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Big Data Usage Intention of Management Accountants: Blending the Utility Theory with the Theory of Planned Behavior in an Emerging Market Context

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Abstract

This work blends the utility theory with the theory of planned behavior to investigate the management accountant's (MA) intention in using big data. The study was conducted in early 2017 using a partial least squares-structural equation modeling technique with a sample of 203 MAs in 11 Indian cities. The research identified attitude as the most significant antecedent of intent to use big data followed by the subjective norms. These findings have significant managerial relevance for the firms in sensitizing their accounting teams on the benefits of using big data to achieve more voluntary buy in from the MAs. The investigation also contributes to the methods by illustrating the application of two advanced techniques, multi group analysis (MGA) and importance-performance map analysis (IPMA) in validating the theory of planned behavior in an emerging market context.

Keywords

Big Data, India, Intention, Management Accountant, PLS-SEM, Theory of Planned Behavior, Utility Theory

1. Introduction

The role of the management accountant (MA) has under gone a substantial transformation in the last few decades. MAs are now active participants in the organization's decision making process. Yiu (2012) [1] established that the usage of big data allows improved decision making, better learning, and higher innovation in firms. Gartner (2016) [2] opined that big data, by definition, was high in volume, velocity, and variety of information which need to be processed appropriately. Fosso Wamba *et al.* (2016) [3] suggested that the "five v" related the dimensions of big data, including volume, variety, velocity, veracity, and value. Since the MAs deal with data possessing the above-mentioned features, it is desirable to probe their intention in using big data for their respective roles. Zicari (2015) [4] pointed out that big data meant a larger variety of data which included websites, texts, sensors, etc. in addition to the traditional sources. This study investigates the actual intentions of MAs in graduating to big data capabilities in the near future. A significant number of these professionals are also engaged in providing inputs for strategy formulation. As observed by Tambe (2014) [5], companies need to revisit their business models owing to the data revolution, and the MAs can contribute proactively to such changes.

There has been a critique of big data by some of the scholars. Kho (2016) [6] was less convinced and asserted that the concept was akin to converting noise into something more meaningful. However, for the accounting professionals, big data can have multiple applications, such as contributing to the risk assessment insights of auditors (Moffitt and Vasarhelyi 2013) [7]. Human limitations in processing large amounts of information for complex decisions (Kleinmuntz 1990) [8] are eliminated with the use of big data analytical tools. For accounting professionals, fraud detection through data mining and data analytics (Bochkay and Levine 2017) [9] and risk quantification are the key benefits of analyzing big data (Russom 2011) [10]. Finally, prediction of a future occurrence is possible (Cukier and Mayer-Schoenberger 2013) [11], which is another incentive for the use of big data by MAs.

An exponential growth has occurred in the data available with the firms. It has been observed that voluminous information leads to suboptimal financial and auditing decisions (Alles *et al.* 2008) [12]. The authors also asserted that big data helps identify patterns which would otherwise be undetectable. This discovery has many positive ramifications in management accounting because of the governance challenges faced by firms in the last two decades. Accountants also need to proactively engage in the firm's development of big data analytics capabilities (BDAC), which have been hailed as "the fourth paradigm of science" (Strawn 2012 p. 34) [13] and also as "the potential to transform management theory and practice" (George *et al.* 2014 p. 325) [14]. As correctly indicated by Mc Afee *et al.* (2012) [15], businesses are dealing with more data than they are capable of handling, and therein lies the need to re-skill the MAs. The research on the behavioral dimensions of accountants is in a nascent stage in emerging markets, such as the Indian scenario.

