IT Managers' Intention to Use Data Visualization Applications: A Sri Lankan Study

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Abstract. This paper presents a preliminary analysis on the behavioral intention of IT managers to use data visualization application. Data visualization entails the visual understanding of data. It is part of the data analytics conducted following data correction. This study aims to determine the effect of effort expectancy, performance expectancy, and other factors in improving performance. The underpinning theory employed to explain the relationship is the Unified Technology Acceptance and Use of Technology. The needed data was collected from IT managers in numerous business sectors in Sri Lanka using a self-administered questionnaire. A total of 278 IT managers make up the active respondents in this study. The Smart PLS 3 software was used to analyze the data. The findings showed that behavioral intention is positively correlated with the factors of facilitating condition, effort expectancy, social influence, and performance expectancy. Theoretically, this study is positively linked to the theory of unified technology acceptance and use of technology. Implications wise, the findings can help boost the behavioral intention of managers in using data visualization software specifically by improving the aspects of facilitating condition, effort expectancy, social influence, and performance expectancy.

Keywords: Data Visualization, UTAUT, Behavioral Intention, IT Managers, Sri Lanka

1 Introduction

Today, the aspect of business intelligence and analysis in various sectors is significantly driven by visualization. Numerous data visualization methods are currently available, whether dynamic or collaborative in nature, whereby different visual insights can be used to visualize datasets. There is a drastic increase in companies that employ this method as a result of advancements in knowledge and computer technologies [1]. The possibility of improving computer systems interactivity is laid out by the Human-Computer Interaction Analysis, but it remains unclear if visualization is involved. Although analysts and experts in visualization acknowledge such interaction principles, most are still in the dark about ways to adapt those principals into their data-oriented requirements and activities. This technological advancement promotes human and corporate learning alike [2]. The individual level would require a higher degree of technology acceptance, failing which, underperformance would occur. Data visualization is commonly used by IT managers, amongst others. Resultantly, information technology experts are looking at ways to boost business efficiency and effectiveness [3]. [4] There is a growing demand for IT managers to prove that they have solid practical capabilities driven by comprehensive theoretical standards. Highly trained managers are created via formal and local procedures [4]. Data visualization is enabled by the mastery

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of visualization applications, for example, Microsoft Power BI. [5] Data visualization technologies are typically utilized by corporate enterprises. Small and medium enterprises (SMEs) commonly use IBM Watson Analytics, Microsoft Excel and Microsoft Power BI to facilitate data visualization presented via charts and graphs.

2 Theoretical Background

Visualization basically aims to create a new perspective or carry out a certain task by emphasizing on the distinctive features of the basic dataset [6]. Insights could entail the investigation of correlations, relationships, patterns, clusters and incidences, or the usage of facts to specific viewers via persuasive, data-oriented tales for the purpose of making decisions [8]. Story telling or reporting entails a systematic procedure, whilst hypothesis formation or verification occurs on an ad-hoc basis and without structure [8]. Ad-hoc assessments on wide-ranging and highly complex datasets seem to benefit more on data visualization [9]. Resultantly, users facing such complications are already employing data visualization. Primary examples include fraud detection [10], network traffic analysis [11] and minimization of costs and consistency improvement in business models [12]. Additionally, data visualization is typically employed in organizations that aim to assess the effect of personalized marketing and social media campaigns on product loyalty and creativity [11] [12].

[13] examined youth reasoning and data comprehension via interactive data visualization, and found that facilitating learners in using their tools of interest is more advantageous than promoting a specific resource usage method or sequence.

The interactive visualization categories as presented earlier (when utilized according to their exact functions and with an optimal design) enable new knowledge discovery [14]. Currently, data insight can facilitate in the recruitment of buyers or streamline maintenance [12]. In the future, however, data insight will determine the competitive advantage of firms [8]. Feedback generation would require the integration of the consumers’ skills and desires into the selection and design process [15]. While individual and group users have been acknowledged as vital in structured or empirical visualization [16], researchers and developers also focus on producing new visualization prospects so as to deliver a cohesive dataset perspective [15]. However, users often disregard their explicit visualization needs and risks with the intention to deceive users or to abandon them altogether [17]. [7] stated three primary levels in generating or selecting suitable visualizations namely: (1) encoding (i.e., selecting and designing apt graphical forms), (2) manipulating (i.e., enabling user-data communication), and (3) entering (i.e., enabling the application of additional data and saving the outcomes) [8]. This current study focuses on the behavioral intention of managers to utilize data visualization such as the Microsoft Power BI Application.

