Jahangirnagar University Journal of Business Research (JUJBR), Vol. 23, June, 2023
ISSN 1681-9748

DOI: 10.53461/jujbr.v23i.3

JUJBR

A Study on the Students' Adoption Intention Behavior Towards Online Classes During COVID 19 Pandemic Applying UTAUT Model Extensions

Sabrin Sultana*
Mohammad Abdullah Mahfuz**

Abstract: *The prime drive of this paper is to examine the factors to define students' intention to the acceptance of online classes in Bangladesh throughout COVID19 pandemic. The paper follows qualitative research for identifying research problems and quantitative research for collecting primary data. Data have been collected through questionnaire survey and analyzed by Structure Equation Modeling by Partial Least Squared (PLS). This study is grounded on Unified Theory of Acceptance and Use of Technology (UTAUT) model invented by Venkatesh, Morris, Davis, and Davis (2003) along with six additional variables that extended the model for this study. The results revealed that Performance Expectancy (PE), Social Influence (SI), Self-Management of Learning (SML), Technology Anxiety (TA) and Complexity (COM) have a substantial impact on Students' Behavioral Intention (BI) towards the adoption of online classes. Alternatively, Effort Expectancy (EE), Facilitating Condition (FC), Perceived Cost (PC), Relative Advantage (RA), and Resistance to Change (RTC) were found insignificant relationship. This study is conducted in a certain period. The different outcomes could be found in another time frame. The result of this study will provide the idea about factors influencing adoption of online classes which may be referred for choosing future teaching-learning techniques in compare with face-to-face learning. Taking online classes may save time, energy, money of both students and teachers along with institutions which become important concern in near future.*

Keywords: *Online Class, UTAUT, COVID 19, Behavioral Intention (BI).*

1. Introduction

Virus named COVID-19 was mainly initiated in Wuhan, a city of China in late December, 2019. The elaboration of COVID-19 is Corona Virus Disease 2019. Since the virus is highly contagious, it has spread in the whole Wuhan dramatically. It did not take much time to outbreak all over the world. WHO (World Health Organization) declared COVID-19 outburst as an epidemic on 11

* Assistant Professor, Department of Marketing Jagannath University, Dhaka-1100
E-mail: sabrindu8@gmail.com

** Associate Professor, Department of Marketing Jagannath University, Dhaka-1100
E-mail: mahfuz2020.jnu@gmail.com

March 2020. No medicine or vaccine was available to prevent this virus that time. Countries all over the world started to follow the WHO's guidelines of social distancing and locking down the country or state. Most of the countries have suspended educational activities to maintain social distancing for mitigating outbreak of the Corona Virus. COVID-19 affected the education sector of whole world unprecedentedly (Hamid, 2020). This pandemic and lockdown disrupted and affected the education system worldwide (Vu et al., 2020) with comprehensive outcomes on learners, teachers, and educational organizations (Mailizar et al., 2020). The education system and classroom teaching method has been replaced by online platforms such as ZOOM, Google Classroom, Facebook Room, Google Meet, etc. Educational institutions were confronting a challenge to adapt this transformation and are striving to choose the right technologies and methods to educate along with students (Rashid & Yadav, 2020). In Bangladesh, the first COVID-19 infected case was diagnosed on March 8, 2020. Henceforth, Corona Virus has spread in Bangladesh geometrically. On March 16, 2020, honorable Education Minister Dr. Dipu Moni declared all the educational institutions would remain closed till March 3, 2020 and the closing period was further extended to December 31, 2021 phase by phase. And the suspension has extended in several phases. Bangladesh has gone through several phases of lockdown from the 26th of March 2020. But now COVID 19 vaccines are invented by various companies such as Mordana, Sinovac, Covieshield, Pfizer etc. Government of Bangladesh has begun to vaccinate people and launch free vaccination program to mass people prioritizing college and university students. After long time closure of educational institutions due to this pandemic, in February, 2022 education ministry of Bangladesh announced the reopening of schools, colleges and universities by phase.

2. Statement of the Problem

With this uncontrollable situation around the world, some are confused about the adoption of online-based learning which will be continuing in post-pandemic, and its future impact on overall education sector. Since educational institutions in Bangladesh are closed for more than eleven months, students' educational activities have significantly been hampered. UGC (University Grant Commission) and different public and private tertiary educational institutions find a different way to recommence educational activities and that is conducting classes using a different online- based platform such as ZOOM, Google Meet, Classroom, Microsoft Teams, and so on. The online class has become new method of learning for most of the students in Bangladesh. Many of our students are not aware enough about these platforms. A large number of students don't have the required devices to attend online classes. There is also a significant issue with the cost of attending online classes. However, adoption of a new path takes time and it will be a time- consuming process.

Justification

This research will contribute to understand students' behavioral intention and key factors that determine intention towards taking up online classes in pandemic circumstances. A different study shows that student's contact with online classes is pleasant with how they are attached with learning. However, studies also indicate that the learners' intention is influenced by various factors (Shrestha et al. 2019; Salloum et al. 2019). Influencing factors such as age, gender, prior knowledge of computer literacy, and the learning ways of individuals are important to technology acceptance by students. There exist various literatures practicing the theories of "technology acceptance" to study students' intentions (Pérez-Pérez et al. 2020). Unified Theory of Acceptance and Use of Technology (UTAUT) model is one of them. Many studies showed the relationship between influencing factors with behavioral intent of university students in various context like in USA, UK, Australia, Bangladesh using TAM model (Alshurideh, 2019; Farahat, 2012; Alshurideh, 2012; Sumak, 2011; Al-Kurdi et al. 2020; Biswas, B. et al. 2020; Kennedy et al. 2006; Kennedy et al. 2008; Kvavik, 2005; Salaway et al. 2008).

This study uses four original constructs of UTAUT model. The model was extended by another six constructs taken from various literatures. The best of our knowledge, there were few research conducted in Bangladesh containing all those factors and population groups covered in this research. The study is done through a previous research gap specifically population group. This study was conducted on both university and college students. An extension of the UTAUT model is used. The underpinning model was developed 2003 (Venkatesh, et al. 2003). There is an integration of perceived cost (Burnham et al.2003), self–management of learning, complexity and relative advantage (Al-Adwan A.S. et al. 2018), resistance to change and technology anxiety (Deng, Z., Mo, X., and Liu, S.2013).

