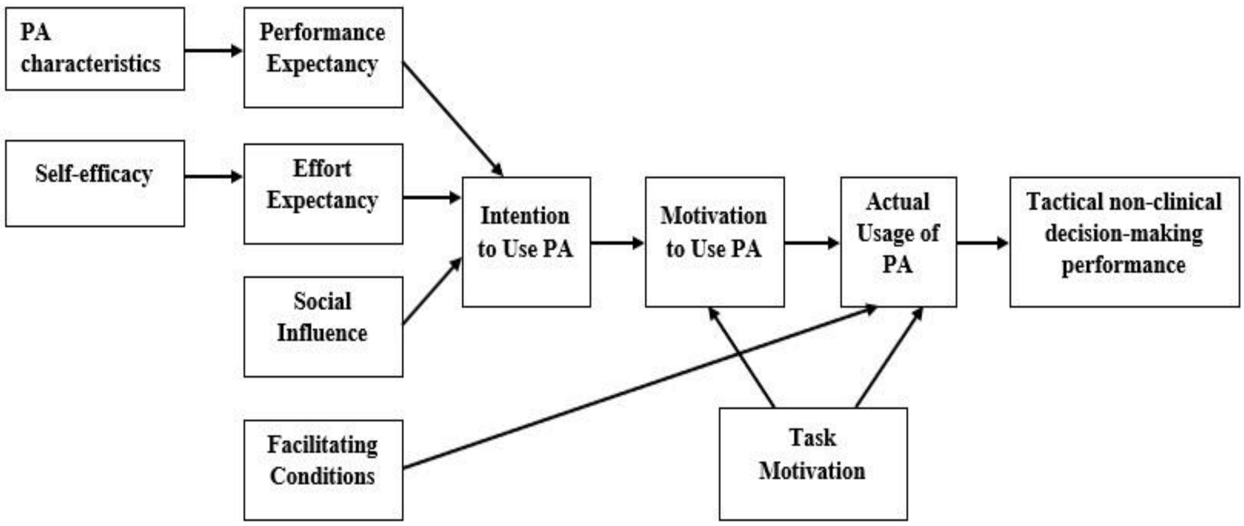

Figure 6: Research Model

4.1 Research variables

4.2 Performance Expectancy

According to the unified theory of acceptance and use of technology (UTAUT) performance expectancy is considered as a main construct and it's the strongest predictor of the intention of usage and its defined as

"*the degree to which an individual believes that using the system will help him or her to attain gains in job performance*" (Viswanath Venkatesh, M. G,.., 2003). In the context of the present research performance expectancy represents the believes of predictive analytics users in hospitals (managers, IT professionals, etc..) that the usage of predictive analytics systems will help them to improve their work performance and results.

4.3 Predictive Analytics Characteristics

According to the motivational framework for understanding the information system use and decision performance the information system characteristics or more specifically the decision support system characteristics include 6 elements which are the ease of use (it's an important element determining the initial acceptance and the continued usage of an information system), presentation format, system restrictiveness, decisional guidance, feedback, and interaction support (Siew H. Chan, 2005; Siew H. Chan and Qian Song, 2010). However, In the context of the present research the focus is on the characteristics of predictive analytics which may also have relationship and affect the performance expectancy. These main characteristics are:

Model quality: it plays a main role in getting accurate predictions and decreasing the biased decisions this can be by using multiple models in a complex predictive model or the integration of various algorithms together, and the right choice of the algorithm and of the data to be used because the wrong choice of the right model and algorithm lead to poor discovering of relation between study and model variables which lead to have weak results . Moreover, the right choice of the variables used in the model will improve the quality of predictions (James ,2015; Kiyana et al, 2013; Alexey V et al,2016; Peter K, Kailash C,2013; Mohammad et al, 2014, ; Peter K, Kailash C, 2013; Prasada, S.Hanumanth, 2014).