3 Research Model and Hypotheses

Technology adoption entails several assumptions. For instance, the operational level entails the technology-organization-environment (TOE) [18], the tri-core model (TCM) [19] and the innovation diffusion principle (IDT) [20]. At the human level, technology usage is viewed from the Technology Acceptance Model (TAM) [21], the Theory of Reason Action (TRA) [22], the Theory of Planning Behavior (TPB) [23] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [22]. The study by [24] relied on the UTAUT in investigating social media usage among university students. [25] investigated the influence of perceived ease of use, device anxiety, perceived satisfaction, and relative advantage on the users' intention to use visualization application again. Meanwhile, [26] analyzed technology adoption by managers for the purpose of visualization by employing the Technology Acceptance Model (TAM). There is limited intention in using the data visualization tool. Literature gaps still exist with regards to the application of Data Visualization. It is also important to determine the factors driving data visualization usage in the workplace by IT managers. Hence, this current study aims to investigate the influence of effort expectancy, facilitating conditions, performance expectancy and social influence on behavioral intention to use data visualization tool. The research framework is as below:

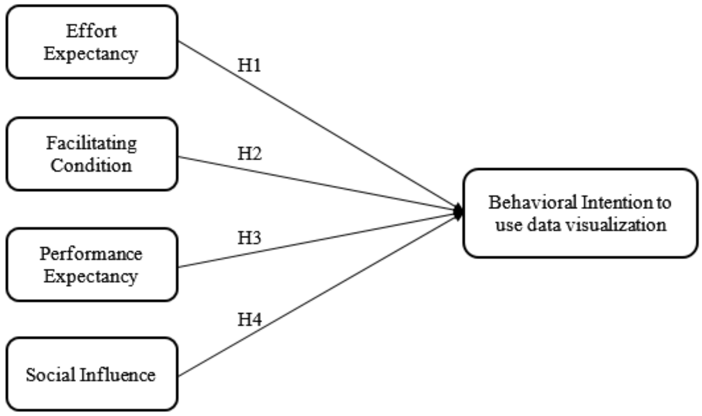

Fig. 1. Research Framework

This theory has been used by numerous studies [24] [27] [28] on the effect of effort expectancy on behavioral intention. Additionally, it was also found that facilitating condition [27] [28] and performance expectancy [24] [27] [28] have an effect on behavioral intention. However, the Commission has no similar effect [27]. Also examined was the impact of social influence on behavioral intention [28], but it was found that no relationship exists between the two [27]. Only one study out of three had examined the behavioral intention to use data visualization programs [5]. Another two studies focused on the usage of ICT [27] and web-based services [28]. Based on all the reviewed works, this current study forms the hypotheses below:

H1. Effort expectancy positively and significantly affects the behavioral intention of IT managers to use data visualization applications (Microsoft Power BI).
H2. Facilitating condition positively and significantly affects the behavioral intention of IT managers to use data visualization applications (Microsoft Power BI).
H3. Performance expectancy positively and significantly affects the behavioral intention of IT managers to use data visualization applications (Microsoft Power BI).
H4. Social influence positively and significantly affects the behavioral intention of IT managers to use data visualization applications (Microsoft Power BI).

