Developing Big Data Analytics, Diagnostic, and Forensic Accounting Skills among Generation Z Accountants

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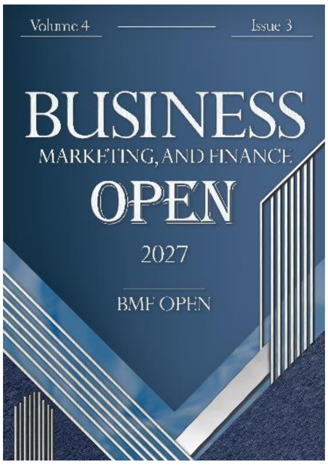

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Abstract: Forensic accounting is an emerging approach to fraud detection that utilizes reliable principles and methodologies to obtain sufficient facts and evidence. The purpose of this study was to develop big data analytics, diagnostic, and forensic accounting skills among Generation Z accountants. Data were collected through a field survey using a standardized questionnaire. The statistical population consisted of Generation Z students of an unspecified size. The sample size was determined based on the formula recommended for structural equation modeling, with a minimum of 140 participants and an optimal sample size of 420 participants at a 95% confidence level and a 5% margin of error. Ultimately, 392 completed questionnaires were obtained and analyzed using the Structural Equation Modeling (SEM) approach in SmartPLS software. The results indicated that big data analytics skills had a positive and significant effect on diagnostic skills. Diagnostic skills also had a positive and significant effect on forensic accounting skills. Furthermore, diagnostic skills exerted a positive and significant influence on forensic accounting skills and mediated the relationship between big data analytics skills and forensic accounting skills. Based on the findings, it is recommended that Generation Z students place considerable emphasis on developing their big data analytics, diagnostic, and forensic accounting skills.

Keywords: Big Data Analytics Skills, Diagnostic Skills, Forensic Accounting Skills.

1. Introduction

The accounting profession is undergoing a profound transformation as organizations increasingly rely on digital systems, large-scale data environments, automated processes, and complex information architectures for financial reporting, internal control, audit evidence, and managerial decision-making. Traditional accounting knowledge remains essential, yet it is no longer sufficient for accountants who must operate in data-intensive and fraud-prone organizational contexts. The growing volume, velocity, variety, and complexity of organizational data have created new opportunities for evidence-based analysis, but they have also intensified the need for accountants to develop advanced analytical, diagnostic, and investigative competencies. In this context, the development of big data analytics skills, diagnostic skills, and forensic accounting skills has become a strategic requirement for the next generation of accounting professionals, particularly Generation Z accountants who are entering the labor market in an era characterized by digital transformation, artificial intelligence, and data-driven governance [1-4].

The conceptual foundations of accounting have long emphasized the role of accounting information in judgment, accountability, and rational decision-making. Early theoretical discussions in accounting highlighted that accounting should not merely record historical transactions but should provide useful information for evaluating economic reality and supporting informed decisions [5]. This orientation has become even more relevant in contemporary organizations, where financial and non-financial information is produced continuously through enterprise systems, digital platforms, customer databases, banking systems, and external data sources. As a result, accountants are expected to interpret not only structured financial statements but also semi-structured and unstructured data that may reveal patterns, anomalies, risks, and fraud signals. The movement from conventional accounting toward data-driven accounting therefore requires a broader skill base, including data quality evaluation, data access capability, technological proficiency, and analytical expertise [6-8].

Big data analytics refers to the systematic process of collecting, managing, processing, and interpreting massive and complex datasets to generate meaningful insights for decision-making. Although much of the early literature on big data focused on technical challenges, such as data storage, processing architecture, scalability, and analytical tools, managerial and professional studies increasingly emphasize the human capabilities required to convert data into actionable knowledge [1, 2]. Big data is valuable only when professionals can evaluate its relevance, reliability, timeliness, and interpretive meaning. In management contexts, big data analytics supports strategic decision-making, operational efficiency, risk identification, and organizational learning by enabling decision-makers to identify hidden relationships and predict future outcomes [9]. In accounting and auditing contexts, these capabilities are particularly important because financial irregularities, manipulation, and fraud may be embedded in large volumes of transactional data that cannot be effectively examined through traditional manual procedures.

The adoption of big data analytics is especially important in financial and banking environments, where high-volume transactions, digital payments, customer behavior data, and automated reporting systems generate extensive data streams. Studies on the adoption of big data analytics in banking and digital industries indicate that organizational readiness, technological infrastructure, data accessibility, and human expertise are central determinants of successful implementation [7]. Similarly, human resource management in the digital era requires organizations to redesign competency development strategies around digital skills, data literacy, and analytic capability [6]. For accounting education and professional development, this implies that accountants must be trained not only in financial reporting standards and audit procedures but also in data analytics, digital platforms, technological tools, and evidence-based interpretation. Generation Z students, who are often regarded as digitally familiar but not necessarily professionally data-literate, require structured educational pathways to transform general digital familiarity into specialized accounting analytics competence.

Recent management literature has also introduced the idea of data-driven leadership and competency frameworks that emphasize the integration of analytical thinking, technological understanding, communication, and decision-making capability [8]. Such frameworks are relevant to accounting because accountants increasingly function as decision-support professionals who communicate complex data insights to managers, auditors, regulators, and legal authorities. Big data analytics skills in accounting therefore include more than technical data handling; they also involve understanding data quality, accessing relevant data sources, selecting appropriate tools, interpreting patterns, and communicating findings in a professional and ethically defensible manner. These competencies are closely connected to diagnostic skills because the ability to interpret data depends on the ability to observe irregularities, identify problems, reason through evidence, and distinguish meaningful signals from irrelevant noise.

Diagnostic skills refer to the capacity to recognize, interpret, and explain problems by collecting relevant evidence, analyzing patterns, and forming professional judgments. Although the concept of diagnosis is frequently discussed in clinical and medical contexts, its logic is highly applicable to accounting and fraud detection. Diagnostic work involves uncertainty, incomplete information, cognitive judgment, communication, and iterative evaluation of possible explanations [10]. In accounting, diagnostic skills enable professionals to detect anomalies in financial data, identify inconsistencies in documentation, evaluate unusual transactions, and distinguish between error, misstatement, manipulation, and fraud. Observation, communication, problem-solving, and professional empathy or responsiveness can enhance the accountant's ability to understand complex organizational situations and interpret evidence within its broader operational and behavioral context.