Data quality and availability: is crucial in the analytical projects, the poor data quality affect seriously the organizations and not solving this issue may lead to increasing the errors and wrong results from analysis results. (James ,2014; James ,2015; Yang et al, 2014). 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. (Samir.E et al, 2014; Raid et al, 2015; Riad Alharbey, 2016; Ali, Vandana P, Alex, 2012; Nawal N, Sreela, 2015) Indeed, to attain desired benefits from using predictive analytics many models and algorithms have been used. Although, the challenges such as the lack of real data to test the models developed constitute a barrier toward having non- bias and accurate results that can be applied in real world and organizations.

Integration of predictive analytics with other systems in hospitals: this will improve the results of predictions and delivering faster decision making (Michael, Sule, Dan, 2015; Prasada, S.Hanumanth, 2014).
Predictive analytics had proven its ability to bring many benefits to healthcare by its use in solving medical problems, reducing costs, better resource management, better clinical decisions, saving people lives, and preventing diseases. However, the presence of predictive analytics characteristics mentioned above by having models with high quality, better data quality and availability of data to test and train the models, in addition to the integration of predictive analytics with other hospitals systems will help in increasing the users trust toward using predictive analytics and this may have positive relationship with the performance expectancy.

4.4 Effort Expectancy

According to UTAUT effort expectancy is defined as *"the degree of ease associated with the use of the system"* (Viswanath Venkatesh, M. G,.., 2003). In the context of the present research effort expectancy presents the degree of ease related with the use of the predictive analytics system in the healthcare context.

4.5 Self-Efficacy

According to (Kirubel B.Sh, Eden.A,M, 2019) self-efficacy can be defined as *"individuals perceived knowledge and skills to use computers effectively for a specific task".* It can be defined also as the personal belief of individuals that they have the skills to succeed when participating in an information technology related tasks or the individual's perception of their capability to use information systems to perform particular tasks (Chao C-M ,2019). In the context of the present research self-efficacy presents the skills and capabilities to use the predictive analytics systems to perform tasks or to take decisions. Moreover, this will affect and/or have relationship with the effort expectancy. Self-efficacy in this research can be determined by three main points which are the decision maker capabilities (Çağdaş, Raya, Sina, 2015), the team skills which affect the ease of use of predictive analytics, thus they must have knowledge in data analysis, data integration, technical skills and understand well the business issues (Elina. K et al, 2013; Lior , Nir, and Adir, 2017), and the training (Çağdaş, Raya, Sina, 2015; Elina. K et al, 2013; Helen W Wu., 2012) provided to team and predictive analytics users.

5. Social Influence

According to UTAUT social influence is defined as *"the degree to which an individual perceives that important others believe he or she should use the new system"* (Viswanath Venkatesh, M. G,.., 2003). In the context of the present research social influence presents the degree to which managers and IT professionals in healthcare are affected by others believes that they should use the predictive analytics system. And here the environment also plays an important role when practically implementing predictive analytics which, integrate information technology, management and modeling together, the environment should be helpful and collaborative to encourage the team in their work. The predictive analytics have given the opportunity to get meaningful business information which allowed to have better revenues and outcomes in organizations. But, to get the desired outcomes from the application of predictive analytics environment, must be taken into consideration (James ,2014; James ,2015) which may allow to get positive social influence toward intention to use predictive analytics.

5.1 Facilitating Conditions

According to UTAUT facilitating conditions are defined as *"the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system"* (Viswanath Venkatesh, M. G,.., 2003). Furthermore, facilitating conditions have direct relationship with the usage of predictive analytics. In the context of the present research facilitating conditions presents the degree to which managers and IT professionals believes that the organizational and technical infrastructure exists to support the usage of predictive analytics systems. In addition, other elements may be included in the facilitating conditions and affect the usage of predictive analytics such as the financial resources (Çağdaş, Raya, Sina, 2015), architecture for the predictive analytics which must be robust due to its importance in the management of predictive analytics models (James ,2014; James ,2015), and the government regulations and policies (John. B.K.., 2015; PricewaterhouseCoopers (PwC), 2015).