4 Results and Discussions

The findings of this study are applicable for IT managers in many organizations. A total of 278 managers served as the study respondents. Primary data was collected via an online survey. The latent dependent variable was denoted by behavioral intention, whilst the latent independent variables consist of effort expectancy, facilitating condition, performance expectancy, and social influence. The four items of behavioral intention are highly significant in information system studies [22]. The six items of performance expectancy relate to the extent to which the managers' capacity to utilize Microsoft Power BI can facilitate them in attaining greater achievements [24]. The four items of effort expectancy entail the extent to which the software is easy to use [29]. The four items of facilitating condition denote the extent to which the individual believes in the existence of an organizational and technical structure that enables the usage of the applications [1]. Finally, the four items of social influence denote the extent to which other people influence one's decision to use or not use certain software [1]. A seven-point Likert scale was used to measure the variables i.e. from strongly disagree to strongly agree. Data analysis was carried out using the SEM-PLS. The measurement and structural models were assessed prior to presenting hypotheses testing results [30] [31].

4.1 Demographic Profile of Respondents

A total of 278 IT managers had participated in this research. Table 1 presents the demographic data of the respondents. In terms of gender, there are 182 (65.47%) male respondents and 96 (34.53%) female respondents. Age wise, respondents aged between 25 and 35 years old make up 112 (40.29%) of the total participants, those between 36 and 45 years old make up 147 (52.88%) whilst those aged 46 years old and above make up 19 (6.83%) of the total respondents. In terms of experience, 74 of the IT managers have less than one year experience (26.62%), 79 have 2-4 years of experience (28.42%), 96 have 4-6 years of experience (34.53%), and 29 have more than 6 years of experience (10.43%). Education wise, 124 of the IT managers hold a bachelor's degree (44.60%), 136 hold a master's degree (48.92%), 9 have a PhD (3.24%) whilst another 9 hold other qualifications (3.24%).

Table 1. Demographic Variables

Demography Data	Category Details	Frequency	Percentage
Gender	Male	182	65.47%
	Female	96	34.53%
Age	25 to 35 years old	112	40.29%
	36 to 45 years old	147	52.88%
	Up to 46 years old	19	6.83%
Experience	Below 1 year	74	26.62%
	2 to 4 years	79	28.42%
	4 to 6 years	96	34.53%
	Above 6 years	29	10.43%
Education	Bachelor	124	44.60%
	Master	136	48.92%
	PhD	9	3.24%
	Other	9	3.24%

4.2 Measurement Model Assessment

As previously mentioned, the SEM-PLS (Smart PLS 3) was employed for data analysis. This is because the SEM-PLS focuses on earlier theories, whereby research and implementation are solid and the maximum knowledge estimation approach is properly based on covariance [32].

Two types of evaluations were carried out i.e. involving the convergent validity and discriminant validity [33].

Table 2. Convergent validity

Construct	Item	Outer Loading	rho_A	Cronbach's Alpha	Composite Reliability	AVE
BI	BI1	0.836	0.899	0.9	0.929	0.767
	BI2	0.899				
	BI3	0.876				
	BI4	0.891				
EE	EE1	0.804	0.862	0.866	0.907	0.708
	EE2	0.862				
	EE3	0.878				
	EE4	0.821				
FC	FC1	0.786	0.766	0.792	0.852	0.592
	FC2	0.857				
	FC3	0.62				
	FC4	0.796				
PE	PE1	0.621	0.879	0.886	0.909	0.628
	PE2	0.774				
	PE3	0.842				
	PE4	0.832				
	PE5	0.847				
	PE6	0.817				
SI	SI1	0.866	0.88	0.882	0.918	0.736
	SI2	0.838				
	SI3	0.899				
	SI4	0.827				

BI: Behavioral Intention, EE: Effort Expectancy, FC: Facilitating Conditions, PE: Performance Expectancy, SI: Social Influence.

The measurement for convergence entails the indicator reliability, internal consistency and average variance extracted [34]. Table 2 presents the Convergent Validity Assessment results. The latent variables were found to have good predictor accuracy as their outer load values are higher than 0.700, with the exception of FC3 and PE1 [35]. The variables' internal consistency values via Cronbach's alpha and composite reliability are also greater than 0.700 [36]. Meanwhile, the variables' average variance extracted (AVE) values are greater than 0.500. Based on these results, it can be concluded that the measurement model has fulfilled all its conditions [36]. [31] suggested for discriminatory validity assessments to be carried out to ensure a better measurement model and to demonstrate that the Fornell-Lacker criterion and cross-loading have been assessed. According to [37], the AVE square root of the latent variable should be greater than the squared correlation between the latent variable and all other variables. Table 3 presents the results for the Fornell-Lacker criteria. The AVE value for behavioral intention (0.876) is shown to be greater than the squared correlation between behavioral intention and the rest of the latent variables (EE, FC, PE, and SI).

