

Analysis of Occupational Frauds Based on SWARA and MARCOS Method

Summary: *Recently, occupational fraud has become more pronounced, making its research highly challenging. This study investigates occupational fraud in various industries and high-risk departments using the SWARA and MARCOS methods. The research showed that, according to the results of the SWARA-MARCOS method, the top five sectors for occupational fraud include construction, religious, charitable, or social services, government and public administration, health care, and education. Occupational fraud is most prevalent in the construction sector, while the information industry experiences the least occupational fraud. Retail also has a relatively low incidence of occupational fraud. The key question is how to suppress or minimize occupational fraud across different sectors. This can be achieved through more effective control of collections, cash theft, cash-on-hand disbursements, unauthorized check and payment tampering, corruption, expense reimbursement fraud, financial statement fraud, cashless payments, payroll fraud, registered payments, and skimming. External audits, internal audits, state audits, and forensic accounting and auditing play significant roles in fraud prevention. Additionally, the digitization of entire business operations has a positive effect on the suppression of occupational fraud. It is necessary to develop ethical values among all participants in the value chain. Regarding occupational fraud in high-risk departments, according to the results of the SWARA-MARCOS method, the highest levels of occupational fraud occur in accounting, followed by finance. Other affected departments include Executive/Senior Management, Administrative Support, Procurement, Operations, Customer Service, and Sales. Occupational fraud is least prevalent in sales. Effective control of the accounting process and financial activities can significantly reduce occupational fraud. External audit, internal audit, forensic accounting, and auditing all play significant roles in this regard. The impact of digitizing accounting and financial operations is also noteworthy. Additionally, maintaining strong ethical standards in accounting and finance is crucial.*

Keywords: *occupational fraud, industry, departments, SWARA, MARCOS*

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INTRODUCTION

As is well known, business fraud has become more pronounced in recent times. It is a highly challenging field of research, requiring appropriate measures for suppression and minimization. This study analyzes business fraud in various industries and high-risk departments using the SWARA and MARCOS methods. The aim is to identify industries and high-risk departments most affected by occupational fraud and propose measures to suppress or minimize it. Effectively managing occupational fraud is challenging, which forms the basis of the main research hypothesis in this study. The findings of this research should contribute to more effective management of occupational fraud across different industries and high-risk departments.

LITERATURE REVIEW

In the literature, occupational fraud is investigated from various perspectives. Below, we highlight some key areas of focus. Due to its significance, special attention is given to business fraud in financial reports (24, 4, 15). Considerable research has also examined the impact of business digitization and artificial intelligence on fraud detection and prevention (3, 9, 34, 22, 12). The specifics of occupational fraud in banks (5, 10, 18, 2, 23) and in the insurance sector (32) have also been explored. Additionally, research emphasizes the role of external and internal audits in fraud detection and prevention (6, 17). Recently, forensic accounting has gained increasing attention for its role in identifying and preventing occupational fraud (1). Another crucial issue in the literature is the role of state audits in detecting and preventing fraud in public institutions (13, 21). Furthermore, researchers have examined occupational fraud in social services (25) and its specifics in small and medium-sized enterprises (26, 36). Multi-criteria decision-making methods are increasingly being applied to the analysis of occupational fraud (33). Overall, the literature provides a comprehensive examination of business fraud, recognizing its significant impact on annual revenue. In this study, the reviewed literature, along with other relevant sources, serves as a theoretical, methodological, and empirical foundation for analyzing occupational fraud in various industries and high-risk departments using the SWARA and MARCOS methods.

METHODOLOGY

The problem of occupational fraud in this study is analyzed on the basis of SWARA and MARCOS methods. Their basic characteristics are shown below.

SWARA

SWARA (Stepwise Weight Assessment Ratio Analysis) is a method that provides the opportunity for decision-makers to choose the best decision based on different situations and the importance of criteria according to their wishes and goals. It is applied in solving various decision-making problems.

The procedure for determining the weights of n criteria using the SWARA method can be summarized as follows (14, 28, 29):

Step 1: Identification and selection of criteria

Step 2: Sort the criteria according to their expected importance, in descending order

Step 3: Determining the relative importance of the criteria. In this step, the relative importance of the first criterion is set to 1, while the relative importance of the others is determined according to the previous one.