The utility theory, in the economics literature creates a broad framework for decision making by individuals or firms, given the alternative choices in products or services, to satisfy the needs. As per Fishburn (1968) [16], the utility theory deals in the people's choices, decisions, preferences, worth and value. Fishburn further recommends the use of utility theory in consumer economics, regarding the spend on various commodities. The theory of planned behavior (TBP) (Ajzen 1991) [17] is an intention model that explains and predicts behavior in multiple contexts (Chang 1998) [18]. Ajzen defines intention as the will to undertake a particular behavior. As per Ajzen, intention has three cognitive antecedents. The first one is the individual's attitude (A), which could be favorable or otherwise for the target behavior. The second pertains to the subjective norms (SN) of the reference groups, which could include the opinion of family, friends, etc. on a behavior. Finally, the perceived behavior control (PBC) highlights how easy or difficult it was for the individual to perform that behavior. It was observed that research on usage intention could not completely rely on the evidence from other domains to validate intention and establish an antecedent of big data usage behavior.

The study was conducted by collecting primary data from 11 major Indian cities and analyzing them using partial least squares structural equation modelling. This study makes three distinct contributions. First, it contributes to literature by blending the utility theory with the theory of planned behavior in the context of the emerging market. Second, the findings suggest that the attitude of the MAs had the highest direct effect on the usage intention of big data. The next important factor was the subjective norms. Counter intuitively, perceived behavior control did not have any significant impact on the usage intention of big data. Also, the gender of the accountant did not have any effect on the usage intention of big data. Finally, the study illustrates the application of some advanced techniques in validating the theory of planned behavior.

The paper is structured as follows. After the introduction, in Section two the conceptual development and hypothesis are discussed. The methods used for the study are discussed in Section three and the results are shown in Section four. This is followed by the discussion and the conclusion in Section five and Section six respectively.

2. Conceptual Development and Hypothesis

Prior studies have classified big data on the basis of origination. For instance, Davenport (2014) [19] categorized big data as machine or human generated. While the former does not require human intervention, the latter is generated by humans with the help of computers. Ji-fan Ren *et al.* (2017) [20] studied the financial impact of big data usage on the companies. Other similar studies suggest that big data entails both benefits and risks (Ernst & Young, 2014) [21]. This is true in the context of accounting as well. For instance, Mayew and Venkatachalam (2012) [22] examined the audio from the quarterly earning calls to detect dissonance in the speech patterns of chief executive officers. This study was possible owing to the advancements in big data usage. Warren *et al.* (2015) [23] asserted that accounting records are of a financial nature and are prepared for both internal and external stakeholders. Most records have their genesis in financial transactions, and these records are getting rapidly digitized. Warren *et* *al.* (2015) [23] further reinforced the need for video enhanced accounting records, especially those related to internal controls. This task is possible with big data adoption. According to Warren *et al.* (2015) [23], big data can help address major concerns in both financial and managerial accounting. In the financial accounting domain, big data can be useful in ensuring completeness and accuracy of the records and in deriving accounting estimates. Reporting transparency, fair value, audit efficiency, effectiveness, etc. could also be achieved. Moreover, big data can assist in addressing the challenges related to management control systems, budgeting, employee productivity, and customer satisfaction.

A great volume of data, as well as advanced data mining tools, are available for the managers and analysts (Sharma *et al.* 2010) [24]. Nonetheless, the main theme of discussion is whether big data provides a competitive advantage for the firms. Bughin *et al.* (2011) [25] asserted that big data is indeed a source of competitive advantage. The idea improves the risk taking ability, which leads to increased innovation (even in a highly controlled environment) and eventually yields a competitive advantage (Varma *et al.* 2018) [26]. Lavalle *et al.* (2011) [27] identified BDAC as the capability to use big data for decision making that is linked to the firm's strategy. Barton and Court (2012) [28] listed three such capabilities: the capability to predict and optimize information technology infrastructure, and the expertise of front line employees in understanding the tools. Another integrative dimension of big data was revealed by Davenport *et al.* (2012) [29] who stated that management, human resource, and technology are all interlinked in the big data environment.

