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NAVIGATING FORENSIC ACCOUNTING BEHAVIORAL INTENTIONS THROUGH THE FRAUD DEVIATION MODEL

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ABSTRACT

Fraud remains widespread in modern business. People who commit fraud often display warning signs through their behavior and actions, which can escalate to aggressive and violent conduct. Researchers have developed various theories to detect and prevent fraudulent behavior, with each theory having specific strengths and limitations depending on the situation. To better understand fraudulent conduct, researchers combined existing fraud theories with behavioral models from other fields to create the Fraud Deviation Model (FDM). This model was validated using Structural Equation Modeling (SEM). The research included primary data collected from 560 participants in India's National Capital Region, comprising registered internal auditors, external auditors, government auditors, and forensic auditors.

Keywords: Fraud, Fraudulent Behavior, Fraud Deviation Model (FDM), Structural Equation Modeling (SEM)

1. INTRODUCTION

The Indians are considered diligent or hardworking all over the world. Although, the person with power called The Babu, controls the whole system. They spread the venom and slow down the progress. Taxes are the primary source of revenue for the government. However, as frauds increase with high tide, the taxpayers feel victimized. They want to support nations' progress and enlargement, not a fraudster. Fraud can be explained as the act of misleading someone or earning money illegally. It has dire ramifications for individuals, organizations, and the economy. Fraud is a savvy disease that arises from selfishness or deceit Silverstone et al. (2012). A report to the nations on a global survey of occupational fraud and abuse (2020), a survey based on 2504 cases in 125 countries, reported fraud causes more than $3.6 billion in yearly losses. The average loss per case is $1,509,000. The global economy is slowly being drained by these vast losses every year. Organizations often have difficulty assessing the extent of the fraud because frauds are not reported and investigated. Victims may not always be eligible for civil or criminal damages. In 68% of cases, there is no value recovery, directly impacting companies' ability to create new jobs KPMG (2009). Forensic accounting gained attention in the act of rapid development in fraud, auditors' shortcomings, lack of experience, and law enforcement agencies inability to discover crimes in time. In general, forensic accounting is mainly used in the legal system Durkin and Harry (1997), Bressler (n.d.). Honigsberg (2020) called it a crime scene investigation. A forensicc accountant has knowledge and skills in auditing and legal issues, so estimating the loss and presence in the court is not difficult. Fraud is unpredictable; thus, the forensic accountant can be called without prior notice. They are responsible for preventing fraud from occurring. Forensic accounting is a vast field that professional chartered accountants have found extremely useful. A forensic accountant's responsibilities extend even beyond the level of the organization. The big, chartered accounting firms with forensic accountants can offer their services in various areas, including consultation, legal servicing, a mediator approved via tribunals, expert presentation, along with any other court-related services.

Research by ASSOCHAM and Grant Thornton indicates India's highest susceptible fraud sectors as Real Estate & Infrastructure (52%), Financial Services (34%), Telecom (5%), Manufacturing (3%), Electronics & IT (2%), Hospitality & Tourism (2%) and other (2%). Some theories like fraud triangle, fraud diamond, fraud pentagon, fraud scale and Hollinger-Clark theory has been developed to understand the behavior of fraudster and the reasons for this alarming increase in fraud. The present study uses the following behavioral theories and models that help in developing Fraud Deviation Model.

Rogers (1975) created the Protection Motivation Theory (PMT), which studies coping mechanisms and fear reactions. PMT is similar to health practices when it comes to fraud prevention. In primary and secondary prevention, it includes threat and coping assessments. Rollo et al. (2017), Chamroonsawasdi et al. (2017), and Liñán et al. (2005) are notable examples of uses. Rosenstock (1974) created the Health Belief Model (HBM), which evaluates perceived benefits, barriers, severity, and susceptibility in order to predict health-related behaviors. HBM applies to accounting procedures Muthusamy et al. (2010) and fraud prevention Janz and Becker (1984), Harrison et al. (1992), with modifications to incorporate media impact Rosenstock et al. (1994). Ajzen and Fishbein (1980) created the Theory of Reasoned Action and Planned Behavior (TR&PA), which uses attitudes and subjective standards to forecast behavior. It has been used in the selection of foods Raats et al. (1995) and the drinking of beer without alcohol Thompson and Thompson (1996). Extending TRA, the Theory of Planned Behavior Thompson and Thompson (1996) covers behavioral control Fishbein and Ajzen (1977) and influences organizational decision-making Muthusamy et al. (2010). Lavidge and Steiner (1961) established the Hierarchy of Effects model (HOE), which describes a step-by-step progression from ignorance to supporting business operations, including knowledge, attitude formation, and behavior. Similarly, seven steps were recognized by Barry and Howard (1990). Murray and Vogel (1997) placed a strong emphasis on knowledge and awareness when applied to business appraisal. The model was modified for fraud detection by Muthusamy et al. (2010), who also emphasized the importance of demographic factors in increasing public knowledge of forensic accounting procedures.

1.1. THE PROPOSED RESEARCH MODEL: FRAUD DEVIATION MODEL (FDM)

Bsed on the above theories and model a model is proposed called Fraud Deviation Model as there are many similarities are found between the theories of PMT, TR&PA, HBM, and HOE. All of the concepts are predicated on the idea that strong expectations generate strong motivation since social cognition is built on achievement. The next component of these models is beliefs that are grounded on a strong conceptual foundation. Last but not the least, all theories are extensively used in behavior anticipation and precautionary measures Muthusamy et al. (2010), Noar and Rick (2005). Although these frameworks have some similarities, even then they each have their strengths and weaknesses. For example, threat perception belief is an essential component of the preventive behavior of threats which is not present in TR&PA or HOE. Secondly, PMT discovered a motivation factor that isn't included in other theories. The cognitive stage of HOE, which includes awareness and knowledge, is absent in HBM or TR&PA. However, awareness is crucial for creating desire. Muthusamy et al. (2010) combined the HOE with the TRA to analyze organizational tendency for usage of investigating audit services to detect or prevent scams from being committed by large Malaysian corporations. This investigation is business enterprises centered and provided novel insight into organizational decision-making. The current research focuses on services provided by auditors because fraud is universal. Other studies Rosenberg et al. (2008) also support the HOE model. These findings support that behavioral change can be facilitated by increased awareness. This study relies on the protection motivation theory, hierarchy of effect models, theory of reasoned and planned action, and theory of health belief models to support the final model.

1.2. HYPOTHESIS FOR THE PROPOSED RESEARCH MODEL

The study approach is built on four factors: external factor, internal factor, motivational factor, and behavioral intention as the outcome. With the exception of gender, the study postulates that internal elements like awareness are influenced by demographic factors such as age, job description, tenure, type, nature, and turnover of auditing companies. While awareness is unrelated to gender, it is influenced by age, job role, service tenure, and organization type; forensic auditors and professionals with longer tenure are predicted to have higher awareness.

Based on the study model, six hypotheses are created.

Hypothesis 1: Awareness of forensic accounting has a negative impact on the perceived benefits of using it against fraud.

Hypothesis 2: Awareness of forensic accounting has a negative impact on the perceived risks of using it against fraud.