5.2 Intention to Use Predictive Analytics

In general, the intention to use can be defined as *"the degree to which a person has formulated conscious plans regarding whether to perform a specified future behavior."* (Chao C-M ,2019). In the context of the present research the intention to use presents the degree to which healthcare managers and IT managers and professionals has formulated conscious plans regarding whether to use predictive analytics systems. The intention to use predictive analytics systems may be affected directly by the performance expectancy, effort expectancy, and social influence.

5.3 Motivation to Use Predictive Analytics

Motivation can be defined as *"internal factors and external factors that influence and encourage someone to increase success, achieve performance or change behavior and attitudes."* (Mahdum, Hadriana, & Safriyanti, M, 2019). The motivation to use information systems or decision support system has been initially suggested by (Siew H. Chan, 2005; Siew H. Chan and Qian Song, 2010) in the motivational framework for understanding information system use and decision performance to study its influence on the actual usage of the information systems. Thus, in the present research the motivation to use predictive analytics systems presents the internal and external forces that support and stimulate healthcare managers and IT managers and professionals to use predictive analytics. The motivation to use predictive analytics is affected and have relationship with the intention to use. Thus, to be motivated to use a system first we must have the intention to use it which will be stimulated by the motivation that may lead to the actual usage.

5.4 Task Motivation

The task motivation is significant for the high-quality performance and it emerges from the person tendency to participate in activities of interest and the consequent progress in learning and development and the growth of the individual's abilities. Furthermore, individuals perform tasks with a specific motivational orientation. Thus, this motivational orientation can be intrinsic motivation, extrinsic motivation, or both and this can determine the person's initial task motivation (Siew H. Chan and Qian Song, 2010). In the context of present research task motivation can help when managers and staff in hospitals have important tasks such as operational decisions, managing and allocating resources, etc… motivational orientation must be specified and this will lead to decide about the needed tasks to do the right activity and increase the motivation to use predictive analytics systems to accomplish these tasks.

5.6 Actual Usage of Predictive Analytics

Previously researches focused more on the measure of the variance in self-reported use not in the direct measure of system use. A good measurement of the actual usage of a system include the nature of the usage activity which contain the three elements of system use which are user, system and use of the system to do a task (Siew H. Chan and Qian Song, 2010). predictive analytics can be used for different purposes in the administration of organizations but usually it's not used for the strategic decisions making but for the tactical or operational purposes in short term (Prasada, S.Hanumanth, 2014). However, in the current research the focus is to discover the relationship between the actual usage of predictive analytics and the tactical non-clinical decision-making performance in hospitals. The actual usage of predictive analytics is a common variable in both models the unified theory of acceptance and use of technology and the motivational framework to understand the use of information systems and decision performance. But, the actual usage in both models is affected by different variables. However, in the current research the actual usage of predictive analytics has direct relationship with the facilitating conditions, motivation to use predictive analytics, and the task motivation.

5.7 Tactical Non-Clinical Decision-Making Performance

(Elina. K et al, 2013) have defined decisions in tactical management as the decisions to handle the medium- term (Misni, F. and Lee, L.S, 2017) and short-term schedules, plans, budgets. Furthermore, they assign the business objectives, procedures and policies for the subunits of the healthcare organization. Additionally, tactical decision-making help in resource management and allocation and controlling the performance of the subunits in the organization comprising the departments, divisions, process teams, project teams and others. The tactical decision makers are usually the middle managers who use information from different resources to make their decisions.

In the other hand, performance as a theoretical construct can be defined as *"the accomplishments or outcomes of an entity."* (H. M. Alhawamdeh, M.A. K. Alsmairat, 2019). A meta-analysis supports the relationship between task motivation and decision performance. Task motivation has been reported to be a strong predictor of performance (Siew H. Chan and Qian Song, 2010). However, in the current research the task motivation is in relationship with actual usage of predictive analytics which may affect or have relationship with the tactical non-clinical decision-making performance.

