Journal of Information Systems & Information Technology (JISIT) **Vol. 5 No.1 2020**
ISSN: 2478-0677 **110-125**

Exploring the Factors Influencing Big Data Technology Acceptance

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Abstract. This research aims to determine the factors influencing big data technology acceptance with an industrial- organizational context. By using existing technology acceptance theories, literature review and industrial technical research on data management technologies, six external factors have been formulated for the quantitative study of this research. The Technology Acceptance Approach provides the theoretical basis for this model. External variables may be plugged into this model's latent construct of perceived ease of use. The quantitative study's primary data collected within big Hadoop User Groups in Sri Lanka who operate in a variety of sectors. Using 432 survey answers, we empirically verified and validated our proposed model using the structural equation modeling (SEM) software Smart PLS 3. The hypothesis tests are significant for seven out of nine route connections, according to the structural model analysis. Scalability, storage and processing, analytics capability, and output quality are four external factors that this research effectively evaluates and verifies in terms of technical capabilities in adopting new technologies. The suggested model finds flexibility and dependability to be non-significant external factors. These results contribute significantly to the advancement of theoretical knowledge and contribute to the groundwork for future study to improve our knowledge in the field of user acceptance behavior. This study advises businesses on what technical characteristics and capabilities to look for when purchasing a complicated piece of equipment.

Keywords: Industrial- Organizational professionals, Big data, Hadoop, Technology acceptance model, External factors

1 Introduction

Big Data is a collection of data that is huge in volume, yet growing exponentially with time. It is a data with so large size and complexity that none of traditional data management tools can store it or process it efficiently. Big data is also a data but with huge size. It helps the organizations to create new growth opportunities and entirely new categories of companies that can combine and analyze industry data. These companies have ample information about the products and services, buyers and suppliers, consumer preferences that can be captured and analyzed. Big data has quickly become a commonplace practice for businesses. Using large-scale, fast-moving, complicated streams of data to make choices has the potential to radically change how companies make decisions. Big data refers to datasets that are both large and diverse, as well as having a rapid rate of change, making them challenging to manage using conventional tools and methods.[1]. Hadoop is the most commonly utilized Big Data processing paradigm today. Hadoop is an open-source large-scale data processing platform

Received: 24th Jun, 2020
Revised and Accepted: 30th Jun, 2020

that uses basic programming paradigms to enable distributed processing of huge amounts of data. In addition to other modules, the Apache Hadoop project includes HDFS and Hadoop Map Reduce. The program is designed to take use of clustered computing's processing capacity while also handling node outages.

2 Review of Literature

Big data is large and complex, and it cannot be stored in conventional database systems. [2] posit that the novelty of big data, hadoop is distinct in terms of its complexity with data structures. Big data has emerged during the last decade. Before the emergence of big data, we used to deal with transactional data that are structured and hence could be stored in conventional relational database systems [3]. The relational database system has been on the market since the early 70s after Dr. Codd gave a model for relational databases based on the mathematical set theory [4]. With the advent of new technologies, the internet, advancement in software and hardware engineering, social network tools, and automation, the data volume has increased significantly [5]. Most of the internet and social media data are unstructured [6]. Data storage cost has also been decreasing gradually. As a result, organizations find it worthwhile to store and process big data to find business opportunities in them [7]. Early users of big data include Google, Yahoo, Facebook, and Amazon to name a few.

