QATAR UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

DATA ANALYTICS IN EDUCATION: FACTORS AFFECTING THE UTILIZATION OF DATA ANALYTICS FOR EDUCATION IN QATAR

BY

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ABSTRACT

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Title: Data Analytics in Education: Factors affecting the utilization of data analytics for education in Qatar

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Data analytics in education is an emerging concept in the field of information technology. The purpose of this study is to examine the factors that affect professors' and lecturers' intention to use data analytics in the context of making evaluation decisions related to students.

The study is based on a modified version of the unified theory of acceptance and use of technology (UTAUT2). Price value, habit, and experience have been replaced by privacy, management support, and trust. The reason for this modification is that the new variables have shown a significant correlation with the intention in the education domain. In contrast, the removed variables harm the measurement of intention in the learning field. Many previous studies on the adoption of technology have demonstrated positive results using UTAUT2. Several studies have been modified to suit the domain. The research question is what are the factors that influence professors' and lecturers' intentions to use data analytics in evaluating students? Eight hypotheses were developed based on the model variables. An online survey was used as the research instrument to collect the data. The targeted respondent was professors and lecturer in higher education institutions in Qatar. The total number of valid responses that were collected was 158.

Results indicate that performance expectations are the most influential factor affecting the intention to use data analytics by higher education educators in Qatar, followed by management support and trust. However, effort expectancy, social influence, facilitating conditions, hedonic motivation, and privacy were not significant. In the equation generated from the three significant variables, the R square is 0.664, The F value is 101.44, and the residual has a degree of freedom of 153. The P value is less than 0.001.

By emphasizing the use of data analytics for student evaluation, the research contributed significantly to the knowledge and literature in Qatar. Universities should ensure the right tools are used in conjunction with the right data, as well as the integrity and availability of the data. University management should help professors, lecturers, instructors, and teaching assistants understand the factors necessary for the successful implementation of data analytics applications.

Keywords: Data analytics, education, Qatar, Universities, Big Data, UTAUT2, LMS, Trust, Learning.

DEDICATION

To my Mother,

To my Father, Elhadi

To my great wife, Somia

To my sisters, Anfal & Dr. Eman

To my work leader, Eng.Khaled Radwan

To my friends, Musaab M. Noor & Ali Hussin

I Owe You All My Success, You Motivated Me to Achieve It.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

In the next decade, Big Data will be the new oil, and the difference between success and failure will be determined by how quickly enterprises adapt to its use in their respective fields. It has become increasingly common for businesses to use big data to improve performance in order to open new business opportunities and provide new insights.

big data is the revaluation that going to transform people’s lives, work, and mindset. Utilizing big data in education is a new topic for discussion, and the use of big data and educational data analytics offers students, lecturers, and researchers new opportunities for learning (Cope & Kalantzis, 2016). There is no doubt that the more digitalization occurs in education, the more data will be available for analysis. By the time the data volume reaches a certain size, it will be difficult to analyze it using conventional computers to gain insights. As a result, most data analytics are performed on cluster computers.

Data creation is more rapid today than ever before, for example, 90 percent of the world's data was generated in the past two years. There are many types of data and various sources of data, for example, sensors, log files, web data, pictures, social media data, and audio data. Volume, velocity, and variety are considered crucial features of big data (Undavia, Patel, & Patel, 2017).

The use of big data in education is still in its infancy, however, the value of the information collected from big data is auspicious for getting better results using more advanced analytics techniques in the future. As part of this study, we will examine the opportunities for using big data to improve students’ evaluation in Qatar.

There are ways in which data analytics can be beneficial to education. It can greatly improve our understanding of why a student succeeds or fails in a particular class or examination by using it to predict a student's academic performance. Hence, it is critical to recognize that the prediction model can be used as a cautionary mechanism to determine the probable capabilities of students. Therefore, advisors and lecturers will be able to make the right decisions to improve the expected results (Rajeswari & Lawrance, 2016). Data analytics in education are also useful for making informed decisions regarding the educational system. Quality assurance can be achieved through the development, evaluation, and management of educational policies (Kharade & Wagh, 2016).

As part of the UAE's efforts to assess overall performance, data analytics is being used to plan the most effective strategy for each class. A student's performance is analyzed individually to identify each student's strengths and weaknesses and provide personalized support as needed (Ray & Saeed, 2018). In this research, the researcher is filling the gap of the effect of data analytics in education for better assessment of the students, and policies as a reference to the study which took place in UAE.

This study relies on the UTAUT2 framework for its high explanatory power and empirical replications (Venkatesh, Thong, & Xu, 2012). However, certain factors may enhance its explanatory power in the context of data analytics utilization and acceptance. In other words, the model can be customized to fit specific characteristics of an educational data analytics application. As a result, the theoretical framework proposed (shown in Fig. 1) includes performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), social influence (SI), hedonic motivation (HM), Management support (MS), Trust (T), Privacy (P), and intention (I). In this study, the intention is the dependent variable which is the goal of the study. It is hypothesized that it should be influenced by the other eight independent variables, which are PE, EE, FC, SI, HM, MS, T, and P.

1.1 Purpose of the Research

The main research question is what are the factors that influence professors' and lecturers' intentions to use data analytics in evaluating students? Attempting to determine the intention of using data analytics in a technological context, management support context, and Qatar higher education context to predicting the future such as probable capabilities of students and academic performance.

The researcher is trying to fill the gap of the effect of management support on adopting data analytics. Moreover, performance expectancy and effort expectancy are crucial factors that will be examined and find their relation to the professors' and the lecturers' trust and intention to use data analytics in education.

1.2 Scope of the Study

The scope of this study is to collect data from professors and lecturers working at any university or higher education institution in Qatar to generate statistical information. So, the population is professors and lecturers in higher education in Qatar and the sample will be collected by surveying the population. This study is self-reported, it will only focus on data analytics applications to measure the factors that affect the intention in using data analytics by professors and lecturers. Moreover, the process of data analytics such as the tools' availability, people acceptance, and ease of use also in the scope.

Students and lecturers who do not belong to Qatar's high education system are not in the scope. Moreover, how to collect educational data or any other part of the data life cycle or any facts about faculty performance or behavior is not in the study scope.

1.3 Motivation behind the study

The huge volume of data collected in education every day is the main motivator for this research. It can be used to improve the quality of education in Qatar. Additionally, improving the accuracy in evaluating students can assist in selecting the appropriate students for suitable scholarships (www.govtech.com, 2016). Furthermore, enhance education institutions' output by predicting the future of students and improving their behavior (Bhardwaj, Tiwari, Hazela, & Dhanda, 2019).

Identifying the factors that will influence professors' and lecturers' intentions regarding the use of data analytics will provide universities with a clear understanding of how they can motivate their staff to utilize their data to improve education quality and to identify the evolving needs of education.

1.4 Benefits of the Study

The significance of this study lies in understanding the factors that will lead professors and lecturers to use data analytics to predict the future and assess students' performance more accurately. It will be imperative for universities to reduce dropout rates and increase the output of their operations because of this initiative. By using a broader set of data and capabilities, educators can evaluate students more efficiently, which will improve their learning process.

In this study, we will investigate the feasibility of adopting an environment that includes the factors which affect the intention of using data analytics by universities. This will increase awareness of the use of data analytics among the students and faculty members. By understanding these factors, educational institutions will be able to identify their strengths and weaknesses. This will enable them to improve the quality of their education and achieve a competitive advantage over their competitors.

Additionally, they will be able to understand the motivations and discouragements of professors and lecturers when it comes to adopting data analytics.

1.5 Structure of the Study

The introduction is the first chapter of the report. It provides details about the research and its value. A literature review is presented in the second chapter of the study to review previous studies in the field of data analytics in education. These studies have been conducted by researchers from the US, Europe, and the Middle East.

In chapter three, the conceptual model is measured based on eight independent variables and one dependent variable. In the following chapter, the model, and its enhancement to fit the study are described in detail. There is a discussion of the results of the study in chapter five, as well as what the data have confirmed. The study concludes with a recommendation and a conclusion.

CHAPTER 2: LITERATURE REVIEW

We will look at previous studies and research about this study in this chapter and how we got to where we are now. The first step is to introduce the big data concept and how it emerged over the past decade. We will then demonstrate how big data analytics can affect higher education. Further investigation into studies on applying data analytics in universities as a new concept for improving education policies, making decisions, and predicting the future. Then will discuss the related studies in the middle east. After that, a discussion about the extended unified theory of acceptance and use of technology as it will be the base model for this study. In conclusion, will discuss how we can change or add to the UTAUT2 model. Price value, experience, and habit have been removed by the researcher based on the literature review. Other variables are added by the researcher, which are management support, trust, and privacy.

2.1 Big Data

Digitalization has developed several methods for the generation, collection, and analysis of data in the field of education. Creating big data content is greatly impacted by learning management systems, online platforms, and educational portals. Educational data includes student information, grades, attendance, quizzes, assignments, previous results, etc (Vieira, 2018).

Even with advanced analysis capabilities, it is difficult to gain insights from educational data collected from a variety of sources, including social media. It will be possible to gain a deeper understanding of students' behaviors, needs, and expectations through the analysis of education big data. Education can be improved by collecting appropriate data and applying appropriate analytics methods (Segura, Alexander, & Thiesse, 2015).

Educational institutions must be able to predict student performance. A university must have data that contains students' information to improve educators' perceptions of students' behavior and give them greater predictive power for the future (Rajeswari & Lawrance, 2016).

2.2 Big data analytics

Data analytics is a process of discovering, analyzing, and interpreting meaningful insights and patterns from large datasets. The process of big data analytics involves analyzing huge quantities of several types of data to identify new insights and unknown relationships between information (Prinsloo, 2019). It is essential for the successful implementation and effective use of data analytics within organizations to have a change in organizational structure and culture. Furthermore, it is necessary to make some changes to how activities are conducted and measured to achieve success. For example, data privacy and data analytics should be part of every organization's policy (Agasisti & Bowers, 2017).

