THE MEDIATING ROLE OF BIG DATA TO INFLUENCE PRACTITIONERS TO USE FORENSIC ACCOUNTING FOR FRAUD DETECTION

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ABSTRACT

Globally, the financial industry in the recent times has witnessed various forms of fraudulent activities in the financial markets creating dilemma for the professionals, and the auditors who owns responsibility of ensuring accuracy and transparency. This article aims at finding the emergence of Big Data technology to fraud and forensic accounting by practitioner accountants in in India. A research model and hypotheses has been developed to examine the relationship between the awareness level of forensic accounting, Big Data and intentions to use it for fraud detection using structural equation modeling. Results indicate that awareness of forensic accounting has a positive influence on practitioners' intentions to its use for fraud detection. Big data technologies mediate the relationship between awareness and intentions to use for fraud detection. The results of the study are useful in implementation of Big Data technologies into the forensic accounting domain that can facilitate combating fraud.

KEY WORDS

big data, fraud, forensic accounting, structural equation modeling

JEL CODES

C1, C3, M4, O3

1 INTRODUCTION

In the recent times, financial industry has been tormented by continuous influxes of financial crimes. The industry has witnessed various forms of fraudulent activities in the financial market that inter-alia include insider-trading scandals in mergers and acquisitions (Sharma and Pulliam, 2009), manipulations in the public offer of securities (Hull et al., 2013), the stock options scandals (Janney and Gove, 2017; Jory et al., 2015), rampant frauds in mortgage industry resulting in a major financial crisis of 2007–2008 (Patterson and Koller, 2011), Ponzi

schemes in major investment funds (Cortés et al., 2016). Nature and forms of these frauds are growing at large pace creating dilemma for the professionals, particularly the auditors of the companies who are bestowed with the responsibility of ensuring fairness, accuracy and transparency.

Fraud, as such, is a complex and elusive concept. It can be defined to include "the obtaining of goods and/or money by deception" or "a human endeavour, involving deception, purposeful intent, intensity of desire, risk of apprehension, violation of trust, rationalization, etc." (Kenny, 1985). Fraud can occur in various ways ranging from misuse of trust or false representations to take an undue advantage or a criminal deception (Gupta and Gupta, 2015) that creates significant implications for stakeholders. Various connotations like violation of Internal Revenue code by publicly traded corporations or misbehaviours of financial market participants to cheat the concerned parties have been quoted (Reurink, 2018). In current times, the frauds are also closely linked to the IT domain given the massive use of IT enables business activities by corporations. In various contexts like curbing frauds risk, corporate governance, corporate surveillance, use of intelligent systems have been suggested by experts and analysts.

Fraudulent activities in the industry can contribute to the collapse of corporations or even be instrumental in a national or global financial crisis as happened in 2007–2008. Most countries were affected directly or indirectly by lack of credit and falling property prices. The imbalances and turbulence in real and national economy are felt most in the emerging economies and it depends on their ability to innovate and complete resistance to fraud (Bănărescu, 2015). The instances of corporate frauds are not confined to an industry or region e.g., Satyam Computers, India in IT, WorldCom, USA in telecommunication, Paramalat, Italy in dairy manufacturing Enron, USA in energy, Punjab National Bank, India in banking etc.

Detection of fraud has become a serious challenge in today's complex business scenario (Abdallah et al., 2016; Mouawi et al., 2019).

With the upsurge in the number of frauds in the corporate world, expert systems for efficient fraud detection mechanism has become an imperative. The instances of corporate frauds are not limited, and the focus of the management and auditors is to observe the initial alarming signs and prevent for occurrence at the early stage.