Research Purpose and Objectives

The major idea of this paper is to examine the factors that determine students' behavioral intention towards the adoption of online classes in Bangladesh during COVID19 pandemic.

3. Literature Review

Online Class

The online class is a method of conducting classes through different online platforms such as Zoom, Google classroom, Google Meet, Facebook room, and so on. The basic difference between regular classroom classes and online classes is the medium of conducting classes. In regular classroom classes, students and teachers interact with each other physically. In online classes, students and teachers almost do the same activities through using internet. Here, the core missing issue is physical interaction. Teachers and students interact virtually rather than physically. Nowadays, the online class has become a buzzword due to the COVID-19 pandemic. The online class has been taking worldwide because most of the educational institutions are closed due to the pandemic. As mentioned earlier in this article, the education ministry of Bangladesh also declared the closure of all the educational institutions of the country. So, online classes have become the only way to run educational activities in Bangladesh.

UTAUT (Unified Theory of Acceptance and Use of Technology)

Numerous hypothetical models have been projected encouraging the comprehension of elements affecting the acceptance of information technologies (Davis, 1989; Chau, 1996; Venkatesh and Davis 2000). Amongst them, Technology Acceptance Model (TAM) is the best potent and robust in clarifying IT/IS context. The vital drive behind TAM was giving evidence to find the effect of external variables on internal intentions affected by beliefs and attitudes. Usefulness along with ease of use is consistently essential indicators in TAM. Perceived usefulness can be considered as the degree to which a person relies on using a program will enhance the competence of his or her knowledge. Perceived ease of use denotes the scope by which a person trusts a method causing low mental stresses (Davis F.D. et al. 1989). At first TAM model was made to analyze IT/IS adoption in business organizations. The model's rationality for anticipating common individual recognition, particularly now higher education, should be investigated.

Venkatesh, et al. (2003) created the Unified Theory of Acceptance and Use of Technology (UTAUT) model solving past TAM related confusions. In the UTAUT model, performance expectancy along with effort expectancy was utilized linking the constructs of perceived usefulness and ease of use in the first TAM study. Regardless of, the UTAUT model sets the Effort Expectancy construct can be vast in deciding user acceptance of information technology. Ease of use may become non-noteworthy over broadened and supported utilization. Therefore, perceived usefulness can be trusted to be more notable just in the opening phases of developing another new technology which may positively affect the perceived usefulness of technology. As well, UTAUT model try to illuminate how person dissimilarities affect the use of technology. More precisely, the association between ease of use, perceived usefulness, and intention of using can be moderated by age, gender, and experience. This model calculated about 70% of the variance in usage intention, better than either of the TAM studies alone. Applying UTAUT model, along with other constructs, on the primary and secondary level students explained variance by 51.3 percent influencing behavioral intention on online blogs (Toh, C. H.2008).

The construction of the model then applied as a tactic for assessing the acceptance of emerging technologies measuring the chances of success using new information technology (Venkatesh et al. 2003). In virtual learning settings like Moodle and interactive whiteboards (Hsu and Lu 2004; Althunibat, 2015; Sumak et al. 2010; Tosuntas et al. 2015), UTAUT has been approached to deal with the behavioral intention of learners to remain using the platform (Chiu and Wang, 2008; Mohammadyari and Singh, 2015; Wang and Shih, 2009). The outcomes of one study were observed and directed that e-learning is more appealing and sustaining the concern and interest of students (Pardamean and Susanto, 2012). They have hopeful opinions on the aptness of e-learning platforms for cooperation and knowledge sharing among groups. Various previous researches encompassed with other variables along with the UTAUT constructs, but the Perceived Cost (PC) was found as an important element. Examining the behavioral intention accepting online classes in this research; "usage behavior" of UTAUT was not included in the projected model. Furthermore, four moderators (i.e., gender, age, voluntariness, and experience) were designed to ascertain issues with various backgrounds in different institutions; however, all college and university students of similar ages were sampled in this study. Moreover, research using UTAUT led in Indonesia identified that age and gender had not any vital effect on performance expectancy, effort expectancy, social influence (Pardamean and Susanto, 2012). In addition, researchers suggested that demographic features like age, gender etc. did not support a moderating impact on virtual learning systems among colleges and universities (Marchewka and Kostiwa, 2007). Consequently, the four moderating variables in the UTAUT model had not been applied in this research. In brief, this study investigates ten independent variables as well as one dependent variable. They are directly predicated on the intention to adopt online classes, including Social Influence, Performance Expectancy, Facilitating Condition, Effort Expectancy, Cost, Technology Anxiety, Self-Management Learning, Relative Advantages, Complexity, Resistance to Change, and Behavioral Intention. All these dependent and independent variables will be discussed below along with relevant sources.

Behavioral Intention towards the Adoption of Online Classes

Behavioral intention denotes that it is the degree to which an individual's awareness about what to execute or not to carry out in particular forthcoming behavior (Davis et al. 1989). Some researchers define behavioral intention as the agent's subjective likelihood whether he or she will perform the behavior (Fishbein & Ajzen, 1975). The two more specific definitions of behavioral intention contain the concept of Davis et al. (1989) and the concept of Ajzen (1991).

A confused decision depicts extremely low behavioral intention whereas an extremely high behavioral intention is taking decision on actions. The moderate behavioral intention denotes the scenario of being unsure about whether to execute the action or not. On the other hand, the behavioral intention in the sense of Ajzen (1991) and even more the goal intention in the sense of Gollwitzer (1993) represent the determination of people whether they are ready to spend, given that they have settled to do so. In this framework, low intention means low effort and high intention means high effort. Hence, it means if students have great intention to adopt online classes, they must have a high effort to make adoption feasible.

However, some factors will determine whether students to embrace online classes or not. This study will examine which factors determine the intention of this adoption process. If students have a negative experience, their intention to adopt online classes will be negative and a positive experience will give them a positive response. But it can be seen that behavioral intention has an effect on the adoption of online classes.

Factors Determining Intention towards the Acceptance of Online Classes

In this research, ten different factors will be examined to identify which factors determine the behavioral intention towards the adoption of online classes. The proposed model contains these variables such as Perceived Cost (PC), Self-Management of Learning (SML), Social influence (SI), Facilitating Conditions (FC), Performance Expectancy (PE), Effort Expectancy (EE), Relative Advantage (RAD), Complexity (COM), Technological Anxiety (TA), Resistance to Change (RTC) and Behavioral Intention (BI).