Cross-loading is the next discriminant validity assessment. According to [31], the predictor's loading on its allocated latent variable must be higher than the loading for the other latent variables. Table 4 presents the results of the cross-loading whereby the loading for behavioral intention (BI1, BI2, BI3 and BI4) is greater than the loading of the other latent variables (bold number). The other indicators including effort expectancy (EE1, EE2, EE3 and EE4) also demonstrated a higher loading than the other latent variables.

Table 3. Discriminant validity - Fornell-Lacker Criterion

Constructs	BI	EE	FC	PE	SI
BI	**0.876**				
EE	0.611	**0.842**			
FC	0.552	0.534	**0.77**		
PE	0.607	0.594	0.493	**0.793**	
SI	0.509	0.461	0.449	0.427	**0.858**

Table 4. Cross Loading

Constructs	BI	EE	FC	PE	SI
BI1	**0.836**	0.479	0.445	0.506	0.474
BI2	**0.899**	0.562	0.541	0.532	0.476
BI3	**0.876**	0.534	0.482	0.568	0.426
BI4	**0.891**	0.564	0.463	0.521	0.41
EE1	0.459	**0.804**	0.426	0.477	0.345
EE2	0.533	**0.862**	0.483	0.511	0.354
EE3	0.523	**0.878**	0.437	0.519	0.429
EE4	0.536	**0.821**	0.449	0.491	0.419
FC1	0.363	0.316	**0.786**	0.378	0.356
FC2	0.527	0.481	**0.857**	0.478	0.355
FC3	0.369	0.44	**0.62**	0.315	0.34
FC4	0.409	0.388	**0.796**	0.321	0.335
PE1	0.411	0.388	0.384	**0.621**	0.397
PE2	0.432	0.414	0.375	**0.774**	0.367
PE3	0.49	0.479	0.375	**0.842**	0.314
PE4	0.528	0.475	0.408	**0.832**	0.35
PE5	0.496	0.518	0.43	**0.847**	0.333
PE6	0.515	0.533	0.374	**0.817**	0.291
SI1	0.448	0.389	0.431	0.374	**0.866**
SI2	0.439	0.436	0.401	0.392	**0.838**
SI3	0.453	0.407	0.375	0.376	**0.899**
SI4	0.404	0.345	0.327	0.322	**0.827**

The Heterotrait-Monotrait ratio (HTMT) is the third discriminant validity criterion to be fulfilled. This entails the average hetero-hetero-method correlation relative to the average mono-hetero-method correlation [31] [38]. As shown in Table 5, the HTMT ratio for all the items is lower than the threshold value (0.90). Hence, the measurement model is demonstrated to have fulfilled the discriminant validity criterion.

Table 5. Discriminant validity: Heterotrait-Monotrait ratio (HTMT)

Constructs	BI	EE	FC	PE	SI
BI					
EE	0.692				
FC	0.655	0.651			
PE	0.682	0.68	0.596		
SI	0.573	0.526	0.55	0.492	

4.3 Structural Model Assessment

Next is the structural model assessment which entails the generation of theories and examination of the correlation between the variables as presented in Figure 2. This assessment was carried out using the bootstrapping approach i.e. a re-sampling method for drawing large numbers of sub-samples from the original data (with replacement) and for estimating each sample's models [31]. The structural model measurement is denoted by its predictive significance and predictive power.