Increasing frauds relating to financials has become a considerable threat among organizations and countries around the globe. An average loss of 5 percent of revenue of an organization every year on account of fraud was anticipated by the Association of Certified Fraud Examiners. According to the findings and estimates of the ACFE report (2014), a typical organization loses 5% of revenues each year to fraud and this potential projected loss amounts to nearly $4 trillion on the global level. The smaller organizations with less than 100 employees face more fraud risks due to financial statement fraud, payroll, and cash larceny schemes than at their larger counterparts. It was also reported that 75% of the cases with small businesses were detected by methods like tip, management review and internal audit. However, the increasing volume of data needs continuous monitoring, identifying inconsistencies in the data set or behavioral patterns of potentially fraudulent activities. These have accentuated scholars as well as investigators to understand the awareness level of the companies about the use of big data techniques for the purpose of prediction, prevention, and detection of fraud.

The information technology has substantially fueled the financial crimes in current times (Krahel and Titera, 2015; Moffitt and Vasarhelyi, 2013; Vasarhelyi et al., 2015). This creates implications for the accountants to cope up by developing advanced technology tools that equip them to prevent and detect frauds and minimize the aftereffects on the stakeholders. Rising white collar crimes have plagued the financial markets all over the world and have drawn attention towards fraud detection through a relatively new field i.e. forensic accounting (Chukwunedu and Okoye, 2012; Morris, 2010).

The use of forensic accounting services has developed as a significant factor in accounting firms (Morris, 2010). Forensic accounting as a field provides a deep insight relating to the frauds that take place along with preventing frauds and taking anti-fraud measures. Forensic accounting includes fraud audit where audit of the books of accounts is done in order to investigate and come out with evidence of the manipulation or fraud committed. However, the discipline of forensic accounting should not be interpreted as solely used for fraud detection work (Williams, 2006). "Forensic accounting is a challenging discipline that substantially interacts with auditing, economics, finance, information systems, and law" (Morris, 2010). The role of forensic accounting has become a vital area in the discipline of accounting, which takes care of examining the fraud, controlling corruption and bribery, extends legal support, looks after expert witnessing and cybersecurity (Hassink et al., 2010; Rezaee and Wang, 2019). It is a discipline that uses skills and techniques of other disciplines like law, accounting, auditing in order to analyze and finding solutions to the problems like damages, encroachment, value maintaining and value-adding for legal purposes (Dong, 2011).

Moffitt and Vasarhelyi (2013), Vasarhelyi et al. (2015) and Appelbaum et al. (2017) are of the opinion that various stakeholders in the accounting domain like practicing accountants, auditors, analysts, researchers etc. will endure advantage if they get more knowledge about big data. They also ascertain that there are audit clients increasingly using big data, which they connect to the necessity for auditors to follow suit. Krahel and Titera (2015) argue that the prescribed principles of accounting and auditing are not in tandem with technological change and still lay emphasis on the old ways of analyzing the data through sampling, accumulation, collection and presentation. Contrarily, through the use of big data, auditors are empowered to scrutinize the manner and process in which data is being generated, including full population testing, thus adding value to the profession of accounting and auditing and to their clienteles (Bhatia and Mittal, 2019). The information literacy created through Big Data enables the professionals to make decisions strategically and managing the risk in advance, moving towards a better future.

It has been widely discussed by the educators and practitioners that Big Data has a significant role in accounting and specifically, forensic accounting. Given the increasing number of business transactions and consequential spurt in accounting entries, the nature of auditor's job in forensic accounting changes dramatically with use of big data. Globally, the education systems have addressed to the demand forensic accounting education by including it in the curriculum of various courses and are making efforts to integrate the big data content with forensic accounting. However, the evidence of the use of Big data techniques to fraud and forensic accounting is very scarce, especially in small organizations. Possibly these firms refrain from the use of modern techniques and technology that are far ahead of those adopted by their client firms (Alles, 2015). This study highlights the importance of Big data and forensic accounting for the practitioners in the business. Secondly, the study presents literature relating to the existing work emphasizing the increasing demand and importance of Big data in forensic accounting due to the rising number of fraud cases in the present times. Finally, the study examines the awareness level of Big Data and its applicability in various sub-domains of fraud and forensic accounting using survey of practitioner accountants in the Delhi-National Capital Region (NCR) region of India. Our study assumes that the awareness of Big data techniques in forensic accounting for the detection of fraud increases the intentions to adopt these technologies by auditors and practitioners. We hypothesize that Big data technologies positively mediate the relationship between awareness and the practitioner's intentions to use forensic accounting techniques in fraud detection.