In the SWARA method, s_{j-1} it has a value of 0 if criterion $j-1$ has the same importance as criterion j , $s_j \in [0,1]$ and a lower value s_{j-1} indicates greater importance of criterion j in relation to criterion $j-1$.

Step 4: Calculation of the value of the coefficient k_j as:

$$k_j = \begin{cases} 1 & \text{if } j = 1 \\ s_j + 1 & \text{if } j > 1 \end{cases} \quad (1)$$

Step 5: Calculation of the value of the converted significance q_j as follows:

$$q_j = \begin{cases} 1 & \text{if } j = 1 \\ \frac{q_{j-1}}{k_j} & \text{if } j > 1 \end{cases} \quad (2)$$

Step 6: Calculating the weight of the criteria w_j as follows:

$$w_j = \frac{q_j}{\sum_{j=1}^n q_k} \quad (3)$$

MARCOS Method

The MARCOS (Measurement of Alternatives and Ranking According to Compromise Solution) method is based on defining the relationship between alternatives and reference values (ideal and anti-ideal alternatives) (8, 16, 19, 20, 23, 30, 31, 35, 7). Based on the defined relationships, the utility functions of the alternatives are determined, and a compromise ranking is made about ideal and anti-ideal solutions. Decision preferences

are defined based on a utility function. Utility functions represent the position of alternatives about ideal and anti-ideal solutions. The best alternative is the one that is closest to the ideal and at the same time furthest from the anti-deal reference point. The MARCOS method proceeds through the following steps (27, 30):

Step 1: Formation of the initial decision-making matrix. A multi-criteria model involves defining a set of n criteria and m alternatives. In the case of group decision-making, a group of r experts is formed who evaluate the alternatives in relation to the criteria. In that case, the expert evaluation matrices are aggregated into the initial group decision matrices.

Step 2: Forming the expanded initial matrix. In this step, the expansion initial matrix is defined with ideal (AI) and anti-ideal (AAI) solutions.

$$X = \begin{matrix} & C_1 & C_2 & \cdots & C_n \\ \begin{matrix} AAI \\ A_1 \\ A_2 \\ \dots \\ A_m \\ AI \end{matrix} & \begin{bmatrix} x_{aa1} & x_{aa2} & \cdots & x_{aan} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \\ x_{ai1} & x_{ai2} & \cdots & x_{ain} \end{bmatrix} \end{matrix} \quad (4)$$

Anti-ideal solution (AAI) is the worst alternative. The ideal solution (AI) is, on the contrary, the alternative with the best characteristics. Depending on the nature of the criteria, AAI and AI are defined using the following equations:

$$AAI = \min_i x_{ij} \text{ if } j \in B \text{ and } \max_i x_{ij} \text{ if } j \in C \quad (5)$$

$$AI = \max_i x_{ij} \text{ if } j \in B \text{ and } \min_i x_{ij} \text{ if } j \in C \quad (6)$$

Where B represents the benefit and C the cost group of criteria.

Step 3: Normalization of the extended initial matrix (X). The elements of the normalized matrix $N = [n_{ij}]_{m \times n}$ are obtained by applying the following equations:

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \text{ if } j \in C \quad (7)$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \text{ if } j \in B \quad (8)$$

Where the elements x_{ij} and x_{ai} represent the elements of the matrix X .

Step 4: Defining the weighting matrix $V = [v_{ij}]_{m \times n}$. The weighting matrix V is obtained by multiplying the normalized matrix N with the weighting coefficients of the criterion w_j using the following equation:

$$v_{ij} = n_{ij}xw_j \quad (9)$$

Step 5: Determining the degree of usefulness of alternatives K_i^- . The degree of usefulness of alternatives to anti-ideal and ideal solutions is determined using the following equations:

$$K_i^- = \frac{S_i}{S_{aai}} \quad (10)$$

$$K_i^+ = \frac{S_i}{S_{ai}} \quad (11)$$

Where S_i ($i = 1, 2, \dots, m$) represents the sum of the elements of the weight matrix V , shown in the following equation:

$$S_i = \sum_{j=1}^n v_{ij} \quad (12)$$

Step 6: Determining the utility function of alternatives $f(K_i^-)$. The utility function is the compromise of the observed alternative about ideal and anti-ideal solutions. The utility function of alternatives is defined by the following equation:

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \quad (13)$$

Where $f(K_i^-)$ represents the utility function of the anti-ideal solution and $f(K_i^+)$ represents the utility function of the ideal solution.