Several studies have shown that big data can be useful in education and that it is likely to be highly utilized in universities and educational institutions in the future (Manohar, Gupta, & Priyanka, 2016). The Microsoft SQL Server Data Mining Add-ins for Excel is a popular tool for universities to predict significant insights and relationships between data, which can aid in taking corrective measures to improve the quality of education and the impact of faculty members on society (Manohar, Gupta, & Priyanka, 2016). The analysis of unstructured data can help to uncover insights and patterns through the process of data mining and knowledge discovery. A wide range of methods and algorithms are available for analyzing unstructured data to use them to their full potential. The purpose of this is to generate quantitative results that can be used to enhance business performance. It is also possible to have a positive impact on the educational sector by using big data analytics (Foster & Francis, 2019).

2.3 Big data analytics in the education sector

Currently, there are no predictive capabilities built into the current education system. This means that it is not able to predict students' performance in specific courses or their likelihood of discontinuing a course based on defined circumstances. The use of data analytics can benefit universities in several ways by providing information for academic advisors and decision-makers to improve the quality of their decision-making and advice (Gagliardi, Parnell, & Carpent, 2018). As an example, by providing the right information about weak or at-risk students, and then letting them know how many dropouts they have at the right time, the number of dropouts can be drastically reduced. It is likely that students and advisors would feel lost without these capabilities, with no clear idea about what should be done regarding coursework, or about which course or track might be most appropriate for them on a long-term basis (Kharade & Wagh, 2016).

Analyzing data can also be defined as the process of finding, analyzing, and interpreting insights, patterns, and meanings that can be derived from a huge amount of data. Education can be benefited from the use of three main categories of data analytics, which are descriptive, predictive, and prescriptive. Predictive analysis can assist in a wide variety of areas due to its ability to reveal hidden connections and relationships that may not have been discovered with other analytics models (bigdata-madesimple.com, 2019). Advanced data analytics can play a key role in the planning of educational programs. There are many problems that can be solved with it, such as deciding which students are or should be enrolled in a particular course, which courses are trending or obsolete, what percentage of students are satisfied with the present education system, designing a better curriculum, evaluating the effectiveness of online education, determining the likelihood that students will transfer, drop out, or fail to finish a particular course (Manohar, Gupta, & Priyanka, 2016).

It is not new for educational organizations to use data for the purpose of making decisions. It is undeniable that the growing awareness of school principals, teachers, parents, stakeholders, and policymakers has led to an increase in the use of big data as a fundamental source for taking the right decisions, analyzing the strengths and weaknesses of the organization, and measuring the effects of data-driven decisions (Agasisti & Bowers, 2017). This means that the development of an innovative and advanced figure of data analytics must be part of an extensive effort aimed at valuing the possibilities of data-driven decision-making in the education sector by taking data as part of an ongoing process (Cope & Kalantzis, 2016). Big data analytics in education has recently started to offer students, teachers, faculty, parents, school administrators, employers, policymakers, and researchers innovative ideas, information, and concepts. Workshop participants and open discussions have confirmed that data-driven pedagogical approaches offer significant potential for increasing the effectiveness of education (Cannistrà, 2022).

Through improvements in data analytics, students of all ages will be able to learn better and access learning in a wider range. It is now time to accelerate the advancement of education-related data science for continuous improvement in the ability to quickly analyze and find insights from large data sets (Dede, 2016). Currently, there are massive amounts of data are stored in the databases of educational institutions around the world. In an effort to predict students' performance, these data can be used as a source of useful information. As part of the educational data analytics research program, our goal is to analyze the data collected in the field of education (Pavlicevic, Seres, & Tumbas, 2018).

Meanwhile, critics have raised concerns about other issues, such as student privacy, student profiling, the use of test-driven teaching methods, and the establishment of teacher accountability frameworks. No matter what your viewpoint is, you can agree that big data analytics are increasingly infiltrating every industry, and that trend will continue in the education sector. (Cope & Kalantzis, 2016).

2.4 Using big data to improve performance in education

Data mining and analytics have recently become prevalent in the educational sector in order to take advantage of abundant data. Education's future can be predicted with the help of big data analytics. Education institutions will be better equipped to deliver quality education to students and improve their behavior if they can predict the future (Bhardwaj, Tiwari, Hazela, & Dhanda, 2019).

As a result of predicting a student's academic performance, we can significantly improve our understanding of the reasons why a student succeeds or fails in a particular class or examination. It is essential to recognize that the prediction model can be used as a cautionary mechanism to recognize the probable capability of students, and thus the advisors and lecturers will be able to make the right decisions to improve the expected outcomes. (Rajeswari & Lawrance, 2016).

Mentioned in (Ang, 2017) a study that took place in Australia in 2017 about Big Educational Data & Analytics, in order to improve student retention and reduce attrition, two emerging areas must be addressed. First, dropout prediction which is a major research topic in learning analytics (LA) for Big Education Data. To determine how likely a student is to drop out during the course, the prediction of dropout is extremely beneficial to instructors. Second, the development of academic early warning systems. It may be necessary for the instructor to adjust during the teaching process to mitigate and reduce the likelihood of a certain event in the future.

When it comes to planning, managing, and evaluating an education system, big data analytics plays an increasingly prominent role. It is extremely critical to have a robust education system that is informative about pedagogical and institutional operations, performance efficiency, shortcomings, and all other needs. In addition to collecting, processing, and analyzing data for the purpose of reporting and making informed decisions, the education system should assist in the design and development of educational policies as well as assist in evaluating and managing them (Muhammad, Tasmin, & Aziati, 2019).

Analyzing data can be an incredibly powerful tool for academic intervention when used appropriately. The use of data analytics in education will enable education organizations to predict with an accuracy of more than 80 percent (Ang, 2017). For example, this system can predict which students are likely to be capable of completing a given course. Organizations can use this information to assist academic advisors in providing support to students in need at the appropriate time. Additionally, faculty members can use it to design and develop academic courses more effectively. Researchers are currently able to use data analytics to understand student learning efforts, implement or restructure student models, measure student interventions, improve teaching support, and predict student behavior based on data analytics (Shidaganti & Prakash, 2021)

A data analytics approach can assist in finding appropriate students for scholarships, instead of only giving scholarships to students with high CGPAs, other factors may be considered to make a more informed decision. To maximize return on investment, students who performed better in specific subjects or in other selected factors should be selected (www.govtech.com, 2016).

2.5 Data analytics in higher education in the gulf countries

There are expectations that big data analytics will play a significant role in the education sector in the UAE soon. The digital economy has given rise to a new generation of educational institutions that can take advantage of the benefits of data to make strategic decisions, for example, through learning analytics. It is expected that there will be no legacy challenges related to data analytics in the UAE as a result of the continuous development of the technology and tools for big data analytics (Najdawi & Stanley, 2021).

In a survey conducted in UAE high education institutions, it was discovered that the expectation among faculty members is that big data analytics will play a vital role in the quality and delivery of education (Mishra, 2019). Data analytics will be used in UAE to assess overall performance to plan the most effective strategy for each class. In contrast, one can analyze each student's performance individually to identify each student's strengths and weaknesses and provide them with personalized support at the appropriate time (Ray & Saeed, 2018).

Saudi Arabia's situation is quite different from that of the UAE. There are different barriers to adoption and gaining benefits from big data analytics. These barriers are primarily in terms of data management, security, processing, and storage. Managing user data and protecting intellectual property rights are two challenges associated with implementing big data analytics in higher education in Saudi universities. Security and encryption systems will be required to manage data for analysis to maintain data privacy, integrity, and credibility. A top management commitment is crucial in spreading awareness of data analytics projects and making investments. Data collection, storage, security, and analysis in Saudi Arabia are challenging due to the lack of suitable IT infrastructure (Almobark, 2021).

Predictive analytics are gradually being used for purposes in higher education in Saudi Arabia, including predicting students' behavior and student classifications. Additionally, it was used to monitor students, make course recommendations, and customize curricula. Some institutions are using data mining to better understand their students and their needs and predict student outcomes (Alsheikh, 2019).

2.6 Data analytics in higher education in Qatar

Qatar is one of the richest countries in the world, and education is considered to be an important strategic factor in Qatar's vision for 2030. Qatar is highly investing to improve its education institutions and system (edarabia.com, 2021). Although Qatar has a growing number of higher education institutions, Qatar University is the main and largest university in Qatar, founded in 1973. Qatar Foundation, also known as Education City, was founded in 1998 as a result of Her Highness Sheikha Mozza bint Nasser's efforts. She was successful in attracting many of the most prestigious universities in the world to open branches in Qatar under the umbrella of the Qatar Foundation (Qf.org.qa, 2022).

Examples include Cornell University, Georgetown University, Carnegie Mellon University, and Virginia Commonwealth University. It is also important to note that there are other institutions at the Qatar Foundation, such as the Canadian University of Calgary, the business school HEC Paris, the College of the North Atlantic, and lastly, the Qatar Faculty of Islamic Studies, which is a university established in Qatar (topuniversities.com, 2022). By 2020, there are a total of thirty-two universities around

Qatar, compared to the year 2014, when there were only sixteen universities. These universities held over 39,000 students for the 2019-2020 academic year. These institutions offered 366 programs for the academic year 2020-2021. Qatar University, HBK University, College of the North Atlantic, and Community College offer 57% of these programs (edu.gov.qa, 2022).

Qatar has not reported any use of data analytics in the field of education yet. The purpose of this research study is to examine the part of using data analytics in higher education in Qatar by analyzing the intention of educators to use data analytics to take decisions in their educational settings.

2.7 The UTAUT2 (Unified Theory of Acceptance and Use of Technology)

The first version of UTAUT2 was called UTAUT, it was developed by Venkatesh, Morris, Davis, and Davis in the year 2003 The development was based on studying and reviewing eight theories and models. In the first version (UTAUT), the study had four variables, which were facilitating conditions, effort expectancy, performance expectancy, and social influence (Venkatesh, Morris, Davis, & Davis, 2003). In 2012, Venkatesh, Thong, and Xu proposed to add new constructs to the model that may influence the consumer's acceptance and use of technology in a positive manner (Venkatesh, Thong, & Xu, 2012).