2   LITERATURE REVIEW

Primarily the management of the organization is responsible for fraud detection while the auditors have a secondary role. However, auditors are expected to carry out sessions and meetings for brainstorming and understanding the business deeply and come out with the possibility of an occasion of fraud. With the introduction of SAS 99, the accountability of auditors was increased and necessitated the auditors to pay attention to the red flags when auditing the accounts of a business. A significant point to note here is that simply the existence of red flags does not ensure the presence of fraud. They are just the hints or indicators of something happening. To be able to take charge of the prevention of fraud, identifying these indicators is a must (Ruankaew, 2013). Existence of just a sole red flag makes auditors alert and sensitive towards the possibility of the presence of a fraud (Krambia-Kapardis, 2002; Hassink et al., 2010) and enables them to reach the root cause of the fraud. Red flags are considered as significant indicators for early fraud detection, but it has been found that they are infrequently used by auditors (Dewi, 2017). These red flags precisely indicate and signify the probable embezzlement and mindset of committing fraud. Red flags are occurrences and circumstances demonstrating opportunity and direction towards potential or actual fraud occurrences. It has been examined time and again throughout the fraud cases occurring across the world that fraud takes place only after it gives some signals. The 2014 ACFE report, conducted on 1483 occupational fraud cases, concluded that at least one red flag was identified in 92% of cases, and two or more in 64% of cases.

Many researchers have discussed the expectations from the auditors, the audit expectation gap (AEG) and their role in fraud detection (Okafor and Otalor, 2013; Ruhnke and Schmidt, 2014; Salehi, 2016; Nickson and Neikirk, 2018). Although, according to IAASB Annual Report (2009), the management of the entity itself is responsible for the fraudulent activities, and the auditor's role is limited and accountable for obtaining reasonable assurance that the financial statements are free from any substantial misstatement.

Now-a-days continuously increasing fraud and the inability of auditors to detect fraud has resulted in an increasing demand for forensic accountants (Rezaee and Burton, 1997). Forensic accountants expand the capability of an auditor to detect and catch fraud and act as a bridge to the audit expectation gap (Chukwunedu and Okoye, 2012).

Due to the inability of the traditional system of database management to manage extensive data formats coming in huge volumes, big data technologies have gained the importance and are transforming the way business practices and procedures take place. With the help of big data technologies, firms are able to go for real-time intelligence extracted from a high volume of data. These advanced processes enable the auditors to do comprehensive analysis in order to bring out meaningful insights from the data and hence make evidence-based decisions. They are equipped to handle diverse and voluminous data with incredible promptness in order to provide significant pieces of information for decision making.

Traditionally, when there were limited resources, it was assumed that the auditor possesses the skills and expertise to detect fraud in the books of a company. But, with the velocity of data that is being generated, it has become impossible for professionals to analyze and extract relevant conclusions without the help of big data technologies. Investment by corporate in big data technologies is increasing year on year (Raguseo, 2018). The capacity and speed of analyzing each and every set of data rather than just using a sampling technique for the data enables the auditors to be more confident in the audit conclusions. Especially the accounting firms are now announcing that big data is becoming a progressively significant part of their assurance policies (Akoglu et al., 2013). The distinctiveness of big data is demonstrated when it discovers unexpected patterns (using the gigantic data set) that are not detectable when small samples are used in typical audits.

Understanding big data only in terms of the size of data is misleading (Mittal, 2020a). "Big data divides the world by intent and timing rather than the type of data. The 'old world' is about transactions, and by the time these transactions are recorded, it is too late to do anything about them: companies are constantly 'managing out of the rear-view mirror'. In the 'new world', companies can instead use new 'signal' data to anticipate what's going to happen and intervene to improve the situation". Big Data has the ability to not only analyze the patterns of what has happened in the past but also to predict future happenings (Mittal, 2020b).