Figure 1

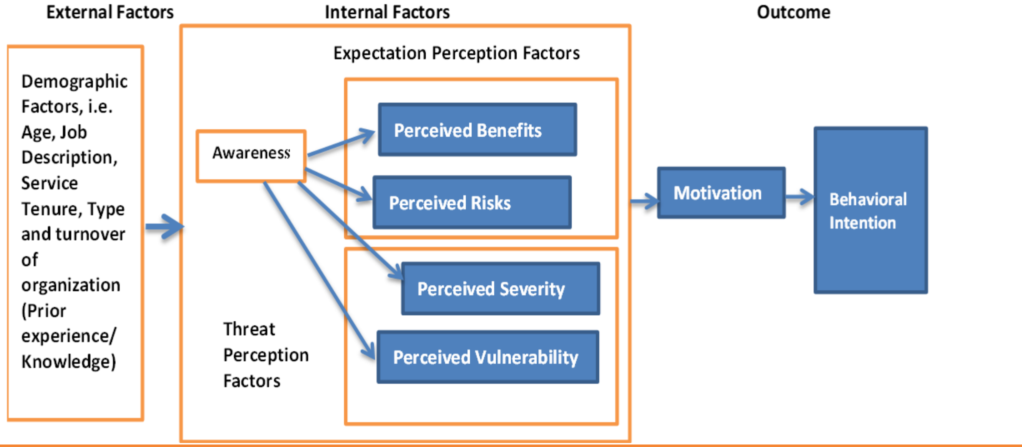

Figure 1 Proposed Model for the Study
Source Researchers' Own Proposed Model

In order to analyze hypotheses 1 and 2, it is required to assess advantages with dangers of utilizing investigative audit. It leads to development and implementation of an approach with consequent behavioral control. According to empirical studies, attitudes are influenced by both perceived risks and benefits. The studies on perceived benefits - Martins (2014), Quaddus and Hofmeyer (2005), Murphy et al. (2005) support the statement. Literature also contains studies of the negative effects on attitude Heijden et al. (2003), Lu et al. (2005), Gewald et al. (2006). The perceived benefits and risks in this study are evaluated using the composite models and theories like planned action and the health belief model Poss (2001), Ham (2017). They are made to directly impact behavior toward forensic accounting as an extraction to behavioral intention since both perceived benefits and risks are significant.

Hypothesis 3: Awareness of forensic accounting has a negative impact on the perceived susceptibility/vulnerability of using it against fraud

Hypothesis 4: Awareness of forensic accounting has a negative impact on the perceived severity of using it against fraud.

The influence of threat perception factors like vulnerability/susceptibility and severity on motivation to use forensic accounting can draw from protective motivation theory, where motivation is a mediating variable. KPMG fraud survey (2005) has consistently found even though organizations perceive that fraud can have severe consequences, there is an illusion of safety within their organization. Only when an organization realizes the severity of fraud and is, therefore, more susceptible to fraud will it take steps to reduce that risk.

Hypothesis 5: Perception of forensic accounting has a negative impact on the motivation to use it against fraud

Sub-Hypothesis 5.1: Perceived Benefits of forensic accounting has a negative impact on the motivation to use it against fraud

Sub-Hypothesis 5.2: Perceived Risks of forensic accounting have a negative impact on the motivation to use it against fraud

Sub-Hypothesis 5.3: Perceived vulnerability/Susceptibility of forensic accounting has a negative impact on the motivation to use it against fraud

Sub-Hypothesis 5.4: Perceived Severity of forensic accounting has a negative impact on the motivation of using it against fraud

Hypothesis 6: Motivation for forensic accounting negatively impacts behavioral intention to use it against fraud.

Abraham and Sheeran (2005) found a certain expectation and risk assessment play crucial part for inspiration. This cognitive trait allows individuals to choose to act to avoid adverse conditions. The organization can determine whether fraud costs are high or low by assessing the perceived severity. However, the perception of susceptibility allows them to recognize their vulnerability and those who may be prone to fraud Muthusamy et al. (2010). One of the ways an organization can combat the threat of fraud is to be able to use forensic accounting methods. Literature has demonstrated the impact of perceived fraud susceptibility Poss (2001), Roden (2004), Doukas et al. (2004), Muthusamy et al. (2010). Literature also supports the impact of behavioral intention and perceived fraud severity Roden (2004), Doukas et al. (2004), Lajunen and Räsänen (2004). By employing motivation as a mediating variable, the current study contends that threat perception strongly predicts an organization's readiness to adopt forensic accounting.

Fraud is a meticulously planned, long-term strategy rather than an instantaneous action. As a result, this study may make use TR&PA. Knowing that fraudsters are more likely to commit fraud than the organization, one can predict the fraudster's intent by analyzing others' influence. The health belief model hypothesis is useful for this research since it can be applied to combat fraud. It is due to perceptions and knowledge's importance in individual responsibility. The theory of the effects model, which is a logical progression that allows an individual to move from being unaware of forensic accounting to wanting to use it in a business environment to fight fraud, is also fundamental. The theory of protection motivation helps in the identification of motivational factors to apply forensic accounting. These theories were modified to create the research model.

2. REVIEW OF LITERATURE

The literature review provides a comprehensive overview of forensic accounting, highlighting its significance, methods, and impact on fraud detection and prevention. Dutta (2018) discussed forensic accounting's role in legal proceedings and the need for specialized skills to address financial fraud. Kumar et al. (2018) advocate the effectiveness of the Benish M-Square Model and stress the importance of transparency in financial statements. The increasing prevalence of financial frauds in India and propose measures, including establishing a forensic accounting cell Lama and Chaudhuri (2018). Lee and Nuxoll (2018) use a case study to illustrate the gap between employer expectations and student performance in forensic accounting, emphasizing the importance of critical thinking skills. Mui (2018) explores auditors' communication skills and knowledge in fraud detection, suggesting continuous learning and certification to enhance capabilities. Patel (2018) expands the fraud triangle to include capability and highlights the need for a proactive approach to prevent white-collar crime. Rathnasiri and Bandara (2018) survey accounting professionals, revealing the importance of multidisciplinary skills for forensic accountants. Waghray (2018) addresses the challenges posed by technological advancements in fraud and emphasizes legislative changes for effective forensic accounting in India. Alshurafat (2019) focuses on using pedagogical books to improve students' writing skills and ethics understanding in accounting. Hossain et al. (2020) underscore the responsibility of auditors and accountants in fraud detection, emphasizing the necessity of forensic accounting education. Ozili (2020) discusses accounting decisions' impact on forensic investigation, providing a theoretical framework for fraud detection and prevention. Rehman and Hashim (2020) link investigative audits to corporate governance sustainability, highlighting the paradigm shift in accounting. Shah (2020) introduces forensic accounting as a response to the uncertainties and complexities of financial statements, calling for regulatory recognition in India. Alhassan (2021) explores the relationship between forensic accounting and fraud detection in Nigeria, suggesting improved internal control systems and training for forensic accountants. Alshurafat et al. (2021) assess the obstacles to forensic accounting's growth in India, emphasizing its impact on the country's socio-economic development. Mbasiti et al. (2021) propose forensic accounting methods to prevent revenue leakage in Nigerian universities, highlighting the relevance of investigative audits. Yu and Rha (2021) evaluate the effectiveness of forensic accounting methods like network text analysis and trend analysis in identifying fraudulent activities. Alfordy (2022) examines fraud deterrence techniques recognized by auditors, emphasizing the need for effective regulatory structures in Saudi Arabia. Cheliatsidou et al. (2022) criticize the fraud triangle for its omission of fraud's nature and propose a theoretical model for global application. Chhabra and Prabhakaran (2022) address institutional-driven cyber fraud in Indian banks, recommending efficient response systems and countermeasures. Kaur et al. (2022) conduct a systematic literature review on forensic accounting methods, emphasizing the correlation between fraud detection and prevention strategies. Navarrete and Gallego (2022) discuss forensic accounting techniques like Benford's rules and fraudulent numerical patterns for preventing financial statement fraud. Owusu et al. (2022) applies the fraud triangle hypothesis to evaluate the determinants of fraud in state-owned businesses, emphasizing the role of pressure, opportunity, and reasoning. Rashid et al. (2023) assess auditors' perspectives on financial statements, revealing internal control issues and the need for improved regulations. Zainal et al. (2022) investigate fraud causes in small and medium-sized businesses, emphasizing the correlation between employee motivation, internal surveillance, and corruption. Konar and Aiyar (n.d.) provide a descriptive study on forensic accounting's global impact, calling for a multi-faceted approach to reduce white-collar crime. The literature collectively underscores the importance of forensic accounting in fraud detection and prevention, advocating for regulatory recognition, education, and multidisciplinary skills in the field.