The relationship between big data analytics skills and diagnostic skills is theoretically meaningful. Data analytics provides access to patterns, outliers, and predictive indicators, while diagnostic reasoning allows professionals to interpret these outputs and determine whether they represent meaningful risks or ordinary variations. Without diagnostic capability, accountants may produce statistical outputs without understanding their implications. Conversely, without analytical capability, diagnostic judgment may remain limited to small samples, subjective impressions, or conventional procedures. The integration of big data analytics and diagnostic reasoning therefore strengthens the accountant's capacity to detect irregularities, assess risk, and make defensible professional judgments in complex environments [8-10].

Forensic accounting has emerged as one of the most important professional domains in which analytical and diagnostic competencies are required. Forensic accounting combines accounting, auditing, investigation, legal knowledge, fraud examination, and evidentiary reasoning to detect, investigate, and prevent fraud and financial misconduct. Foundational works in forensic accounting define it as a specialized field that applies accounting and investigative techniques to matters involving legal consequences, fraud disputes, and financial evidence [11, 12]. Historically, forensic accounting and auditing have been closely connected, particularly in their shared concern with evidence, professional skepticism, fraud risk, and accountability [13]. However, modern forensic accounting extends beyond traditional audit procedures because it requires investigative orientation, litigation support, digital evidence interpretation, and the ability to communicate findings in legal and organizational settings.

The demand for forensic accounting has increased due to the growing sophistication of fraud schemes, financial information manipulation, cyber-enabled misconduct, and complex organizational structures. Fraud can no longer be understood merely as an accounting error; it often involves intentional concealment, collusion, document manipulation, digital traces, and exploitation of control weaknesses. Forensic accountants therefore need a distinctive set of competencies, including fraud identification, knowledge of laws and regulations, professional judgment, ethical reasoning, and financial data analysis [14, 15]. Research on forensic accounting education also shows that curricula must adapt to include fraud investigation, forensic analytics, investigative interviewing, digital evidence, and legal dimensions of accounting practice [16, 17]. These educational developments are particularly relevant for Generation Z accounting students who will enter a profession increasingly shaped by digital forensics, automated controls, and data-driven fraud detection.

Empirical studies have consistently emphasized the importance of forensic accounting skills for fraud detection and prevention. Research indicates that forensic accounting contributes to fraud deterrence, investigation, litigation support, and socio-economic development by improving transparency and accountability [18]. The application of forensic accounting services has also been examined in public-sector and organizational contexts, where institutions seek specialized expertise to detect and prevent fraud [19]. Studies on financial information manipulation show that forensic accounting techniques can improve the detection of intentional distortions in financial reports and enhance confidence in accounting information [20]. Moreover, auditor competency supported by digital forensic tools has been linked to improved fraud detection capability, suggesting that technological and professional competencies must operate together [21].

Recent research further highlights the interaction between forensic accounting skills and computer-assisted audit tools and techniques. Evidence from Egypt shows that forensic accounting skills play a significant role in fraud detection and that the application of computer-assisted audit tools can strengthen this relationship [22]. This finding is particularly relevant to the present study because it suggests that forensic accounting effectiveness is enhanced when accountants possess both investigative skills and technology-based analytical capabilities. In modern fraud environments, accountants must be able to use digital tools, interpret large datasets, identify suspicious patterns, and connect analytical results to legal and professional standards. Therefore, forensic accounting skills should be conceptualized not as isolated investigative competencies but as the outcome of integrated analytical, diagnostic, technological, and professional capabilities.

Generation Z accountants represent a strategically important population for studying these competencies. This generation has grown up in a digital environment and is often more familiar with online platforms, digital interfaces, and technology-mediated communication than previous generations. However, familiarity with technology does not automatically translate into professional competence in big data analytics, diagnostic reasoning, or forensic accounting. The accounting profession requires disciplined, evidence-based, and ethically grounded use of data. Therefore, accounting education must cultivate the ability to evaluate data quality, access and analyze information, use technological tools appropriately, and interpret findings through diagnostic and forensic reasoning. This need becomes more urgent as artificial intelligence and intelligent systems reshape professional work by automating routine tasks and increasing the value of higher-order analytical judgment [4].

Methodologically, studying these relationships requires analytical approaches capable of modeling latent constructs and testing direct and indirect effects among them. Partial Least Squares Structural Equation Modeling is appropriate for examining complex relationships among latent variables, particularly when the research model includes multiple constructs, dimensions, and mediation paths [23]. Reliability and validity assessment are also essential in such models because constructs such as big data analytics skills, diagnostic skills, and forensic accounting skills are multidimensional and cannot be directly observed. Internal consistency, convergent validity, discriminant validity, and predictive relevance must therefore be assessed before interpreting structural relationships. In this regard, reliability thresholds and measurement quality criteria remain important considerations, especially when some dimensions include a limited number of items [24].

Despite the growing literature on big data analytics, digital transformation, and forensic accounting, there remains a need for empirical models that explain how analytical capabilities contribute to forensic accounting competence through diagnostic skills. Much of the existing literature treats big data analytics, diagnostic reasoning, and forensic accounting as separate professional domains. However, in practice, these competencies are interdependent. Big data analytics provides the informational and technological foundation for identifying patterns and anomalies; diagnostic skills transform those patterns into professional judgments; and forensic accounting skills apply those judgments to fraud detection, legal interpretation, and financial investigation. Understanding this chain of relationships is especially important for Generation Z accounting students because their professional development should be aligned with the emerging demands of data-intensive accounting environments.

Accordingly, this study aims to examine the development of big data analytics, diagnostic, and forensic accounting skills among Generation Z accountants and to investigate the mediating role of diagnostic skills in the relationship between big data analytics skills and forensic accounting skills.

2. Methodology

This study was grounded in the positivist research paradigm and adopted an applied research orientation. From a methodological perspective, the study employed an inductive approach and a quantitative research design. Data were collected through a field survey using a cross-sectional survey strategy. The research objective was descriptive in nature and aimed to investigate the relationships among big data analytics skills, diagnostic skills, and forensic accounting skills among Generation Z students. The conceptual framework of the study was adapted from the model proposed by Emejaye et al. (2024).