Issa and Kogan (2014) argue that the demand for auditors who possess Big Data knowledge to make professional options is rising. In a recent survey conducted by Rezaee and Wang (2019), authors establish that there is a growing interest in Big data/data analytics and Forensic Accounting in practice and education. The authors suggest that the big data and forensic accounting should be integrated in the business curriculum, as the techniques are important in improving forensic accounting education. Gepp et. al. (2018) highlight the limited practice and use of big data techniques in auditing in comparison to other related fields. It is observed from the literature that Big Data can play an important role in forensic and special purpose fraud audits that can be conducted by auditors and practitioners. However, we find a gap to examine the role of big data on intentions of practitioners to adopt forensic accounting. Our study endeavours to provide a significant information about the accounting practitioners in India using big data for forensic accounting practices, which is presently lacking in most of the previous studies.

3 RESEARCH METHODOLOGY

3.1 Research Model

We propose that intentions to adopt forensic accounting coupled with the availability and knowledge of Big Data technologies influence the awareness of forensic accounting on practitioners' intentions to use forensic accounting techniques in fraud detection. In our model, Big Data technologies play a mediating role among the two construct variables i.e., level of awareness of practitioners' and intentions to use forensic accounting techniques in fraud detection. We have used a non-parametric structural equation modeling (PLS-SEM) to examine the relations between the constructs. The evaluation has been carried out in two stages: a measurement model to establish the construct reliability and validity of the constructs and an assessment of the structural model to impute the relationships between the constructs.

We consider Partial Least Squares (PLS) regression/path analysis as SEM tool which is a superior to OLS regression, canonical correlation for analysis of systems of endogenous and exogenous variables developed by Wold et al. (1984). It has the ability to handle both formative and reflective indicators in contrast to other SEM techniques. The advantage of using PLS is that it does not make the assumption of multivariate normality and has ability to handle multi-collinearity among the independents unlike the SEM techniques of LISEREL and AMOS. Further, PLS has no limitations on sample size than the other SEM techniques (Chin and Newsted, 1999; Chin, 1998; Westland, 2007).

3.2 Hypotheses Development

Although it is difficult to manage the enormous data, big data technologies are making out way for professionals to analyze information and extract hidden facts for detection of business frauds. The availability of smarter technologies is enabling the practitioners to use forensic accounting in fraud detection. Big data technologies, that is, the use of data mining techniques contribute in decision making and detecting fraud by the auditors. Data mining has a significant role when it comes to fraud

detection in financial accounting, because it is often useful to discover and extract the hidden patterns in huge collected data (Ngai et al., 2011). Hence the availability of big data technologies enables the practitioners to detect fraud by using forensic accounting techniques (Gepp et al., 2018; Rezaee and Wang, 2019).

H_1: Knowledge of Big data technologies has an insignificant influence on practitioners' intentions to use forensic accounting techniques in fraud detection.

The current revised standards of accounting and auditing define an enlarged role and responsibility of auditors in detecting fraud, but efficient detection of accounting fraud has forever been a tricky deal for accounting profession. Forensic accounting has come into picture as the internal audit system of an organization is not able to identify accounting frauds efficiently.

Forensic accounting as a discipline is relatively new to the practitioners. However, it has come into the limelight due to the rapid increase in frauds over decades. The role of Forensic accounting becomes vital in discovering the frauds which are challenging to detect through mere internal auditing by employing accounting, auditing, and investigative skills (Morris, 2010). But mere awareness of forensic accounting tools and procedures does not ensure the intentions of practitioners to use forensic accounting for prevention and detection of frauds.

H_2: Awareness of forensic accounting has an insignificant influence on practitioners' intentions to use forensic accounting techniques in fraud detection.