3. RESEARCH METHODOLOGY

To know the impact of auditors' awareness and perception on behavioral intention to use forensic accounting, the data has been collected on Five-point Likert Scale from 560 internal auditors, external auditors, govt. auditors and forensic auditors registered in National Capital Region, India where 1 - Strongly Disagree and 5- Strongly Agree. The total 90796 registered firms were categories based on number of firms below 500, 500-1000, 1000-1500, and 1500 above. On the basis of number of registered firms in random selection Rohtak, Gautam Budh Nagar, New Delhi, and South Delhi has been selected as a sample. The data was collected from online and offline questionnaire. To know impact of independent variables awareness and perception, on the dependent variable behavioral intention, Structural Equation Modeling is used. Here, motivation is taken as mediating variable.

4. ANALYSIS AND INTERPRETATION

4.1. FACTOR ANALYSIS

Factor analysis is a technique of data reduction; it combines many variables in one factor that is highly correlated within them and less correlated with other factors. This technique helps to convert a large set of uncontrollable variables into few manageable factors which help in decision-making. The variables having low communality i.e. less than 0.5 are deleted. The contributing components are identified using the extraction method PCA. The varimax rotation method is used for factor rotation because it uses a method based on science to maximize the low- or high-value factor loading and decrease the mid-value factor loading.

Table 1

Table 1 Summary of Factor Analysis Tables for Independent and Dependent Variables

	Statements/ Variables	Factor Loadings	Factor Order	Labeling of Factor	Total Variance Explained (%)	Cronbach's Alpha
	Awareness and perception					
PB1	Increase Auditor's Responsibilities (S14)	.831	Factor 1	Perceived Benefits (PB)	18.219	.937
PB2	Forensic accounting is an Anti-fraud pro-active strategy (S15)	.811				
PB3	Win professional reputation (S22)	.805				
PB4	Attends court as an expert witness (S23)	.802				
PS1	Frauds are increasing at an alarming rate (S11)	.818	Factor 2	Perceived Severity (PS)	16.691	.768
PS2	Larger the organization, the more possibility of fraud (S13)	.795				
PS3	Every part of the organization is infected with fraud (S3)	.765				
PS4	Forensic accounting skilled auditors demand is increasing nowadays (S18)	.725				
PV1	Investments are decreasing due to the risk of fraud (S8)	.847	Factor 3	Perceived Susceptibility/ Vulnerability (PV)	12.825	.728
PV2	Financial fraud is very common in organization (S6)	.809				
PV3	My auditing organization has been a victim of fraud (S5)	.798				
PV4	Every organization is susceptible to fraud (S7)	.769				
A1	Forensic accounting is more useful than financial accounting (S12)	.794	Factor 4	Awareness (A)	12.629	.827
A2	Forensic accounting is related to fraud prevention and detection (S1)	.793				
A3	The importance of forensic accounting techniques has increased in the past few years (S2)	.792				

PR1	Awareness of forensic accounting will increase the cost of the audit (S16)	.760	Factor 5	Perceived Risk (PR)	8.082	.794
PR2	It will invite competition among audit firms, legal firms, and specialized forensic audit firms (S17)	.773				
PR3	Forensic accounting cannot help in stolen resources (S19)	.711				
M1	We use forensic accounting to reduce fraudulent activities (S4)	.813				
M2	Forensic accounting can bridge the expectation gap between auditors and investors (S21)	.770	Factor 6	Motivation (M)	5.691	.883
			Behavioral Intention			
	Easily Identify red flags (Fraud Signals)	.840	Factor 1	Behavioral Intention to use forensic accounting (BI)	65.067	.811
	Proper implementation of forensic accounting techniques	.810				
	Identify best-suited fraud detection and prevention techniques for auditing organization	.7890				
BI1	Helpful for the proper implementation of lawful activities	.771				
	Increase investigative skills	.700				
	Reduce fictitious transactions	.735	Factor 2			
	Risk calculation will help in locating fraud	.782				
	Auditors will take a different approach in verifying books of accounts	.720				
BI2	Strengthen the credibility of financial reporting	.810				
	Knowledge of forensic accounting strengthens fraud control in the business	.857	Factor 3			
BI3	A proper review of management policies	.729				
	Segregation of accounting function	.753				
	Provide assistance in cross-examination	.818	Factor 4			
BI4	Forensic accounting would go a long way in the fight against fraud	.888				

Source Researcher's Own Created Through Various Factor Analysis Tables

5. CONFIRMATORY FACTOR ANALYSIS

The main objective of CFA is to verify whether data fit the hypothesized measurement model. It is established on specific theories. This method allows us to determine if the observed variables represent a smaller set of constructs.

- **Evaluation of the Overall Measurement Model**

Items can only weight on one construct (i.e., there is no cross-loading), latent constructs may correlate, and all factor loadings for this developed measurement model are exempt (i.e., estimated). The model's seven structures are depicted in the Figure. The constructs are awareness of forensic accounting (A), perceived benefits (PB), perceived risks (PR), perceived severity of fraud (PS), perceived susceptibility/vulnerability (PV), and behavioral intention to use forensic accounting (BI). Variables A1, A2, and A3 are linked to the construct A. The term PB is linked to four different variables: PB1, PB2, PB3, and PB4.

Besides, four variables (PS1, PS2, PS3, and PS4) show the construct PS, while four (PV1, PV2, PV3, and PV4) are moderately connected with the construct PV. Three variables (PR1, PR2, and PR3) are related to the construct PR. The construct BI is finally described by the four variables BI1, BI2, BI3, and BI4. Additionally, each measurement variable includes a corresponding error term, abbreviated ‘er.’