There are three new variables that have been added from the perspective of the technology used. The variables that are derived from several research findings are Habit (Limayem, Hirt, & Cheung, 2007), Hedonic Motivation (Heijden, 2004), and Price Value (Brown & Venkatesh, 2005). As a result of conducting research in Hong Kong on a large sample using a two-stage survey method, it was concluded that the three newly added constructs are significant and they affect intention to use technology behaviors either directly or indirectly as a result of age, gender, and experience (Venkatesh, Thong, & Xu, 2012). The final version of UTAUT2 is demonstrated in figure1.

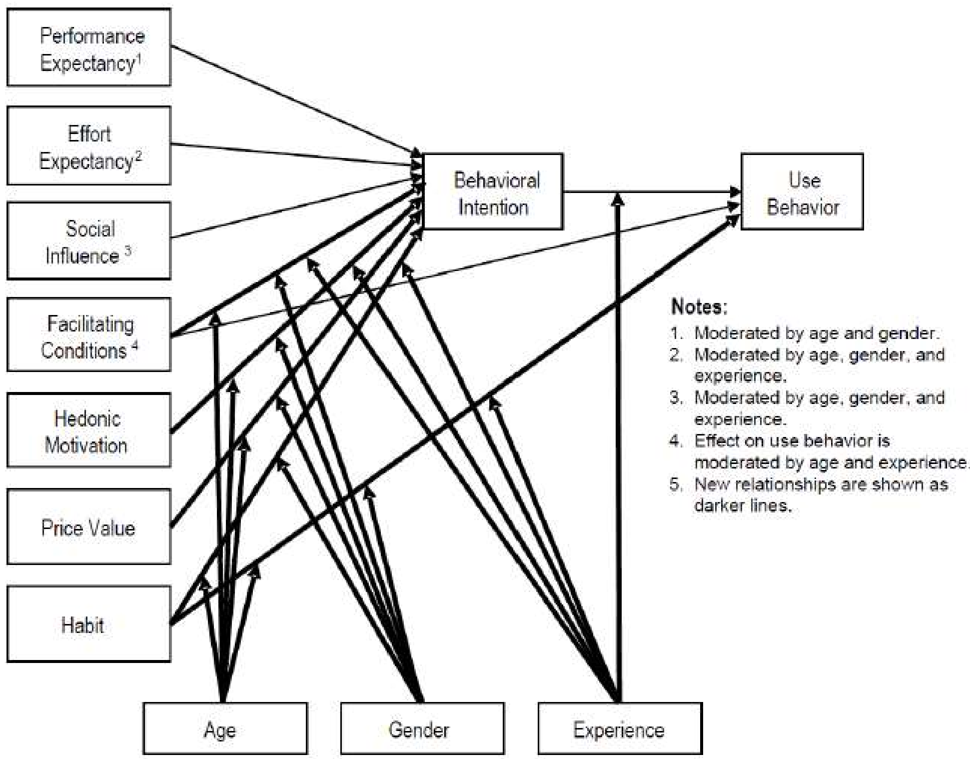

Figure 1. UTAUT2 original theory

2.8 Management support

In education, a positive relationship exists between management support, users' awareness of its usefulness, and the feeling of ease of use associated with technology adoption. Management support is essential to the success of educational technology adoption eventually (Jabor, 2011). It is the support provided by management that pertains to the fundamental direction an institution pursues as it seeks to adopt modern technology or processes to increase its efficiency. Further, administrative support plays a critical role in the effective and efficient utilization of technology by faculty members and the success of IT applications. There may be a strong correlation between management support and reducing teacher resistance to technology changes. (Bakkenes, Vermunt, & Wubbels, 2010). The same can be said for better management support, which can not only enhance perceived usefulness and ease of use but also create a more favorable organizational climate. (Wang & Wang, 2009).

2.9 Trust

The level of trust attached to a tool can be measured by its ability to produce reliable and consistent results (Everson, Lee, & Friedma, 2022). The investigation of how individuals and organizations use information systems to perform work reliably will enhance both the richness and relevance of IS research. This is because it will provide insight into how individuals and organizations are affected by trust in performing work (Butler & Gray, 2006). Users' trust can be measured in terms of reliability, truthfulness, strength, and ability. As a result of individual differences, educational level, gender, age, and experience were the factors that moderated the effects of trust constructs (Kwateng, Atiemo, & Appiah, 2018).

As the term trust implies, it refers to a person's consideration of the application as a trustworthy resource. It is primarily concerned with their opinion of the benefits that can be gained from using the application. The degree to which a person is willing to entrust a computer system with certain functions is also indicative of the level of trust he or she has in it. Whether they are willing to utilize the system depends on the level of trust they have in it.

Several researchers have examined the effect of trust on users' intentions to adopt technology in education. There was a study that was conducted in 2020 about improving the quality of LMS based on Student Perspectives. As stated by the authors, trust was added to UTAUT2 because it has a fundamental effect on user behavior. It can have a considerable influence on how users behave when using LMS applications (Meyliana, et al., 2020). A second study which took place in Qatar examined the enhancement of LMS in teaching and learning processes using UTAUT2. They found that trust is an influential factor that may influence the adoption of technology (Jessica, et al., 2019). The result in different contexts was positive, with a significant impact of trust on users' intention to adopt a technology.

2.10 Privacy

When we use the term Privacy, we refer to a construct consisting of four components. First, the collection reflects concern regarding the collection and storage of substantial amounts of personally identifiable information. Second, there is concern regarding the use of information collected from individuals for one purpose but being used for a secondary purpose without the consent of those individuals. This issue is commonly called unauthorized secondary use. Third, there was a growing concern over the inadequacy of protections against deliberate and accidental mistakes in personal data due to insufficient precautions. Fourth, the concerns regarding improper access to data reflect the concern that data about individuals are readily available to people who are not authorized to view or work on data about individuals (Smith, Milberg, & Burke, 1996).

An individual's privacy concerns are defined as the degree to which the organization and technical infrastructure are available to prevent the unauthorized disclosure of personal information. The effect of privacy on the behavioral intention to adopt technology was positive with a significant impact (Xu & Gupta, 2009).

2.11 Previous Studies

There is no doubt that a researcher should look at previous studies and do an in-depth literature review so that there is no gap that needs to be filled and there is an opportunity to contribute to the literature by completing his research. According to literature reviews, two types of related studies have been identified. First, studies related to UTAUT2 in education. A second type is technology adoption or acceptance using the UTAUT2 model. In both types of studies, there is some modification to the UTAUT2 model to increase its effectiveness.

First, will go through the studies related to UTAUT2 in education. There is a study that has been conducted in Malaysia that used UTAUT2 with a few modifications to evaluate the learning value of the LMS. As a result of the modification, the construct of price value has been changed to the construct of learning value, and they have also added more dependent variables, such as the actual use of the LMS (Ain, Kaur, & Waheed, 2016). In 2020, a study was conducted in Jordan on the use of social networks for education. The study used UTAUT2 with some modifications. A modification was made by adding two factors, namely lecturer support and student-related factors. On the other hand, they removed the price value from the main model (AbuGharrah & Aljaafreh, 2021).

There is a study about the acceptance of mobile learning that was conducted in Pakistan. The study used the UTAUT2 model with modifications. The modification included three independent variables, which were ubiquity, information quality, appearance quality, and system quality. Moreover, the author added one dependent variable which is satisfaction (Arain, Hussain, Rizvi, & Vighio, 2019). From the above-mentioned three studies related to education. UTAUT2 was used with some modifications to increase its effectiveness. The result of the three studies was supporting this study has the modification required to measure professors' and lecturers' intentions to use data analytics to evaluate students.

The second step will be to look at studies related to UTAUT2 in the field of technology adoption. An article was published in the UK in 2002 about the acceptance of IT meta-analytics by consumers. The study used the original version of UTAUT2 with no modifications (Tamilmani, Rana, & Yogesh, 2020). There is a study about the acceptance of mobile banking that was conducted in Jordan. The study used the UTAUT2 model with modifications. The modification included one variable which was trust. trust has a direct effect on the customers' intention to adopt Mobile banking (Alalwan, Dwivedi, & Rana, 2017).

In Malaysia, there has been a study that has been conducted in which the UTAUT2 has been modified with a few improvements. The purpose of the study was to evaluate both the medical staff's acceptance of the stored data and the level of trust they have. The modification has resulted in the removal of the construct of price value. On the other hand, they have added one independent variable which is trust, and one dependent variable which is the actual use of the data (Alazzam, et al., 2016). As a result of the mentioned studies, this study had the modification it needed to measure the providers' and instructors' intention to use data analytics to evaluate student performance.

CHAPTER 3: RESEARCH METHODOLOGYAND HYPOTHESIS

Throughout this chapter, we will present an overview of the hypotheses used in the research. We will also present the proposed model, define the variables, as well an explanation of the methodology employed in the research process. In addition, we will provide information about how data was collected to get enough information about the factors that influence faculty members' and educators' intentions to use data analytics in education in Qatar. This is a quantitative study. This means that the researchers were able to collect primary data that contributed to the testing of hypotheses, comparing the responses, and generalizing the conclusions of their findings.

3.1 Proposed hypothesis

According to chapter one, the study aims to provide answers to the following main question to achieve its objectives: what are the factors that influence professors' and lecturers' intentions to use data analytics in evaluating students? We have therefore developed a model and hypotheses based on the literature review. These reflect our assumptions regarding the antecedents of the intention to utilize data analytics in evaluating students in higher education in Qatar.

H1. Performance expectancy has a positive effect on the intention to use data analytics.

H2. Effort expectancy has a positive effect on the intention to use data analytics.

H3. Social influence has a positive effect on the intention to use data analytics.

H4. Facilitating conditions have a positive effect on the intention to use data analytics.

H5. Hedonic motivation has a positive effect on the intention to use data analytics.

H6. Management support has a positive effect on the intention to use data analytics.

H7. Trust has a positive effect on the intention to use data analytics.

H8. Privacy has a positive effect on the intention to use data analytics.

3.2 Research Proposed Model

Upon reviewing previous studies related to technology adoption and satisfaction measurement methods, TAUT2 is deemed the most suitable fit for this research. It will be used as the base model with minimal customization to fit the research. The customization includes adding privacy, Trust, and management support. Further customization was removing habit, price value, and experience. The reason for this customization was discussed in the literature review. Figure 2 demonstrates the newly generated and proposed model.