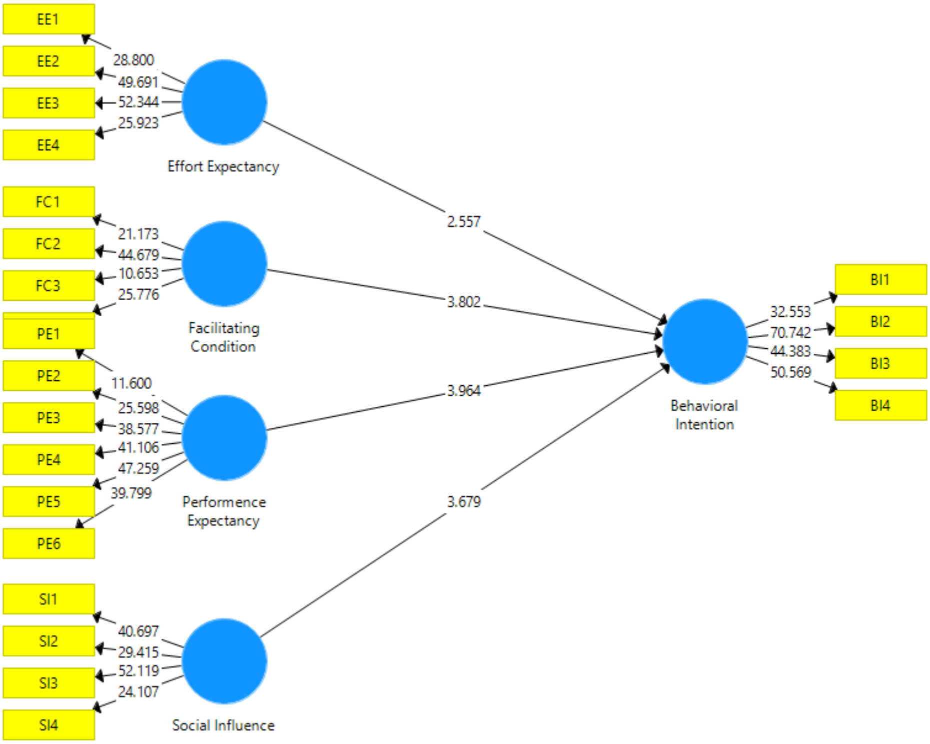

Fig. 2. Structural Model with T Statistics

Table 6. Assessment of Structural Model

Hypotheses	Relationship	Std Beta	Std Error	t-value	Decision	f^2	q^2	P Values	95% CI LL	95% CI UL
H1	EE -> BI	0.257	0.1	2.557*	Supported	0.074	0.042	0.011	0.034	0.444
H2	FC -> BI	0.198	0.051	3.802*	Supported	0.051	0.030	0.000	0.112	0.285
H3	PE -> BI	0.281	0.071	3.964*	Supported	0.097	0.056	0.000	0.148	0.428
H4	SI -> BI	0.182	0.05	3.679*	Supported	0.051	0.030	0.000	0.094	0.284

For predictive purposes, the usage of PLS necessitates predictive capacity measurement. Predictive relevance (Q^2) is measured using the blindfolding procedure. Table 6 presents the structural model assessment results, which shows that the Q^2 value is higher than 0.00 thus

demonstrating a strong statistical relevance. It also demonstrates a strong predictive value being greater than 0.30 [38]. Meanwhile, the R^2 value is 59.60 percent, indicating that 59.60 percent of the behavioral intention variance is explained by all the latent independent variables while the remaining are explained by other variables that had been dropped from this study. Categorically, this attribute is deemed as a major predictive skill [39].
Table 6 shows the four hypotheses developed in this study. The first hypothesized relationship i.e. between effort expectancy and behavioral intention demonstrated a p value of 0.011 and a path coefficient of 0.557; this indicates that a higher level of effort expectancy results in a higher level of behavioral intention to use Data Visualization. Hence, H1 is supported. The second hypothesized relationship i.e. between facilitating condition and behavioral intention is demonstrated to be positive and significant with a p value of 0.00 and a path coefficient of 3.802. Hence, H2 is supported. The third hypothesized relationship i.e. between performance expectancy and behavioral intention is also demonstrated to be positive and significant with a p value of 0.00 and a path coefficient of 3.964. Hence, H3 is also supported. The fourth and final hypothesized relationship i.e. between social influence and behavioral intention is also shown to be positive and significant with a p value of 0.00 and a path coefficient of 3.679. Hence, H4 is also supported.