The theory of planned behavior (TBP) when blended with the utility theory, helps address questions, such as the roles of attitude and other's opinion in the intention to adopt big data, and finally, how easy and controllable is it to use big data. The overarching question remains as to whether MAs see "utility" in big data usage. The theory posits that the attitude should be positive, subjective norms ought to be favorable, and perceived behavior control must be high for an intention to result in the desired behavior, in this case, the usage of big data. A high intention to adopt big data is most likely to result in its usage in the near future since intention is the antecedent of behavior. Ajzen (2002) [30] revised the TPB by proposing linkages between past behavior and future behavioral intent. Morris *et al.* (2005) [31] studied the role of gender in intention, and it was worth probing whether this aspect played a part in the usage of big data.

The above discussion leads to the following hypothesis:

H1: MA's attitudes towards big data positively influence their intention to use it.

H2: MA's subjective norms towards big data positively influence their intention to use it.

H3: MA's perceived behavioral control towards big data positively influences their intention to use it.

H4: MA's gender will not have an effect on their intention to use big data.

3. Methods

3.1. Data Collection, Research Setting, and Sample

The hypothesis based on the theory of planned behavior was tested on the practicing accountants from 11 Indian cities so that the results could be generalized (Birnberg and Snodgrass 1988) [32]. These cities are the major industrial and commercial hubs in the country. The respondents were sensitized on the "five v" characteristics of big data so that they could differentiate the concept from data or information in general.

A questionnaire that was pretested (Chin 1998) [33] and validated by a pilot study (DeVellis 2016) [34] was administered to the MAs. The form was well-labeled and used a seven point self-rating Likert scale to maximize the variances. The survey was performed using 450 persons, and a final usable sample of 203 accountants was obtained. This process provided us with a response rate of 45.11%. The author can attribute this high rate to the choice of using the hard copy of the questionnaire along with a follow up procedure involving two contacts with the unresponsive respondents.

The majority of the respondents were males in the age group of 36 and above (**Table 1**) which mirrors the actual population characteristics of MAs in India.

The MAs were defined as those professionals who were designated by their respective organizations and were primarily responsible for either one or more sub-domains, such as cost and financial accounting, management audit, legal, taxation, or compliance work. A minimum work experience of three years was a prerequisite to be considered for the study. After getting the responses, the usable questionnaires were carefully screened to avoid any non-accounting professionals being included in our sample. The face validity of the questionnaire was established by taking the inputs of three academicians and two industry experts. Among the respondents, 29.06% were female. The sample description is given in **Table 1**.

Podsakoff *et al.* (2003) [35] suggested a procedure to control the common method variance. All the respondents were assured beforehand that the responses were being used for academic and research purposes only and will be kept anonymous. The participants were also assured that there is no correct or incorrect answer and that they should answer with honesty. The sequence of questions was also varied.

3.2. Statistical Analysis

For data analysis, a partial least-square structured equation model (PLS-SEM) is the most relevant choice as it does not have any assumptions regarding the distribution of data. Furthermore, this study aims to integrate two theories and PLS SEM does not suffer from identification problems due to small sample sizes. In the present context, PLS-SEM is reliable as the technique comprises a non-parametric multivariate analysis that simultaneously measures both the structural and the measurement models (Lowry and Gaskin 2014 [36]; McIntosh

Table 1. Sample description, $n = 203$.

Variable	Values	%
Age	25 - 35	18.71
	36 and above	81.29
Gender	Male	70.94
	Female	29.06
Educational background	Professional qualification, such as a degree in Chartered Accountancy, Cost Accountancy, Company Secretary ship.	83.74
	Master's level qualification in Commerce and allied disciplines, with a specialization in Accountancy, Information Technology, or allied disciplines.	16.26

et al. 2014 [37]). The Smart PLS package version 3.2.7 (Ringle *et al.* 2015) [38] was employed for the data analysis.