2.1 Big Data Technology and Hadoop

The extant literature suggests that over the past three decades the information technology field has shown the biggest technological advances [8]. Today, Hadoop is the most widely used Big Data processing model. Hadoop is an open-source large-scale data processing platform that makes use of fundamental programming concepts to allow distributed data processing. The Apache Hadoop project contains HDFS and Hadoop Map Reduce, among other components. The software is built to take use of clustered computing's processing power while simultaneously dealing with node failures[9]. Apache Hadoop is a prominent software framework in the big data world. The evolution of Hadoop is now spanning over 10 years. The seeds of Hadoop were planted back in 2002 by two creative thinkers: Doug Cutting and Mike Cafarella. Their project name was Nutch which was originally aimed to develop a state-of-the-art open-source search engine based on Internet archives with the capability to crawl and index millions of pages [10]. The project was able to crawl and index hundreds of millions of pages. But to work on billions of pages, a more robust architecture and scalability were needed. And right after their first working version, Google published papers on the Google File System in October 2003 and the MapReduce in December 2004 which helped to build Nutch [10]. By the year 2020, a few cloud-based big data platforms (public clouds) have evolved along with their own storage systems as an alternative to HDFS: Microsoft Azure, Google Cloud, and Amazon Elastic MapReduce, to name a few

2.2 Technology Acceptance Model

[11] introduces this technology model which was rooted in theory of research action [12]. Later, [13] developed a revised version called technology acceptance model 2. [14] report that overall, the technology acceptance model could describe about 40% of the overall system's use. The technology acceptance model is made up on two main concepts: 'perceived usefulness' and 'perceived ease of use,' both of them are influenced by independent factors,

which in turn influence the latent variable, 'behavioral intention to use.' The technology acceptance model is the most frequently used and important paradigm, particularly in the area of information systems.[15]. The main strength of technology acceptance model is parsimony[16]. This research attempts to extend the technology acceptance model to more complex adoption scenarios such as acceptance of the complex platform/ infrastructure, Hadoop by its intended users. One study [17] has investigated technology acceptance model using big data as the application. It finds all core constructs of technology acceptance model valid. However, this study has not used big data-related independent variables. What makes big data technology useful? What technological capabilities make big data technology useful? Therefore, in addition to employing technology acceptance model's core constructs, antecedents specific to the big data technology and technological capabilities are sought by our study. One key aspect of technology acceptance model is that it provides a framework to examine the influence of external factors on the usage of a system. Several external factors have been applied to technology acceptance model factors. For the construct, perceived ease of use these external variables have been used: scalability, storage, and processing, analytics capability, flexibility, reliability and output quality [18].

[19] conduct Several empirical studies, articles and a systematic literature review that published results of empirical studies that used technology acceptance model. The authors find that behavioral intention is correlated with actual usage. Current research makes an attempt to come up with a definition of 'usefulness'. That helps in the qualitative study process in identifying external factors that point to perceived usefulness. [20] observe that only a few studies are conducted on actual system use. Hence, we add this construct to our research model.

3 Research Model and Research Hypotheses

The research model is primarily based on technology acceptance model which includes factors such as perceived usefulness, perceived ease of use, behavioral intention, and actual use. One key aspect of technology acceptance model is that it provides a framework to examine the influence of external factors on the usage of a system [11]. The technology acceptance model is frequently used to examine the usage behavior of a system from an individual perspective. This research uses this model to examine the usage behavior from an organizational context. In this model, six external factors have been selected through a quantitative study including scalability, storage, and processing, flexibility, analytics capability, reliability, and output quality. The corpus of knowledge is anticipated to benefit from successful testing of the impact of these variables on the technology acceptance model. This study would want to verify these variables using survey data since this model is founded on six criteria that were chosen. As a result, we create a model for research.