5 Conclusion

Industry managers put great significance on technology adoption. For the purposes of documentation, data evaluation, performance analysis and decision-making, managers of small and medium-sized enterprises typically use the Microsoft Power BI as a data visualization tool. Yet, there are no studies so far on the behavioral intention of IT managers to utilize the Microsoft Power BI as a data visualization tool. This current study also investigates the extent to which such behavioral intention is influenced by effort expectancy, facilitating condition, performance expectancy, and social influence. A total of 278 managers were involved in this study. It was found that effort expectancy, facilitating condition, performance expectancy and social influence positively affect the managers' behavioral intention to use Microsoft Power BI. In terms of theoretical contribution, the findings indicate that the IT managers' behavioral intention to use Microsoft Power BI is underpinned by the theory of unified acceptance and use of technology. In terms of practical implications, the findings suggest that the behavioral intention of managers can be improved by enhancing the factors of effort, facilities, performance and social conditions. Limitations wise, this study had only focused on IT managers as the respondents, used minimal independent variables, and applied only one underpinning theory. Future studies can thus be extended to incorporate marketing and finance managers as the respondents, amongst others. Future research can also add other independent variables in the theory of unified technology acceptance and use technology.

References

[1] Samsudeen SN, Thowfeek MH. Small Medium Entrepreneurs' Intention to Use Cloud Computing: Reference to Eastern Province of Sri Lanka. Journal of Management. 2014:1-0.

[2] Šebjan U, Tominc P. Impact of support of teacher and compatibility with needs of study on usefulness of SPSS by students. Computers in Human Behavior. 2015 Dec 1;53:354-65.

[3] Apostolou B, Dorminey JW, Hassell JM, Rebele JE. A summary and analysis of education research in accounting information systems (AIS). Journal of Accounting Education. 2014 Jun 1;32(2):99-112.
[4] Sanjeetha MB, Nawaz SS, Kariapper RK. Small and Medium-Sized Entrepreneurs' Behavioural Intention to Use Accounting Information Systems in Eastern Province of Sri Lanka. Solid State Technology. 2020 Dec 1;63(6):17260-72.
[5] Diamond M, Mattia A. Data visualization: An exploratory study into the software tools used by businesses. Journal of Instructional Pedagogies. 2017 Mar;18.
[6] Lurie NH, Mason CH. Visual representation: Implications for decision making. Journal of marketing. 2007 Jan;71(1):160-77.
[7] Brehmer M, Munzner T. A multi-level typology of abstract visualization tasks. IEEE transactions on visualization and computer graphics. 2013 Oct 16;19(12):2376-85.
[8] Perkhofer L, Hofer P, Walchshofer C. BIG data visualisierungen 2.0. Optimale Gestaltung und Einsatz neuartiger Visualisierungsmöglichkeiten. Proceedings of CARF. 2019:76-104.
[9] Chen CP, Zhang CY. Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. Information sciences. 2014 Aug 10;275:314-47.
[10] Singh K, Best P. Anti-money laundering: using data visualization to identify suspicious activity. International Journal of Accounting Information Systems. 2019 Sep 1;34:100418.
[11] Keim DA, Mansmann F, Schneidewind J, Schreck T. Monitoring network traffic with radial traffic analyzer. In2006 IEEE symposium on visual analytics science and technology 2006 Oct 31 (pp. 123-128). IEEE.
[12] Appelbaum D, Kogan A, Vasarhelyi M, Yan Z. Impact of business analytics and enterprise systems on managerial accounting. International Journal of Accounting Information Systems. 2017 May 1;25:29-44.
[13] Wilkerson MH, Laina V. Youth reasoning with interactive data visualizations: A preliminary study. InProceedings of the 2017 Conference on Interaction Design and Children 2017 Jun 27 (pp. 411-416).
[14] Grammel L, Tory M, Storey MA. How information visualization novices construct visualizations. IEEE transactions on visualization and computer graphics. 2010 Oct 28;16(6):943-52.
[15] Perkhofer L, Walchshofer C, Hofer P. Does design matter when visualizing Big Data? An empirical study to investigate the effect of visualization type and interaction use. Journal of Management Control. 2020 Feb 17:1-41.
[16] Yigitbasioglu OM, Velcu O. A review of dashboards in performance management: Implications for design and research. International Journal of Accounting Information Systems. 2012 Mar 1;13(1):41-59.
[17] Perkhofer L, Hofer P, Walchshofer C. BIG data visualisierungen 2.0. Optimale Gestaltung und Einsatz neuartiger Visualisierungsmöglichkeiten. Proceedings of CARF. 2019:76-104.
[18] Tornatzky LG, Fleischer M, Chakrabarti AK. Processes of technological innovation. Lexington books; 1990.
[19] Swanson EB. Information systems innovation among organizations. Management science. 1994 Sep;40(9):1069-92.
[20] Rogers EM. Diffusion of innovations. Simon and Schuster; 2010 Jul 6.
[21] Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS quarterly. 1989 Sep 1:319-40.
[22] Ajzen I, Fishbein M. Attitude-behavior relations: A theoretical analysis and review of empirical research. Psychological bulletin. 1977 Sep;84(5):888.
[23] Ajzen I. The theory of planned behavior. Organizational behavior and human decision processes. 1991 Dec 1;50(2):179-211.
[24] Sanjeetha MBF, and Nawaz SS. Students' intention to use social media for academic purposes: A study of south eastern university of sri lanka. Journal of Information system and Information Technology, 2020; 5(2):50-60.
[25] Rajasa A, Faturachman F. Predicting the Intention to Re-Use on Accounting Application Software (The Case of Accurate™ Application Software Users in Indonesia). The International Journal of Business & Management. 2015 Aug 1;3(8).