3.3. Measurement Variables

The constructs were operationalized using the scales established by Nasco *et al.* (2008) [39]. The construct attitude was operationalized with five items: subjective norms with four items, perceived behavior control with three items, and intention with three items. The wordings in some of the questions were modified as per the observations of the pilot test. Subsequently, the validity and reliability of the scales were established.

4. Results

The results were obtained by analyzing the measurement and structural models. It was ensured that the constructs were well-measured for subsequent evaluation of the structural model.

4.1. Evaluation of the Measurement Model

All the constructs in the model were reflectively measured. Composite reliability (CR) (**Table 2**) estimates the internal consistency of the constructs. The CR was greater than 0.7 and Cronbach's alpha (Nunnally 1978) [40] was also more than 0.7 for all the constructs. The outer loadings were higher than 0.7 and were significant at 95% level. The measure of convergent validity, average variance extracted (AVE) was greater than 0.5 and significant at the 95% level. The Heterotrait Monotrait ratio (HTMT), which is morerigorous than the Fornell and Larcker (1981) [41] criteria were used to determine the discriminant validity. Since the HTMT ratio (**Table 3**) was below 0.85, the validity was established. Only for the construct intention-attitude it was 0.891 which was acceptable as it was close to the acceptable limit. With the above well-measured constructs (**Table 2**), all the constructs were used for overall assessment of the structural model.

Table 2. Reliability and validity.

Construct	Items	Factor Loadings	CR	Cronbach Alpha	AVE
Attitude			0.886	0.840	0.611
	A1	0.857			
	A2	0.765			
	A3	0.623			
	A4	0.841			
	A5	0.799			
Subjective Norm			0.881	0.821	0.651
	SN1	0.813			
	SN2	0.825			
	SN3	0.848			
	SN4	0.736			
Perceived Behaviour Control			0.902	0.841	0.754
	PCB1	0.868			
	PCB2	0.871			
	PCB3	0.866			
Intention			0.921	0.872	0.796
	I1	0.921			
	I2	0.901			
	I3	0.854			

CR = composite reliability; Ave = average variance extracted.

Table 3. Results of the Heterotrait Monotrait ratio (HTMT) analysis.

	ATTITUDE	INTENTION	PERCEIVED BEHAVIOR CONTROL	SUBJECTIVE NORM
ATTITUDE				
INTENTION	0.891			
PERCEIVED BEHAVIOR CONTROL	0.410	0.291		
SUBJECTIVE NORM	0.834	0.756	0.522	

4.2. Evaluation of the Structural Model

Before undertaking the structural model assessment, a collinearity check was carried out (Sarstedt *et al.* 2014) [42]. This was measured with the help of the variance inflation factor (VIF) for each construct, and it was found to be less than 5, indicating that multi-collinearity was not present (Hair *et al.* 2006) [43]. The outer and inner VIF values are given in **Table 4** and **Table 5**, respectively.

Table 4. Outer VIF values.

Outer VIF Values	VIF
A1	2.246
A2	1.886
A3	1.446
A4	2.146
A5	1.868
I1	2.887
I2	2.716
I3	1.919
PBC1	2.530
PBC2	1.801
PBC3	2.066
SN1	2.266
SN2	2.278
SN3	1.917
SN4	1.613

Table 5. Inner VIF values.

Inner VIF Values	ATTITUDE	INTENTION	PERCEIVED BEHAVIOR CONTROL	SUBJECTIVE NORM
ATTITUDE		1.956		
INTENTION				
PERCEIVED BEHAVIOR CONTROL		1.245		
SUBJECTIVE NORM		2.127		

The path coefficients are shown in **Figure 1**. The PLS algorithm aims to reject a set of path-specific null hypothesis of no effect. The "R square" value 0.633 was encouragingly high. As presented in **Table 6**, attitude had the highest direct effect as an antecedent for intention to use big data (β = 0.644****, t = 10.227), which supports hypothesis (1). This was followed by the direct effect of subjective norms on the intention to use big data (β = 0.227****, t = 3.597), which supports hypothesis (2). However, no support for hypothesis 3 was found (β = −0.062 n.s, t = 1.490).