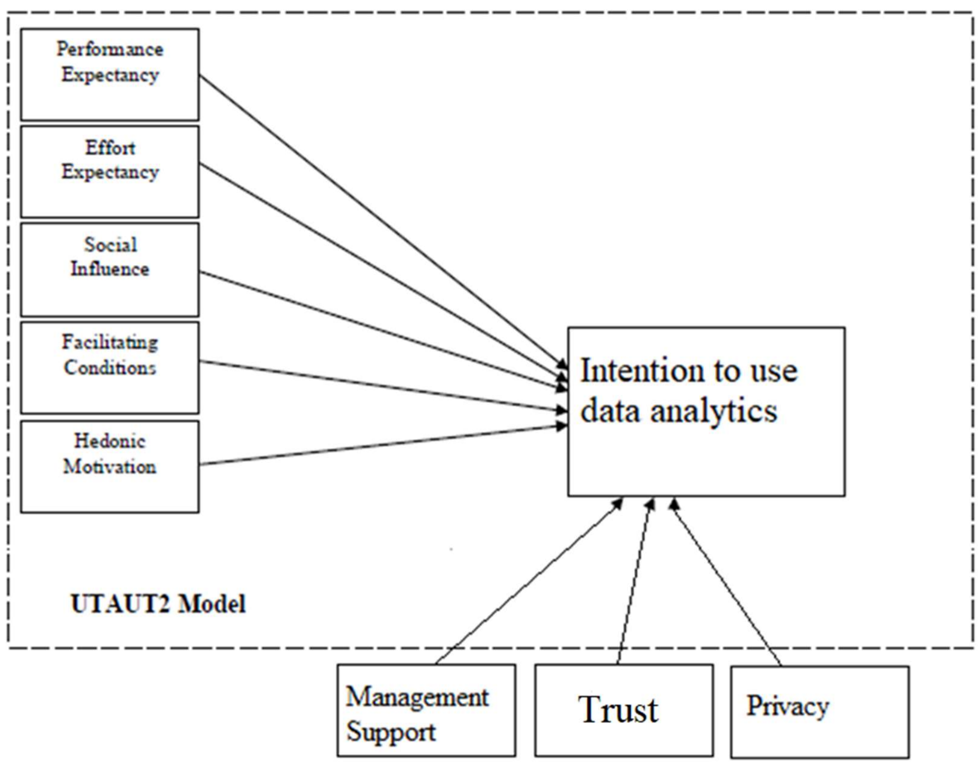

Figure 2. Proposed Model

3.3 Variables Definitions

We have employed the UTAUT2 framework as a base model for the present study to take advantage of its high explanatory power and its ability to replicate empirical findings (Venkatesh, Thong, & Xu, 2012). It is possible, however, that certain factors may enhance the explanatory power of data analytics in the context of data analytics employed in education. Moreover, customization of the model may address the peculiar characteristics of data analytics in the education field. Considering this, the proposed theoretical framework can be summarized as follows: (shown in Fig. 1).

The definition of the factors is as follows: performance expectancy (PE) is "The degree to which using a technology will provide benefits to consumers in performing certain activities." Effort expectancy (EE) is "The degree of ease associated with consumers' use of technology." Facilitating condition (FC) is "Consumers' perceptions of the resources and support available to perform a behavior." Social influence (SI) is the consumers perceive those important others (e.g., family and friends) believe that they should use a particular technology." Hedonic motivation (HM) is "The pleasure or enjoyment derived from using a technology" (Venkatesh, 2012). Management Support (MS) is the support provided by management that pertains to the fundamental direction an institution pursues as it seeks to adopt recent technology or processes to increase its efficiency (Jabor, 2011).

Trust (T), Technology components that consistently perform according to specifications to achieve a specific goal or objective (Everson, Lee, & Friedma, 2022). The definition of data privacy (P) is the level of privacy protection an individual has while data is being analyzed. It covers the amount of protection for personal data. Moreover, privacy is typically associated with the proper handling and storage of data (Xu & Gupta, 2009).

3.4 Survey Design & Measurement Development

The research was conducted in the form of a quantitative empirical study which incorporated a questionnaire as the instrument to validate the conceptual model as an appropriate tool for measuring individual perceptions and intentions as well as the validity of the model itself (Abu-Shanab & Knight, 2009). Based on the reported literature and the research model, the survey was designed to integrate different variables from the original UTAUT study and other related and supporting studies. From the original UTAUT paper (Venkatesh, Morris, Davis, & Davis, 2003), the performance expectation, effort expectation, and facilitating conditions question was developed. The hedonic motivation question was developed from the UTAUT2 theory (Venkatesh, Thong, & Xu, 2012). Three factors were added to the model in this study, they have no questions in the original theory questionnaire. These three factors are Management support, Reliability, and Privacy.

For management support, which is the factor that is not from the original UTAUT2, the questions were used earlier in another related study about the effect of management support on technology adoption (Jabor, 2011). Trust questions were developed based on the study about Improving Questionnaire Reliability using Construct Reliability for Research in Educational Technology (Rosli, et al., 2021) and (Everson, Lee, & Friedman, 2022). The question related to privacy was generated from a previous study related to privacy in technology adoption (Xu & Gupta, 2009). Finally, questions that are measuring intention were developed from a study about learning using UTAUT2 with modifications (Roca, Chiu, & Martı´nez, 2006).

As the survey is online, it was able to reach a large number of participants. In this test, each item of the eight test variables is scored on a five-point Likert scale to measure the subjects' response to each item. Responses ranged from strongly disagree to strongly agree, Five-point Likert scale ranged from “Strongly disagree” = 1 and “Strongly agree” = 5 (ARMSTRONG, 1987). On the first page, a brief explanation of data analytics is provided. In addition, we asked for the consent of the respondents to participate in the survey. We ensured that their privacy would be protected, and no personal information would be collected.

The main objective of the study is to measure the effect of the independent variables on the dependent variable which is the professors' and lecturers' intention to utilize data analytics in higher education in Qatar. The language of the survey was English only, that is because all participants targeted in the survey are expected to be fluent in English. QU-IRB approval was received on December 8, 2021, under project title number 1807662-1.

3.5 The Study Population and Sampling

In this study, the population of the study consisted of Qatari citizens or expatriates who were lecturers, professors, teaching assistants, or educators in higher education in Qatar. The inclusion criteria were the following: First, the participant wanted to take part in the study. In addition, the participant must be an active lecturer, professor, teaching assistant, or educator at any higher education institution in Qatar. It is also critical that the participant is fluent in English as well.

In the study, random sampling was used as a simplified method. Simple random sampling means that each individual in the population has an equal chance of being included in the sample (Taherdoost, 2020). The survey link was distributed randomly to all targeted populations that the researcher and his contacts can reach. We began the empirical data collection process by disseminating the study instrument, which is an online survey, in February 2021. Students at Qatar University started this initiative. Then we had professors and lecturers from Qatar University. After that, the link was sent to all universities in Qatar. Some of the contributors received a direct email link from the researchers. Some respondents received the link from a faculty member who helped the researcher collect data. As mentioned, earlier, 172 responses were collected.

CHAPTER 4: DATA ANALYSIS AND DISCUSSION

Finding out the main influencing factors for the university lecturers' and professors’ intention to utilize data analytics for decision-making requires an analysis of the collected data to extract useful information that helps answer the research questions. The collected data consists of a total of 173 respondents.

They have been completed online and offline by meeting some of the respondents to get their answers. two responded that they do not want to participate in the survey. Thirteen have responded that they are not teaching in any high institution in Qatar. So, fifteen responses were considered invalid and the remaining 158 responses are considered valid for further analysis.

There are four analyses will be conducted. First is the demographic of the sample, then the validity and reliability of the variable’s items, which will be discussed using Pearson’s Correlation Matrix. After that will discuss descriptive analysis. Finally, multiple regression to assess the hypothesis of the research.

4.1 Study Sample Demographics

According to the survey, the majority of respondents are not Qataris. Qataris represented 23 or 15% of total respondents, while non-Qataris respondents represented 135 or 85%. The respondents were categorized into three main categories based on their age. The majority of respondents were aged 35-55 years old, with 112 respondents or 71%, followed by those aged more than 55 years old with 29 respondents or 18%, and the third category was respondents who were less than 35 years old, only 17 or 11% of the total number of respondents.

There were three main categories for education in the survey. The highest percentage was Ph.D., which accounted for 129 or 82% of the respondents. The second highest was Master's, which accounted for 28 or 18% of the respondents. The most surprising fact is that there was one respondent who possessed a bachelor's degree.

Table 1. Response percentages based on demographics

Variable	Frequency	Percentage
Nationality		
Non-Qatari	135	85%
Qatari	23	15%
Age		
Less than 35 years old	17	11%
Between 35 and 55 years old	112	71%
More than 55 Years old	29	18%
Education		
Bachelor	1	>1%
Masters	28	18%
PhD	129	82%
Gender		
Male	121	77%
Female	37	23%

Lastly, it should be noted that 121 respondents in total were males or 77% of the respondents. Meanwhile, the number of females who responded to the survey was 37, or 23% of the total number of respondents.

4.2 Validity and Reliability

The first part will be the internal consistency (reliability) analysis of the model. Reliability describes whether your methods for collecting data and analyzing them would reproduce the same results if they had been repeated on another occasion or if they had been repeated by another researcher on a different occasion (Everson, Lee, &

Friedma, 2022). Its measurement tool is Cronbach's alpha. Cronbach's alpha measures the internal consistency between items on a scale. A measure of internal consistency reliability is an evaluation of composite reliability that considers the outer loadings of indicator variables. There is a range of values between 0 and 1 for composite reliability. The greater the value, the higher the level of reliability. In exploratory research, composite reliability values of 0.60 to 0.70 are acceptable. It is generally considered satisfactory to have a value between 0.70 and 0.90 in complex research studies (Butler & Gray, 2006).