Performance Expectancy can be termed as the extent to which a person relies on handling the system will assist him or her to develop the performance of a task or work (Venkatesh et al. 2003). Effort Expectancy is the degree of simplicity regarding operation of the system (Venkatesh et al. 2003). Facilitating Conditions denotes the level to which a person's trust on institutional and technical settings to maintain the system using (Morris et al. 2003).

Social influence denote as the degree to which an individual's observations about others' motivations who are critical to him or her for using the new system (Venkatesh, V., Morris, M. G., Davis, G. B. & Davis, and F. D.2003). Perceived Cost (PC) can be understood as the measure in which a parson believes using e-Services such as an m-banking is more expensive as than other modes (Luarn and Lin, 2005).

Self-Management of Learning (SML), Smith et al. (2003), can be termed as "the extent to which an individual become aware of self-discipline along with connecting autonomous learning". Relative Advantage is the notion to which the adoption of innovation is viewed as having greater benefits rather than other existing product (Kwon et al., 1987). Complexity refers to the degree to which a revolution is recognized as a service or product comparatively challenging to know and use (Rogers, 2005).

Technological Anxiety refers to the discomfort that arises when a person experiences apprehension and stress due to using new technology. Computer anxiety is the main predecessor of anxiety about technology (Heinssen et al.1987). Resistance to Change is defined as a comprehensive resistance to change resulting from the probable adverse consequences (Bhattacherjee and Hikmet 2007).

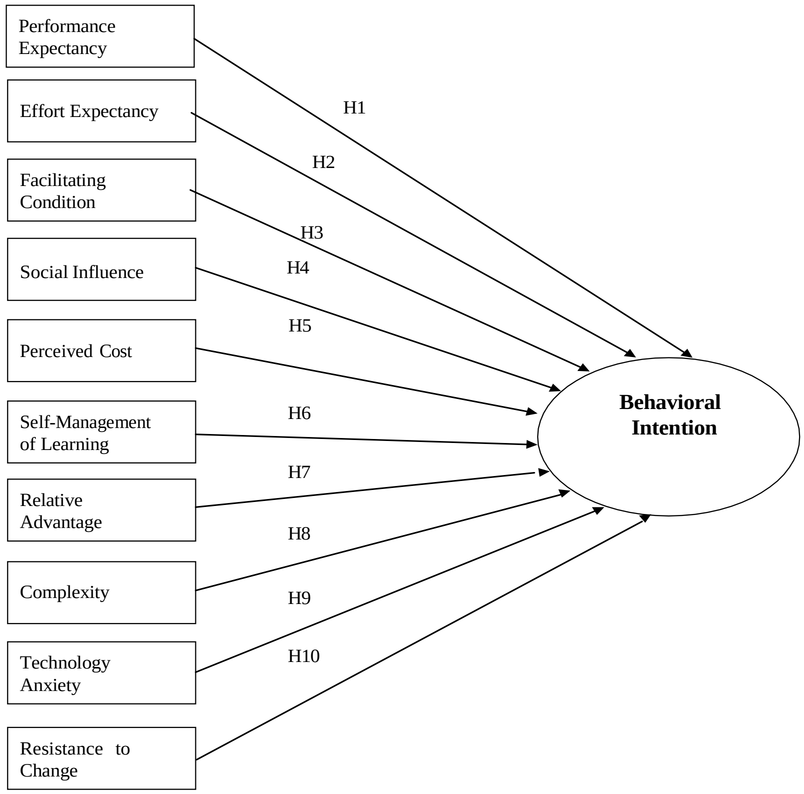

Figure 1: Proposed research model

4. Research Methodology

Research can be termed as logical and ordered attempt for investigating a specific dilemma with arranging a solution (Sekaran, 2000). There are three basic categories of research: qualitative, quantitative, and mixed methods research (Creswell, 2008; Gliner et al. 2003; Kothari, 2010; Cohen et al. 2007). This research is designed as a quantitative study, aiming to identify factors determining the students' behavioral intention to adopt online classes. Aliaga and Gunderson (2002) defined quantitative research can be defined as an analysis about a social problem; refer to some phenomena by gathering numerical data and are examined with mathematically structured methods. Among various quantitative research methods, survey research was applied to scrutinize the factors that determine students' behavioral intention. According to Fraenkel and Wallen (2006) "all survey has a major objective to illustrate the characteristics of the population".

Hypothesis Development

The hypothesis is an accurate, testable statement of what the researcher(s) forecasts about the outcome of the study. This generally comprises offering a probable association between the two variables: the dependent variable (what the research measures) and the independent variable (what the researcher changes).

The proposed research structure consists of ten independent variables and one dependent variable. Based on the impact of independent variables on the dependent variable, here some proposed hypotheses were developed.

***H1**: Performance Expectancy will have a significant positive influence on students' Behavioral Intention to adopt online classes.*

***H2**: Effort Expectancy will have a significant positive influence on students' Behavioral Intention to adopt online classes.*

***H3**: Facilitating Conditions will have a significant positive influence on students' Behavioral Intention to adopt online classes.*

***H4**: Social Influence will have a significant positive influence on students' Behavioral Intention to adopt online classes.*

***H5**: Perceived Cost will have a significant negative influence on students' Behavioral Intention to adopt online classes.*

***H6**: Self-Management of Learning will have a significant positive influence on students' Behavioral Intention to adopt online classes*

***H7**: Relative Advantage will have a significant positive influence on students' Behavioral Intention to adopt online classes.*

***H8**: Complexity will have a significant negative influence on students' Behavioral Intention to adopt online classes.*

***H9**: Technology Anxiety will have a significant negative influence on students' Behavioral Intention to adopt online classes.*

***H10**: Resistance to Change will have a significant negative influence on students' Behavioral Intention to adopt online classes.*

Data Collection

Data need to be gathered after the development of the research questions (Cavana et al. 2001). Data can be composed by means of either qualitative (example – focus groups) or quantitative (example – questionnaires) techniques. In this study, a structured questionnaire had been used to arrange primary data. Various research articles were studied to develop the literature which is used to support the research objective.