An auditor who understands that its firm is at a threat of financial fraud makes all efforts to detect the fraud in order to save the firm from huge financial losses. Big data technologies play the role of mediator between the mere awareness and actual use of forensic accounting techniques by the practitioners. Practitioners need to adopt the appropriate data mining techniques based on the requirements of accounting fraud detection in order to successfully bridge the gap between knowing

forensic accounting and actual intentions of using such techniques towards meaningful steps for fraud detection. A specialized set of tools and techniques (for example Data mining) is used by Big Data technologies with an objective to discover and gather vital information that may help detection of fraud (Morris, 2010; Akoglu et al., 2013). Use of Big Data techniques in scrutinising enormous populations of data provides useful outcomes which can be easily comprehended by auditors, thus bridging the gap between awareness about forensic accounting and actually using the techniques for the purpose of detection of fraud.

H_3: Knowledge of Big data technologies has no mediation effect in the relationship between awareness and practitioners' intentions to use forensic accounting techniques in fraud detection.

3.3 Sample Design and Data Collection

The study adopted a non-probability purposive sampling approach for the survey. A structured questionnaire was developed to collect data for this research. The constructs of awareness, Big data, Perceived intentions to use forensic accounting included a total of 18 question items as depicted in Tab. 1. Section A labeled 'Awareness about Forensic Accounting', section B as 'Big data' and section C as 'Intentions to use forensic accounting' for fraud detections. The respondents submitted their response based on the five-point likert scale (1 – 'strong disagreement' to 5 – 'strong agreement') appropriate for conducting structural equation modeling.

The universe of this research comprises of all accounting practitioners represented by firms registered as "Chartered Accountants (CA)" with a statutory body known as Institute of Chartered Accountants of India (ICAI). The sample represent CA firms registered as individual, LLP partnership firms etc. with ICAI. The survey has been conducted in the National Capital Region (NCR) of India. The sample firms operate on all India basis with clients that include large public enterprises, and firms

Tab. 1: Description of Variables and Summary Statistics

Item Number	Item Description	Mean	SD
A: Awareness of Forensic Accounting			
I (A)	FA can be used for financial statement analysis	4.056	0.860
II (A)	FA can be used in fraud detection programs	3.873	0.877
III (A)	FA can identify misappropriated assets	3.958	0.869
IV (A)	FA improves financial statements' credibility	3.845	1.023
V (A)	FA makes financial data more reliable	3.817	0.946
VI (A)	FA ensures compliance with laws and regulations	3.831	0.956
VII (A)	FA evaluates corporate governance system	3.606	0.853
VIII (A)	FA evaluates internal controls	3.690	0.803
B: Knowledge of Big data technology			
I (B)	BD can analyze data on real time basis	3.690	0.919
II (B)	BD is able to analyze tests and relationships	3.465	0.923
III (B)	BD provides advanced analytics algorithms, data visualization, social networking analytics	3.408	0.821
IV (B)	BD provides high-performance, inexpensive processing power	3.549	0.891
V (B)	BD provides high-velocity data streaming processes	3.845	1.154
C: Intentions to use FA			
I (C)	Practitioners' are willing to use FA	3.789	1.054
II (C)	Practitioners' prioritize need of government compliance	3.718	1.124
III (C)	Practitioners' prioritize risk identification, analysis and more control	3.535	0.983
IV (C)	Practitioners' prioritize the company's image and preventing frauds	3.620	0.851
V (C)	Practitioners' are concerned about the high cost of FA	2.817	1.086

operating on all India basis. The respondents in the sample firms are either partners or senior personnel entrusted with forensic accounting or related activities. From the data base of ICAI and published reports of various consulting agencies, we have arrived at a list of 167 firms having registered office in NCR appropriate for the study. The questionnaire has been executed by mail to accounting practitioners in these sample firms. The practitioners have been asked to opine on the level of awareness, knowledge of Big data technology and its use in forensic accounting practices. In order to ensure high response rate, telephonic conversations, personal visits were conducted. 85 practitioners responded to the survey and finally we arrived at 71 valid responses for the purpose of analysis. The description of variables and summary statistics is given in Tab. 1.