There is often a method of determining the reliability of a survey by comparing the answers to similar or identical survey questions. The assumption is that answers to questions measuring the same underlying concept are likely to be highly correlated, which leads to the conclusion that the survey is reliable (Everson, Lee, & Friedman, 2022).

Table 2. Construct wise Cronbach's Alpha Value

Constructs	N	Number of items	Cronbach's alpha
Performance Expectancy (PE)	158	4	0.929
Effort Expectancy (EE)	158	4	0.945
Social Influence (SI)	158	3	0.912
Facilitating Conditions (FC)	158	6	0.924
Hedonic Motivations (HM)	158	3	0.941
Management support (MS)	158	3	0.84
Reliability (R)	158	3	0.876
Privacy (P)	158	4	0.912
Teacher Intention (TI)	158	3	0.923

As shown in table 2, Construct or factor Cronbach's Alpha is measured and resulted in seven of the nine alpha values exceeding 0.9, which is excellent according to the literature (Larcker & Fornell, 1981). Among the nine variables, only two have Cronbach's alpha less than 0.9 and more than 0.8, which are Management support and Reliability. On the other hand, the total Cronbach's Alpha where all factors are compared together is 0.966. This survey instrument has a high level of reliability, it could be used in future studies.

The second part will be about the validity of the questionnaire. Validity is defined as the extent to which the collected data is representative of the area that is under investigation. There are several definitions of validity, but essentially the definition is "measure what you intend to measure" (Taherdoost, 2020). For validity, factor analysis has been conducted on all variables items. The selected cut was considered under 0.5.

The result has shown that five out of the 33 questions are not loading on the right factor. Table 3 shows all 33 questions with their respective loading. The first item was question number three on Management support which is “My university has initiated a rewarding system for using data analytics to improve performance”. The second item was question number two on facilitating conditions which is “I have the necessary knowledge to use data analytics”. Finally, Factor analysis rejected all measurement items for social influence. The first question is “People who influence my career decisions think that I should use data analytics.”, the Second question is “People who are important to me think that I should use data analytics.”, the third question is “Students are helpful in the support of using data analytics”. Table 4 shows the correct loading after removing the question that caused an issue for the loading table. All Five questions were considered invalid, so they have been removed from further analysis. All the loading was between 0.5 and 0.9. Table 4 shows the loading of the items in detail.

Table 3. Rotated Component Matrix (Including all items)

	Component								
	1	2	3	4	5	6	7	8	9
EE1		0.784							
EE2		0.812							
EE3		0.757							
EE4		0.756							
FC1			0.62						
FC2									
FC3			0.709						
FC4			0.725						
FC5			0.788						
FC6			0.779						
PE1	0.771								
PE2	0.762								
PE3	0.732								
PE4	0.626								
P1					0.85				
P2					0.857				
P3					0.898				
P4					0.865				
T1						0.705			
T2						0.778			
T3						0.745			
I1	0.542								
I2	0.684								
I3	0.598								
MS1							0.832		
MS2							0.786		
MS3								0.754	
HM1				0.703					
HM2				0.704					
HM3		0.506		0.621					
SI1				0.609					
SI2				0.664					
SI3				0.568					

Note: PE = Performance expectancy, EE= effort expectancy, FC = Facilitating conditions, HM = Hedonic Motivations, MS = Management Support, T = Trust, P = Privacy, and I = Intention.

Table 4. Rotated Component Matrix

	Component							
	EE	FC	P	PE	HM	T	I	MS
EE1	0.784							
EE2	0.825							
EE3	0.768							
EE4	0.732							
FC1		0.634						
FC3		0.731						
FC4		0.747						
FC5		0.787						
FC6		0.795						
P1			0.849					
P2			0.863					
P3			0.892					
P4			0.865					
PE1				0.796				
PE2				0.766				
PE3				0.747				
PE4				0.624				
HM1					0.765			
HM2					0.751			
HM3					0.65			
T1						0.61		
T2						0.76		
T3						0.774		
I1							0.715	
I2							0.693	
I3							0.742	
MS1								0.829
MS2								0.791

Note: PE = Performance expectancy, EE= effort expectancy, FC = Facilitating conditions, HM = Hedonic Motivations, MS = Management Support, T = Trust, P = Privacy, and I = Intention.

4.3 Descriptive Variables

The descriptive analysis examines the factual results of the collected data through the used instrument to determine how respondents perceived each item.

Researchers have suggested that researchers should use the following classification system as a basis for grouping the results of a five-point Likert scale when explaining its results: 1.33-2.33 indicates low agreement, 2.33-3.66 indicates moderate agreement and 3.66-5 indicates high agreement.

According to Table 5, 23 out of 36 items have means between 2.33 and 3.66, which is considered moderate. On the other hand, the means of the other 13 items exceed 3.66. In terms of mean values, privacy (P) has the highest value of 4.04, Followed by management support (MS) at 3.85.

This indicates the high level of agreement regarding the importance of privacy and management support (both higher than 3.66) from the perspective of the respondent. All other contracts have a mean between 3.66 to 3.09 which indicates a moderate level of agreement regarding the importance of another construct from the perspective of the respondent. For example trust (T) mean is equal to 3.64, where hedonic motivation has the least value of 3.09. Almost all the standard deviations within the construct of a variable are similar. Furthermore, the variables have similar means to each other, indicating an analogous dispersion of data around the mean.

4.4 Study Hypotheses Testing

The first step will start by evaluating the correlation relationships among independent constructs, and with the dependent construct Intention (I). Table 6, the correlation between factors that affect professors' and lecturers' intention to utilize data analytics in education in Qatar. All correlations are positive, and the highest correlation with Intention was Performance Expectancy (0.7), Then Trust (0.664), then followed by

Table 5. Descriptive Analysis

	N	Mean	Std. Deviation
PE1	158	3.45	1.25
PE2	158	3.45	1.22
PE3	158	3.35	1.25
PE4	158	3.29	1.29
Average.PE	158	3.38	1.14
EE1	158	3.07	1.32
EE2	158	3.12	1.36
EE3	158	3.12	1.36
EE4	158	3.13	1.35
Average.EE	158	3.11	1.25
FC1	158	3.35	1.32
FC3	158	3.41	1.26
FC4	158	3.39	1.29
FC5	158	3.53	1.30
FC6	158	3.49	1.26
Average.FC	158	3.43	1.11
HM1	158	3.08	1.33
HM2	158	3.03	1.37
HM3	158	3.15	1.36
Average.HM	158	3.09	1.28
MS1	158	3.89	1.11
MS2	158	3.82	1.12
Average.MS	158	3.85	1.06
T1	158	3.68	1.13
T2	158	3.70	1.07
T3	158	3.53	1.20
Average.T	158	3.64	1.02
P1	158	3.96	1.12
P2	158	3.96	1.06
P3	158	4.04	1.03
P4	158	4.20	0.98
Average.P	158	4.04	0.93
I1	158	3.45	1.18
I2	158	3.75	1.17
I3	158	3.61	1.17
Average.I	158	3.60	1.09

Note: PE = Performance expectancy, EE= effort expectancy, FC = Facilitating conditions, HM = Hedonic Motivations, MS = Management Support, T = Trust, P = Privacy, and I = Intention.

social influence (0.66), then Effort Expectancy (0.621), then Facilitating Conditions (0.613), then Hedonic Motivation (0.608), followed by Management support (0.567), and the lower correlation was with Privacy (0.296).

According to Table 7, the model was found significant in terms of predicting the intention to use data analytics as all the variables were found significant at 0.01. As per SPSS, ** means the correlation is significant at the 0.01 level (2-tailed). When multiple regression is generated for the first time using the "Enter" method, there were 3 significant variables. These three variables were performance expectancy, Management support, and Trust. After repeating the multiple regressions with the stepwise option. The result stepwise confirmed the enter method as shown in Table 8.

Table 6. Pearson's Correlation Matrix

	Average.PE	Average.EE	Average.FC	Average.HM	Average.MS	Average.T	Average.P	Average.I
Average.PE	1							
Average.EE	.733**	1						
Average.FC	.583**	.640**	1					
Average.HM	.721**	.767**	.582**	1				
Average.MS	.354**	.321**	.495**	.310**	1			
Average.T	.569**	.511**	.573**	.578**	.583**	1		
Average.P	.228**	.168*	.380**	0.130	.420**	.314**	1	
Average.I	.731**	.621**	.613**	.608**	.558**	.664**	.296**	1

In table 8, We can find the model summary, even though we had seven independent variables as possible candidates for inclusion in the regression equation, we can see that SPSS ultimately chose only three of those predictors. As we can see the value of R is corresponding with the correlation of independent variables with the dependent variable. R squire is increasing with the addition of other independent variables, it started at 0.534 in the first model which included only one variable (Performance expectancy), and reached 0.637 by adding the second significant variable, the new model includes (Performance expectancy and Management support. Then the final model includes the three selected variables which are (Performance expectancy, Management support, and Trust). The R2 accounted for in intention in the third model was 0.664, which is within a highly acceptable range, exceeding recommended values, such as 40% (Straub, Boudreau, & Gefen, 2004).

The three independent variables that build the model are Average Performance Expectancy, Average Management Support, and Average Trust. The intention is the dependent variable, and the model's power of prediction is the value of R which is 0.815. Table 9 shows the ANOVA table, and again there are 3 models, each model has an F value which is testing for the statistical significance of the model. each model of the 3 is statistically significant, so once we get the bottom of the 3rd model which we reported for analysis, has an F value of 101.441, and 153 degrees of freedom in the residual. The P is less than 0.001.