Sample and Sampling Procedure

Sample is a portion of the entire group that represents the population. Sampling is a way of choosing sample from the population. In this study, students of different Colleges and Universities in Bangladesh are population and the particular portion of the students from whom data were collected is sample.

Sample design

The convenience sampling technique was applied in this research. A non-probability sampling method like convenience sampling is applied where the sample is collected from a group of people that available to contact and cost effective (Eze et al. 2011). Non-probability sampling techniques are more reliable than others and may contribute to potentially valuable population knowledge (Cavana et al. 2001). In this study, peer students, acquaintances, and other convenience sources were used to collect data.

Sample Size

The sample size is a part of the population selected for surveys or experiments. The requirement of the sample is an integral part of any analytical analysis to draw inferences. The larger the sample sizes the more accurate representation of the population. A structured questionnaire was sent to 400 respondents through online. But usable data were collected from 370 respondents.

Data Collection Tools

A self-administered, quantitative, and structured questionnaire is developed for data collection and distributed to respondent through online. The questionnaire was developed by using google form. Google form link was distributed among the students of different universities and colleges in Bangladesh. The Structured questionnaire consisted of two sets. SET-A consists of demographic questions such as name, gender, age, occupation, etc. In the demographic section, there were open-ended and multiple-choice questions used. In SET-B, there are 11 constructs containing 37 items on 5 points Likert scale ranging from 1-Strongly Disagree to 5- Strongly Agree.

Data analysis

To carry out the descriptive analysis of this study and to observe the proposed research model, data were examined through IBM SPSS version 23. Smart-PLS (Version: 3) software was applied to deal with Partial Least Squares (PLS) method. Researchers opined that foremost advantage of PLS-SEM is that it permits the use of formative measures, which differ considerably from the reflective measures (Wong et al. 2013).

Demographic and other Information

The demographic profile of respondents (n=370) has been recorded below in Table-1. It shows that the majority of the respondent was in the age range 15-20 and all the respondents were in the age range 15 to 25. The table also reveals that 72.2% of respondents are male and 27.8% of respondents are female. However, most of the respondents are Under-graduate students which are 48.4% of the total respondents. 31.1% of respondents are HSC level students and 20.5% are post-graduation level students. There was no school-level student counted in this study.

Table-1: Demographic profile of the respondents

Aspects	**Frequency**	**Percentage (%)**
Age		
15-20	297	80.3
20-25	73	19.7
25-30	0	0
Above 30	0	0
Total	370	100.0

Aspects	Frequency	Percentage (%)
Gender		
Male	267	72.2
Female	103	27.8
Total	370	100.0
Education level		
Post-Graduate	76	20.5
Under-Graduate	179	48.4
HSC	115	31.1
Total	370	100.0

5. Model Assessment

Previous researchers suggested two steps analytical method of SEM or PLS, which are;

Step 1: Assessment of the measurement model.

Step 2: Assessment of the structural model Analysis of the Measurement Model.

Step 1: Assessment of the measurement model

PLS model is analyzing the measurement properties essentially to check item reliability, discriminant validity and internal consistency. Hair et al. (2017) suggested that convergent validity can be examined by calculating item loading. For exploratory research design, factor loadings value above 0.70 or higher are accepted and lower thresholds are acceptable but values must not be lower than .600 (Henseler et al., 2009). The tested result showed that the outer loading value is reflected pleasing for all the items reported below in table 1 in Appendix. Composite reliability values for this study are acceptable due to all values are above 0.70. Researchers have lately used Cronbach's alpha (CA) and composite reliability (CR) to evaluate reliability or internal consistency based on latent variables in PLS structural equation models (Wong, 2013).

A largely accepted rule is that Cronbach's Alpha (CA) of 0.6-0.7 indicates an acceptable level of reliability and 0.8 or greater is a very good level. Conversely, values higher than 0.95 are not necessarily good due to a sign of redundancy (Hulin, Netemeyer and Cudeck, 2001). The tested result showed that the composite reliability (CR) value above 0.70. The calculated value CR (range from 0.838 to 0. 922) and Cronbach's Alpha CA (0.745 to0 .886) which are more than the accepted values. Hence, Convergent validity can also be proved by calculating the Average Variance Extracted (AVE). Urbach and Ahlemann (2010) offered that the AVE of each construct is 0.50 or higher are acceptable for evaluating convergent validity. The AVE values of this study range from 0.637 to 0.793 which are more than 0.50. Therefore, both validity and reliability analyses indicate that these constructs are valid and reliable for further advanced research

Table 2: Discriminant Validity and Correlations (Fornell-Larcker Criterion)

	BI	COM	EE	FC	PC	PE	RA	RTC	SML	SI	TA
BI	**0.859**										
COM	0.559	**0.816**									
EE	0.47	0.533	**0.819**								
FC	0.523	0.552	0.645	**0.822**							
PC	-0.124	-0.17	-0.111	-0.052	**0.891**						
PE	0.518	0.432	0.548	0.614	-0.049	**0.864**					
RA	0.513	0.648	0.475	0.586	-0.149	0.602	**0.847**				
RTC	-0.088	-0.015	-0.076	-0.089	0.15	-0.086	-0.11	**0.798**			
SML	0.44	0.439	0.267	0.276	-0.1	0.246	0.435	0.225	**0.831**		
SI	0.448	0.349	0.396	0.506	0.058	0.454	0.396	-0.01	0.305	**0.752**	
TA	-0.172	-0.146	-0.308	-0.287	0.16	-0.103	-0.086	0.278	0.091	-0.001	**0.87**

Estimating discriminant validity result for empirical study, according to the Fornell-Larcker criterion a factor's AVE should be higher than its squared correlations with all other factors in the model. The square root of AVE (diagonal value) for each variable should exceed the correlation of latent variables, which is being met in the present study shown in Table-2. All correlation coefficients are the positive value more than 0.70 and significant at level 0.01. Moreover, it endorses that all constructs fulfill the criteria with the indication of establishing discriminant validity.