The target population consisted of Generation Z university students. Participants were selected using a simple random sampling technique to ensure that all members of the population had an equal probability of being included in the study. The required sample size was determined using the formula recommended for Structural Equation Modeling (SEM), which considers the number of observed variables, the number of latent variables, the expected effect size, the correlation coefficient, and Type I and Type II error rates. Based on these calculations, the minimum required sample size was estimated to be 140 participants, while the optimal sample size was determined to be 420 participants. A total of 392 completed questionnaires were ultimately collected and deemed suitable for statistical analysis, exceeding the minimum sample size requirement and providing sufficient statistical power for structural equation modeling.

Data were collected using a researcher-developed questionnaire designed to assess the principal constructs of the study. The instrument consisted of three sections measuring forensic accounting skills, big data analytics skills, and diagnostic skills. The forensic accounting skills scale contained 25 items evaluating respondents' competencies related to fraud detection, investigative accounting procedures, evidence evaluation, and the application of accounting knowledge in legal and regulatory contexts. The big data analytics skills scale comprised 12 items assessing participants' abilities to collect, process, interpret, and utilize large and complex datasets for decision-making and problem-solving purposes. The diagnostic skills scale included 8 items designed to measure participants' capabilities in identifying, analyzing, and diagnosing accounting irregularities, anomalies, and organizational problems through analytical reasoning and professional judgment.

All questionnaire items were measured using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Higher scores indicated greater levels of the corresponding skill or competency. The questionnaire was developed based on an extensive review of the relevant literature and existing theoretical frameworks related to forensic accounting, data analytics, and diagnostic competencies. Prior to the main analysis, the measurement properties of the instrument were evaluated through reliability and validity assessments. Internal consistency reliability, convergent validity, and discriminant validity were examined to ensure that the instrument adequately measured the intended constructs.

Data analysis was conducted using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach implemented in SmartPLS software. The analysis proceeded in two stages. In the first stage, the measurement model was assessed to evaluate the reliability and validity of the latent constructs. Indicator loadings, composite reliability, Cronbach's alpha, average variance extracted (AVE), and discriminant validity measures were examined to verify the adequacy of the measurement model.

In the second stage, the structural model was evaluated to test the hypothesized relationships among big data analytics skills, diagnostic skills, and forensic accounting skills. Path coefficients, significance levels, and explanatory power were assessed to determine the strength and direction of the proposed relationships. The overall predictive and explanatory capability of the model was evaluated using the coefficient of determination (R^2), predictive relevance (Q^2), and the Goodness-of-Fit (GOF) index. Furthermore, mediation analysis was performed within the PLS-SEM framework to examine the indirect effect of big data analytics skills on forensic accounting skills through diagnostic skills. Statistical significance was determined at the 95% confidence level.

3. Findings and Results

The construct of big data analytics skills was measured using 12 items and four dimensions, namely data quality, data access, technological tools, and expertise. Diagnostic skills were measured using 8 items and four dimensions, namely observation, communication, problem-solving, and compassion. Forensic accounting skills were measured using 25 items and four dimensions, namely fraud identification, legal knowledge, professionalism, and financial data analysis. All items were measured on a five-point Likert scale ranging from 1 to 5. The descriptive statistics of the research variables and dimensions are presented in Table 1.

Table 1. Descriptive Statistics of the Research Variables and Dimensions

Variables and Dimensions	N	Mean	Median	Mode	SD	Skewness	Kurtosis	Minimum	Maximum
Data quality	392	2.73	2.67	2.00	0.96	0.12	-1.00	1.00	4.67
Data access	392	2.93	3.00	3.00	0.87	-0.48	-0.64	1.00	4.25
Technological tools	392	2.61	2.33	2.33	0.95	0.30	-0.75	1.00	5.00
Expertise	392	3.14	3.50	4.00	1.25	-0.19	-1.33	1.00	5.00
Big data analytics skills	392	2.85	3.13	3.63	0.83	-0.46	-0.97	1.00	4.15
Observation	392	3.14	3.33	4.00	1.21	-0.46	-1.04	1.00	5.00
Communication	392	2.58	2.50	1.00	1.16	0.07	-1.16	1.00	5.00
Problem-solving	392	2.64	3.00	1.00	1.27	0.18	-1.10	1.00	5.00
Compassion	392	2.67	3.00	3.00	1.17	0.07	-0.93	1.00	5.00
Diagnostic skills	392	2.76	3.13	3.25	0.93	-0.45	-1.09	1.08	4.17
Fraud identification	392	3.08	3.17	3.67	0.88	-0.24	-0.92	1.33	4.67
Legal knowledge	392	2.67	3.00	3.17	0.91	-0.32	-1.09	1.00	4.33
Professionalism	392	2.81	2.86	3.57	0.92	-0.21	-1.04	1.14	4.57
Financial data analysis	392	2.80	3.00	3.33	0.90	-0.24	-0.95	1.00	4.50
Forensic accounting skills	392	2.84	3.09	3.73	0.81	-0.38	-1.19	1.16	4.10

The normality assumption was examined using skewness and kurtosis indices. Since the observed skewness and kurtosis values for all research variables were within the acceptable range of -2 to +2, the distributions were considered sufficiently normal and symmetric. Therefore, parametric statistical tests were used for data analysis.

Because both the measurement model and the structural model were reflective, the reliability and validity of the constructs were first assessed, followed by the examination of the factorial structure among the constructs. In the PLS path modeling approach, hierarchical component models can be specified using repeated indicators. Accordingly, a higher-order latent variable is formed by all observed indicators of its lower-order components. In this study, the second-order construct of big data analytics skills was formed by the first-order dimensions of data quality, data access, technological tools, and expertise. Similarly, diagnostic skills and forensic accounting skills were modeled as second-order constructs consisting of their respective first-order dimensions. The repeated-indicator approach was therefore used to estimate the hierarchical structure of the model.

Reliability was assessed through Cronbach's alpha, Spearman reliability, and composite reliability. As shown in Table 2, all coefficients were within acceptable ranges. Cronbach's alpha values above 0.70 indicate acceptable internal consistency, although values above 0.60 may also be acceptable for constructs with a small number of items.

Composite reliability values above 0.70 also indicate adequate internal consistency. Therefore, the reliability of all constructs and dimensions was confirmed.