4.3. Test for Goodness of Fit

The goodness of fit measure (Heseler and Sarstedt 2013) [44] was applied to ascertain the standardized root mean square residual (SRMR). The obtained value was 0.077, which was below the threshold limit of 0.14 (**Table 7**).

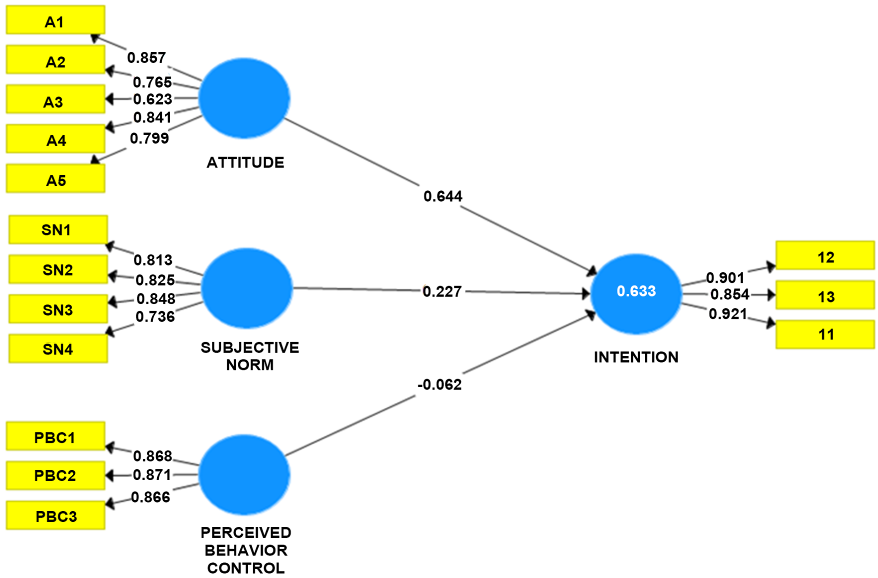

Figure 1. The structural model.

Table 6. Significant individual path coefficients in the structural model.

Structural Path	Path Coefficient (t value)	p values	Effect Size (f square)	Conclusion
ATTITUDE → INTENTION	0.644 (10.227)	0.000	0.578	H1 is supported
PERCEIVED BEHAVIOR CONTROL → INTENTION	−0.062 (1.490)	0.137	0.008	H3 is not supported
SUBJECTIVE NORM → INTENTION	0.227 (3.597)	0.000	0.066	H2 is supported
GENDER → INTENTION	From the Multi group analysis			H4 is supported

n.s. not-significant; *|t| ≥ 1.65 at $p = 0.10$ level; **|t| ≥ 1.96 at $p = 0.05$ level; ***|t| ≥ 2.58 at $p = 0.01$ level; ****|t| ≥ 3.29 at $p = 0.001$ level.

Table 7. Test for goodness of fit.

SRMR	Original Sample (O)
Saturated Model	0.077
Estimated Model	0.077

4.4. Importance-Performance Map Analysis (IPMA)

The performance of the construct "attitude" was the lowest at 21.668 (Table 8). This result means that there is the highest scope for improvement in this construct. The findings suggest that since attitude is the most impactful construct (total effect = 0.644) and has the least performance (Figure 2), further improvement of the MAs attitude towards the usage of big data is the best strategy to be pursued by the firms. This analysis gives a clear plan of action to the firms for focusing on the attitude improvement of MAs and building their big data capabilities.