6. Hypotheses

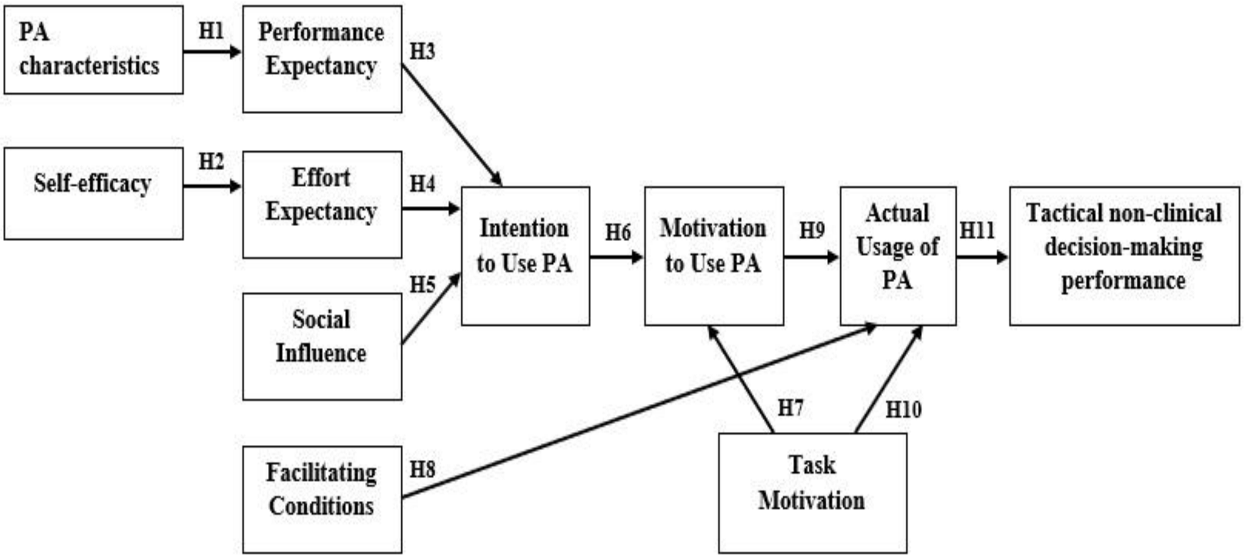

Figure 7: Description of the hypotheses

7. Factors influencing the Intention to use Predictive Analytics

The research model shows that there is relationship between three main constructs and the intention to use predictive analytics which are performance expectancy that has been validated in previous research as the strongest predictor of the intention to use, effort expectancy, and social influence. Moreover, the model shows that there is a relationship between the performance expectancy and the predictive analytics characteristics, and relationship between the effort expectancy and the self-efficacy.

H1: There is a significant relationship between the predictive analytics characteristics and the performance expectancy

H2: There is a significant relationship between the self-efficacy and the effort expectancy.

H3: There is a significant relationship between the performance expectancy and intention to use of predictive analytics.

H4: There is a significant relationship between the effort expectancy and intention to use of predictive analytics.

H5: There is a significant relationship between the social influence and intention to use of predictive analytics.

8. Factors influencing the Motivation to use Predictive Analytics

The motivation to use is considered as an important construct to predict the actual usage of information system. Furthermore, previous studies have reported that there is a positive relationship between the motivation and the intention to use a system (S.H. Chan, et al., 2017) and that the motivation to use is influenced by the task motivation, thus more the decision maker is motivated by the task the higher will be the motivation to use the system (S.H. Chan, et al., 2017). In the research model the motivation to use predictive analytics mediate the relationship between the intention use predictive analytics and the actual usage of predictive analytics. Moreover, the model shows a relationship between the task motivation and motivation to use predictive analytics.

H6: There is a significant relationship between the intention to use of predictive analytics and the motivation to use predictive analytics.

H7: There is a significant relationship between task motivation and the motivation to use predictive analytics.