Utility functions for ideal and anti-ideal solutions are determined using the following equations:

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \quad (14)$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \quad (15)$$

Step 7: Ranking of alternatives. The ranking of alternatives is based on the final value of the utility function. The alternative that has the highest possible value of the utility function is preferred.

RESULTS AND DISCUSSION

In this study, the research is directed in two directions, namely: Occupational fraud in various industries and occupational fraud in high-risk departments based on the SWARA and MARCOS methods.

Occupational fraud in various industries

The analyzed criteria are based on the nature of the problem being studied. Table 1 presents the relevant criteria for occupational fraud, the observed industries (alternatives), and the original empirical data.

Table 1. What are the most common occupational fraud schemes in different industries? (in %)

Industry	Occupational fraud										
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	12	12	18	14	44	6	5	16	4	4	8
A2	27	6	4	7	55	17	6	29	10	1	9
A3	24	15	8	14	52	15	4	15	18	4	11
A4	38	9	8	12	47	21	1	22	16	2	9
A5	19	8	9	8	60	13	4	29	10	3	6
A6	17	10	13	5	40	6	0	32	3	9	14
A7	38	12	7	19	52	25	10	25	23	4	23
A8	36	9	13	10	43	17	0	16	7	6	19
A9	19	6	6	20	49	12	9	16	10	6	9
A10	28	9	2	9	65	11	3	32	14	0	5
A11	18	10	18	7	52	12	2	33	10	3	7
A12	36	17	24	17	45	29	3	10	7	2	16
A13	15	10	10	0	62	10	2	27	6	0	10
Statistics											
Mean	25.1538	10.2308	10.7692	10.9231	51.2308	14.9231	3.7692	23.2308	10.6154	3.3846	11.2308
Median	24.0000	10.0000	9.0000	10.0000	52.0000	13.0000	3.0000	25.0000	10.0000	3.0000	9.0000
Std. deviation	9.34386	3.16633	6.24705	5.79456	7.67196	6.86126	3.11325	7.82255	5.76684	2.56705	5.32531
Minimum	12.00	6.00	2.00	.00	40.00	6.00	.00	10.00	3.00	.00	5.00
Maximum	38.00	17.00	24.00	20.00	65.00	29.00	10.00	33.00	23.00	9.00	23.00

Industry	Occupational fraud
A1	Banking and financial services
A2	Production
A3	Government and public administrations
A4	Health care
A5	Energy
A6	Retail
A7	Construction
A8	Education
A9	Insurance
A10	Technology
A11	Transport and storage
A12	Religious, charitable, or social services
A13	Information
C1.	Billing
C2.	Cash theft
C3.	Cash on hand
C4.	Check and payment interference
C5.	Corruption
C6.	Expense reimbursements
C7.	Financial reporting fraud
C8.	No cash
C9.	Payroll
C10.	Register payments
C11.	Skimming

Source: Occupational Fraud 2024: A Report to the Nations. Association of Certified Fraud Examiners – ACFE. Author's statistics.

In the context of classical analysis, we will refer, for example, to the issue of corruption. According to the data presented, corruption is the least prevalent in retail and most prevalent in the technology sector. It is strongly correlated with registered payments. To combat corruption, all relevant measures should be taken, such as promoting ethical business practices among both employees and clients.

Using the SWARA method, the weight coefficients of the criteria were determined (Table 2). (In this study, all calculations and results are by the authors.)