Table 2. Reliability Coefficients of the Constructs

Main Construct	Dimension	Cronbach's Alpha	Spearman Reliability	Composite Reliability
Big data analytics skills	Data quality	0.70	0.71	0.83
Big data analytics skills	Data access	0.70	0.72	0.82
Big data analytics skills	Technological tools	0.72	0.76	0.84
Big data analytics skills	Expertise	0.83	0.87	0.92
Big data analytics skills	Total	0.87	0.89	0.90
Diagnostic skills	Observation	0.84	0.84	0.90
Diagnostic skills	Communication	0.75	0.75	0.89
Diagnostic skills	Problem-solving	0.81	0.84	0.91
Diagnostic skills	Compassion	1.00	1.00	1.00
Diagnostic skills	Total	0.89	0.90	0.91
Forensic accounting skills	Fraud identification	0.80	0.83	0.85
Forensic accounting skills	Legal knowledge	0.81	0.83	0.87
Forensic accounting skills	Professionalism	0.82	0.83	0.86
Forensic accounting skills	Financial data analysis	0.81	0.86	0.87
Forensic accounting skills	Total	0.94	0.95	0.94

The reliability of individual items was evaluated using standardized factor loadings. As shown in Table 3, the factor loadings of the observed indicators were generally above the acceptable threshold of 0.40 and were statistically significant. This indicates that the items were meaningfully associated with their underlying latent dimensions and that the measurement model had an acceptable item-level structure.

Table 3. Measurement Model and Item-Level Evaluation Indices

Main Construct	Dimension	Item	Factor Loading	t-value	p-value
Big data analytics skills	Data quality	qa1	0.82	54.03	0.000
Big data analytics skills	Data quality	qa2	0.78	30.52	0.000
Big data analytics skills	Data quality	qa3	0.78	29.07	0.000
Big data analytics skills	Data access	qa4	0.78	30.22	0.000
Big data analytics skills	Data access	qa5	0.71	18.29	0.000
Big data analytics skills	Data access	qa6	0.65	12.91	0.000
Big data analytics skills	Data access	qa7	0.76	36.26	0.000
Big data analytics skills	Technological tools	qa8	0.78	27.19	0.000
Big data analytics skills	Technological tools	qa9	0.90	93.51	0.000
Big data analytics skills	Technological tools	qa10	0.72	25.23	0.000
Big data analytics skills	Expertise	qa11	0.94	268.80	0.000
Big data analytics skills	Expertise	qa12	0.90	53.42	0.000
Diagnostic skills	Observation	qb1	0.87	58.53	0.000
Diagnostic skills	Observation	qb2	0.89	72.10	0.000
Diagnostic skills	Observation	qb3	0.85	47.55	0.000
Diagnostic skills	Communication	qb4	0.89	89.91	0.000
Diagnostic skills	Communication	qb5	0.89	83.02	0.000
Diagnostic skills	Problem-solving	qb6	0.89	60.49	0.000
Diagnostic skills	Problem-solving	qb7	0.93	193.84	0.000
Diagnostic skills	Compassion	qb8	1.00	—	—
Forensic accounting skills	Fraud identification	qc1	0.71	29.48	0.000
Forensic accounting skills	Fraud identification	qc2	0.83	39.30	0.000
Forensic accounting skills	Fraud identification	qc3	0.86	74.85	0.000

Forensic accounting skills	Fraud identification	qc4	0.64	14.88	0.000
Forensic accounting skills	Fraud identification	qc5	0.57	13.62	0.000
Forensic accounting skills	Fraud identification	qc6	0.58	13.24	0.000
Forensic accounting skills	Legal knowledge	qc7	0.86	74.38	0.000
Forensic accounting skills	Legal knowledge	qc8	0.60	15.13	0.000
Forensic accounting skills	Legal knowledge	qc9	0.55	11.99	0.000
Forensic accounting skills	Legal knowledge	qc10	0.77	36.23	0.000
Forensic accounting skills	Legal knowledge	qc11	0.80	39.52	0.000
Forensic accounting skills	Legal knowledge	qc12	0.73	30.28	0.000
Forensic accounting skills	Professionalism	qc13	0.62	16.65	0.000
Forensic accounting skills	Professionalism	qc14	0.62	17.36	0.000
Forensic accounting skills	Professionalism	qc15	0.77	30.07	0.000
Forensic accounting skills	Professionalism	qc16	0.74	25.44	0.000
Forensic accounting skills	Professionalism	qc17	0.80	42.40	0.000
Forensic accounting skills	Professionalism	qc18	0.54	10.08	0.000
Forensic accounting skills	Professionalism	qc19	0.73	30.95	0.000
Forensic accounting skills	Financial data analysis	qc20	0.73	25.55	0.000
Forensic accounting skills	Financial data analysis	qc21	0.74	27.03	0.000
Forensic accounting skills	Financial data analysis	qc22	0.58	13.89	0.000
Forensic accounting skills	Financial data analysis	qc23	0.83	56.39	0.000
Forensic accounting skills	Financial data analysis	qc24	0.90	139.63	0.000
Forensic accounting skills	Financial data analysis	qc25	0.51	9.69	0.000

Convergent validity was examined using the Average Variance Extracted (AVE). According to Fornell and Larcker (1981), AVE values above 0.50 indicate acceptable convergent validity; however, values above 0.40 may also be considered adequate in applied measurement models when other reliability indicators are acceptable (Magner et al., 1996). The AVE values indicated that the constructs had adequate convergent validity. Discriminant validity was further assessed using the Fornell–Larcker criterion. As shown in Table 4, the square root of the AVE for each construct, presented on the diagonal, was greater than its correlations with other constructs, indicating acceptable discriminant validity.

Table 4. Convergent Validity and Fornell–Larcker Discriminant Validity

No.	Construct	AVE	1	2	3	4	5	6	7	8	9	10	11	12
1	Data quality	0.63	0.79											
2	Data access	0.53	0.54	0.73										
3	Technological tools	0.65	0.60	0.49	0.80									
4	Expertise	0.85	0.58	0.70	0.58	0.92								
5	Observation	0.76	0.70	0.63	0.59	0.74	0.87							
6	Communication	0.80	0.54	0.69	0.53	0.65	0.75	0.89						
7	Problem-solving	0.84	0.49	0.44	0.48	0.46	0.61	0.51	0.91					
8	Compassion	1.00	0.45	0.45	0.26	0.40	0.60	0.44	0.36	1.00				
9	Fraud identification	0.50	0.49	0.55	0.45	0.66	0.64	0.54	0.45	0.45	0.71			
10	Legal knowledge	0.53	0.49	0.63	0.60	0.78	0.67	0.65	0.49	0.46	0.61	0.73		
11	Professionalism	0.48	0.42	0.53	0.49	0.58	0.60	0.59	0.41	0.30	0.66	0.69	0.69	
12	Financial data analysis	0.53	0.48	0.53	0.50	0.66	0.61	0.70	0.48	0.30	0.65	0.69	0.70	0.73