9. Factors influencing the Actual usage of Predictive Analytics

In previous models that studied the usage of information systems the focus was more on measuring the behavior intention to use rather than the actual usage of the system (S.H. Chan, et al., 2017). And the studies have shown low correlations between the intention to use and system use because it's not accurate to assume that the behavioral intention will lead to system use. Moreover, we can consider the motivation as an important construct to predict the actual usage of predictive analytics and this has been proofed in the literature (S.H. Chan, et al., 2017). Furthermore, decision makers are willing to expend more effort to use a system to get more accurate work and results when their task motivation is high. The research model shows that a relationship exists between the motivation to use predictive analytics and the actual usage of predictive analytics. Moreover, facilitating conditions and task motivation is an important construct to be considered when studying the actual usage of predictive analytics.

H8: There is a significant relationship between facilitating conditions and the actual usage of predictive analytics.

H9: There is a significant relationship between motivation to use predictive analytics and the actual usage of predictive analytics.

H10: There is a significant relationship between task motivation and the actual usage of predictive analytics.

10. Tactical non-clinical decision-making performance

Previous researches have been divided into different results some research have demonstrated that the decision-making performance is positively affected by the decision support system use and others produced inconsistent results regarding enhancement of performance. However, the system usage and the direct experience with using a system is important to improve the decision performance. The research model shows a direct relationship between the actual usage of predictive analytics and the tactical non-clinical decision-making performance.

H11: There is a significant relationship between the actual usage of predictive analytics and the tactical non-clinical decision-making performance.

11. Conclusion

This research studies the relationship between the use of predictive analytic systems and the tactical non-clinical decision-making performance in Qatar hospitals. The research model was developed on the basis of the unified theory of acceptance and use of technology (UTAUT) and the motivational framework for understanding information system use and decision performance. Gaps in this research are that most of the current research in predictive analytics is focusing only on the technical side for medical challenges in hospitals by developing models to predict medical and health issues such as heart disease, diabetes, etc… There is lack of research frameworks and models, and lack of focus on the importance of using predictive analytics to assist in the management and administration of hospitals and their role to improve the tactical non-clinical decision making such as resource management. Therefore, the aim of this research is to overcome the weaknesses which will be developed in a model that shows predictive analytics use in management, tactical non-clinical decision making in hospitals through the unified theory of acceptance and use of technology (UTAUT) and the motivational framework for understanding information system use and decision performance.

12. Future work

The future work is collecting data through the questionnaire (appendix 1) from various hospitals by focusing on information technology staff and managers, health information systems professionals and managers, administration staff and middle managers. The empirical findings will be published after analyzing the data and getting the results of the analysis.

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APPENDIX

APPENDIX 1: QUESTIONNAIRE

Section 1: Background Information

1.1 Gender: ❑ Male ❑ Female

1.2 Age range: ❑ 22-29 ❑ 30-39 ❑ 40-49 ❑ 50+

1.3 Please select your position in the hospital:

❑ Information Technology (professional or manager)
❑Health information system (Professional or manager)
❑ Administration staff
❑ Middle manager or first line manager

1.4 Please select your years of experience: ❑0-5 ❑ 6-10 ❑ 11-15 ❑ 15+

1.5 Please select your level of experience with predictive analytics, choose all that apply:
❑ I have experience in the use of predictive analytics
❑ I have experience in making predictions based on analytical results
❑ I have experience in taking decision based on predictive analytics results
❑ I have experience in creating predictive models and algorithms

1.6 What is the purpose of using predictive analytics in your hospital, choose all that apply:
❑ To predict chronic disease
❑ To predict length of stay of patients
❑ To predict patient readmissions
❑ To predict risks
❑ To manage hospital staff and distribution of workforce
❑ To manage hospital resources
❑ To make financial decisions
❑ To make strategic corrections in the hospital
❑ To make tactical non-clinical decisions
❑ To make budget decisions and reduce costs
❑ To make staff training and development decisions
❑ To make technology acquisition decisions