Table 2. Weight coefficients of criteria - SWARA

Criteria	s_j	k_j	w_j	q_j	q_j	Criteria	Ranking
C3	0	1	1	0.15	0.15	C1	2
C1	0.15	1.15	0.87	0.13	0.13	C2	3
C2	0.04	1.04	0.84	0.13	0.13	C3	1
C5	0.29	1.29	0.65	0.10	0.10	C4	5
C4	0.02	1.02	0.64	0.10	0.10	C5	4
C6	0.04	1.04	0.61	0.09	0.09	C6	6
C7	0.1	1.1	0.56	0.08	0.08	C7	7
C8	0.2	1.2	0.46	0.07	0.07	C8	8
C9	0.18	1.18	0.39	0.06	0.06	C9	9
C10	0.25	1.25	0.31	0.05	0.05	C10	10
C11	0.12	1.12	0.28	0.04	0.04	C11	11
			6.60	1			

The most important criterion in this case is cash on hand. Switching to cashless payments can, among other things, significantly affect the suppression of occupational fraud.

The ranking of industries according to occupational fraud, based on the calculated weight coefficients of the criteria, was performed using the MARCOS method. Tables 3 - 7 show the procedures and results of the MARCOS method.

Table 3. Initial Matrix

Weight of criteria	0.13	0.13	0.15	0.1	0.1	0.09	0.08	0.07	0.06	0.05	0.04
Kind of criteria	1	1	1	1	1	1	1	1	1	1	1
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	12	12	18	14	44	6	5	16	4	4	8
A2	27	6	4	7	55	17	6	29	10	1	9
A3	24	15	8	14	52	15	4	15	18	4	11
A4	38	9	8	12	47	21	1	22	16	2	9
A5	19	8	9	8	60	13	4	29	10	3	6
A6	17	10	13	5	40	6	0	32	3	9	14
A7	38	12	7	19	52	25	10	25	23	4	23
A8	36	9	13	10	43	17	0	16	7	6	19
A9	19	6	6	20	49	12	9	16	10	6	9
A10	28	9	2	9	65	11	3	32	14	0	5
A11	18	10	18	7	52	12	2	33	10	3	7
A12	36	17	24	17	45	29	3	10	7	2	16
A13	15	10	10	0	62	10	2	27	6	0	10
MAX	38	17	24	20	65	29	10	33	23	9	23
MIN	12	6	2	0	40	6	0	10	3	0	5

Table 4. Extended Initial Matrix

Weight of criteria	0.13	0.13	0.15	0.1	0.1	0.09	0.08	0.07	0.06	0.05	0.04
Kind of criteria	1	1	1	1	1	1	1	1	1	1	1
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
AAI	12	6	2	0	40	6	0	10	3	0	5
A1	12	12	18	14	44	6	5	16	4	4	8
A2	27	6	4	7	55	17	6	29	10	1	9
A3	24	15	8	14	52	15	4	15	18	4	11
A4	38	9	8	12	47	21	1	22	16	2	9
A5	19	8	9	8	60	13	4	29	10	3	6
A6	17	10	13	5	40	6	0	32	3	9	14
A7	38	12	7	19	52	25	10	25	23	4	23
A8	36	9	13	10	43	17	0	16	7	6	19
A9	19	6	6	20	49	12	9	16	10	6	9
A10	28	9	2	9	65	11	3	32	14	0	5
A11	18	10	18	7	52	12	2	33	10	3	7
A12	36	17	24	17	45	29	3	10	7	2	16
A13	15	10	10	0	62	10	2	27	6	0	10
AI	38	17	24	20	65	29	10	33	23	9	23