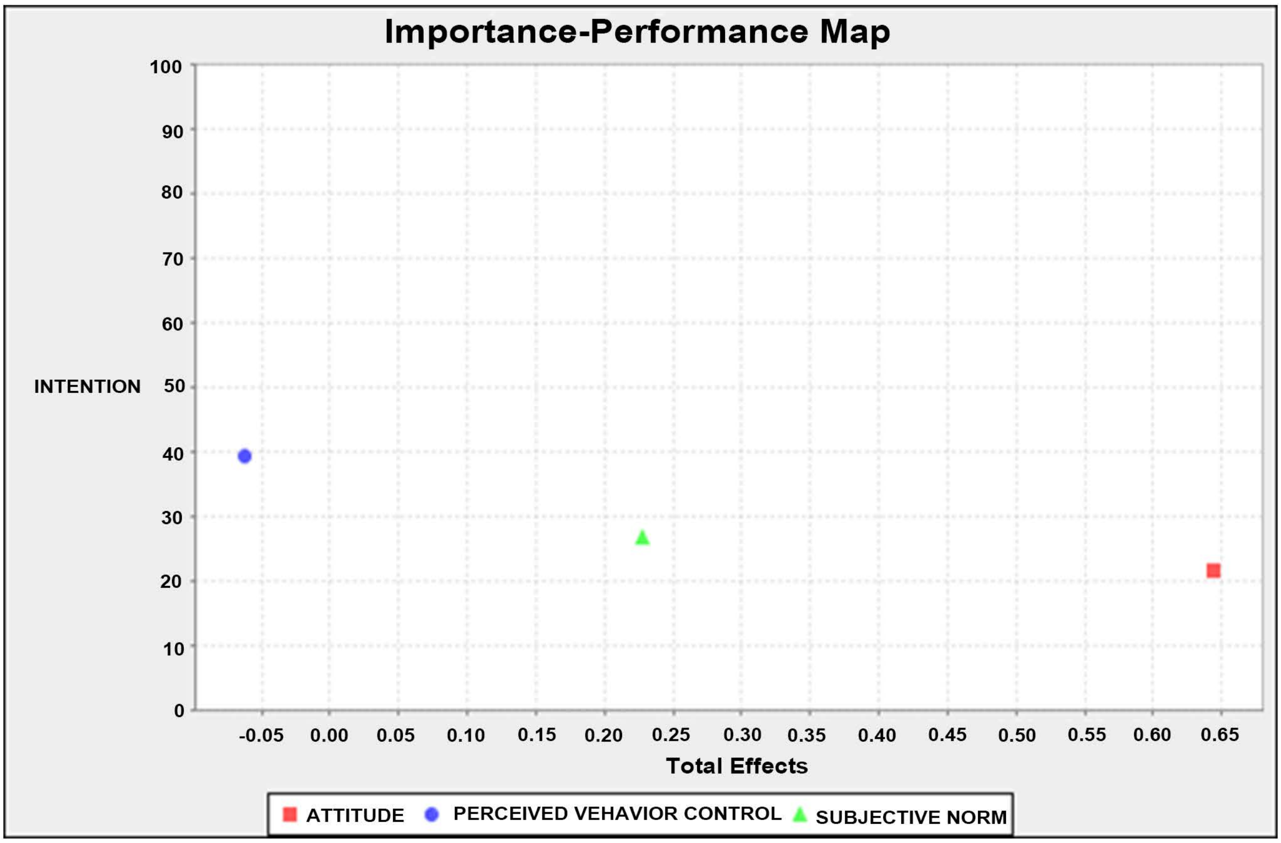

Figure 2. IPMA graph.

4.5. Multi Group Analysis (MGA) on the Basis of Gender

Morris *et al.* (2005) [31] suggested that gender differences in behavior intent should be probed, and hence, in this study, the employee's views on new technology adoption were ascertained with regard to the gender. As per the multi group analysis based on the gender of the respondents, it was found that there was no difference in the intention to adopt big data on the basis of gender. As given in **Table 9**, all the p values in the parametric test are non-significant.