[26] Syafrudin V. An empirical study of Accounting software Acceptance among Bengkulu City students. Asian journal of Accounting and governance. 2012;3:99-112.

[27] Attuquayefio S, Addo H. Using the UTAUT model to analyze students' ICT adoption. International Journal of Education and Development using ICT. 2014 Aug 30;10(3).

[28] Arif M, Ameen K, Rafiq M. Factors affecting student use of Web-based services: Application of UTAUT in the Pakistani context. The Electronic Library. 2018 Jun 4.

[29] Venkatesh V, Davis FD. A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management science. 2000 Feb;46(2):186-204.

[30] Hair Jr JF, Hult GT, Ringle C, Sarstedt M. A primer on partial least squares structural equation modeling (PLS-SEM). Sage publications; 2016 Feb 29.

[31] Esposito Vinzi V, Chin WW, Henseler J, Wang H. Handbook of partial least squares: Concepts, methods and applications. Heidelberg, Dordrecht, London, New York: Springer; 2010.

[32] Chin WW, Newsted PR. Structural equation modeling analysis with small samples using partial least squares. Statistical strategies for small sample research. 1999;1(1):307-41.

[33] Hair Jr JF, Sarstedt M, Hopkins L, Kuppelwieser VG. Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. European business review. 2014 Mar 4.

[34] Hulland J. Use of partial least squares (PLS) in strategic management research: A review of four recent studies. Strategic management journal. 1999 Feb;20(2):195-204.

[35] Bagozzi RP, Yi Y. On the evaluation of structural equation models. Journal of the academy of marketing science. 1988 Mar;16(1):74-94.

[36] Fornell C, Larcker DF. Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. J Mark Res [Internet]. 1981;18(3):382. Available from: http://www.jstor.org/stable/3150980?origin=crossref.

[37] Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the academy of marketing science. 2015 Jan;43(1):115-35.

[38] Henseler J. On the convergence of the partial least squares path modeling algorithm. Computational statistics. 2010 Mar;25(1):107-20.

[39] Wong KK. Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. Marketing Bulletin. 2013 Jan 1;24(1):1-32.