Table 5. Normalized Matrix

Weight of criteria	0.13	0.13	0.15	0.1	0.1	0.09	0.08	0.07	0.06	0.05	0.04
Kind of criteria	1	1	1	1	1	1	1	1	1	1	1
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
AAI	0.315789	0.117647	0.083333	0	0.615385	0.206897	0	0.30303	0.130435	0	0.217391
A1	0.3158	0.7059	0.7500	0.7000	0.6769	0.2069	0.5000	0.4848	0.1739	0.4444	0.3478
A2	0.7105	0.3529	0.1667	0.3500	0.8462	0.5862	0.6000	0.8788	0.4348	0.1111	0.3913
A3	0.6316	0.8824	0.3333	0.7000	0.8000	0.5172	0.4000	0.4545	0.7826	0.4444	0.4783
A4	1.0000	0.5294	0.3333	0.6000	0.7231	0.7241	0.1000	0.6667	0.6957	0.2222	0.3913
A5	0.5000	0.4706	0.3750	0.4000	0.9231	0.4483	0.4000	0.8788	0.4348	0.3333	0.2609
A6	0.4474	0.5882	0.5417	0.2500	0.6154	0.2069	0.0000	0.9697	0.1304	1.0000	0.6087
A7	1.0000	0.7059	0.2917	0.9500	0.8000	0.8621	1.0000	0.7576	1.0000	0.4444	1.0000
A8	0.9474	0.5294	0.5417	0.5000	0.6615	0.5862	0.0000	0.4848	0.3043	0.6667	0.8261
A9	0.5000	0.3529	0.2500	1.0000	0.7538	0.4138	0.9000	0.4848	0.4348	0.6667	0.3913
A10	0.7368	0.5294	0.0833	0.4500	1.0000	0.3793	0.3000	0.9697	0.6087	0.0000	0.2174
A11	0.4737	0.5882	0.7500	0.3500	0.8000	0.4138	0.2000	1.0000	0.4348	0.3333	0.3043
A12	0.9474	1.0000	1.0000	0.8500	0.6923	1.0000	0.3000	0.3030	0.3043	0.2222	0.6957
A13	0.3947	0.5882	0.4167	0.0000	0.9538	0.3448	0.2000	0.8182	0.2609	0.0000	0.4348
AI	1	1	1	1	1	1	1	1	1	1	1

Table 6. Weighted Normalized Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
AAI	0.041053	0.015294	0.0125	0	0.061538	0.018621	0	0.021212	0.007826	0	0.008696
A1	0.0411	0.0918	0.1125	0.0700	0.0677	0.0186	0.0400	0.0339	0.0104	0.0222	0.0139
A2	0.0924	0.0459	0.0250	0.0350	0.0846	0.0528	0.0480	0.0615	0.0261	0.0056	0.0157
A3	0.0821	0.1147	0.0500	0.0700	0.0800	0.0466	0.0320	0.0318	0.0470	0.0222	0.0191
A4	0.1300	0.0688	0.0500	0.0600	0.0723	0.0652	0.0080	0.0467	0.0417	0.0111	0.0157
A5	0.0650	0.0612	0.0563	0.0400	0.0923	0.0403	0.0320	0.0615	0.0261	0.0167	0.0104
A6	0.0582	0.0765	0.0813	0.0250	0.0615	0.0186	0.0000	0.0679	0.0078	0.0500	0.0243
A7	0.1300	0.0918	0.0438	0.0950	0.0800	0.0776	0.0800	0.0530	0.0600	0.0222	0.0400
A8	0.1232	0.0688	0.0813	0.0500	0.0662	0.0528	0.0000	0.0339	0.0183	0.0333	0.0330
A9	0.0650	0.0459	0.0375	0.1000	0.0754	0.0372	0.0720	0.0339	0.0261	0.0333	0.0157
A10	0.0958	0.0688	0.0125	0.0450	0.1000	0.0341	0.0240	0.0679	0.0365	0.0000	0.0087
A11	0.0616	0.0765	0.1125	0.0350	0.0800	0.0372	0.0160	0.0700	0.0261	0.0167	0.0122
A12	0.1232	0.1300	0.1500	0.0850	0.0692	0.0900	0.0240	0.0212	0.0183	0.0111	0.0278
A13	0.0513	0.0765	0.0625	0.0000	0.0954	0.0310	0.0160	0.0573	0.0157	0.0000	0.0174
AI	0.13	0.13	0.15	0.1	0.1	0.09	0.08	0.07	0.06	0.05	0.04