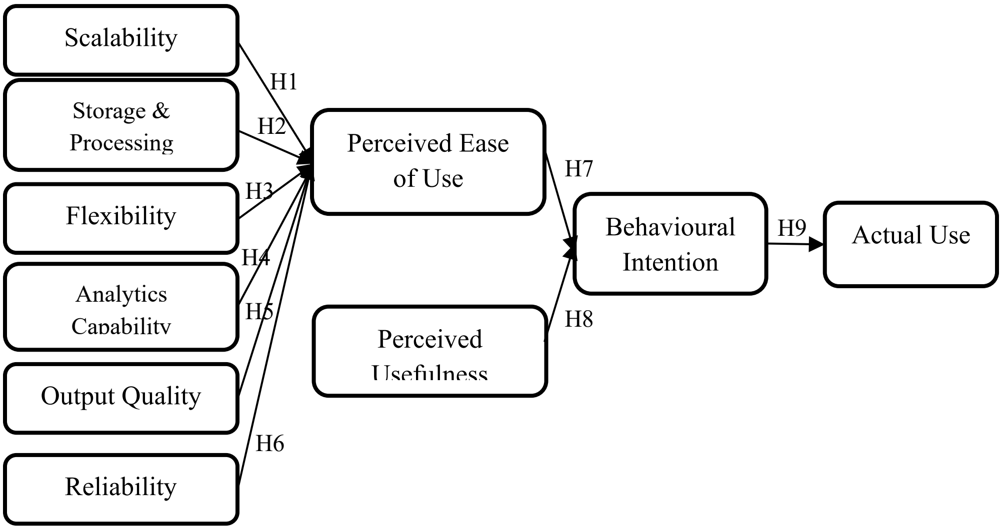

Figure 01: Proposed Model

The results of hypothesis testing must be informative in order to assess the research model. We generated the following hypotheses against each concept based on the suggested study model. To represent the big data environment in this research, metrics from prior studies have been included. Several new structures and measurements have also been created.

3.1 Scalability

Most of the traditional relational databases lack scalability in dealing with hundreds of terabytes of data. In big data, new NoSQL technologies emerged to provide performance and scalability [21]. One of the technical obstacles to the adoption of big data analytics, according to research results, is performance and scalability [22]. In terms of storage, data processing, and developing a strong machine learning model, big data technologies are scalable. For reasons of availability, tolerance, and scalability, big data pioneers like Facebook chose Hadoop and HBase. [23]. Hence,

Hypothesis H1: Scalability has a positive effect on perceived ease of use of Big Data-Hadoop.

3.2 Storage & Processing

In terms of storage and data processing, Hadoop is regarded as extremely scalable. “By spreading storage and processing over a large number of servers, the resource may scale to meet demand while staying cost-effective at any scale” [24]. Traditional databases are neither scalable or capable of handling hundreds of terabytes of data. It's interesting investigating if Hadoop's storage and processing capabilities are linked to big data adoption. Hence,

Hypothesis H2: Storage and processing have a positive effect on perceived ease of use of Big Data-Hadoop.

3.3 Flexibility

Big data technology and tools provide you more options. assemble data from many different sources and keep it in a single location (Hadoop HDFS). Traditional data from enterprise resource planning (ERP), and new data, such as data collected in social media, data collected from sensors, emails, and so on, are among these sources. Hadoop may be used for a number of tasks, including streaming real-time content and its processing, processing log files, setting up a data warehouse, analyzing marketing campaigns, and detecting fraud [25]. Data mining and business intelligence skills are enhanced when data is consolidated onto a single platform[5]. Hence,

Hypothesis H3: Flexibility has a positive effect on perceived ease of use of Big Data-Hadoop.

3.4 Analytics Capability

One Data is kept in the Hadoop distributed file system (HDFS) and does not need to be moved to relational database systems, which is a fundamental feature of the Hadoop-based architecture. All analytical, data mining, and reporting applications will be done using HDFS. By using Hadoop's distributed file system, there's a good chance you'll be able to perform sophisticated data mining on a large collection of data stored in HDFS. By converting batch data processing into a real-time stream mining platform, [26] acquired the capacity to mine real-time streams. To find knowledge from huge healthcare claims data, [27] used clustering data mining algorithms to a large dataset comprising of 10 years of historical data recorded in the hospital information system. [28] and [29] provide forth a comprehensive foundation for big data analytics. This is something worth looking into. Hence,

Hypothesis H4: Data analytics capability is positively related to perceived ease of use of Big Data-Hadoop.