Section 2: Usage of Predictive Analytics

Please indicate the extent to which you agree or disagree (level of agreement) with the following statements. (check your ✓ answer)

	Strongly Disagree	Disagree	Uncertain	Agree	Strongly agree
Performance expectancy					
I find predictive analyticssystems useful in my job					
I believe that using predictive analytics systems helps me making predictions anddecisions more quickly					
I believe that using predictive analytics systems will improve my work performance					
I believe that using predictive analytics systems, will increase quality of healthcare services and management					
Predictive analytics characteristics					
Good predictive model plays a main role in getting accurate prediction and reduce biased decisions					
Choosing the right model and the variables used in the model will improve quality of predictions					

poor data quality increases the errors and lead to wrong results from analysis					
The Unavailability of right data for the right model to get right predictions affect the quality of results					
Integration of predictive analytics with other systems in hospitals will improve the results of predictions and delivering faster decision making					
Effort expectancy					
I would find predictive analytics systems easy to use					
It would be easy for me to develop my skills for using predictive analytics					
I clearly understand how to make predictions and decisions from the results of predictive analytics models					
I clearly understand the benefits from using predictive analytics systems in healthcare					
Self-efficacy					
Using predictive analytics systems, I could make decisions if have the necessary capabilities					
working in team with high skills could make the use of predictive analytics system easier to me					
Having knowledge in data analysis, data integration, technical skills, and understanding business issues could make the use of predictive analytics easier to me					
Providing training for predictive analytics users could make the use of predictiveanalytics system easier to me					
Social influence					
People who influence my behavior think that I should use the predictive analytics systems					
Work and team environment encourage me to use the predictive analytics systems					
I would use the predictive analytics systems if my co-workers used it					
The senior management of the hospital has been helpful in the use of the predictive analytics systems					
In general, the hospital has supported the use of predictive analytics systems					
Facilitating conditions					
I have the resources necessary to use the predictive analytics systems					
I have the knowledge necessary to use the predictive analytics systems					
Organizational infrastructure exists to support the usage of predictive analytics systems					
Technical infrastructure exists to support the usage of predictive analytics systems					
Financial resources exist to support the usage of predictive analytics systems					
Government regulations and policies support the usage of predictive analytics systems					
Intention to use predictive analytics					
I intend to use the predictive analytics systems in the future					
I predict I would always use the predictive analytics systemsin my daily work					
I will try to use predictive analytics systems in my daily work					
I estimate there would be high chance for me using predictive analytics systems at the present					
I plan to use predictive analytics systems frequently					

Motivation to use predictive analytics					
I like using predictive analytics systems to assist in predicting best tactical administrative decisions					
I believe that being good in using predictive analytics systems in hospitals is important					
I believe that usage of predictive analytics to guide decisions in hospitals is interesting					
Doing well in using predictive analytics systems in hospitals is highly important for me					
Task motivation					
I like to participate in tasks that have relationship with predictive analytics					
I like to participate in tasks for using predictive analytics to guide a specific administrative decision making					
I believe that being good at the tasks of using predictive analytics for administrative purposes is important					
I believe that tasks of using predictive analytics to guide administrative decision-making are highly important					
Doing well in tasks of using predictive analytics systems in hospitals is highly Important for me					
Actual usage of predictive analytics					
I have used predictive analytics a lot in the past months					
I have been using predictive analytics regularly in the past months					
I'm using predictive analytics for more than 1 hour in my daily work					
I'm using predictive analytics for less than 1 hour in my daily work					
I do not use predictive analytics to make analysis and predictions					
I do not use predictive analytics results to guide decision making					
Tactical Non-Clinical Decision-Making Performance					
Predictive analytics help me identifying problems					
Predictive analytics help me making high quality decisions					
Predictive analytics help me making more effective decisions					
Predictive analytics help me in guiding my tactical management decisions					

COMMENT: ____

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