The cross-loading matrix was also examined as a complementary assessment of discriminant validity. The results showed that the observed indicators generally had stronger associations with their theoretically corresponding constructs than with unrelated constructs. The primary loading ranges were 0.78 to 0.82 for data quality, 0.65 to

0.78 for data access, 0.72 to 0.90 for technological tools, 0.90 to 0.94 for expertise, 0.85 to 0.89 for observation, 0.89 for communication, 0.89 to 0.93 for problem-solving, 1.00 for compassion, 0.57 to 0.86 for fraud identification, 0.55 to 0.86 for legal knowledge, 0.54 to 0.80 for professionalism, and 0.51 to 0.90 for financial data analysis. Therefore, the cross-loading evidence was interpreted as supporting the discriminant validity of the measurement model. In the Fornell–Larcker assessment, second-order constructs were not included in the same matrix with their first-order dimensions because higher-order constructs are formed by their lower-order components and are not expected to show discriminant separation from those components.

The predictive quality of the structural model was examined using the Q^2 index. Positive Q^2 values indicate that the model is capable of reconstructing and predicting the observed values of endogenous reflective constructs. According to Henseler et al. (2009), Q^2 values of 0.02, 0.15, and 0.35 may be interpreted as weak, moderate, and strong predictive relevance, respectively. As shown in Table 5, the Q^2 values of the endogenous constructs were positive and generally above 0.25, indicating desirable predictive relevance. The overall goodness-of-fit index was also calculated using the square root of the product of the mean communality and the mean R^2. The obtained GOF value was 0.67, which exceeded the strong threshold of 0.36 proposed by Tenenhaus et al. (2004), indicating an acceptable overall fit of the model.

Table 5. Predictive Relevance, Coefficient of Determination, and GOF Inputs

Main Construct	Dimension	AVE	R^2	Adjusted R^2	SSO	SSE	Q^2
Big data analytics skills	Data quality	0.63	0.67	0.67	1176.00	699.08	0.41
Big data analytics skills	Data access	0.53	0.70	0.70	1568.00	1022.77	0.35
Big data analytics skills	Technological tools	0.65	0.63	0.63	1176.00	715.74	0.39
Big data analytics skills	Expertise	0.85	0.75	0.75	784.00	309.67	0.61
Big data analytics skills	Total	0.53	—	—	4704.00	4704.00	—
Diagnostic skills	Observation	0.76	0.89	0.89	1176.00	407.32	0.65
Diagnostic skills	Communication	0.80	0.73	0.73	784.00	339.11	0.57
Diagnostic skills	Problem-solving	0.84	0.57	0.57	784.00	422.01	0.46
Diagnostic skills	Compassion	1.00	0.43	0.43	392.00	224.83	0.43
Diagnostic skills	Total	0.57	0.67	0.67	3136.00	1991.50	0.36
Forensic accounting skills	Fraud identification	0.50	0.83	0.83	2352.00	1447.38	0.38
Forensic accounting skills	Legal knowledge	0.53	0.87	0.87	2352.00	1308.37	0.44
Forensic accounting skills	Professionalism	0.48	0.81	0.81	2744.00	1730.87	0.37
Forensic accounting skills	Financial data analysis	0.53	0.79	0.79	2352.00	1422.78	0.40
Forensic accounting skills	Total	0.52	0.64	0.64	9800.00	7325.37	0.25

GOF was calculated as follows: $GOF = \sqrt{(\text{mean AVE} \times \text{mean } R^2)} = \sqrt{(0.65 \times 0.71)} = 0.67$. This value demonstrates the desirable overall fit of the measurement and structural components of the research model.

After evaluating the measurement model, the structural relationships among the constructs were examined. The significance of the path coefficients was assessed using the bootstrapping procedure with 5,000 resamples, as recommended in the partial least squares approach (Davari & Rezazadeh, 2014). Before testing the main hypotheses, the factor structure between the main constructs and their dimensions was examined. As shown in Table 6, all relationships between the higher-order constructs and their lower-order dimensions were positive and statistically significant.

Table 6. Ranking of the Dimensions of Each Main Construct

Main Construct	Dimension	Path Coefficient	t-value	R^2	p-value	Rank
Big data analytics skills	Data quality	0.82	45.50	0.67	0.000	3

Big data analytics skills	Data access	0.84	55.94	0.70	0.000	2
Big data analytics skills	Technological tools	0.80	38.87	0.63	0.000	4
Big data analytics skills	Expertise	0.86	66.77	0.75	0.000	1
Diagnostic skills	Observation	0.95	187.63	0.89	0.000	1
Diagnostic skills	Communication	0.85	67.03	0.73	0.000	2
Diagnostic skills	Problem-solving	0.76	36.03	0.57	0.000	3
Diagnostic skills	Compassion	0.66	18.77	0.43	0.000	4
Forensic accounting skills	Fraud identification	0.91	141.23	0.83	0.000	2
Forensic accounting skills	Legal knowledge	0.93	137.87	0.87	0.000	1
Forensic accounting skills	Professionalism	0.90	81.43	0.81	0.000	3
Forensic accounting skills	Financial data analysis	0.89	77.62	0.79	0.000	4

The results of the ranking showed that expertise had the highest loading among the dimensions of big data analytics skills, followed by data access, data quality, and technological tools. Among the dimensions of diagnostic skills, observation ranked first, followed by communication, problem-solving, and compassion. Among the dimensions of forensic accounting skills, legal knowledge ranked first, followed by fraud identification, professionalism, and financial data analysis. These findings indicate that the factorial structure between the main constructs and their dimensions was statistically significant and theoretically meaningful.

The first hypothesis stated that big data analytics skills have a significant effect on diagnostic skills. The results in Table 7 show that big data analytics skills had a positive and significant effect on diagnostic skills ($\beta = 0.82$, $t = 42.16$, $p < 0.001$). The bootstrap confidence interval ranged from 0.78 to 0.86 and did not include zero. Therefore, the first hypothesis was supported. This result indicates that higher levels of big data analytics skills are associated with higher levels of diagnostic skills.