3.5 Output Quality

Veracity is one of the five qualities of big data, and it encompasses data integrity and quality. In order to map the data lineage, new technologies are being developed [5]. This project is currently in its early stages. According to [30], "a firm's desire to use big data analytics may be favorably influenced by its ability to preserve the quality of corporate data." [31] claim that if big data is unable to offer quality choices owing to data integrity, freshly mined information will not persuade the analytical community. Big data, on the other hand, is seen to have the potential to enhance the quality of clinical trial monitoring while simultaneously reducing government expenditure [32]. Hence,

Hypothesis H5: Output Quality are positively related to the perceived ease of use of Big Data-Hadoop.

3.6 Reliability

The degree to which consumers believe a new technology is reliable is referred to as reliability. To achieve dependability and efficiency, organizations embrace new technology to overcome unreliability and inadequacies, or to start on next generation tools and technologies. Users want to know that any tools or technology they use are dependable and that they can demonstrate that spending money on them is a good investment. Hence,

Hypothesis H6: Reliability is positively related to perceived ease of use of Big Data-Hadoop.

3.7 Perceived Ease of Use

TAM's fundamental component is this factor. This construct is dependent on another fundamental construct, behavioral intention. Prior empirical study has shown and verified it. As a result, the following hypothesis was developed:

Hypothesis H7: Perceived Ease of Use has positive effect on Behavioral Intention to using Big Data-Hadoop.

3.8 Perceived Usefulness

TAM's fundamental component is this factor. Prior empirical study has shown and verified it. As a result, the following theory was devised:

Hypothesis H8: Perceive Usefulness has positive effect on Behavioral Intention in using Big Data-Hadoop.

3.9 Behavioral Intention

TAM's fundamental component is this factor. According to the existing research, behavioral intention is the most powerful predictor of system usage [11] [33]. Prior empirical study has shown and verified it. This is one of the two constructions that has a direct impact on Hadoop use. As a result, the following theory was devised:

Hypothesis H9: Behavioral Intention has a positive effect on Actual Use of Big Data-Hadoop.

4 Methodology

A quantitative approach based on questionnaire survey with cross-sectional design was employed to explore the factors influence big data technology acceptance by industrial-organizational professionals in the Sri Lankan context. The study population consisted of industrial-organizational professionals those who working with big data technologies such as Hadoop software. Since some of these organizations normally do not reveal the actual number of such professionals and their details due to privacy concerns [34], more over due to this COVID 19 pandemic situation, the researcher could not determine the population framework; hence, They utilized a simple sampling technique that is often used in technology adoption research. The sample size was carefully calculated using a variety of supporting literatures. "Each independent variable is anticipated to contain 10 data records," according to [35]. "Sample sizes greater than 30 and fewer than 500 are acceptable for most research," according to [36]. SEM studies are generally required to have a sample size of at least 200 answers [37]. As a result, 450 people were chosen as the sample size for this research.

The variables and their items were obtained from the same academics, and the questions were contextualized to the big data-Hadoop area, since the study methodology was mainly based on current TAM [11]. For the online survey, simple and impartial wordings were chosen in the questionnaire so that respondents could readily comprehend the questions. The respondents were asked to rate their preference for the constructs of scalability, storage and processing, analytics capability, output quality, flexibility, reliability, perceived ease of use, perceived usefulness, and behavioral intention on a five-point Likert scale, with 1 representing Strongly Disagree and 5 representing Strongly Agree. Google Forms was used to create the online survey. The questionnaire's weblink was shared on numerous social media sites, including LinkedIn, Facebook, WhatsApp, public forums, and emails addressed to known professional connections. A total of 442 answers were received when the survey was completed. Because ten of the answers were incomplete, they were deleted, leaving 432 responses for further research. SmartPLS 3 was used to import the clean Excel Worksheet for further investigation. The Partial Least Square Structural Equation Modelling (PLS- SEM) method was used using the SmartPLS 3 software to verify the data and test hypotheses.

5 Data Analysis

Partial Partial least squares structural equation modeling (PLS-SEM) [38] [39] was applied to analyze the research model. PLS-SEM is a powerful approach for analyzing simple and robust models in business management [35] [40], and has gained the attention of SCM scholars [41] [3]. Its main advantages are its flexibility in working with small samples and its formative and reflective constructs [40].