Figure 2

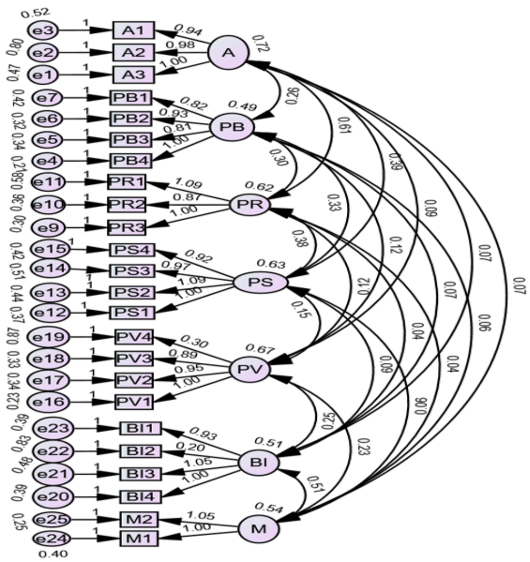

Figure 2 Overall Measurement Model

Source Researchers’ Development Through SPSS AMOS 28

The unstandardized regression weights corresponding to the observed and unobserved variables are displayed in the Figure. It also displays the co-variances and variances. The figure shows, for example, that the associated unstandardized regression weight of A1 on A is $\beta= 0.94$ and A2 on A is $\beta = 0.98$, and so on

The above path model needs to be tested, whether it is fit or not. For this purpose, some parameters are measured. The likelihood ratio chi-square ($\chi2$) statistic, most critical measure for overall fit, is only statistically based measure of goodness of fit in structural equation modeling Jöreskog and Sörbom (1993). Chi-square test is usually used to reject null hypotheses and support the alternative, i.e., there is a significant difference between observed and expected. Hence, the enormous value of Chi-square is considered good.

According to Ho (2006), when structural equation modeling is applied, the researcher should be looking for significant differences in the actual and predicted matrices. The researcher is not trying to reject null hypotheses in this instance. Therefore, the model's fit will be better if chi-square value is smaller than actual matrices. The chi-square will increase as the sample size increases because it is sensitive to variations from multivariate normality in observed variables. So, Chi-Square should be used in conjunction with other goodness-of-fit metrics.

CMIN/DF (Chi-Square Fit Statistics/Degree of Freedom), GFI (Goodness-of-Fit Index); AGI (Adjusted Goodness of Fit); RMR (Root Mean Square Residue); NFI (Normed Fit Index; CFI (Comparative Fit Index); PNFI (Parsimonious Normed Fit Index); and RMSEA (Root Mean Square Error of Approximation. McDonalds and Ho (2002) discovered that the most frequently reported fit indices are CFI, GFI, and NFI (TLI). Hu and Bentler (1999) recently developed the Threshold level. They suggested a two-index presentation format. It includes SRMR, NNFI (TLI), RMSEA, or CFI. Kline (2005) strongly advocates for Chi-Square test, RMSEA, CFI, and RMR. Boomsma (2000) offers similar recommendations but advises that the multiple squared correlations of each equation be reported.

Table 2

Table 2 Cutoff criteria for Fitness of the Model

Measures	Terrible	Acceptable	Excellent	Authors' Reference
CMIN/DF	>5	>3	>1	Hu and Bentler (1999)
GFI	<.90	≥.90	≥.95	Shevlin and Miles (1998)
AGFI	<.90	≥.90	≥.95	Tabachnick and Fidell (2007)
RMR	>.08	<.08	<.05	Hu and Bentler (1999)
NFI	<.90	≥.90	≥.95	Hu and Bentler (1999)
NNFI(TLI)	<.90	≥.90	≥.95	Hu and Bentler (1999)
CFI	<.90	≥.90	≥.95	Hu and Bentler (1999)
PNFI	<.50	≥.50	≥.90	Mulaik et al. (1989)
RMSEA	>.08	>.05	<.05	Hu and Bentler (1999)

Source Researchers Collected Values from Various Sources

There are no universal rules to assess model fit. Therefore, it's essential to report diversity of indices because contrasting indications can emulate distinctive conditions of model fit Crowley and Fan (1997).

Table 3

Table 3 Comparison of Threshold Values with the Default Model

Measures	Threshold Level	Default Model	Remark
CMIN/DF	>3	3.503	Accepted
GFI	≥.90	.902	Accepted
AGFI	≥.90	.873	Rejected
RMR	<.08	.090	Rejected
NFI	≥.90	.884	Rejected
NNFI(TLI)	≥.90	.897	Rejected
CFI	≥.90	.914	Accepted
PNFI	≥.50	.740	Accepted
RMSEA	>.05	.065	Accepted

Source Researchers Calculation Through SPSS AMOS 28

From the above table, it is clear that the model fits 5 criteria and is rejected in 4. The acceptance rate is more than 50%, but some modifications also allowed for fitting the model and completing most criteria. So, the researcher accepts the modifications. The following table shows the modifications allowed in the path model.

- **Modification Indices**

Following table indicates the modification allowed in the measurement model.

Table 4

Table 4 Modification Indices

			M.I.	Par Change
e22	<-->	PS	19.053	.110
e22	<-->	PB	29.223	.128
e19	<-->	PV	17.166	-0.128
e19	<-->	PS	30.428	.143
e19	<-->	PR	13.512	.078
e19	<-->	PB	34.997	.143
e19	<-->	e22	45.892	.236
e13	<-->	PR	12.238	.059
e13	<-->	e19	13.331	.105
e11	<-->	A	18.92	.092
e10	<-->	e22	10.178	.077
e6	<-->	e19	15.314	.093
e3	<-->	e10	10.787	-0.069
e3	<-->	e6	15.693	-0.080
e2	<-->	e11	23.801	.157

Source Researchers' Calculation Through SPSS AMOS 28

- **Model fit after Modifications**

After doing the above modification, the researcher develops the following Overall Path Model.

Figure 3

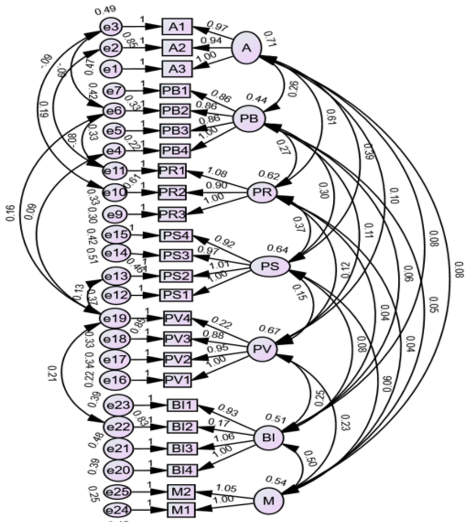

Figure 3 Revise the Overall Measurement Model After Modification Indices

Source Researchers' Development Through SPSS AMOS 28

The default model is compared with threshold levels to check whether the model is fit or not.