Table 7. Results of the MARCOS Method

		Si	Ki-	Ki+	f(K-)	f(K+)	f(K)		Ranking
	AAI	0.1867							
Banking and financial services	A1	0.5221	2.7961	0.5221	0.1574	0.8426	0.5072	0.5072	8
Production	A2	0.4924	2.6370	0.4924	0.1574	0.8426	0.4784	0.4784	11
Government and public administrations	A3	0.5955	3.1889	0.5955	0.1574	0.8426	0.5785	0.5785	3
Health care	A4	0.5695	3.0496	0.5695	0.1574	0.8426	0.5532	0.5532	4
Energy	A5	0.5018	2.6871	0.5018	0.1574	0.8426	0.4875	0.4875	9
Retail	A6	0.4711	2.5227	0.4711	0.1574	0.8426	0.4576	0.4576	12
Construction	A7	0.7734	4.1413	0.7734	0.1574	0.8426	0.7513	0.7513	1
Education	A8	0.5607	3.0027	0.5607	0.1574	0.8426	0.5447	0.5447	5
Insurance	A9	0.5420	2.9025	0.5420	0.1574	0.8426	0.5265	0.5265	7
Technology	A10	0.4933	2.6419	0.4933	0.1574	0.8426	0.4793	0.4793	10
Transport and storage	A11	0.5437	2.9116	0.5437	0.1574	0.8426	0.5282	0.5282	6
Religious, charitable, or social services	A12	0.7498	4.0152	0.7498	0.1574	0.8426	0.7284	0.7284	2
Information	A13	0.4230	2.2653	0.4230	0.1574	0.8426	0.4109	0.4109	13
	AI	1.0000							

According to the results of the SWARA-MARCOS method, the top five industries for occupational fraud include: Construction, Religious, charitable, or social services, Government and Public Administration, Health Care, and Education. Occupational fraud is on the rise in construction. The least occupational fraud is in the information industry. There are small occupational scams in retail. The key question is how to suppress or

minimize occupational fraud in various industries. This can be achieved by controlling billing, cash theft, cash-on-hand payments, unauthorized check, and payment tampering, corruption, expense reimbursement, financial statement fraud, non-cash payments, payroll, registered payments, and skimming. External audits, internal audits, state audits, and forensic accounting and auditing play significant roles. Digitization of the entire business has a positive effect on the suppression of occupational fraud. It is necessary to continuously develop ethical values for all participants in the value chain.

Occupational Fraud in High-Risk Departments

The most common fraud schemes at work in high-risk departments are presented in Table 8.

Table 8. What are the most common fraud schemes at work in high-risk departments? (in %)

Department	Occupational fraud										
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	22	7	10	8	44	13	2	20	12	2	8
A2	33	19	17	32	36	21	9	16	15	6	21
A3	13	9	7	4	49	7	4	20	4	2	12
A4	10	11	15	12	40	6	2	25	3	3	10
A5	33	11	10	14	65	24	11	18	16	4	8
A6	33	8	6	4	79	6	4	21	4	3	5
A7	31	15	19	15	46	17	4	18	10	4	20
A8	20	23	24	22	45	17	11	11	11	4	13

Department	Occupational fraud
A1 Operations	C1. Billing
A2 Accounting	C2. Cash theft
A3 Sales	C3. Cash on hand
A4 Customer service	C4. Check and payment interference
A5 Executive/upper management	C5. Corruption
A6 Procurement	C6. Expense reimbursements
A7 Administrative support	C7. Financial reporting fraud
A8 Finance	C8. No cash
	C9. Payroll
	C10. Register payments
	C11. Skimming

Source: Occupational Fraud 2024: A Report to the Nations. Association of Certified Fraud Examiners – ACFE

In the analysis of occupational fraud in high-risk departments, the same criteria were used as in the previous case and their calculated weight coefficients using the SWARA method. The ranking of alternatives (departments) was performed using the MARCOS method. Tables 9 - 13 show the calculation and results of the MARCOS method.

Table 9. Initial Matrix

Weight of criteria	0.13	0.13	0.15	0.1	0.1	0.09	0.08	0.07	0.06	0.05	0.04
Kind of criteria	1	1	1	1	1	1	1	1	1	1	1
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	22	7	10	8	44	13	2	20	12	2	8
A2	33	19	17	32	36	21	9	16	15	6	21
A3	13	9	7	4	49	7	4	20	4	2	12
A4	10	11	15	12	40	6	2	25	3	3	10
A5	33	11	10	14	65	24	11	18	16	4	8
A6	33	8	6	4	79	6	4	21	4	3	5
A7	31	15	19	15	46	17	4	18	10	4	20
A8	20	23	24	22	45	17	11	11	11	4	13
MAX	33	23	24	32	79	24	11	25	16	6	21
MIN	10	7	6	4	36	6	2	11	3	2	5