5.1 Demographic Analysis

The characteristics of the responders are shown in Table 1. Almost all of the responders were men, accounting for almost 80% of the total. The majority of responders (49.54 percent) were between the ages of 34 and 41. A total of 45.83 percent of respondents had a postgraduate diploma, which was the highest level of education in our sample, followed by 33.33 percent with bachelor's degrees and 20.83 percent with a master's degree. When asked about their work experience at their respective organizations, 55.79 percent said they had worked there for 2-5 years, 20.14 % said they had worked there for 6-10 years, 13.19 % said they had worked there for 11-15 years, and 10.88% said they had worked there for less than one year. Finally, logistics analysts made up 24.54% of the sample, followed by transportation managers (18.98%), operations managers (27.31%), and supply chain managers (29.17%).

Table 01: Demographic profile of respondents

	Frequency	**Percentage**
Gender		
Male	351	81.25
Female	81	18.75
Age		
22-33	117	27.08
34-41	214	49.54

42-49	87	20.14
50 and above	14	3.24
Highest education level		
Bachelor degree	144	33.33
Postgraduate diploma	198	45.83
Master of Science (MSc)	90	20.83
Number of years spent working in the organization		
Less than one year	47	10.88
2-5 years	241	55.79
6-10 years	87	20.14
11-15 years	57	13.19
Occupation		
Logistics analyst	106	24.54
Operations manager	118	27.31
Transportation manager	82	18.98
Supply chain manager	126	29.17

5.2 Measurement model

SmartPLS 3 [40] [38] was used to examine the study model. The model's loadings, Cronbach's alpha, composite reliability, average variance extracted, and discriminant validity were all evaluated first. Table 02 shows that all of the outside loadings surpassed the 0.70 level suggested in the literature [40]. Also included are the major construct dependability and item internal consistency metrics. Cronbach's alpha and composite reliability were both more than 0.70 in this research, and all average variance extracted values were greater than 0.50 [40] [42]. As a result, the model's use of all constructs has been verified. The discriminant validity findings are shown in tables 04 and 05. In this scenario, the square root of each construct's average variance retrieved should be higher than the correlations between them [43] [44]. Our findings are greater than the 0.70 threshold [43], indicating that discrimination exists across all constructs [45].

Table 02: Factor Loadings and Reliability Measures

Construct	Indicators	Loadings	CA	rho_A	CR	AVE
Analytics Capability	AC1	0.812	0.774	0.785	0.869	0.689
	AC2	0.89				
	AC3	0.785				
Actual Use	AU1	0.761	0.795	0.808	0.867	0.621
	AU2	0.813				
	AU3	0.855				
	AU4	0.715				
Behavioral Intention	BI2	0.809	0.777	0.791	0.856	0.598
	BI3	0.751				
	BI4	0.801				
	BI5	0.729				
Flexibility	FL1	0.726	0.729	0.871	0.797	0.599
	FL3	0.672				
	FL5	0.699				
	FL6	0.811				

Output Quality	OQ1	0.797	0.821	0.829	0.881	0.651
	OQ2	0.843				
	OQ3	0.84				
	OQ4	0.742				
Perceived Ease of Use	PE1	0.844	0.778	0.798	0.871	0.693
	PE2	0.885				
	PE4	0.764				
Perceived Usefulness	PU1	0.789	0.819	0.822	0.88	0.647
	PU2	0.818				
	PU3	0.806				
	PU5	0.805				
Reliability	RL2	0.76	0.731	0.752	0.848	0.651
	RL3	0.882				
	RL4	0.775				
Scalability	SC1	0.719	0.858	0.866	0.898	0.639
	SC2	0.82				
	SC3	0.82				
	SC4	0.848				
	SC6	0.782				
Storage, and processing	SP1	0.837	0.819	0.847	0.879	0.647
	SP2	0.798				
	SP4	0.846				
	SP6	0.73				

Table 03: Discriminant validity (Fornell-Larcker's test)