Step 2: Assessment of the structural model

Goodhue et al., (2006) denotes PLS containing two nonparametric approaches to test the relationship between variables: either jackknife or bootstrap techniques. The bootstrap technique is approached to analyze data in this study. The outcome of this study exposes that tested the extended UTAUT model explain 48.9% of the variance in intention to adopt online classes by the student. Wong et al. (2013) recommend that path coefficient valued at approximately 0.670 is significant, values around 0.333 is average, and values of 0.190 is usual and lower weak. Therefore, this study's proposed model's path coefficient valued in typical range. Alternatively, the extended model of this study has found that supported hypothesis 1, 4,6,8,9 and other hypothesis 2, 3, 5,7,10 were found not supported. The summary of the study bootstrapping analysis is shown in Table-4 whereas the Figure-2 is showing PLS analysis results.

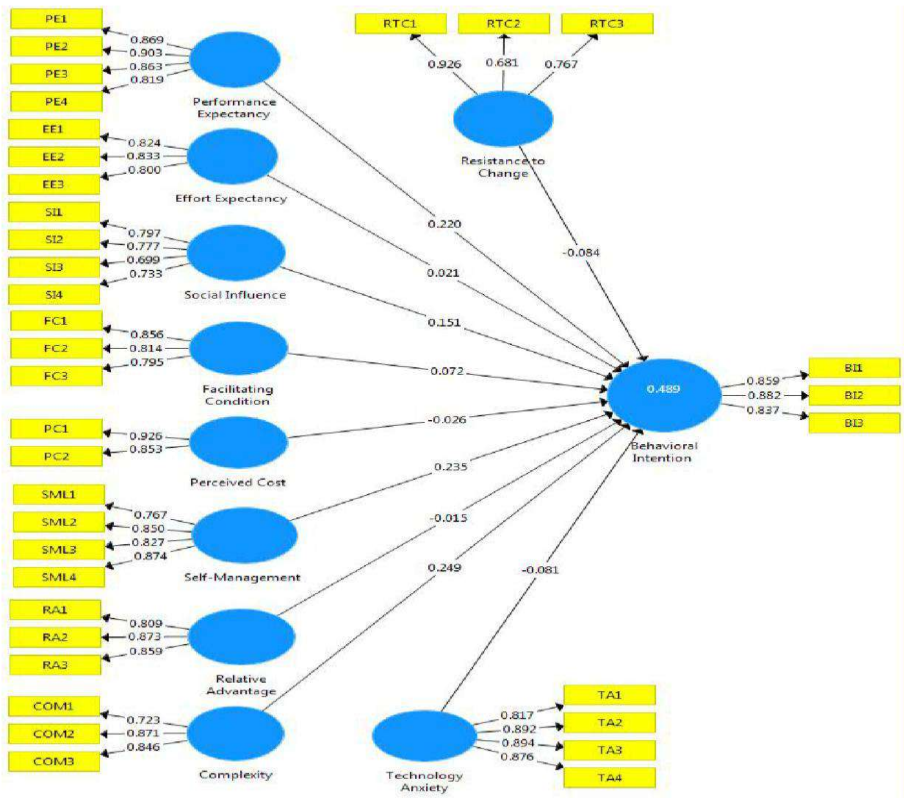

Figure 2: Tested Result for the proposed model

Table 4: Summary of Bootstrapping Result

Hypothesis No.	Path Relation	Path Coefficient	T Statistics (|O/STDEV|)	P Values	Result
H1	PE -> BI	0.22	4.148	0	**Supported**
H2	EE -> BI	0.021	0.378	0.706	Not supported
H3	FC -> BI	0.072	1.103	0.271	Not supported
H4	SI -> BI	0.151	2.803	0.005	**Supported**
H5	PC -> BI	-0.026	0.634	0.527	Not supported
H6	SML -> BI	0.235	4.413	0	**Supported**
H7	RA -> BI	-0.015	0.221	0.826	Not supported
H8	COM-> BI	0.249	3.73	0	**Supported**
H9	TA -> BI	-0.081	1.906	0.057	**Supported**
H10	RTC -> BI	-0.084	1.567	0.118	Not supported

P<0.05* (t > 1.645) significant, P <0.01 ** (t > 1.96) Very significant, P<0.001*** (t>2.58) extremely significant.

6. Data Analysis & Findings

This portion incorporates the explanation of the results about the proposed research model shown in Figure-2. This paper mainly argues to identify the factors to ascertain behavioral intention to adopt online classes by the students. With thorough examination of literature review, this study put forward students' Behavioral Intention (BI) to adopt online classes is effected by Effort Expectancy (EE), Performance Expectancy (PE), Facilitating Conditions (FC), Perceived Cost (PC), Social influence (SI), Self-Management of Learning (SML), Relative Advantage (RA), Complexity (COM), Technological Anxiety (TA) and, Resistance to Change (RTC). In this study, the research result supports hypothesis H1 Performance Expectancy ((β = 0.22, p =0.000), H4 Social Influence (β =0.151, p =0.005), H6 Self- Management of Learning (β = 0.235, p =0.000) have a strong positive influence and H8 Complexity (β = 0.249, p =0.000), H9 Technological anxiety (β = -0.081, p =0.057) that have a significant negative influence on students' Behavioral Intention (BI) to accept online classes. This result has supported the previous study conducted by Rogers (2005) in which complexity as well as Jackman and Roberts (2014) in which technological anxiety was an adverse effect on the adoption rate of innovation. On the other hand, performance expectancy, Self-Management of Learning, social influence has found the positive relations with behavioral intentions to adopt innovation (Khan et al. 2021 and Oliveira et al. 2014) which is similar to our study. But some studies shows that factors have not significant influence on behavioral intention of students to adopt technological innovation ((Boonsiritomachai & Pitchayadejanant, 2019; Kwateng et al. 2018; Verkijika, 2018). Conversely, H2 Effort Expectancy (β = 0.021, p =0.706), H3 Facilitating Condition (β = 0.072, p =0.271), H5 Perceived Cost (β = - 0.026, p =0.527), H7 Relative Advantage (β = -0.015 p =0.826), and H10 Resistance to Change (β = -0.084, p =0.118) were not supported by the result of this research. Some study results supported that Effort Expectancy, Facilitating Condition and Cost is a strong contributor to adopt technological innovation (Baptista et al. 2015) which contradict with other studies (Venkatesh et al. 2012; Mahfuz et al. 2013) that similar to our study.