Table 5

Table 5 Comparison of Threshold Level with Default Model

Measures	Threshold Level	Default Model	Remark
CMIN/DF	>3	2.819	Accepted and improved from earlier
GFI	≥.90	.925	Accepted and improved from earlier
AGFI	≥.90	.900	Accepted and improved from earlier
RMR	≤.08	.088	Accepted and improved from earlier
NFI	≥.90	.910	Accepted and improved from earlier
NNFI(TLI)	≥.90	.925	Accepted and improved from earlier
CFI	≥.90	.939	Accepted and improved from earlier
PNFI	≥.50	.735	Accepted and improved from earlier
RMSEA	≥.05	.055	Accepted and improved from earlier

Source Researchers' Calculation Through SPSS AMOS 28

CMIN/DF (chi-square fit statistics/degree-of-freedom= 628.701/223) is 2.819, which shows an improvement over earlier. The major consideration for overall fit is the likelihood ratio of the Chi-square (χ 2) statistic. In structural equation modeling, it is also the solitary goodness of fit statistic Jöreskog and Sörbom (1993). When there is a substantial difference amidst observed and expected. Chi-Square test is usually implemented to reject H0 and support the alternative. The greater the chi-square value in this situation much better. Moreover, the researcher will be fronting since significant disparity amidst predicted as well as actual matrices when chi-square is used in structural equation modeling Ho (2006). Here, the researcher is not trying to reject null hypotheses. Therefore, the model's fit would better if Chi-Square value is smaller than actual matrices.

The Chi-square is conscious to observe variable deviation from multivariate normality and increases as sample size rises. So, Chi-Square should be used in combination with other goodness-of-fit metrics. There are more metrics available, including GFI and RMSEA. GFI and AGFI are measures of how well a model fits compared to no model Joreskog and Sorbom, 1989, Ho (2006). It is not based on statistics. It has a scale from 0 to 1, with 0 denoting a bad fit and 1 denoting a perfect fit. The table also shows the GFI value of .925 and AGFI Value of .900, which indicate a better fit. Data from current study fit the model perfectly. RMR is square root of the difference in the residuals from sample covariance matrix compared to hypothesized covariance model. Scales of each indicator determine RMR. If a questionnaire has items ranging from 1-5 or when it ranges from 1 to 7, it will be vice versa. Then, it cannot be easy to interpret the RMR Kline (2005). This problem is solved by the Standardized RMR (SRMR). RMR can give the best results because the study uses a 5-point Likert scale ranging from 1-5. RMR values ranging from 0-1 are good for a model's fit. Values closer to 0 indicate a better fit. RMR is 0.088, which indicates a good model. NFI (Normal Fit Index) evaluates model by comparing its value to null model. This statistic has a range of values amidst 0 to 1. Bentler and Bonett (1980) recommend values higher than 0.90 as sign of a good fit. The NFI value of the current study is .910. It clearly shows model fit. NFI has a major flaw. It is sensitive to sample size and underestimates fit for samples smaller than 200 Mulaik et al. (1989), Bentler (1990) and is not recommended to be solely relied on Kline (2005). The NNFI (Non-Normed Fit Index) is created to address this problem. It is also known as TLI-Tucker-Lewis Index. LTI index prefers simple models. However, NNFI can have a problem with its value exceeding 1, making it difficult to understand Byrne (1998). It is best to have NNFI's value >=.90. The table shows that the NNFI value is .925, which is acceptable. CFI is a modified version of the NFI that considers sample size. It performs well even with small sample sizes Tabachnick and Fidell (2007). This index is now included in all SEM programs. It is one of the most commonly reported fit indices because it is the least affected by sample size Fan et al. (1999). This statistic is similar to the NFI. Its values range from 0.0 to 1.0, with values closer than 1.0 meaning a good fit. Overall path model fulfills the cut-off criteria of CFI >= 0.90. PNFI adjusts for degrees of freedom. It is based on the NFI. The PNFI index severely penalizes model complexity, resulting in parsimony-fit index values significantly lower than other goodness-of-fit indices. Mulaik et al. (1989) note that parsimony fit index values can be obtained within the .50-.80 range, while other goodness-of-fit indices may achieve values exceeding .90. The model also has PNFI .735, a good fit model symptom. RMSEA measures discrepancy per degree that takes into account error in population approximation. Browne and Cudeck (1993), as cited in Ho (2006), (p. 285), state that RMSEA can be used to determine 'How well the model with unknown but closer values would fit the population covariance matrix if measured' Values ranging between 0.05 and 0.08 indicate acceptable fit, and values ranging from 0.08 and 0.10 indicate poor fitting. The RMSEA value of the measurement model in the current study is 0.055. The model is therefore acceptable.

- **Unstandardized and Standardized Regression Weights**

After satisfying the criteria, it is time to assess unstandardized regression weights and standardized regression weights derived from the maximum likelihood procedure. Each unstandardized regression coefficient is associated with the regression weights table by the critical ratio (C.R.) value and standard error (S.E). Expected variation of an estimated coefficient is standard error. It quantifies how independent variables accurately predict the dependent variables Ho (2006). All S.E. scores, in this case, are minimal. They can range from 0.043 to 0.061.

Table 6

Table 6 Unstandardized and Standardized Regression Weights

			Estimate	S.E.	C.R.	P	Label				Estimate
A3	<---	A	1.000					A3	<---	A	.775
A2	<---	A	.939	.060	15.55	***	par_1	A2	<---	A	.653
A1	<---	A	.975	.054	17.951	***	par_2	A1	<---	A	.763
PB4	<---	PB	1.000					PB4	<---	PB	.818
PB3	<---	PB	.861	.051	16.944	***	par_3	PB3	<---	PB	.704
PB2	<---	PB	.86	.051	16.994	***	par_4	PB2	<---	PB	.704
PB1	<---	PB	.861	.054	15.852	***	par_5	PB1	<---	PB	.661
PR3	<---	PR	1.000					PR3	<---	PR	.822
PR2	<---	PR	.902	.045	20.095	***	par_6	PR2	<---	PR	.780
PR1	<---	PR	1.077	.056	19.164	***	par_7	PR1	<---	PR	.734
PS1	<---	PS	1.000					PS1	<---	PS	.796
PS2	<---	PS	1.005	.053	19.043	***	par_8	PS2	<---	PS	.764
PS3	<---	PS	.971	.054	18.114	***	par_9	PS3	<---	PS	.736

PS4	<---	PS	.920	.050	18.505	***	par_10	PS4	<---	PS	.750
PV1	<---	PV	1.000					PV1	<---	PV	.866
PV2	<---	PV	.947	.045	20.914	***	par_11	PV2	<---	PV	.800
PV3	<---	PV	.885	.043	20.507	***	par_12	PV3	<---	PV	.783
PV4	<---	PV	.224	.046	4.825	***	par_13	PV4	<---	PV	.195
BI4	<---	BI	1.000					BI4	<---	BI	.753
BI3	<---	BI	1.056	.061	17.308	***	par_14	BI3	<---	BI	.736
BI2	<---	BI	.172	.055	3.125	0.002	par_15	BI2	<---	BI	.133
BI1	<---	BI	.931	.054	17.129	***	par_16	BI1	<---	BI	.728
M1	<---	M	1.000					M1	<---	M	.758
M2	<---	M	1.045	.054	19.397	***	par_17	M2	<---	M	.838

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Critical ratio (CR) is used to test the implication of the path coefficient. Path coefficient can be captured by dividing parameter estimates with corresponding standard error. It is located as z Ho (2006). So, the extreme value of CR can be ± 1.96, and its significance path is $p < 0.05$. Unstandardized regression weights fulfill this criterion in above table. Here, the critical ratio and significant value are > ± 1.96, $p < 0.05$, except for those parameters where the value is fixed to 1.

Standardized regression weights measure the standard deviation of dependent variables. It estimates how a dependent variable will transit when one standard deviation increases in the independent variable. The standardized regression estimate is almost more than .6, which indicates the goodness of model fit.