	AC	AU	BI	FL	OQ	PE	PU	RL	SC	SP
AC	0.83									
AU	0.591	0.788								
BI	0.61	0.586	0.773							
FL	0.573	0.417	0.432	0.706						
OQ	0.875	0.581	0.628	0.622	0.807					
PE	0.565	0.959	0.554	0.397	0.557	0.833				
PU	0.758	0.61	0.611	0.509	0.766	0.593	0.804			
RL	0.678	0.393	0.312	0.5	0.636	0.366	0.512	0.807		
SC	0.65	0.628	0.615	0.469	0.673	0.6	0.634	0.396	0.799	
SP	0.257	0.184	0.263	0.26	0.283	0.166	0.252	0.147	0.175	0.804

Table 04: Discriminant validity (Ratio Heterotrait-Monotrait -HTMT)

	AC	AU	BI	FL	OQ	PE	PU	RL	SC	SP
AC										
AU	0.747									
BI	0.778	0.727								
FL	0.599	0.419	0.477							
OQ	0.891	0.71	0.782	0.597						
PE	0.719	1.222	0.693	0.402	0.687					
PU	0.954	0.749	0.749	0.509	0.835	0.734				

RL	0.904	0.513	0.407	0.525	0.83	0.481	0.665			
SC	0.792	0.749	0.733	0.438	0.8	0.721	0.748	0.497		
SP	0.314	0.225	0.338	0.309	0.336	0.204	0.314	0.181	0.195	

5.3 Structural model

We looked at the values of the path coefficients and the explained variance of the endogenous variables to see how well the structural model worked (R^2). The route coefficients represent how strong the connection between the independent and dependent variables is. The reliability of the calculated route coefficients was determined using a bootstrapping method with 432 samples, as shown in Table 05 and Figure 02, respectively. The path coefficient data are highlighted in Table 05.

Table 05: Path coefficients

Hypotheses	Path	Beta	Standard Deviation	T Statistics	P-Values	Results
H1	SC -> PE	0.38	0.068	5.581	0	Supported
H2	SP -> PE	0.509	0.038	13.394	0	Supported
H3	FL -> PE	0.042	0.044	0.958	0.339	Not Supported
H4	AC -> PE	0.235	0.084	2.791	0.005	Supported
H5	OQ -> PE	0.376	0.083	4.53	0.002	Supported
H6	RL -> PE	0.014	0.061	0.228	0.82	Not Supported
H7	PE -> BI	0.295	0.053	5.59	0	Supported
H8	PU -> BI	0.436	0.053	8.191	0	Supported
H9	BI -> AU	0.586	0.041	14.397	0	Supported