5. Discussion

This work is an amalgam of the utility theory with the theory of planned behavior in the context of big data usage intention in the emerging market. The utility theory in economics is characterized by the choices made by the "rational man". This rationality assumption is valid and can be taken in the context of professionals. It was probed whether MAs perceive "utility" in big data usage. Harrison *et al.* (1997) [45] revealed that the theory of planned behavior has adequate explanatory power in the American context, but the theory's robustness in making predictions about developing markets is not well established (Nasco *et al.* 2008) [39]. The present study is an attempt in this direction.

It was observed that attitude had the highest direct effect as an antecedent for intention to use big data ($\beta = 0.644$****, $t = 10.227$), which supports hypothesis

Table 8. IPMA performance.

Construct Performances for [INTENTION]	Performances
ATTITUDE	21.668
PERCEIVED BEHAVIOR CONTROL	39.209
SUBJECTIVE NORM	26.698

Table 9. Parametric test for MGA based on gender.

Parametric Test	Path Coefficients	*t*-Value	*p*-Value
ATTITUDE → INTENTION	0.084	0.625	0.533
PERCEIVED BEHAVIOR CONTROL → INTENTION	0.052	0.592	0.555
SUBJECTIVE NORM → INTENTION	0.008	0.053	0.957

(1). This was followed by the direct effect of subjective norms ($\beta = 0.227$****, $t = 3.597$), which supports hypothesis (2). It is inffteresting to note that TBP in the context of American samples did not display a strong effect of subjective norms on intentions (Pavlou and Fygenson 2006) [46]; however, in this study, subjective norms exerted a significant effect.

The study did not find perceived behavior control to have an effect on the intention to adopt big data. This result is supported by the findings of Riemenschneider *et al.* (2003) [47] who observed that perceived behavior control is not a significant predictor of intention. In the present study too, no support was found for hypothesis (3). The reason for this finding could be discerned from the study by Armitage and Conner (2001) [48] who highlighted the conceptual ambiguities that may cause inconclusive results of PBC. Finally, Randall (1991) [49] also concluded that PBC provides very limited explanation for the accountant's intention to use information technology. With the multi group analysis, hypothesis (4) was also supported, which meant that gender did not influence the MA's intention to adopt big data.

This study makes three distinct contributions. First, it contributes to literature by blending the utility theory with the theory of planned behavior in the context of the emerging market. It uses the predictive approach rather than prescriptive approach towards big data usage intentions. Secondly, it guides the firms to focus on attitude building of all MAs. It also suggests aiming for an enhanced acceptance of big data by all the MAs irrespective of their gender (as per the results of the MGA). Finally, the study illustrates the application of MGA and IPMA in validating the theory of planned behavior.

The study does have certain limitations, including its reliance on self-reported information. However, as Ajzen (1991) [17] asserts, self-reports are quite accurate when the data collected is not of a sensitive nature. In this study, sensitive information was not gathered, which enhances the acceptability of the results. The second limitation is the sample size. Lastly, since it is not possible to measure the actual behavior of the accountant while adopting big data subsequently, an attempt was not made in this direction.

6. Conclusions

The TPB theorizes that intention will eventually lead to action. Prior studies have highlighted that the theory can be applied to self-oriented behavior, others oriented behavior, and strategic decision making (Reimenschneider *et al.* 2003) [47] under the overarching utility theory. Drawing upon the TBP, it was inferred that the accountants' attitudes, followed by subjective norms, influenced their intention to adopt big data. The perceived behavior control had an insignificant impact on big data usage intentions. These findings have profound policy implications for all stakeholders in the big data domain. In order to have an increased eventual big data usage, attitude building should be focus area of firms.

It was further observed that attitude also had the highest potential for impact on the intention to use big data (as per IPMA), and thus it confirms the suggestion that firms should focus on attitude building to have a better buy in from their MAs since the MAs already perceive utility in big data usage. Finally, the research also provided an understanding that the usage intention of big data by accountants needs to be appreciated from multiple perspectives.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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