6. EVALUATION OF THE STRUCTURAL MODEL (SEM)

After the modified measurement model is confirmed, fit of structural path model is checked. Structural modeling is used to know the causal relationship between the constructs. So, it is also called a casual model.

The graphical display of the structural model's findings, following figure, shows the unstandardized regression weights for each association as well as the accompanying variances and covariance. The figure, for instance, shows that the effect of Awareness (A) on Perceived Benefits (PB) is related to unstandardized regression weight $\beta = 0.46$, whereas that of A on Perceived Risks (PR) is $\beta = 0.89$. Variations for perceived fraud severity (PS) and perceived fraud susceptibility (PV) are also 0.61 and 0.19, respectively. Also, following figure further reveals that unstandardized regression weight of the influence of PB on M is $\beta = 0.05$. Similarly, variance for Perceived Severity of fraud, PS and Perceived Vulnerability/Susceptibility to fraud PV are 0.04 and 0.35 respectively. However, PR negatively influences M as $\beta = -0.03$.

Figure 4

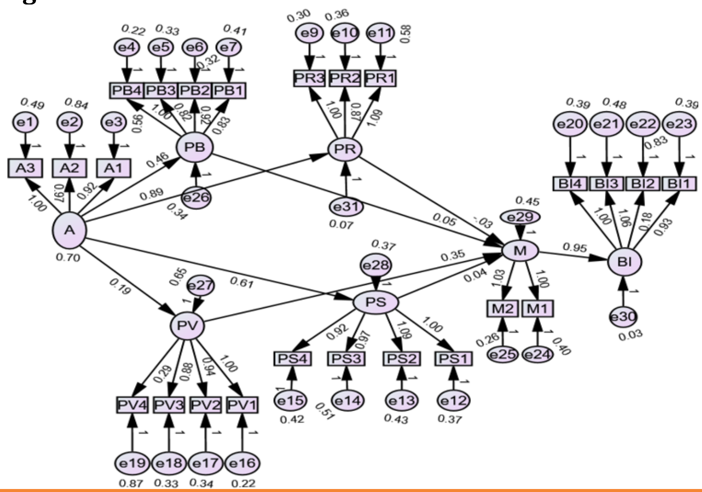

Figure 4 Structural Equation Model

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The structural model also needs to complete the criteria. The following table shows the cut-off criteria for the structural model:

Table 7

Table 7 Comparison of Threshold level with the Default Model

Measures	Threshold Level	Default Model	Remark
CMIN/DF	>3	3.756	Accepted
GFI	≥.90	0.882	Rejected
AGFI	≥.90	0.854	Rejected
RMR	<.08	0.099	Rejected
NFI	≥.90	0.869	Rejected
NNFI(TLI)	≥.90	0.886	Rejected
CFI	≥.90	0.9	Accepted
PNFI	≥.50	0.765	Accepted
RMSEA	≥.05	0.068	Accepted

Source Researchers' Calculation Through SPSS AMOS 28

From the above table, it is clear that the model fits 4 criteria and is rejected in 5. The rejection rate is more than 50%, but some modifications also allowed for fitting the model and completing most of the criteria. So, the researcher accepts the modifications. The following table shows the modifications allowed in the path model.

- **Modification Indices**

Table 8 shows the modification allowed to fit the structure model.

Table 8

Table 8 Modification Indices

			M.I.	Par Change
e28	<-->	e27	10.039	0.081
e26	<-->	e28	57.501	0.149

e22	<-->	A	40.044	0.211
e22	<-->	e28	39.876	0.169
e22	<-->	e26	51.122	0.18
e19	<-->	A	102.67	0.347
e19	<-->	e28	57.113	0.207
e19	<-->	e31	14.789	0.082
e19	<-->	e26	66.499	0.211
e19	<-->	e22	46.858	0.239
e13	<-->	e31	11.33	0.058
e13	<-->	e19	16.748	0.118
e11	<-->	e28	14.493	-0.092
e11	<-->	e26	17.102	-0.094
e10	<-->	e22	11.219	0.081
e9	<-->	e26	10.56	0.056
e6	<-->	e27	11.292	0.076
e6	<-->	e19	20.091	0.108
e4	<-->	e28	11.603	0.057
e4	<-->	e19	11.422	0.074
e3	<-->	e26	18.531	-0.095
e3	<-->	e10	12.855	-0.077
e3	<-->	e6	18.937	-0.091
e2	<-->	e11	28.588	0.173
e2	<-->	e10	10.087	-0.081
e2	<-->	e5	12.108	-0.086

Source Researchers' Calculation Through SPSS 28

- Model Fit After modifications

After doing the above modification, the researcher develops the following Structural Model.

Figure 5

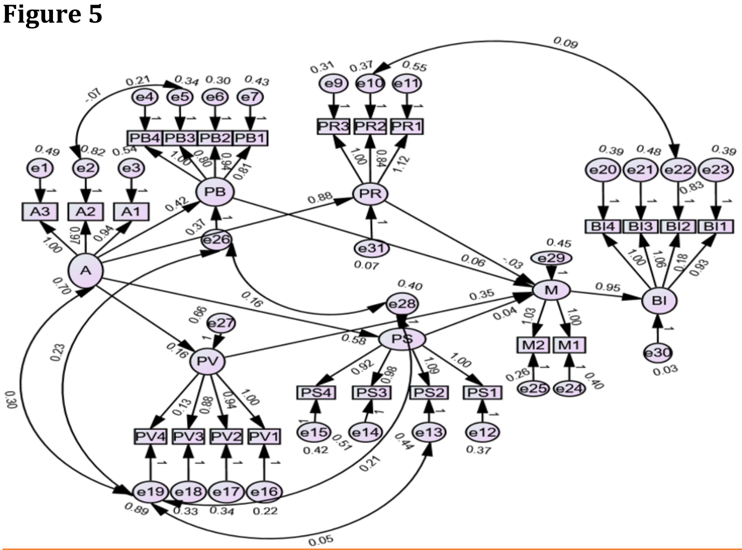

Figure 5 Structural Equation Model After Modifications

Source Researchers' Development Through SPSS AMOS 28

The default model is compared with the threshold levels to check whether the model is fit or not.

Table 9

Table 9 Comparison of Threshold Value with the Default Model			
Measures	**Threshold Level**	**Default Model**	**Remark**
CMIN/DF	>3	2.520	Accepted and improved from earlier
GFI	≥.90	.926	Accepted and improved from earlier
AGFI	≥.90	.905	Accepted and improved from earlier
RMR	≤.08	.064	Accepted and improved from earlier
NFI	≥.90	.915	Accepted and improved from earlier
NNFI(TLI)	≥.90	.937	Accepted and improved from earlier
CFI	≥.90	.946	Accepted and improved from earlier
PNFI	≥.50	.782	Accepted and improved from earlier
RMSEA	≥.05	.050	Accepted and improved from earlier

Source Researchers' Calculation Through SPSS AMOS 28

After structural model fit, it is necessary to begin by assessing unstandardized regression weights and standardized regression weights generated from maximum likelihood procedure.