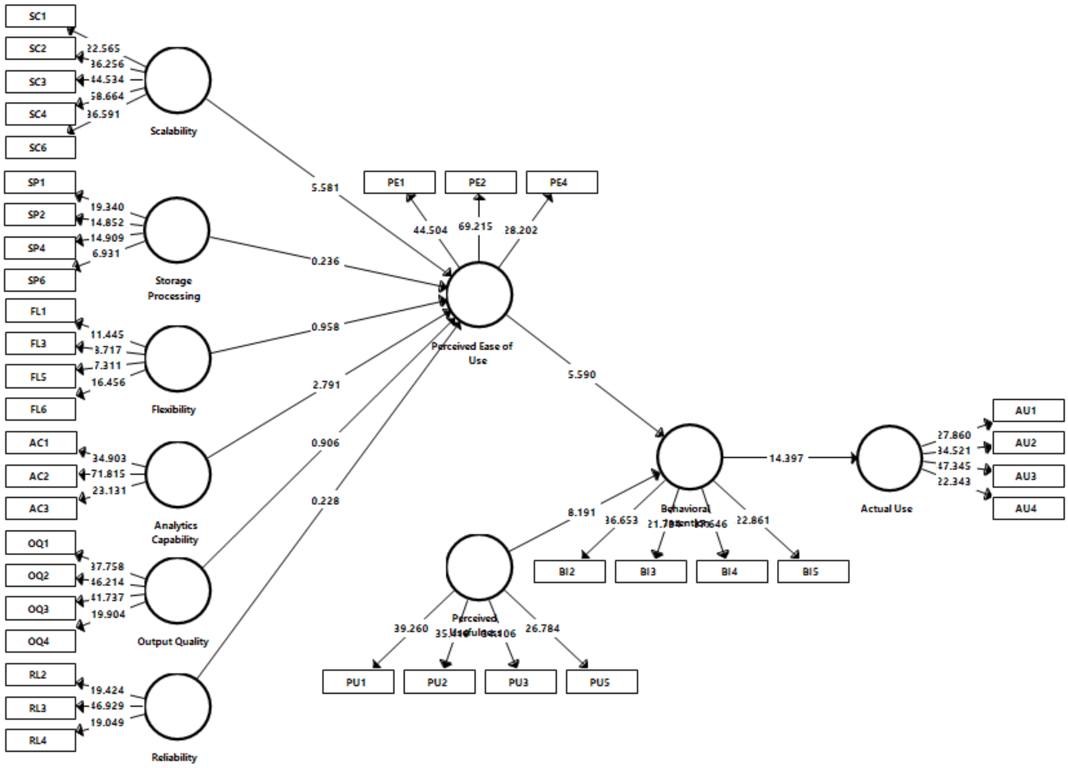

Figure 02: Results of the model (Bootstrapping)

The model explains 34.2% of the variation in actual use and 42.7% of the variation in behavioral intention (Table 06 and figure 03), and perceived ease of use 40.8% all three of which exceed the minimum level of 10% recommended by [46].

Table 06: R^2 results (dependent variables)