The second hypothesis stated that big data analytics skills have a significant effect on forensic accounting skills. The results showed that big data analytics skills had a positive and significant effect on forensic accounting skills ($\beta = 0.30$, $t = 4.68$, $p < 0.001$). The bootstrap confidence interval ranged from 0.17 to 0.42, confirming the significance of the effect. Therefore, the second hypothesis was supported. This finding indicates that the development of big data analytics skills contributes to the improvement of forensic accounting skills.

The third hypothesis stated that diagnostic skills have a significant effect on forensic accounting skills. As shown in Table 7, diagnostic skills had a positive and significant effect on forensic accounting skills ($\beta = 0.54$, $t = 9.10$, $p < 0.001$). The bootstrap confidence interval ranged from 0.42 to 0.65 and did not include zero. Therefore, the third hypothesis was supported. This finding demonstrates that higher diagnostic skills lead to stronger forensic accounting skills.

Table 7. Direct Hypothesis Testing Results

Hypothesis	Path	Path Coefficient	t-value	R^2	Effect Size	p-value	2.5% CI	97.5% CI	Result
H1	Big data analytics skills → Diagnostic skills	0.82	42.16	0.67	—	0.000	0.78	0.86	Supported
H2	Big data analytics skills → Forensic accounting skills	0.30	4.68	0.64	0.08	0.000	0.17	0.42	Supported
H3	Diagnostic skills → Forensic accounting skills	0.54	9.10	0.64	0.27	0.000	0.42	0.65	Supported

The fourth hypothesis examined the mediating role of diagnostic skills in the relationship between big data analytics skills and forensic accounting skills. As shown in Table 8, the indirect effect of big data analytics skills on forensic accounting skills through diagnostic skills was positive and statistically significant (β = 0.44, t = 8.08, p < 0.001). The bootstrap confidence interval ranged from 0.34 to 0.55 and did not include zero. Therefore, the mediating hypothesis was supported. This result indicates that big data analytics skills enhance forensic accounting skills not only directly but also indirectly through the improvement of diagnostic skills.

Table 8. Mediation Hypothesis Testing Result

Hypothesis	Indirect Path	Indirect Effect	t-value	R^2	p-value	2.5% CI	97.5% CI	Result
H4	Big data analytics skills → Diagnostic skills → Forensic accounting skills	0.44	8.08	0.64	0.000	0.34	0.55	Supported

Overall, the findings confirmed all four research hypotheses. Big data analytics skills positively and significantly predicted diagnostic skills, and both big data analytics skills and diagnostic skills positively and significantly predicted forensic accounting skills. Moreover, diagnostic skills played a significant mediating role in the relationship between big data analytics skills and forensic accounting skills. These results suggest that strengthening big data analytics competencies among Generation Z accounting students can enhance their diagnostic capabilities and, consequently, improve their forensic accounting skills.

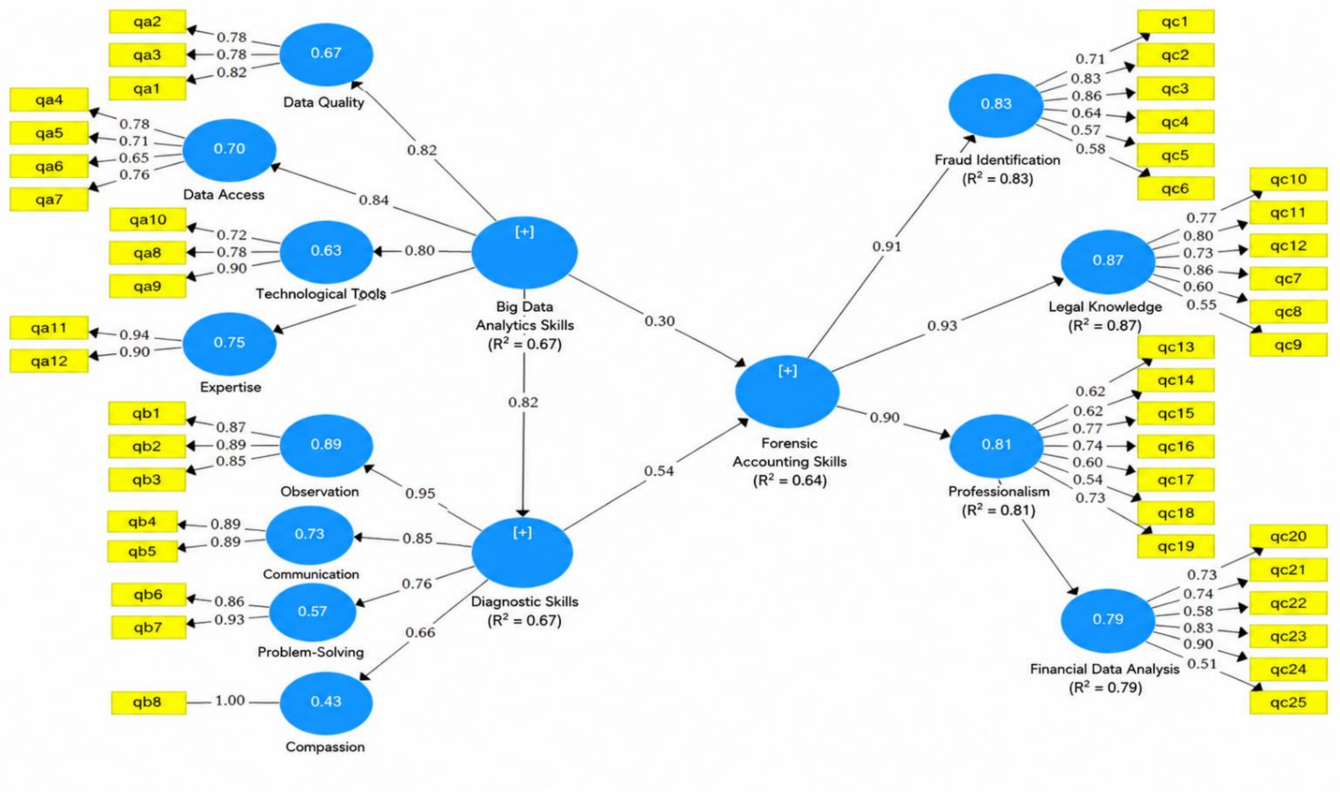

Figure 1. Path Coefficients and Coefficients of Determination of the Hypothesized Model