- **Unstandardized and Standardized Regression Weights**

The standard error and critical ratio values are listed next to each estimated unstandardized regression coefficient in regression weights table. Predicted variation of the calculated coefficient is represented by the standard error of the coefficients. It measures how well predictor factors performed in predicting endogenous variable Ho (2006). Usefulness of S.E. is that predictor variable is more effective smaller it is. All of the S.E. scores in this instance are low. They vary from 0.041 to 0.061. The critical ratio, which is calculated by dividing the parameter estimate by the corresponding standard error, evaluates the relevance of the route coefficient. It is generally distributed as z Ho (2006). Consequently, a critical ratio that is significantly different from ± 1.96 indicates a significant path ($p < 0.05$).

Table 10

Table 10 Unstandardized Regression Weights and Standardized Regression Weights												
			Estimate	**S.E.**	**C.R.**	**P**	**Label**				**Estimate**
PB	<---	A	.424	.041	10.416	***	par_18	PB	<---	A	.506
PS	<---	A	.576	.047	12.223	***	par_19	PS	<---	A	.606
PV	<---	A	.158	.047	3.398	***	par_20	PV	<---	A	.160
PR	<---	A	.880	.049	17.99	***	par_22	PR	<---	A	.940
M	<---	PB	.057	.064	.890	.373	par_23	M	<---	PB	.054
M	<---	PR	-0.03	.055	-0.532	.595	par_24	M	<---	PR	-0.032
M	<---	PV	0.348	.043	8.130	***	par_25	M	<---	PV	.392
M	<---	PS	.042	.061	.679	.497	par_26	M	<---	PS	.045
BI	<---	M	.947	.057	16.633	***	par_21	BI	<---	M	.973
A3	<---	A	1.000					A3	<---	A	.766

A2	<---	A	.968	.061	15.887	***	par_1	A2	<---	A	.667
A1	<---	A	.937	.054	17.413	***	par_2	A1	<---	A	.728
PB4	<---	PB	1.000					PB4	<---	PB	.834
PB3	<---	PB	.805	.046	17.394	***	par_3	PB3	<---	PB	.694
PB2	<---	PB	.942	.048	19.429	***	par_4	PB2	<---	PB	.767
PB1	<---	PB	.815	.050	16.320	***	par_5	PB1	<---	PB	.658
PR3	<---	PR	1.000					PR3	<---	PR	.817
PR2	<---	PR	.842	.044	18.960	***	par_6	PR2	<---	PR	.735
PR1	<---	PR	1.117	.057	19.633	***	par_7	PR1	<---	PR	.762
PS1	<---	PS	1.000					PS1	<---	PS	.792
PS2	<---	PS	1.089	.055	19.718	***	par_8	PS2	<---	PS	.795
PS3	<---	PS	.976	.054	18.188	***	par_9	PS3	<---	PS	.736
PS4	<---	PS	.923	.050	18.541	***	par_10	PS4	<---	PS	.749
PV1	<---	PV	1.000					PV1	<---	PV	.871
PV2	<---	PV	.940	.045	20.813	***	par_11	PV2	<---	PV	.798
PV3	<---	PV	.879	.043	20.460	***	par_12	PV3	<---	PV	.783
PV4	<---	PV	.134	.042	3.192	.001	par_13	PV4	<---	PV	.115
BI4	<---	BI	1.000					BI4	<---	BI	.753
BI3	<---	BI	1.057	.061	17.289	***	par_14	BI3	<---	BI	.736
BI2	<---	BI	.182	.056	3.261	0.001	par_15	BI2	<---	BI	.141
BI1	<---	BI	.927	.054	17.024	***	par_16	BI1	<---	BI	.725
M1	<---	M	1.000					M1	<---	M	.756
M2	<---	M	1.034	.054	19.323	***	par_17	M2	<---	M	.827

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According to this criterion, Table's findings show critical ratio test of all the unstandardized regression weights are positive ($> \pm 1.96$, $p < 0.05$) (except for those parameters that were fixed to 1). Standardized regression weight in above table indicates that awareness is positively related to PB, PS, PV, and PR (β = 0.506, .606, .160, .940, respectively).

Hence, more awareness will promote a more positive perception of forensic accounting. It, therefore, implies that greater awareness of forensic accounting, higher perceived benefits of using forensic accounting services. Similarly, perceived severity of fraud positively relates to awareness (β=0.606). Therefore, auditors will also intend to use forensic accounting services as the perceived severity of fraud increases. Furthermore, perceived susceptibility/vulnerability to fraud is significantly and positively related to awareness (β = 0.160). Hence, higher perceived susceptibility to fraud, more auditors will be aware of forensic accounting services. Moreover, awareness is positively related to perceived risk or barrier to using forensic accounting services (β =.940). Thus, there is more awareness and knowledge about the barriers and risks in implementing forensic accounting services. When Auditors perceive fewer risks or barriers in using forensic accounting, they will go for it. The risks or barriers here may be in terms of cost of acquiring services of expert forensic accountant and more competition among audit firms for providing forensic accounting services, which may hamper the quality of service, as forensic accounting does not take any guarantee of payback of stolen money, but, if the forensic accountant is called upon the reputation of the organization will be on the stake as investors will think something wrong is happening in the organization, so, the investment will reduce. Therefore, awareness regarding perceived barriers and risks can be used to overcome these obstacles.

The standardized regression weights in above table further reveal that the perceived benefits of using forensic accounting are positively related to motivation (β = 0.054). Additional advantages of forensic accounting encourage auditors to adopt these services. However, perceived risks negatively motivate to use of forensic accounting as Perceived Risk is negatively related to motivation (β = -0.032). It means that when the auditors are aware of the risks that cannot be controlled, it will negatively motivate them not to use forensic accounting. Perceived susceptibility/vulnerability and perceived severity also positively impact motivation as β = .392, and .045 respectively. Finally, motivation positively impacts behavioral intention to use forensic accounting services as β = .973, which is the highest and near 1.

- **Squared Multiple Correlations**

Having assessed regression and standardized regression weights, one can now examine explanatory powers of the model. Falk and Miller (1992) suggest that minimum coefficient of determination, R2, should be 0.10 for a model to be considered influential. Below table shows squared multiple correlations of structural model. The Table 12 presents coefficients of determination and R2 of all endogenous constructs.

Table 11

Table 11 Squared Multiple Correlations of the Structural Model

	PV	**PS**	**PR**	**PB**	**M**	**BI**	**M2**	**M1**	**BI1**
Estimate	0.026	0.368	0.884	0.256	0.163	0.947	0.685	0.572	0.526
	BI2	BI3	BI4	PV4	PV3	PV2	PV1	PS4	PS3
Estimate	0.02	0.542	0.568	0.027	0.613	0.637	0.759	0.561	0.542
	PS2	PS1	PR1	PR2	PR3	PB1	PB2	PB3	PB4
Estimate	0.631	0.628	0.581	0.541	0.667	0.433	0.589	0.482	0.696
	A1	A2	A3						
Estimate	0.53	0.444	0.587						

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Table 12

Table 12 Summary of coefficient of determination R2 for endogenous constructs

Construct	**R^2**
Perceived Susceptibility/Vulnerability	.026
Perceived Severity	.368
Perceived Risk	.884
Perceived Benefits	.256
Motivation	.163
Behavioral Intention	.947

Source Researchers' Calculation Through SPSS AMOS 28

Above table shows all R2 values that are above the minimum requirement of 0.10. Above all, model's overall coefficient of multiple determination (R2) value is

0.947. It means that data fit the model well, and model explains 94.70 percent of deviation from the impulsion to adoption of forensic accounting services. The value is much greater than the recommendations of Muthusamy et al. (2010) and Efiong and Joel (2013) in which case the model was able to explain 39.50% and 68.20% of the total variance. For this study, unexplained 0.053 percent variance in the behavioral intention of using forensic accounting services is attributed to residual. Hence, a relatively high percentage of auditors intend to use forensic accounting in fraud prevention or detection.