This indicate that H2, H3, H5, H7 and H10 have not significant influence on student's intention to accept online classes. However, this study reveals that PE plays a vital role in the BI of the students adopting online classes. Students believe that online class could improve their performance as well as their results. Materially, SI is one of the key determinants that influence BI greatly means that students are biased by their friends, family members to involve in online classes. Hence, SML is significant influence to adopt any self-directed task; there is no difference in this research perspective. The findings of this research depict that Complexity (COM) to use technologies one of the major obstacles to adopting online classes.

7. Concluding Remarks

This research is accompanied to ascertain the factors determining the behavioral intention of the students to adopt online classes. An extended UTAUT model was proposed where Perceived Cost (PC), Self-Management of Learning (SML), Relative Advantage (RA), Complexity (COM), Technological Anxiety (TA), and

Resistance to Change (RTC) added as additional variables along with original UTAUT model. These variables seemed important in this study and play a significant role to adopt online classes by the targeted group. Perceived cost depicts a very dynamic role as the acceptance of online classes. Because, for conducting online classes requires installation of a high-speed Wi-Fi or internet connection, obtaining a laptop/desktop, or other smart devices. The students may have to go through a substantial cost. Moreover, SML also a very important factor for any online or self-driven learning or task. RA refers to ROI and it plays an important role because students spend their time, cost, and other effort. COM, TA, and RTC all these variables refer to difficulties, anxiety to use new technology, and resistance to adopt a new method respectively. Students consider these factors to adopt online classes so that these factors were included in the proposed model. However, this research finding shows that there is a significant association between Behavioral Intention (BI) with Performance Expectancy (PE), Social Influence (SI), Self-Management of Learning (SML), Technological Anxiety (TA), and Complexity (COM). These factors significantly influence the BI to adopt online classes. Other variables such as Effort Expectancy (EE), Facilitating Condition (FC), Perceived Cost (PC), Relative Advantage (RA) and Resistance to Change (RTC) of the proposed model have not a substantial impact on BI as per the research outcomes. Governments and educational institutions may encourage students and parents to appreciate the advantages and opportunities of online classes through using mass as well as social media.

This study provides new insights on Behavioral Intention to adopt online classes as well as the impact of these constructs. Though the research gap of the prior study e.g., sample design is covered in this study, the current study has some limitations as well. Larger sample like School-level students or different context can be taken in future studies. However, the findings of this study could be implemented in different perspectives such as m-Banking, Online shopping etc. and could result in a positive outcome.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50, 179-211.

Al-Adwan, A.S., Al-Madadha, A., and Zvirzdinaite, Z. (2018). Modeling students' readiness to adopt mobile learning in higher education: An empirical study. *International Review of Research in Open and Distributed Learning*, 19(1).

Althunibat Ahmed (2015). Determining the factors influencing students' intention to use m-learning in Jordan higher education. *Journal of Computers in Human Behavior*, 52, pp.65- 71.

Alshurideh, M. T., Salloum, S. A., Al Kurdi, B., Abdel Monem, A., & Shaalan, K. (2019). Understanding the Quality Determinants that Influence the Intention to Use the Mobile Learning Platforms: A Practical Study. *International Journal of Interactive Mobile Technologies*, 13, 157-183. https://doi.org/10.3991/ijim.v13i11.10300

Alshurideh, M., Nicholson, M., & Xiao, S. (2012). The Effect of Previous Experience on Mobile Subscribers' Repeat Purchase Behavior. *European Journal of Social Sciences*, 30, 366-376.

Al-Kurdi, B., Alshurideh, M., & Salloum, S. A. (2020). Investigating a Theoretical Framework for E-Learning Technology Acceptance. *International Journal of Electrical and Computer Engineering (IJECE)*, 10, 6484-6496. https://doi.org/10.11591/ijece.v10i6.pp6484-6496.

Aliaga, M., and Gunderson, B. (2002). Interactive Statistics. [Thousand Oaks]: Sage Publications.

Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior*, 50, 418-430.

Biswas, B., Roy, S. K., & Roy, F. (2020). Students Perception of Mobile Learning during COVID-19 in Bangladesh: University Student Perspective. *Aquademia*, *4*(2), ep20023. https://doi.org/10.29333/aquademia/8443

Burnham, T. A., Frels, J. K., and Mahajan, V. (2003). Consumer switching costs: a typology, antecedents, and consequences. *Journal of the Academy of marketing Science*, 31(2), pp. 109-126.

Bhattacherjee, A., and Hikmet, N. (2007). Physicians' resistance toward healthcare information technology: a theoretical model and empirical test. *European Journal of Information Systems*, 16(6), pp.725–737. doi: 10.1057/palgrave.ejis. 3000717

Boonsiritomachai, W., & Pitchayadejanant, K. (2019). Determinants affecting mobile banking adoption by generation Y based on the unified theory of acceptance and use of technology model modified by the technology acceptance model concept. *Kasetsart Journal of Social Sciences*, 40(2), 349–358. https://doi.org/10.1016/ j.kjss.2017.10.005

Chiu, C.M., and Wang, E. T. G. (2008). Understanding Web-based learning continuance intention: The role of subjective task value. *Information & Management*, 45(3), pp. 194-201. doi: 10.1016/j.im.2008.02.003.

Cavana, R., Delahaye, B., and Sekeran, U. (2001). Applied business research: Qualitative and quantitative methods. *John Wiley & Sons*. pp. 30-32.

Creswell J. W. (2008). *Educational research: Planning, conducting, and evaluating quantitative and qualitative research*. Upper Saddle River, NJ: Pearson/Merrill Education. Pp. 45-46.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13, pp.319- 340.

Davis, F. D., R. P. Bagozzi and P. R. Warshaw, (1989). User acceptance of computer technology a comparison of two theoretical models. *Management Science*, 35 (8). Pp. 982- 1003.

Deng Z, Mo X, and Liu S. (2013). Comparison of the middle-aged and older users' adoption of mobile health services in China. *International journal of medical informatics*, 2014 Mar; 83(3): pp. 210-224. doi: 10.1016/j.ijmedinf.2013.12.002

Eze, U. C., Manyeki, J. K., Yaw, L. H., & Har, L. C. (2011). Factors affecting internet banking adoption among young adults: Evidence from Malaysia.

Paper presented at the International Conference on Social Science and Humanity.