Again the 3 models appear with a significant ability to predict the intention. We can notice that the standardized beta weight is decreasing in magnitude. That is because as more and more predictors are added to the equation, there is less variance to predict the independent variable. Table 11 shows the process of excluding the four variables based on their significance level. First Privacy has been excluded with a significance of

Table 7. Multiple regression coefficient table

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
	B	Std. Error	Beta			Zero-order	Partial	Part
(Constant)	0.07	0.26		0.265	0.79			
Average.PE	0.411	0.07	0.432	5.645	<.001	0.73	0.419	0.264
Average.EE	0.058	0.07	0.066	0.795	0.43	0.62	0.065	0.037
Average.FC	0.09	0.07	0.092	1.313	0.19	0.61	0.107	0.061
Average.HM	0.007	0.07	0.009	0.108	0.92	0.61	0.009	0.005
Average.MS	0.228	0.06	0.221	3.583	<.001	0.56	0.281	0.167
Average.T	0.214	0.07	0.2	2.888	0	0.66	0.229	0.135
Average.P	-0.01	0.06	-0.006	-0.11	0.92	0.3	-0.01	-0.01

a. Dependent Variable: Average.I

(0.912), then Hedonic Motivations (0.353), after that Facilitating Condition (0.072), and finally Effort Expectancy (0.124). all of them have a significant value of more than (0.05). Based on this analysis, we were able to conclude that some hypotheses were supported, whereas others were not. In Table 12, the results of testing the different hypotheses are summarized. Based on Table 5, it can be concluded that all variables can be used to predict intentions, however, when set together, some variables are no longer needed, which means they are weakened by the other variables.

Table 8. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.731[a]	0.534	0.532	0.745
2	.798[b]	0.637	0.632	0.66
3	.815[c]	0.664	0.657	0.637

According to the results, the first hypothesis is supported, which confirms UTAUT2's base model. Thus, it can be said that performance expectations have a significant correlation with the intention of professors and lecturers to use data analytics. However, the other hypothesis related to UTATU2 was not validated by this study.

Table 9. ANOVA Test

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	99.552	1	99.552	179.116	<.001
	Residual	86.704	156	0.556		
	Total	186.256	157			
2	Regression	118.574	2	59.287	135.773	<.001
	Residual	67.682	155	0.437		
	Total	186.256	157			
3	Regression	123.672	3	41.224	101.441	<.001[d]
	Residual	62.584	154	0.406		
	Total	186.256	157			

d. Predictors: (Constant), Average.PE, Average.MS, Average.T

Table 10. The coefficient table

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	1.246	0.19		6.704	<.001			
	Average.PE	0.697	0.05	0.731	13.38	<.001	0.731	0.731	0.731
2	(Constant)	0.28	0.22		1.27	0.21			
	Average.PE	0.581	0.05	0.61	11.78	<.001	0.731	0.687	0.571
	Average.MS	0.352	0.05	0.342	6.6	<.001	0.558	0.468	0.32
3	(Constant)	0.088	0.22		0.403	0.69			
	Average.PE	0.49	0.05	0.514	9.047	<.001	0.731	0.589	0.423
	Average.MS	0.248	0.06	0.241	4.184	<.001	0.558	0.319	0.195
	Average.T	0.248	0.07	0.232	3.542	<.001	0.664	0.274	0.165

a. Dependent Variable: Average.I

H2, H3, H4, and H5 are not supported by the analysis. That means Effort expectancy, social influence, facilitating conditions, and Hedonic motivation had no significant correlation with the intention. The three variables that were added to the UTAUT2 model as modifications were not all supported. Management support and trust were found to have significant correlations with intention. Nevertheless, there was no support for the concept of privacy. This means that the privacy of the user has not been found to have a significant correlation with the intention.

Table 11. Excluded Variables

Model		Beta In	t	Sig.	Partial Correlation
1	Average.EE	0.183	2.316	0.022	0.183
	Average.FC	0.283	4.461	<.001	0.337
	Average.HM	0.168	2.161	0.032	0.171
	Average.MS	0.342	6.6	<.001	0.468
	Average.T	0.367	6.15	<.001	0.443
	Average.P	0.136	2.463	0.015	0.194
2	Average.EE	0.139	1.966	0.051	0.156
	Average.FC	0.156	2.468	0.015	0.195
	Average.HM	0.13	1.87	0.063	0.149
	Average.T	0.232	3.542	<.001	0.274
	Average.P	0.016	0.294	0.769	0.024
3	Average.EE	0.107	1.546	0.124	0.124
	Average.FC	0.114	1.812	0.072	0.145
	Average.HM	0.066	0.931	0.353	0.075
	Average.P	0.006	0.11	0.912	0.009

4.5 Discussion

This study found that the intention of professors and lecturers to use data analytics to evaluate students, through the UTAUT2 model was greatly influenced by performance expectations, management support, and trust. Based on our suggestion, the results we got by adding management support, trust, and privacy factors to enhance

Table 12. Hypotheses testing results summary

Hypotheses	Beta	Sig.	Hypotheses Status
H1. Performance expectancy has a positive effect on the intention to use data analytics.	0.514	<.001	Supported
H2. Effort expectancy has a positive effect on the intention to use data analytics.	0.066	0.43	Not Supported
H3. Social influence has a positive effect on the intention to use data analytics.	0.079	0.31	Not Supported
H4. Facilitating conditions have a positive effect on the intention to use data analytics.	0.092	0.19	Not Supported
H5. Hedonic motivation has a positive effect on the intention to use data analytics.	0.009	0.92	Not Supported
H6. Management support has a positive effect on the intention to use data analytics.	0.241	<.001	Supported
H7. Trust has a positive effect on the intention to use data analytics.	0.232	<.001	Supported
H8. Privacy has a positive effect on the intention to use data analytics.	-0.01	0.92	Not Supported

the prediction power of the UTAUT2 model are perfect. Compared to the UTAUT2 basic model, which explains 58% of behavior intention variance, the UTAUT2 with extension model explains 66%. As a result, the explanatory power of the model has increased. Including management support, trust, and privacy will provide a better understanding of the determinants of using data analytics to evaluate students.

As mentioned earlier, professors' and lecturers' intentions to use data analytics applications were significantly influenced by their performance expectations in higher education institutions in Qatar. The use of information technology in education was shown to be directly related to performance expectations and behavioral intentions in some studies (Ain, Kaur, & Waheed, 2016) in the context of LMS, and (Sumak, Polančič, & Heričko, 2010) in the context of Virtual Learning Environment adoption. Therefore, the usefulness of the data analytics application in evaluating students explains 51.4% of its application.

The study supports the hypothesis that management support has a significant influence on the determinant of intention to use data analytics to evaluate higher education students. Management support explains 24.1% of the variance of intention. This is supported by other studies which concluded similar results. In a study conducted in Saudi Arabia related to data analytics, it was found that management support is considered to be a barrier to adopting big data analytics (Almobark, 2021). Another study has found that management support has a significant impact on technology adoption (Hsu, Liu, Tsou, & Chen, 2018).

According to research, professors' and lecturers' trust increases their intention to evaluate students using data analytics. trust is a significant determinant of the willingness to use data analytics in the evaluation process of higher education students. As mentioned earlier, trust is explaining 23.2% of the variance in the professors' and lecturer intention. Educators believe that the reliability and strength of the application of data analytics have a significant effect on their intention to use data analytics to evaluate students. This is supported by other studies which concluded similar results in the context of the use of mobile banking (Kwateng, Atiemo, & Appiah, 2018). Moreover, there is another study in the context of trust in storage data, it was concluded that trust has a significant impact on the intention (Alazzam, et al., 2016). Moreover, it has been found that trust plays a significant role in explaining the intention to adopt e-learning systems in Qatar (El-Masri & Tarhini, 2017).

Meanwhile, there are some factors found to have no significance on the intention of professors and lecturers to use data analytics to evaluate students. Some of the factors are from the original UTAUT2 theory, which are Effort expectancy, Hedonic motivation, Social Influence, and Facilitating conditions. The other variable was added based on the literature review which is privacy.

For hypothesis two, the results did not support effort expectation and its influence on intention. The reason for this may be the fact that professors and lecturers place more emphasis on the usefulness and trustworthiness of data analytics applications. This finding is consistent with previous studies, such as those (Bellaaj & Albugami, 2014). According to their study, there is no significant relationship between effort expectancy and behavioral intention when they are investigating the use of internet banking. On the other hand, there is a study which was conducted in a comparison between Qatar and USA found that effort expectation has significantly affected the intention in Qatar but not in the USA. (El-Masri & Tarhini, 2017). This concludes that geographic location and different cultures have influenced the result.

Hypothesized relationship between facilitating conditions and the intention was not supported. The reason could be since the universities will provide all the necessary resources and professors and lecturers will use data analytics to evaluate students, the facilitating conditions do not significantly affect the intention. Another reason could be that effort expectancy has been shown to have a significant effect on facilitating conditions. This is because the effect of facilitating conditions is captured by effort expectancy (Venkatesh, Morris, Davis, & Davis, 2003). Notably, this result was consistent with the result of the effort expectancy, which also failed to support it. (Jessica, et al., 2019) found no significant relationship between facilitating conditions and students' behavioral intentions toward utilizing LMS in the teaching process. According to the results of this study regarding facilitating conditions, the results were different from those of other studies using UTAUT2 for guidance, including (Tseng, Lin, Wang, & Liu, 2022) in the context of teachers' intention to adopt massive open online courses

Behavioral intention and hedonic motivation are hypothesized to have a significant correlation. However, in this study, the relation was not significant. As a result, professors and lecturers do not enjoy using data analytics to evaluate students. It is possible that this is due to the nature of the task. Data analytics is used to evaluate students in a utilitarian manner, as opposed to a hedonistic manner. In addition, some studies reported similar findings and argued that hedonic motivation didn't play a significant role in influencing the intention to adopt technology in education (AbuGharrah & Aljaafreh, 2021). The results of this study regarding hedonic motivation were found to be different from those of other studies using UTAUT2 as a base model, such as (Nikolopoulou, Gialamas, & Lavidas, 2020) in the context of teachers' intention to use mobile in education.

The hypothesized relationship between social influence and intention was not supported as well. The social influence construct was rejected during validation. There may be a reason for this since effort expectancy has been shown to have a significant effect on social influence. This is because the social influence construct is affected by effort expectancy (Venkatesh, 2003). Although this result was consistent with the effort expectation result in this study. It is noteworthy that this result was consistent with (Alalwan, Dwivedi, & Rana, 2017) who also failed to support social influence, they found no significant relationship between social influence and behavioral intentions toward the adoption of mobile banking. This study's results regarding social influence in the education domain were found to be different from other studies that used UTAUT2 as a guiding model, such as (Meyliana, et al., 2020).