7. TEST OF MODEL HYPOTHESIS

Hypothesis 1: Awareness of forensic accounting has an impact on the perceived benefits of using it against fraud.

H0: Awareness of forensic accounting has a negative impact on the perceived benefits of using it against fraud.

H1: Awareness of forensic accounting has a positive impact on the perceived benefits of using it against fraud.

The result of study shows that awareness of forensic accounting services positively influences the perceived benefits (β= 0.42) of using it. This finding is similar to that of Muthusamy et al. (2010), Efiong and Joel (2013), and Wei et al. (2017). It, therefore, means that more auditors are aware of forensic accounting services, more they will perceive the benefits of using it in their organizations.

Hypothesis 2: Awareness of forensic accounting has an impact on the perceived risks of using it against fraud.

H0: Awareness of forensic accounting has a negative impact on the perceived risks of using it against fraud.

H1: Awareness of forensic accounting has a positive impact on the perceived risks of using it against fraud.

The result of the study shows that awareness of forensic accounting services positively influences perceived risks (β= 0.88) of using it. It means that more auditors are aware of forensic accounting services, more they will perceive risks of using them and how to handle these risks or barriers in their organizations.

Hypothesis 3: Awareness of forensic accounting has an impact on the perceived susceptibility/vulnerability of using it against fraud.

H0: Awareness of forensic accounting has a negative impact on perceived susceptibility/vulnerability of using it against fraud.

H1: Awareness of forensic accounting has a positive impact on perceived susceptibility/vulnerability of using it against fraud.

In this hypothesis, researchers test the influence of awareness on the threat perception factor, i.e., Perceived Susceptibility/Vulnerability, as β = 0.16. This finding is similar to that of Muthusamy et al. (2010), Efiong and Joel (2013), and Wei et al. (2017). Therefore, it means that the more auditors are aware of fraud and its negative impact on the organization, the more they will use forensic accounting services.

Hypothesis 4: Awareness of forensic accounting has an impact on the perceived severity of using it against fraud.

H0: Awareness of forensic accounting has a negative impact on the perceived severity of using it against fraud.

H1: Awareness of forensic accounting has a positive impact on the perceived severity of using it against fraud.

Similarly, statistical analysis confirmed positive influence of awareness on the perceived severity of fraud as β is 0.58. Nowadays, frauds are increasing as the pandemic, and the need for more awareness arises. This finding also marked an improvement in the insignificant influence obtained by Muthusamy et al. (2010).

Hypothesis 5: Perceived benefits of forensic accounting have an impact on motivation to use it against fraud.

H0: Perceived benefits of forensic accounting have a negative impact on motivation to use it against fraud.

H1: Perceived benefits of forensic accounting have a positive impact on motivation to use it against fraud.

The overall structural model shows positive β = 0.06 with Motivation, so it can be said that perceived benefits have a positive impact on motivation to use forensic accounting services. So, H0 is not accepted.

Hypothesis 6: Perceived risks of forensic accounting have an impact on motivation to use it against fraud.

H0: Perceived risks of forensic accounting have a negative impact on motivation to use it against fraud.

H1: Perceived risks of forensic accounting have a positive impact on motivation to use it against fraud.

The figure shows negative β = -0.03 with Motivation, so it can be said that perceived risks have a negative impact on motivation to use it. So, H0 is accepted.

Hypothesis 7: Perceived susceptibility/vulnerability of forensic accounting has an impact on motivation to use it against fraud.

H0: Perceived susceptibility/vulnerability of forensic accounting has a negative impact on motivation to use it against fraud.

H1: Perceived susceptibility/vulnerability of forensic accounting has a positive impact on motivation to use it against fraud.

The overall structural model shows perceived susceptibility/vulnerability has positive β = 0.35 with motivation, so it can be said that perceived susceptibility/vulnerability positively impacts motivation to use it. So, H0 is not accepted.

Hypothesis 8: Motivation to use forensic accounting has an impact on behavioral intention to implement it for fraud prevention or detection.

H0: Motivation to use forensic accounting has a negative impact on behavioral intention to implement it for fraud prevention or detection.

H1: Motivation to use forensic accounting has a positive impact on behavioral intention to implement it for fraud prevention or detection.

Overall structural model shows motivation has a positive value of β = 0.95 with the behavioral intention to implement forensic accounting for fraud prevention or detection. So, H0 is not accepted.

8. CONCLUSION

Fraud is omnipresent in the corporate world. Fraud and its type have significant contribution in the severe financial crisis, and its negative consequences paralyze the economic entities all over the world. Hence, it is important to understand the nature of fraud and try to prevent before its occurrence. The traditional financial auditors are not capable enough to identify the red signals of fraudulent activities. They only come to know the fraud after its occurrence. The stakeholders expect from the financial auditors to provide them a true and fair position of the financial statement without any symptom of fraud, but the auditor's perception is that they can provide their opinion on truthfulness; they are not trained to identify the fraud. Hence, an expectation gap is arising between auditors and stakeholders. Here, forensic accountants can play a major role to identify the fraud before its occurrence even they can assist in court. The forensic accountants not only recognize the fraud symptoms and typologies but also provide suggestions regarding human capital investment that increase employees' sensitivity to identify the fraud and discourage the participation in financial crime.

There are many theories develop by eminent scholars which shows the factors that motivate an employee to commit fraud like fraud triangle, diamond theory of fraud, fraud pentagon, etc. This research provides new theoretical framework based on various models & theories and develop a new research model named as "Fraud Deviation Model". The quantitative data was used to know the impact of auditor's awareness and perception on forensic accounting. Furthermore, the gender has no association with level of awareness but the other demographic variables like age, job description, service tenure of auditor, type, nature, and turnover of the auditing organization have significant and positive relationships. The impact of awareness and perception on behavioral intention to use forensic accounting is analyzed with the help of structure equation modeling. The outcome shows that awareness positively impacts perceived benefits, perceived risk, perceived vulnerability/susceptibility, and perceived severity. Further, the three factors (perceived benefits, perceived vulnerability/susceptibility, and perceived severity) positively influence and motivate the use of forensic accounting, but the perceived risk negatively motivates forensic accounting. However, the negative influence of using forensic accounting is less in comparison to its positive impact. So overall, motivation creates positive behavior among auditors and organizations to use forensic accounting.

On the whole, the present research provides insights on current status of auditor's awareness and perception on forensic accounting and its impact on behavioral intention to use forensic accounting technique as fraud detection and preventive tool. There is a need to increase level of awareness among auditors as well as top management. Forensic accounting should be part of curriculum that can help in spread out the awareness and in the aftermath promote the forensic accounting as fraud prevention and detective measure. Although forensic accounting is in its blossoming point in India but due to increasing scams and frauds it becomes a new emerging field of accounting now-a-days.

CONFLICT OF INTERESTS

None.

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None.

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