Farahat, T. (2012). Applying the Technology Acceptance Model to Online Learning in the Egyptian Universities. *Procedia Social Behavior Science*, 64, pp. 95-104. https://doi.org/10.1016/j.sbspro.2012.11.012

Fishbein, M. and Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Massachusetts, Reading, MA.

Fraenkel, J. R., and Wallen, N. E. (2006). *How to design and evaluate research in education* (6th ed.). New York, NY McGraw-Hill. pp. 87-90.

Gollwitzer, P. M. (1993). Goal achievement: The role of intentions. In W. Stroebe& M. Hewstone (Eds.), *European Review of Social Psychology*, 4, pp. 141-185. Chicester: Wiley.

Goodhue, Lewis, and Thompson. (2012). Does PLS Have Advantages for Small Sample Size or Non-Normal Data? *MIS Quarterly*, 36(3), pp. 981. doi: 10.2307/41703490.

Gliner, J. A., Morgan, G. A., Harmon, R. J., and Harmon, R. J. (2003). Meta-Analysis: Formulation and Interpretation. *Journal of the American Academy of Child & Adolescent Psychiatry*, 42(11), pp. 1376 -1379. doi: 10.1097/01.chi.0000 085750.71002.01

Heinssen, R. K., Jr., Glass, C. R., and Knight, L. A. (1987). Assessing computer anxiety: Development and validation of the computer anxiety rating scale. *Computers in Human Behavior*, 3, pp. 49-59.

Hair, J., C. L. Hollingsworth, A. B. Randolph, and A. Y. L. Chong. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, 117 (3):pp. 442–458. doi:10.1108/IMDS-04-2016-0130.

Hamid, H. (2020, May 16). What are our plans for education in Corona? *Daily Prothom Alo*, 5. https://www.prothomalo.com/bangladesh.

Henseler, J., C. M. Ringle, and R. R. Sinkovics. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing (AIM)*, 20: pp.277–320.

Hulin, C., Netemeyer, R., and Cudeck, R. (2001). Can a Reliability Coefficient Be Too High? *Journal of Consumer Psychology*, 10(1), pp.55-58.

Jackman, W. M., and Roberts, P. (2014). Students' Perspectives on YouTube Video Usage as an E-Resource in the University Classroom. *Journal of Educational Technology Systems*, 42(3), pp.273–296. doi:10.2190/et.42.3. f.

Khan, M. A., Vivek, Nabi, M. K., Khojah, M., & Tahir, M. (2021). Students' Perception towards E-Learning during COVID-19 Pandemic in India: An Empirical Study. *Sustainability*, 13, Article No. 57. https://doi.org/10.3390/ su1301005

Kwon, Tae H. and Robert W. Zmud, (1987). Unifying the Fragmented Models of Information Systems Implementation, in R.J. Boland and R. Hirschheim (Eds.), *Critical Issues in Information Systems Research*, John Wiley, Chichester, England, 1987, pp. 227-251.

Kennedy, G. E., Judd, T. S., Churchward, A., Gray, K., & Krause, K. L. (2008). First Year Students' Experiences with Technology: Are They Really Digital Natives? *Australasian Journal of Educational Technology*, 24, 108-122. https://doi.org/ 10.14742/ajet.1233

Kwateng, K. O., Atiemo, K. A. O., & Appiah, C. (2018). Acceptance and use of mobile banking: An application of UTAUT2. *Journal of Enterprise Information Management*, 32(1), 118–151.

Kennedy, G., Krause, K. L., Gray, K., Judd, T., Bennett, S. J., Maton, K. A., Dalgarno, B., &Bishop, A. (2006). Questioning the Next Generation: A Collaborative project in Australian Higher Education. In L. Markauskaite, P. Goodyear, & P. Reimann (Eds.), *Proceedings of the Annual Conference of the Australasian Society for Computers in Learning in Tertiary Education* (pp. 413-417). Sydney University Press.

Kvavik, R .B. (2005). Convenience, Communications, and Control: How Students Use Technology. In D. G. Oblinger, & J. L. Oblinger (Eds.), *Educating the Next Generation*, pp. 71-72. Educause. https://library.educause.edu/-/media/files/library/ 2005/1/pub7101g-pdf.pdf

Kothari C.R., (2010). *Research Methodology: Methods and Technique*. New Delhi: New Age International Publishers, p. 31.

Loogma, K., Kruusvall, J., and Ümarik, M. (2012). E-learning as innovation: Exploring innovativeness of the VET teachers: community in Estonia. *Computers & Education*, 58(2), pp. 808- 817.

Luarn, P., and Lin, H. H. (2005). Toward an understanding of the behavioral intention to use mobile banking. *Computers in Human Behavior*, 21(6), pp. 873-891.

Lu, Y., Yang, S., Chau, P. Y., and Cao, Y. (2011). Dynamics between the trust transfer process and intention to use mobile payment services: A cross-environment perspective. *Information & Management*, 48(8), pp. 393-403.

Louis Cohen, Lawrence Manion and Keith Morrison (2007). *Research Methods in Education*. Sixth Edition. Pp. 638. London and New York: Routledge.

Mahfuz, M. A, Hu, W, Khanam, L. (2016). The influence of cultural dimensions and website quality on m-banking services adoption in Bangladesh: Applying the UTAUT2 model using PLS. Paper presented on International conference on Electrical, Electronics and optimization Techniques (ICEEOT)-2016, Chennai, Tamil Naru, India. http://iceeot.org/conference_proceedings2,html

Mailizar, Almanthari, A., Maulina, S., & Bruce, S. (2020). Secondary School Mathematics Teachers' Views on E-Learning Implementation Barriers during the COVID-19 Pandemic: The Case of Indonesia. *Eurasia Journal of Mathematics, Science and Technology Education*, 16, Article No. em1860. https://doi.org/ 10.29333/ejmste/8240

McCarthy, J. (2013). Learning in Facebook: First year tertiary student reflections from 2008 to 2011. *Australasian Journal of Educational Technology*, 29(3), pp.337-356.

Mohammadyari, S., and Singh, H. (2015). Understanding the effect of e-learning on individual performance: The role of digital literacy. *Computers & Education*, 82, pp. 11–25. doi: 10.1016/j.compedu.2014.10.025.