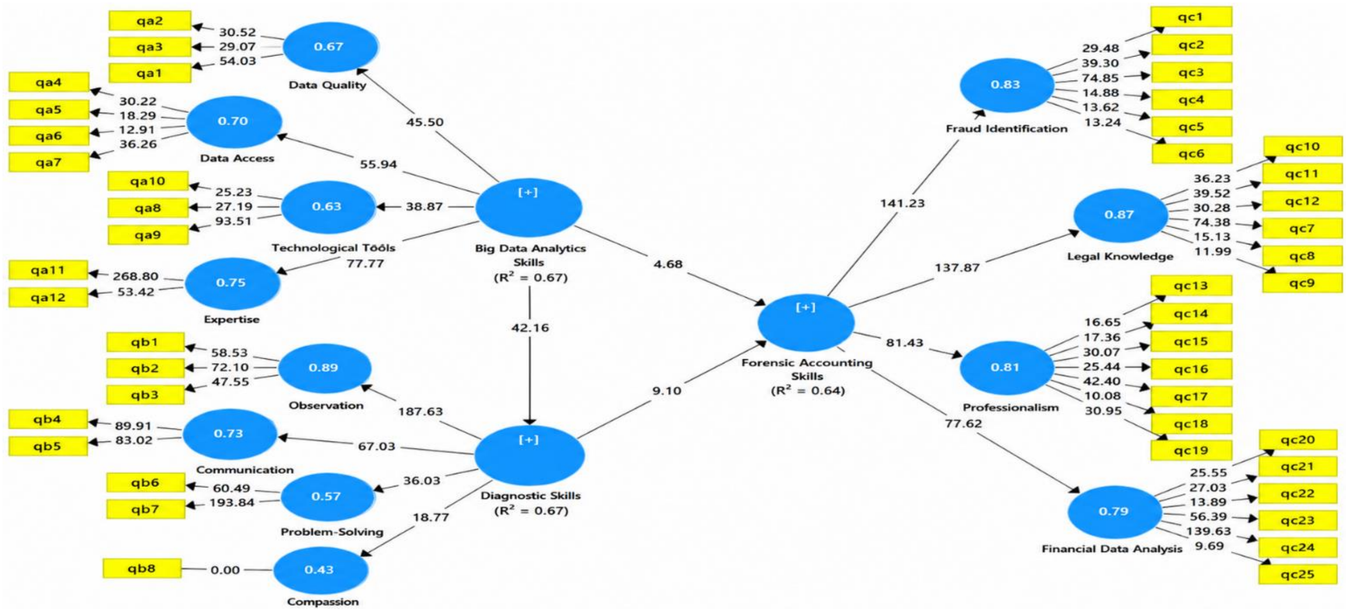

Figure 2. Significance Coefficients of the Hypothesized Model

4. Discussion and Conclusion

The present study investigated the relationships among big data analytics skills, diagnostic skills, and forensic accounting skills among Generation Z accounting students. The findings revealed that big data analytics skills exerted a positive and significant effect on diagnostic skills. Furthermore, big data analytics skills directly and positively influenced forensic accounting skills. Diagnostic skills also demonstrated a significant positive effect on forensic accounting skills. Finally, diagnostic skills played a significant mediating role in the relationship between big data analytics skills and forensic accounting skills. Overall, the results indicate that the development of analytical competencies associated with big data can substantially enhance the diagnostic capabilities of future accountants and subsequently improve their forensic accounting competencies.

The first finding showed that big data analytics skills positively and significantly affect diagnostic skills. This result suggests that individuals who possess stronger competencies in data quality assessment, data accessibility, technological tools, and analytical expertise are better able to observe patterns, communicate findings, solve problems, and make informed judgments. This finding is consistent with the growing literature emphasizing that data-driven environments require professionals to move beyond traditional information processing and develop analytical reasoning capabilities. Big data analytics provides access to extensive information resources and enables professionals to identify trends, anomalies, and relationships that may otherwise remain hidden. Consequently, the availability of analytical insights enhances an individual's ability to diagnose organizational problems and interpret complex situations [8, 9].

The findings can also be interpreted through the theoretical lens of data-driven decision-making. Big data analytics is not merely a technological capability but a cognitive process through which individuals transform raw information into meaningful knowledge. As organizations increasingly rely on large datasets for operational and strategic decisions, professionals must acquire the ability to evaluate data quality, recognize relevant indicators, and extract actionable insights. These activities naturally strengthen diagnostic competencies because diagnosis requires observation, interpretation, pattern recognition, and evidence-based reasoning. Previous studies have similarly argued that advanced analytical technologies support intelligent decision-making by enabling professionals to identify hidden relationships and evaluate multiple alternatives simultaneously [2, 4]. Therefore, the present findings reinforce the notion that analytical competence constitutes a foundational element in the development of diagnostic capabilities.

The significance of the expertise dimension as the strongest component of big data analytics skills further supports this interpretation. Expertise enables individuals to effectively combine technical knowledge with practical judgment, thereby transforming data into meaningful professional conclusions. Similarly, the prominent role of observation within the diagnostic skills construct demonstrates that individuals who are able to carefully examine available evidence are more likely to benefit from analytical information. These findings align with research emphasizing the importance of analytical literacy and data-oriented competencies in contemporary professional environments [6, 7]. As organizations continue to generate increasingly large volumes of information, the capacity to analyze and interpret data becomes inseparable from the ability to diagnose organizational problems accurately.

The second finding demonstrated that big data analytics skills have a direct and positive effect on forensic accounting skills. This result indicates that Generation Z accounting students who possess stronger analytical capabilities are better prepared to perform activities related to fraud identification, legal interpretation, professional judgment, and financial data analysis. This finding is highly consistent with the contemporary evolution of forensic accounting as a technologically driven discipline. Traditional forensic accounting relied heavily on manual investigations and documentary analysis, whereas modern forensic accounting increasingly utilizes digital evidence, analytical software, and large-scale data examination to detect fraudulent activities and financial irregularities [11, 12].

The positive relationship identified in this study can be explained by the nature of fraud itself. Modern fraud schemes often involve complex transactions, electronic records, and concealed patterns distributed across large datasets. As a result, forensic accountants must possess analytical capabilities that allow them to identify unusual behaviors, investigate suspicious transactions, and evaluate evidence within extensive information systems. Big data analytics enables the detection of patterns that would be difficult or impossible to identify using traditional accounting procedures. Consequently, individuals with stronger analytical skills are more capable of conducting forensic investigations and uncovering fraudulent activities [15, 20].