3.4 Construct Validity and Reliability

Tab. 2 present the results of reliability and convergent validity tests. The items with factor loadings greater than 0.6 are considered for the intended factors. The analysis observed one of the factor loadings related to awareness level less than 0.6 and thus was deleted in order to ensure uni-dimensionality of the constructs and improve model fit indices. The internal consistency of the constructs was tested using Cronbach's alpha coefficient. All constructs in this study was observed with high Cronbach's alpha coefficient ≥ 0.80, indicating high internal consistency (Hair et al., 2010).

Tab. 2: Reliability and convergent validity test

Construct	Loadings	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
A: Awareness of Forensic Accounting				
I (A)*	0.544	0.895	0.913	0.604
II (A)	0.630			
III (A)	0.824			
IV (A)	0.869			
V (A)	0.748			
VI (A)	0.903			
VII (A)	0.726			
VIII (A)	0.705			
B: Knowledge of Big data technology				
I (B)	0.850	0.882	0.911	0.671
II (B)	0.764			
III (B)	0.854			
IV (B)	0.824			
V (B)	0.801			
C: Intentions to use FA				
I (C)	0.885	0.849	0.841	0.547
II (C)	0.925			
III (C)	0.788			
IV (C)	0.661			
V (C)*	0.202			

Note: *) items deleted loadings < 0.6

Tab. 3: Correlation Matrix for the assessment of Discriminant Validity

Constructs	A: Awareness of Forensic Accounting	B: Big data technology	C: Intentions to use FA
A: Awareness of Forensic Accounting	0.777		
B: Big data technology	0.665	0.819	
C: Intentions to use FA	0.621	0.740	0.795

We have computed average variance extractions (AVE) for each construct to evident the convergent validity. It was found that the AVE of all constructs were higher than the suggested minimum estimate of 0.50 (Fornell and Larcker, 1981), supporting evidences for convergent validity. Tab. 2 summarizes the standardized factor loadings, Cronbach's Alpha, Composite reliability, and AVE estimates.

Tab. 3 provides a correlation matrix for an assessment of Discriminant validity and was evaluated by comparing AVE for each construct with the squared correlation between that construct and other constructs. AVE for the three constructs (the diagonal values of the matrix) was greater than the squared correlation with all other constructs showing sufficient evidence of Discriminant validity (Fornell and Larcker, 1981; Hair et al., 2010).

4   RESULTS

We have used structural equation modeling (SEM) using SmartPLS 3.2.8 to test the research hypotheses. We advocate the use of SEM because of its capability to answer the set of interrelated research questions using both measurement and structural model. We examine three relations in the SEM model. First, the relation between the awareness of forensic accounting (Independent variable) and the intentions to adopt forensic accounting (Dependent variable). Second, relation seeks to examine the influence of big data technology on intentions to use the forensic accounting as dependent variable. Third, the mediating effect of big data in the first relation has been evaluated in the model.

We started by testing the opinion about the influence of big data technologies on intentions to use forensic accounting for fraud detection. The estimate of the standardized regression weight (β value) from big data to intentions to use FA by practitioners was 0.685, significant at $p < 0.001$. Therefore, H_1 was rejected and indicates the positive impact of big data on intentions to use forensic accounting for fraud detection by practitioners in Delhi-NCR region.

To test the mediating effect and the other hypotheses, the bootstrapping re-sampling method was applied (Shrout and Bolger, 2002). The direct effect of awareness of FA with the presence of big data (the mediating variable) was found insignificant ($\beta = 0.166$, $p > 0.05$), implying that full mediation is possible. The bootstrapping results showed that the standardized indirect effect of awareness on intentions to use FA through big data was 0.455, significant at $p < 0.001$ with confidence inter-

vals between 0.324 and 0.607. Thus, H_3 was rejected and hence confirm that knowledge of big data strongly mediates the relationship between awareness and intentions to use FA for fraud detections in Delhi-NCR. Fig. 1 shows the mediating role of big data (structural model). Tab. 4 provides summary of the tested hypotheses.