Marchewka K. and Kostiwa K., (2007). An application of the UTAUT model for understanding student perceptions using course management software. *Communications of the IIMA*, 7(2), pp. 93-10.

Oliveira, T., Faria, M., Thomas, M. A., & Popovic, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management*, 34(5), 689–703.

Patrick Y.K. Chau (1996). An Empirical Assessment of a Modified Technology Acceptance Model. *Journal of Management Information Systems*, 13(2), pp. 185-204, DOI: 10.1080/07421222.1996.11518128

Pardamean, B., and Susanto, M. (2012). Assessing user acceptance toward blog technology using the UTAUT model. *International Journal of Mathematics and Computers in Simulation*, 1(6), pp. 203–216.

Pérez-Pérez, M., Serrano-Bedia, A. M., & García-Piqueres, G. (2020). An Analysis of Factors Affecting Students' Perceptions of Learning Outcomes with Moodle. *Journal of Further and Higher Education*, 44, 1114-1129. https://doi.org/10.1080/0309877X.2019.1664730

Rogers, E. (2005). *Diffusion of innovation*. New York: Free Press. pp.40-42.

Rashid, S., & Yadav, S. S. (2020). Impact of COVID-19 Pandemic on Higher Education and Research. *Indian Journal of Human Development*, 14, 340-343. https://doi.org/10.1177/0973703020946700

Salaway, G., Caruso, J. B., & Nelson, M. R. (2008). The ECAR Study of Undergraduate Students and Information Technology. *EDUCAUSE Center for Applied Research*, 6.

Salloum, S. A., Al-Emran, M., Shaalan, K., & Tarhini, A. (2019). Factors affecting the E-learning acceptance: A case study from UAE. *Education and Information Technologies*, 24(1), 509–530.

Sripalawat, J., Thongmak, M., and Ngramyarn, A. (2011). M-banking in metropolitan Bangkok and a comparison with other countries. *Journal of Computer Information Systems*, 51(3), pp.67-76.

Shrestha, E., Mehta, R. S., Mandal, G., Chaudhary, K., & Pradhan, N. (2019). Perception of the Learning Environment among the Students in a Nursing College in Eastern Nepal. *BMC Medical Education*, 19, Article No. 382. https://doi.org/10.1186/s12909-019-1835-0

Sumak, B., Polancic, G., and Hericko, M. (2010). An Empirical Study of Virtual Learning Environment Adoption Using UTAUT. Paper presented at the 2010. Second International Conference on Mobile, Hybrid, and On-Line Learning.

Smith, P.J., Murphy, K.L. and Mahoney, S.E. (2003).Towards Identifying Factors Underlying Readiness for Online Learning: An Exploratory Study. *Distance Education*, 24(1), pp.57-67.

Sekaran, U. (2000). *Research Methods for Business: A Skill Building Approach*. New York: John Wiley & Sons. pp. 70-72.

Toh, C. H. (2008). Factors affecting the adoption of blogging in Singapore schools. (Doctoral dissertation).

Tosuntaş, Ş. B., Karadağ, E., and Orhan, S. (2015). The factors affecting acceptance and use of interactive whiteboard within the scope of FATIH project: A structural equation model based on the Unified Theory of acceptance and use of technology. *Computers & Education*, 81, pp. 169–178. doi: 10.1016/j.compedu.2014.10.009.

Nils, U., and Frederik, A. (2010) Structural Equation Modeling in Information Systems Research Using Partial Least Squares, *Journal of Information Technology Theory and Application (JITTA)*, 11(2), Article 2. Available at: https://aisel.aisnet.org/jitta/vol11/iss2/2

Venkatesh, V., James Y. L. Thong, Xin Xu (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36(1), pp. 157-178. https://doi.org/ 10.2307/41410412

Venkatesh, V. and Zhang, X. (2010). Unified theory of acceptance and use of technology: US vs. China. *Journal of Global Information Technology Management*, 13(1), pp. 5-27.

Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27, pp. 425-478.

Venkatesh, V., and F. D. Davis. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science,* 46 (2): pp. 186–204. doi:10.1287/ mnsc.46.2.186.11926.

Verkijika, S. F. (2018). Factors influencing the adoption of mobile commerce applications in Cameroon. *Telematics and Informatics*, 35(6), 1665–1674.

Vu, C. T., Hoang, A. D., Than, V. Q., Nguyen, M. T., Pham, H. H., & Nguyen, Y. C. (2020). Dataset of Vietnamese Teachers' Perspectives and Perceived Support during the COVID-19 Pandemic. *Data in Brief*, 31, Article ID: 105788. https://doi.org/10.1016/j.dib.2020.105788

Wang, Y.S. and Shih, Y.W. 2009, Why Do People Use Information Kiosks? A Validation of the Unified Theory of Acceptance and Use of Technology. *Government Information Quarterly*, 26, pp. 158–165.

Wong, C. A., Cummings, G. G., and Ducharme, L. (2013). The relationship between nursing leadership and patient outcomes: a systematic review update. *Journal of Nursing Management*, 21(5), pp. 709–724. doi:10.1111/jonm.12116.

Appendix

Table 1: Convergent validity and Reliability

Items	Outer Loading	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
BI1	0.859	0.823	0.894	0.738
BI2	0.882			
BI3	0.837			
COM1	0.723	0.749	0.856	0.666
COM2	0.871			
COM3	0.846			
EE1	0.824	0.754	0.859	0.671
EE2	0.833			
EE3	0.800			
FC1	0.856	0.761	0.862	0.676
FC2	0.814			
FC3	0.795			
PC1	0.926	0.745	0.884	0.793
PC2	0.853			
PE1	0.869	0.886	0.922	0.746
PE2	0.903			
PE3	0.863			
PE4	0.819			
RA1	0.809	0.804	0.884	0.718
RA2	0.873			
RA3	0.859			
RTC1	0.926	0.926	0.926	0.637
RTC2	0.681			
RTC3	0.767			
SML1	0.767	0.849	0.899	0.69
SML2	0.850			
SML3	0.827			
SML4	0.874			
SI1	0.797	0.745	0.839	0.566
SI2	0.777			
SI3	0.699			
SI4	0.733			
TA1	0.817	0.893	0.926	0.757
TA1	0.817			
TA2	0.892			
TA3	0.894			
TA4	0.876			