The present findings are also supported by studies emphasizing the role of technological competencies in fraud detection. Research has demonstrated that digital forensic support significantly enhances auditors' ability to detect fraud and evaluate financial misconduct [21]. Similarly, studies examining the application of computer-assisted audit tools have shown that analytical technologies improve investigative efficiency and the quality of fraud detection outcomes [22]. Therefore, the positive effect observed in the present study reflects the growing convergence between data analytics and forensic accounting. In contemporary accounting environments, the ability to manage and analyze large volumes of data represents a critical prerequisite for successful forensic investigation.

The third finding revealed that diagnostic skills positively and significantly affect forensic accounting skills. This finding suggests that individuals who are better able to observe, communicate, solve problems, and demonstrate professional responsiveness are more effective in conducting forensic accounting activities. The result is theoretically logical because forensic accounting fundamentally involves diagnosis. Fraud detection requires accountants to identify anomalies, investigate causes, evaluate evidence, and determine whether suspicious patterns represent legitimate transactions, errors, or intentional misconduct. These activities rely heavily on diagnostic reasoning and professional judgment.

The findings are consistent with prior literature emphasizing that uncertainty and evidence evaluation are central elements of diagnostic processes [10]. In forensic accounting, professionals frequently encounter incomplete information, conflicting evidence, and ambiguous circumstances. Therefore, the ability to interpret available evidence and formulate defensible conclusions becomes essential. Research on forensic accounting education similarly highlights the importance of investigative thinking, critical analysis, and problem-solving competencies for successful fraud examination [16, 17]. The current results extend these observations by empirically demonstrating that diagnostic skills contribute significantly to forensic accounting capabilities among Generation Z accounting students.

The particularly strong contribution of observation to diagnostic skills and legal knowledge to forensic accounting skills offers additional insight into the mechanisms underlying this relationship. Effective observation enables individuals to recognize discrepancies and unusual patterns, whereas legal knowledge provides the framework necessary for interpreting these findings within regulatory and investigative contexts. These dimensions complement each other and illustrate how diagnostic reasoning supports forensic accounting performance. This interpretation is consistent with previous studies emphasizing that forensic accounting combines investigative techniques, legal understanding, and analytical judgment in the pursuit of fraud detection and prevention [13, 14].

Perhaps the most important contribution of the present study lies in the finding that diagnostic skills mediate the relationship between big data analytics skills and forensic accounting skills. The significant indirect effect suggests that big data analytics does not improve forensic accounting solely through direct technological mechanisms. Instead, analytical capabilities first strengthen diagnostic reasoning, which subsequently enhances forensic accounting competence. This finding provides a more comprehensive understanding of how analytical technologies contribute to professional performance.

From a theoretical perspective, this mediation relationship supports the argument that technology alone cannot generate effective professional outcomes. Data analytics tools provide information, but individuals must interpret that information through cognitive and diagnostic processes before it can be applied to fraud detection and forensic investigation. Thus, diagnostic skills serve as a bridge between analytical resources and forensic accounting outcomes. This interpretation aligns with studies emphasizing that organizational value is generated not by data itself but by the ability of professionals to transform data into meaningful insights and decisions [8, 9].

The mediating role of diagnostic skills is also consistent with contemporary perspectives on intelligent systems and human-centered analytics. Although artificial intelligence and advanced analytical technologies can process large volumes of information, human judgment remains essential for evaluating context, interpreting evidence, and making professional decisions. Consequently, the effectiveness of analytical technologies depends substantially on the diagnostic competencies of their users [4]. The findings of this study therefore suggest that educational programs aimed at developing forensic accounting competencies should not focus exclusively on technological training. Instead, they should simultaneously cultivate diagnostic reasoning, problem-solving abilities, and investigative thinking.

Another important implication concerns accounting education for Generation Z students. Although this generation is frequently characterized as technologically adept, technological familiarity does not necessarily translate into professional analytical competence. The results indicate that effective forensic accounting development requires structured educational experiences that integrate analytical tools, diagnostic reasoning, and investigative methodologies. This conclusion supports previous calls for curricular reform in accounting education, particularly regarding the incorporation of forensic accounting, fraud examination, digital analytics, and investigative techniques into academic programs [16, 17]. Universities and professional institutions must therefore ensure that future accountants are equipped with the integrated competencies required in modern digital environments.

The study also contributes to the broader discussion concerning the evolution of accounting in the digital age. As organizations increasingly adopt big data technologies and intelligent systems, accounting professionals are expected to function as analysts, investigators, and strategic advisors rather than merely record keepers. The significant relationships observed among big data analytics skills, diagnostic skills, and forensic accounting skills provide empirical support for this transformation. The findings demonstrate that analytical competence, diagnostic reasoning, and forensic expertise constitute interconnected capabilities that collectively enhance professional effectiveness in contemporary accounting environments.

Several limitations should be considered when interpreting the findings of this study. First, the study relied on self-reported questionnaire data, which may be affected by social desirability bias and subjective perceptions. Second, the sample consisted exclusively of Generation Z students rather than practicing accountants, potentially limiting the generalizability of the findings to professional settings. Third, the cross-sectional design does not permit causal conclusions regarding the long-term development of analytical, diagnostic, and forensic accounting skills. Finally, cultural and educational characteristics specific to the study context may have influenced participants' perceptions and responses.

Future studies may examine these relationships among professional accountants, auditors, forensic investigators, and financial analysts to assess whether similar patterns emerge in workplace environments. Longitudinal studies could investigate how big data analytics skills and diagnostic competencies develop over time and contribute to professional expertise. Researchers may also explore additional mediating and moderating variables, such as digital literacy, critical thinking, artificial intelligence competency, professional skepticism, and organizational support. Comparative studies across countries, educational systems, and professional sectors could further enhance understanding of how contextual factors influence the development of forensic accounting capabilities.

Educational institutions should integrate big data analytics, diagnostic reasoning, and forensic accounting content into accounting curricula through practical projects, case studies, simulation exercises, and technology-based learning environments. Professional organizations should provide specialized training programs focused on fraud analytics, digital investigation techniques, and evidence-based decision-making. Organizations seeking to strengthen fraud prevention and detection systems should invest in both analytical technologies and human competency development, recognizing that technological tools are most effective when combined with strong diagnostic and investigative skills. Particular attention should be devoted to preparing Generation Z accountants to operate effectively in data-rich and technologically sophisticated professional environments.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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