The results clearly indicate the significance of knowledge about the big data technology between awareness of FA and intentions to its use in fraud detection. Awareness among practitioners to use FA is important to monitor financial transaction and fraud detection alongwith the knowledge of big data technology as also highlighted by Gepp et al. (2018) and Rezaee and Wang (2019). The mediation of big data in relationship of awareness to use of FA surely will benefit in detection of spurious transactions at a very early stage as confirmed by the outcome of the present study. The results also indicate a huge gap in the knowledge level of accounting practitioners about the big data technology application in financial accounting. We argue that for a major reason for such gap is the absence of technology courses in the programme curriculum of chartered accountancy and lack of initiatives by the ICAI to supplement big data/data analytics knowledge to its member professionals. We find that in various countries like USA, UK, Australia, Singapore etc. the use of data analytics is embedded to the professional accountancy programs like certified information system auditor (CISA), certified fraud examiners (CFE) etc. In addition, a culture should develop at initial stage of the professional programs as to use of information technology.

5   CONCLUSIONS

Since use of big data is among the most important techniques to handle voluminous data, accounting practitioners must take the benefits of it in forensic accounting to detect fraudulent transactions. This study concludes

that big data is a significant enabler and could be considered as a key to enhance practices and use of forensic accounting. By using big data techniques models can be build which can identify and spot the risk of occurring of a fraud
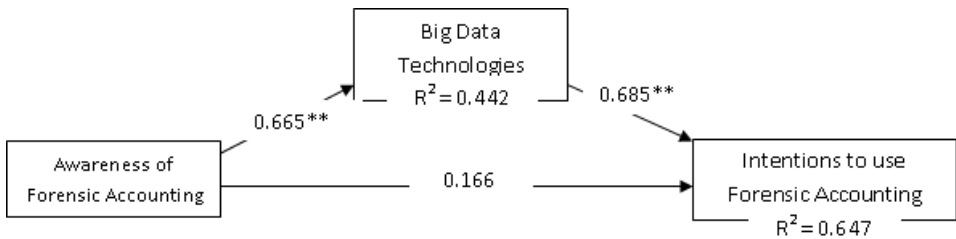
Fig. 1: Awareness of Forensic Accounting – Big data – Intentions to use

Tab. 4: Summary of Results

Hypothesis	Path	Mediation Model	Results
H_1	Big data – Intentions to use FA	0.685 ($p < 0.001$)	Significant
H_2	Awareness of FA – Intentions to use FA	0.166 ($p > 0.05$)	Insignificant
H_3	Awareness of FA – Big Data-Intentions to use FA	0.665 ($p < 0.001$)	Significant

along with designing new innovative techniques for prevention of fraud in the area of financial reporting. Our study has significant implications for Government and other accounting or related professional bodies who should put more efforts on conducting training programs in big data. It is necessary to take steps to make it a part of curriculum at different level of education in accounting practices.

Recently, Ministry of electronics and information technology (MEITY), Government of India and some premier technology institutions of the country like Indian Institute of Information Technology (IIT) have taken initiative to promote the use of big data technology through academic and training programs. However, the clear gap is the inability to link these endeavours to forensic accounting and fraud detection. This calls for joint endeavour between the technology imparting institution and statutory accounting bodies like ICAI, ICWAI etc. so that the emerging problems of knowledge gaps of auditors in country like India can be addressed.

It is accepted that auditors struggle while trying to integrate numerous fragments and pieces of proofs and evidence in certain situations. Big Data techniques become useful here as they are exceptional in integrating the varied bits and pieces of information and converting them into reliable deciding factors in a particular situation. Therefore, use of big data technologies would add value to the profession of audit, research on audit and the practicing audit professionals. Combining diligent analysis with the traditional audit techniques and expert opinion could provide many opportunities to use big data techniques in auditing. We also emphasize the need for further research as to how big data can be integrated with auditing in various context in tune with accounting standards.

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