A significant correlation is hypothesized between intention and privacy. According to this study, there was no significant correlation between the two variables. As a result, professors and lecturers do not have to worry about data privacy before using it for analytics to evaluate students. Educators may not be required to protect the privacy of student data as part of their duties. Furthermore, some studies argued that privacy did not play an effective role in influencing intentions in the domain of artificial intelligence (Guede & Antonovica, 2022). Contrary to the previous studies using UTAUT2 as a base model (Weinhard, Hauser, & Thiesse, 2017), the privacy construct had a significant impact on the intention in the domain of Adoption of Pervasive Retail Systems.

Theoretical Implications

Studying the most significant factors influencing higher education professors' and lecturers' intentions to use data analytics to evaluate students in Qatar, the current study contributes significantly to existing knowledge about the acceptance of data analytics in Qatari education. This study represents a worthwhile initiative because it investigates an area that has not been well evaluated in Qatari education. By emphasizing the use of data analytics for student evaluation, the research contributed significantly to the knowledge and literature in Qatar. It also calls for further investigation by examining other relevant factors using advanced statistical analysis methods.

The conceptual model is based on UTAUT2, which describes technology acceptance from the users. Perspective. By initiating the construction of a conceptual model based on a theoretical foundation appropriate to the context of education, this study constitutes a substantial contribution to understanding educators' intentions toward data analytics. Furthermore, this study is capable of capturing the most significant aspects that determine customer intentions. A noteworthy fact is that Venkatesh empirically tested the validity of UTAUT2 to explain mobile Internet services in Hong Kong, which is a developed Asian country. In this regard, this study contributes to the advancement of the application of UTAUT2 by examining another technology, namely data analytics. It does so in a different context, that of education in a developing country such as Qatar.

Besides the constructs Venkatesh proposed in UTAUT2, this study includes trust, management support, and privacy as additions to the original UTAUT2. Thus, UTAUT2's theoretical horizon has been significantly expanded as a result of this contribution.

Managerial Implications

In terms of practicality, statistics indicate that effort expectancy, management support, and trust play an influential role. As a result, universities should emphasize aspects related to these factors in their efforts to motivate their professors and lecturers to use data analytics to make decisions. As mentioned earlier, this study provided clues for Qatari universities about the importance of trust. Consequently, universities should ensure that data analytics applications are capable of evaluating students. The right tools must be used in conjunction with the right data. Management should ensure the integrity and availability of the data. Additionally, the necessary data should be readily available for educators to overcome challenges promptly.

According to the literature review, management support is a significant factor when it comes to utilizing data analytics in an educational setting. Previous research has also confirmed that management support is critical for the successful adoption of technology. University management should help professors, lecturers, instructors, and teaching assistants understand the factors necessary for the successful implementation of data analytics applications. Managers at educational institutions should consider all the factors in this study that improve the acceptance of data analytics and its use. The effort associated with evaluating students using data analytics needs to be considered. An environment that facilitates decision-making based on data analytics, and a rewarding system to support those who use data analytics to take decisions. This will not only improve educators' intentions toward data analytics but also improve students' acceptance and support for decisions made based on data analytics.

CHAPTER FIVE: FUTURE WORKS AND CONCLUSIONS

As we conclude all previous chapters in this chapter, we will provide a comprehensive overview of how professors and lecturers intend to use data analytics to evaluate students in higher education in Qatar. The results of the study will be presented along with possible managerial implications and recommendations for educators, and management of higher education institutions in Qatar. In addition, it will describe the limitations of the current study and the future works that we recommend for researchers to examine.

Future Works and Limitations

Although this study contributes to our understanding of the acceptance and use of technology in education, some improvements should be made in the future. For example, further research may examine the effect of moderate variables such as the respondent major. The major may affect the perception of the response toward technology adoption. For example, the medical field may vary from technology field professors. The variables in the proposed theoretical model explained a significant amount of the variance in educators' intentions to use data analytics, with R2 = 0.664, but this could be improved by using major as the moderator.

Additionally, this study is the first one, to our knowledge, that has looked at the adoption of data analytics in higher education in Qatar using the modified UTAUT2 model. The model proposed here should be tested in other countries and with other technologies in the future to verify its strength. In light of this, future research should focus on universities in other countries for the purpose of conducting crosscomparisons. Finally, Management support can be examined on the other construct since it's an important factor and can have a significant influence on other constructs.

Mainly there are two limitations, first, the number of respondents to the survey was lower than expected which reflects respondents' cautions regarding emails with links and university security policies. The questionnaire was distributed through department heads, but this strategy was insufficient to encourage a higher response rate.

Secondly, some of the respondents had a limited understanding of Big Data concepts and how they could be applied to education. Even though there is a clear explanation of big data and analytics in the consent, some of the professors and lecturers do not understand how it can be beneficial in the education sector.

Conclusion

Through our study, we aimed to investigate the determinants of the intention of professors and lecturers in higher education institutions in Qatar. It was done by combining the UTAUT2 model with privacy, management support, and trust. In explaining the acceptance and use of technology, the UTUAT2 model is chosen to consider the particularities of customer use contexts. Management support, trust, and privacy constructs have been added to UTUAT2 to account for the assumption that these factors are related to technology adoption in the education sector.

We found that the proposed model in this study has stronger explanatory power than the original UTAUT2 model. The findings reveal that performance expectations, trust, and management support are significant determinants of the intention of professors and lecturers in higher education institutions in Qatar to utilize data analytics in evaluating students. We provide more predictive power to the existing UTAUT2 model by adding privacy, management support, and trust to the model in our proposed framework.

References

AbuGharrah, A., & Aljaafreh, A. (2021). WHY STUDENTS USE SOCIAL NETWORKS FOR EDUCATION: EXTENSION OF UTAUT2. *Journal of Technology and Science Education*, 53-66.

Abu-Shanab, E., & Knight, M. (2009). THE TECHNOLOGY ACCEPTANCE MODEL: THE EFFECT OF AGREEABILITY. *DIAS Technology Review*, 1-22.

Agasisti, T., & J. Bowers, A. (2017). Data Analytics and Decision-Making in Education: Towards the Educational Data Scientist as a Key Actor in Schools and Higher Education Institutions. 1-23.

Agasisti, T., & Bowers, A. (2017). Data Analytics and Decision-Making in Education: Towards the Educational Data Scientist as a Key Actor in Schools and Higher Education Institutions. 1-23.

Ain, N., Kaur, K., & Waheed, M. (2016). The influence of learning value on learning management system use: An extension of UTAUT2. *SAGA*, 1306-1321.

Alalwan, A., Dwivedi, Y., & Rana, N. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, 99-111.

Alazzam, M., Basari, A., Sibghatullah, A., Ibrahim, Y., Ramli , M., & Naim, M. (2016). Trust in stored data in EHRs acceptance of medical staff: Using UTAUT2. *International Journal of Applied Engineering*, 2736-2748.

Almobark, B. A. (2021). Identifying Barriers to Big Data Analytics: Design-Reality Gap Analysis in Saudi Higher Education. *International Journal of Computer Science and Network Security*, 261-266.

Alsheikh, N. A. (2019). DEVELOPING AN INTEGRATED FRAMEWORK TO

UTILIZE BIG DATA FOR HIGHER EDUCATION INSTITUTIONS IN SAUDI ARABIA. *International Journal of Computer Science & Information Technology*, 31-42.

Ang, L.-M. (2017). Big Educational Data & Analytics: Survey, Architecture and Challenges. *IEEE Access*.

Arain, A., Hussain, Z., Rizvi, W., & Vighio, M. (2019). Extending UTAUT2 toward acceptance of mobile learning in the context of higher education. *Springer*, 659-673.

ARMSTRONG, R. (1987). The midpoint on a five-point likert-type scale. *Perceptual and Motor Skills*, 359-362.

Bakkenes, I., Vermunt, J., & Wubbels, T. (2010). Teacher learning in the context of educational innovation: Learning activities and learning outcomes of experienced teachers. *Learning and Instruction 20 ()*, 533-548.

Bellaaj, M., & Albugami, M. (2014). THE CONTINUED USE OF INTERNET BANKING: COMBINING UTAUT2 THEORY AND SERVICE QUALITY MODEL. *Journal of Global Management Research*, 11-28.

Bhardwaj, B., Tiwari, S., Hazela, B., & Dhanda, N. (2019). Extension of Data Science Techniques in Education Prognosis. *IOSR Journal of Engineering*, 5-8.

bigdata-madesimple.com. (2019). *https://bigdata-madesimple.com/do-you-know-how-universities-and-colleges-use-big-data/*. Retrieved from bigdata-madesimple.com: https://bigdata-madesimple.com/do-you-know-how-universities-and-colleges-use-big-data/

Brown, S. A., & Venkatesh, V. (2005). Model of Adoption of Technology in Households: A Baseline Model Test and Extension Incorporating Household Life Cycle. *MIS Quarterly*, 399-426.

Butler, B., & Gray, P. (2006). Reliability, Mindfulness, and Information Systems. *MIS Quarterly*, 221-224.

Cannistrà, M. (2022). Data analytics in education: are schools on the long and winding road? *Qualitative Research in Accounting & Management*, 286-304.

Cope, B., & Kalantzis, M. (2016). Big Data Comes to School: Implications for Learning, Assessment, and Research. *AERA Open*, 1–19.

Dede, C. (2016). Next Steps for "Big Data" In Education: Utilizing Data-Intensive Research. *Educational Technology*, 37-42.

edarabia.com. (2021). *List of best Qatar univerisites*. Retrieved from edarabia.com: https://www.edarabia.com/universities/qatar/

edu.gov.qa. (2022). Retrieved from edu.gov.qa: https://www.edu.gov.qa/en/Pages/higheredudefault.aspx?ItemID=58

El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). *Springer*, 743-763.

Everson, J., Lee, S.-Y., & Friedma, C. (2022). Reliability and validity of the American Hospital Association's national longitudinal survey of health information technology adoption. *Med Inform Assoc*, 257-263.

Everson, J., Lee, S.-Y., & Friedman, C. P. (2022). Reliability and validity of the American Hospital Association's national longitudinal survey of health information technology adoption. *Everson*, e257-e263.