	R Square	R Square Adjusted
AU	0.344	0.342
BI	0.430	0.427
PE	0.416	0.408

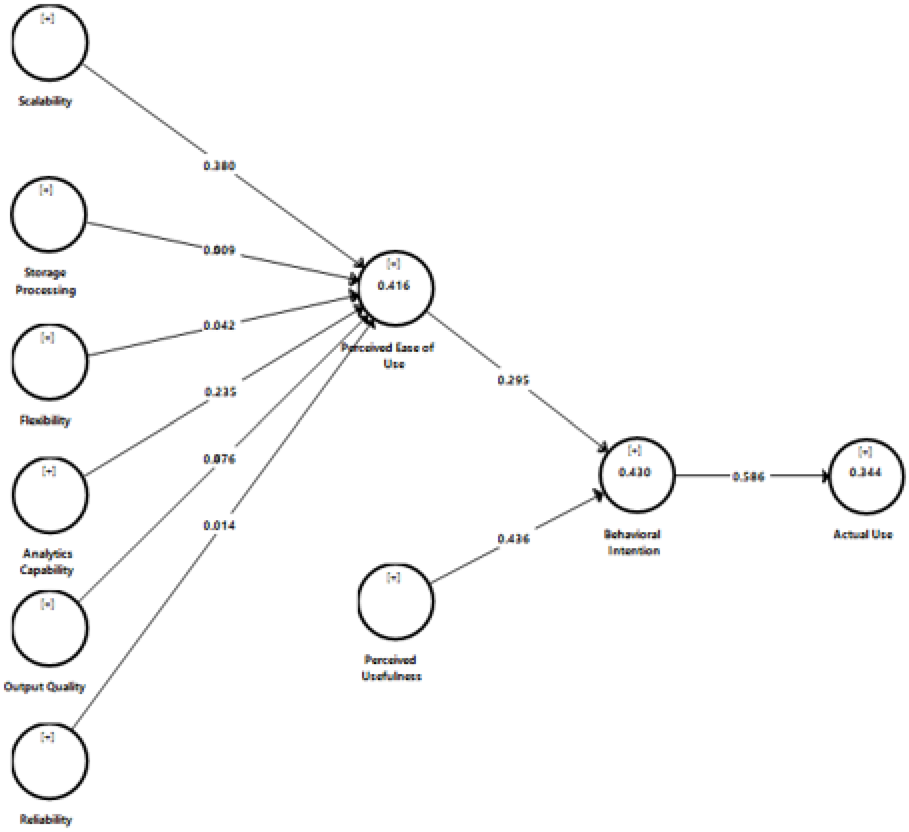

Figure 3: R^2 results of the model

6 Discussions

The findings indicated that scalability has a significant positive effect on perceived ease of use (β = 0.38, p < 0.001). Thus, H1 is supported. H2 hypothesized that storage and processing has a significant positive effect on perceived ease of use. The results (β = 0.509, p < 0.001) support H2. H4 theorized that analytics capability has a significant positive effect on perceived ease of use. This hypothesis was also supported (β = 0.235, p = 0.005). Next, H5 argued that ouput quality has a significant positive effect on perceived ease of use. Our results (β = 0.376, p = 0.002) support this hypothesis. Then, H7 argued that perceived ease of use has a significant positive effect on behavioral intention. The results supported H7 (β = 0.295, p < 0.001). H8 theorized that perceived usefulness has a significant positive effect on behavioral intention. The results supported H8 (β = 0.436, p < 0.001). Finally, H9 argued that behavioral intention has a significant positive effect on actual use. The results supported H9 (β = 0.586, p < 0.001). The rest of the hypotheses had unexpected results. H3 theorized that flexibility has a significant positive effect on perceived ease of use. Surprisingly, the relationship was found to be negative and non-significant [47]. Therefore, H3 was not supported (β = 0.042, p = 0.339). H6 argued that reliability has a significant positive effect on perceived ease of use. This hypothesis was not supported either (β = 0.014, p = 0.82). Theoretically the outcome shows that, the factors influencing big data technology (Hadoop) among industrial-organizational professionals could be fully clarified by the extant technology acceptance model. Practically, management may improve the behavioral intention and actual use by improving the scalability, storage, and processing, analytics capability, and output quality [48]

7 Conclusion and Future Recommendation

This study explores what factors influence big data technology (Hadoop) adoption. Also, this research has successfully validated the Davis' technology acceptance model along with a few new independent variables. The development and test of our TAM-based model with new factors advance theory and research of the technology acceptance model. This research examines the external factors that influence a firm whether to adopt or not adopt the big data technology, Hadoop. Based on a quantitative study this research selected six factors, to use them as external variables of the research model. A survey instrument was developed based on construct items from extant literature and also based on several new items relevant to big data technology. An online survey was administered for those who participated in the survey come from major industries including software/internet services, financial services, healthcare, consulting services, telecommunication, manufacturing, retail, insurance, advertising, and logistics. The model found seven constructs as significant predictors for the adoption of big data technology, Hadoop. These factors include scalability, storage and processing, output quality, perceived ease of use, perceived usefulness, and behavioral intention. The SEM model also found two other external variables to be non-significant. Hence, these factors were rejected: flexibility, and reliability. This shows consistency between extant literature and the current study results. This research makes a contribution by investigating and testing existing IS theory in a new information technology context. We extended the TAM through the addition of six external variables. This is a significant contribution to theory and knowledge.

Future Recommendation

This research provides some insights and directions for future research. As this research has taken on some new challenges using extant as well as new constructs, this opens up avenues for further research. This research has successfully validated six external variables and made them be part of TAM. This is a great contribution to the theory and knowledge. However further studies can add more external variables into this existing variable. The survey instrument of this research was destined for the actual users who possess hands-on experience in using the Hadoop. As part of future research, this survey could be conducted using the first-line managers, mid-level managers, and executives of companies as well. This could provide us an insight as to whether collecting data from direct users versus company executives would make any difference. Finally, this study was conducted with data from users in Sri Lankan context. The results cannot be generalized to organizations outside of Sri Lanka. Hence, conducting a comparative analysis of big data technology use or intention to use in similar industries and alternative geographical areas could provide some useful insights.

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