Foster, C., & Francis, P. (2019). A systematic review on the deployment and effectiveness of data analytics in higher education to improve student outcomes. *Taylor and francis online*, 1-20.

Gagliardi, J., Parnell, A., & Carpent, J. (2018). The Analytics Revolution in Higher

Education. *The Magazine of Higher Learning*.

Guede, J., & Antonovica, A. (2022). Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. *Frontiers in Psychology*, 1-20.

Heijden, H. v. (2004). User Acceptance of Hedonic Information Systems. *MIS Quarterly*, 695-704.

Hsu, H.-Y., Liu, F.-H., Tsou, H.-T., & Chen, L.-J. (2018). Openness of technology adoption, top management support and service innovation: a social innovation perspective. *Journal of Business & Industrial Marketing*.

Jabor, k. (2011). Faculty Online Technology Adoption: The Role of Management Support and Organizational Climate. *ACADEMIA*.

Jessica, Jovian, Petrus, S., Santoso, S., Widjaja, H., & Meyliana. (2019). The Enhancement of Learning Management System in Teaching Learning Process with the UTAUT2 and Trust Model. *International Conference on Informatics and Computational Sciences*.

Kharade, B., & Wagh, K. (2016). Data Analytics in Educational Management System. *International Journal of Computer Applications*, 22-25.

Kwateng, K., Atiemo, K., & Appiah, C. (2018). Acceptance and use of mobile banking: an application of UTAUT2. *Journal of Enterprise Information Management*.

Larcker, D., & Fornell, C. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 39-50.

Limayem, M., Hirt, S. G., & Cheung, C. M. (2007). How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance1. *MIS Quarterly*, 705-737.

Manohar, A., Gupta, P., & Priyanka, V. (2016). Utilizing Big Data Analytics to Improve Education.

Meyliana, Widjaja, H., Santoso, S., Surjandy, Fernando, E., & Condrobimo, A. (2020). Improving the Quality of Learning Management System (LMS) based on Student Perspectives Using UTAUT2 and Trust Model. *International Conference on Informatics and Computational Sciences*.

Mishra, R. (2019). Usage of Data Analytics and Artificial Intelligence in Ensuring Quality Assurance at Higher Education Institutions. *IEEE*.

Muhammad, Tasmin, & Aziati, N. (2019). Sustainable Competitive Advantage of Big Data Analytics in Higher Education Sector. *Journal of Physics: Conference Series*, 1-6.

Najdawi, A., & Stanley, J. S. (2021). Exploring the Role of Big Data Analytics in Reinnovating Higher Education: The Case of UAE. *International Conference on Innovative Practices in Technology and Management*.

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2020). Acceptance of mobile phone by university students for their studies: an investigation applying UTAUT2 model. *Springer*, 4140-4155.

Pavlicevic, Seres, & Tumbas. (2018). DIGITAL TRANSFORMATION OF HIGHER EDUCATION: COMPETING ON ANALYTICS. *Proceedings of INTED2018 Conference*, 9491-9497.

Prinsloo, P. (2019). A social cartography of analytics in education as performative politics. *British Journal of Educational Technology*, 1-14.

Qf.org.qa. (2022). *qf.org.qa*. Retrieved from Qatar Foundation: https://www.qf.org.qa/about/profile/her-highness-sheikha-moza-bint-nasser

Rajeswari, S., & Lawrance, R. (2016). Classification model To Predict the Learners'

Academic Performance using Big Data.

Ray, S., & Saeed, M. (2018). *Applications of Educational Data Mining and Learning Analytics Tools in Handling Big Data in Higher Education.* Springer.

Roca, J., Chiu, C.-M., & Martı´nez, F. (2006). Understanding e-learning continuance intention: An extension of the Technology Acceptance Model. *Int. J. Human-Computer Studies*, 683-700.

Rosli, M., Saleh, N., Alshammari, S., Ibrahim, M., Atan, A., & Atan, N. (2021). Improving Questionnaire Reliability using Construct Reliability for Researches in Educational Technology. *Interactive Mobile Technologies*, 109-116.

Segura, S., Alexander, & Thiesse, F. (2015). Extending UTAUT2 to Explore Pervasive Information Systems. *Association for Information Systems*, 1-18.

Shidaganti, G., & Prakash. (2021). A Comprehensive Framework for Big Data Analytics in Education. *International Journal of Advanced Computer Science and Applications*, 218-227.

Smith, J., Milberg, S., & Burke, S. (1996). Information Privacy: Measuring Individuals' Concerns About Organizational Practices. *MISQ uarterly*, 167-196.

Straub, D., Boudreau, M.-C., & Gefen, D. (2004). Validation Guidelines for IS Positivist Research. *Communications of the Association for Information Systems*, 380- 427.

Sumak, B., Polančič, G., & Heričko, M. (2010). An Empirical Study of Virtual Learning Environment Adoption Using UTAUT. *IEEE Xplore*, 17-22.

Taherdoost, H. (2020). Sampling Methods in Research Methodology; How to Choose a Sampling Technique for Research. *International Journal of Academic Research in Management (IJARM)*, 18-27.

Taherdoost, H. (2020). Validity and Reliability of the Research Instrument; How to

Test the Validation of a Questionnaire/Survey in a Research. *International Journal of Academic Research in Management*, 28-29.

Tamilmani, K., Rana, N., & Yogesh. (2020). Consumer Acceptance and Use of Information Technology: A Meta-Analytic Evaluation of UTAUT2. *Springer*.

topuniversities.com. (2022). *topuniversities.com*. Retrieved from https://www.topuniversities.com/where-to-study/asia/qatar/guide

Tseng, T., Lin, S., Wang, Y.-S., & Liu, H.-X. (2022). Investigating teachers' adoption of MOOCs: the perspective of UTAUT2. *Interactive Learning Environments*, 635-650.

Undavia, J., Patel, S., & Patel, A. (2017). Future trends and scopes of Big Data analytics in the field of Education. *International Journal of Engineering and Technology*, 9-14.

Venkatesh, V. (2003). USER ACCEPTANCE OF INFORMATION TECHNOLOGY: TOWARD A UNIFIED VIEW1. *MIS Quarterly*, 425-478.

Venkatesh, V. (2012). Consumer Acceptance And Use Of Information Technology Extending The Unified Theory Of Acceptance And Use Of Technology. *MIS Quarterly*, 157-178.

Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). USER ACCEPTANCE OF INFORMATION TECHNOLOGY: TOWARD A UNIFIED VIEW1. *MIS Quarterly*, 425-478.

Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer Acceptance And Use Of Information Technology Extending The Unified Theory Of Acceptance And Use Of Technology. *MIS Quarterly*, 157-178.

Vieira, C. (2018). Visual Learning Analytics of Educational Data: A Systematic Literature Review and Research Agenda. *Computers & Education*.

Wang, W.-T., & Wang, C.-C. (2009). An empirical study of instructor adoption of web-based learning systems. *elsevier*, 761–774.

Weinhard, A., Hauser, M., & Thiesse, F. (2017). Explaining Adoption of Pervasive Retail Systems with a Model based on UTAUT2 and the Extended Privacy Calculus. *Twenty First Pacific Asia Conference on Information Systems, Langkawi*.

www.govtech.com. (2016). *7 Ways Smart Universities Use Data and Analytics*. Retrieved from https://www.govtech.com/education/7-Ways-Smart-Universities-Use-Data-and-Analytics.html: https://www.govtech.com/education/7-Ways-Smart-Universities-Use-Data-and-Analytics.html

Xu , H., & Gupta, S. (2009). The effects of privacy concerns and personal innovativeness on potential and experienced customers' adoption of location-based services. *Springer*, 137-149.

Xu, H., & Gupta, S. (2009). The effects of privacy concerns and personal innovativeness on potential and experienced customers' adoption of location-based services. *Springer*, 137-149.

Appendix 1. Survey Questions in English Language

Survey Question	Code	Construct	Source
1- I find using data analytics is useful in evaluating students	PE1	Performance Expectancy	Venkatesh et al. (2003)
2- Using data analytics allows me to better assess students overall performance	PE2		
3- Using data analytics increases my evaluation accuracy	PE3		
4- Using data analytics increases my chances of being a better teacher	PE4		
5- I find applying data analytics is clear and understandable	EE1	Effort Expectancy	
6- It is easy for me to become skillful at using data analytics	EE2		
7- I find data analytics easy to use	EE3		
8- Learning to utilize data analytics is easy for me	EE4		
9- People who influence my career decisions think that I should use data analytics.	SI1	Social Influence	
10- People who are important to me think that I should use data analytics	SI2		
11- Students are helpful in the support of using data analytics	SI3		
12- I have the necessary tools and resources to utilize the data for analytics purposes	FC1	Facilitating Conditions	
13- I have the necessary knowledge to use data analytics	FC2		
14- I use systems that are compatible and support data analytics	FC3		
15- I can easily access the required data for analysis	FC4		
16- I can get help from expert data analysts in the university	FC5		
17- I can get any software I need for data analytics	FC6		

18- Using data analytics is fun for me	HM1	Hedonic Motivations	Venkatesh, Thong, & Xu, 2012
19- Using data analytics is entertaining for me	HM2		
20- Using data analytics satisfies my needs	HM3		
21- My university supports using data analytics	MS1	Management Support	Jabor, 2011
22- My university encourages faculty to use data analytics	MS2		
23- My university has initiated a rewarding system for using data analytics to improve performance	MS3		
24- I can trust the result I get from data analytics.	R1	Trust	Rosli, et al., 2021
25- The data collected from students is reliable and useful	R2		
26- I can find the needed data to overcome any weakness	R3		
27- Only the right people have access to the data	P1	Privacy	Xu & Gupta, 2009
28- I use anonymous data for the analysis	P2		
29- All data are safe and secure	P3		
30- Faculty members trust the university to data integrity	P4		
31- I will always try to use data analytics for improvements	I1	Intention	Roca, Chiu, & Martı´nez, 2006
32- I intend to use data analytics in the future	I2		
33- I will recommend using data analytics for my colleagues	I3		