Table 10. Extended Initial Matrix

Weight of criteria	0.13	0.13	0.15	0.1	0.1	0.09	0.08	0.07	0.06	0.05	0.04
Kind of criteria	1	1	1	1	1	1	1	1	1	1	1
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
AAI	10	7	6	4	36	6	2	11	3	2	5
A1	22	7	10	8	44	13	2	20	12	2	8
A2	33	19	17	32	36	21	9	16	15	6	21
A3	13	9	7	4	49	7	4	20	4	2	12
A4	10	11	15	12	40	6	2	25	3	3	10
A5	33	11	10	14	65	24	11	18	16	4	8
A6	33	8	6	4	79	6	4	21	4	3	5
A7	31	15	19	15	46	17	4	18	10	4	20
A8	20	23	24	22	45	17	11	11	11	4	13
AI	33	23	24	32	79	24	11	25	16	6	21

Table 11. Normalized Matrix

Weight of criteria	0.13	0.13	0.15	0.1	0.1	0.09	0.08	0.07	0.06	0.05	0.04
Kind of criteria	1	1	1	1	1	1	1	1	1	1	1
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
AAI	0.30303	0.304348	0.25	0.125	0.455696	0.25	0.181818	0.44	0.1875	0.333333	0.238095
A1	0.6667	0.3043	0.4167	0.2500	0.5570	0.5417	0.1818	0.8000	0.7500	0.3333	0.3810
A2	1.0000	0.8261	0.7083	1.0000	0.4557	0.8750	0.8182	0.6400	0.9375	1.0000	1.0000
A3	0.3939	0.3913	0.2917	0.1250	0.6203	0.2917	0.3636	0.8000	0.2500	0.3333	0.5714
A4	0.3030	0.4783	0.6250	0.3750	0.5063	0.2500	0.1818	1.0000	0.1875	0.5000	0.4762
A5	1.0000	0.4783	0.4167	0.4375	0.8228	1.0000	1.0000	0.7200	1.0000	0.6667	0.3810
A6	1.0000	0.3478	0.2500	0.1250	1.0000	0.2500	0.3636	0.8400	0.2500	0.5000	0.2381
A7	0.9394	0.6522	0.7917	0.4688	0.5823	0.7083	0.3636	0.7200	0.6250	0.6667	0.9524
A8	0.6061	1.0000	1.0000	0.6875	0.5696	0.7083	1.0000	0.4400	0.6875	0.6667	0.6190
AI	1	1	1	1	1	1	1	1	1	1	1

Table 12. Weighted Normalized Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
AAI	0.039394	0.039565	0.0375	0.0125	0.04557	0.0225	0.014545	0.0308	0.01125	0.016667	0.009524
A1	0.0867	0.0396	0.0625	0.0250	0.0557	0.0488	0.0145	0.0560	0.0450	0.0167	0.0152
A2	0.1300	0.1074	0.1063	0.1000	0.0456	0.0788	0.0655	0.0448	0.0563	0.0500	0.0400
A3	0.0512	0.0509	0.0438	0.0125	0.0620	0.0263	0.0291	0.0560	0.0150	0.0167	0.0229
A4	0.0394	0.0622	0.0938	0.0375	0.0506	0.0225	0.0145	0.0700	0.0113	0.0250	0.0190
A5	0.1300	0.0622	0.0625	0.0438	0.0823	0.0900	0.0800	0.0504	0.0600	0.0333	0.0152
A6	0.1300	0.0452	0.0375	0.0125	0.1000	0.0225	0.0291	0.0588	0.0150	0.0250	0.0095
A7	0.1221	0.0848	0.1188	0.0469	0.0582	0.0638	0.0291	0.0504	0.0375	0.0333	0.0381
A8	0.0788	0.1300	0.1500	0.0688	0.0570	0.0638	0.0800	0.0308	0.0413	0.0333	0.0248
AI	0.13	0.13	0.15	0.1	0.1	0.09	0.08	0.07	0.06	0.05	0.04

Table 13. Results of the MARCOS Method

		Si	Ki-	Ki+	f(K-)	f(K+)	f(K)		Ranking
	AAI	0.2798							
Operations	A1	0.4656	1.6641	0.4656	0.2186	0.7814	0.4388	0.4388	6
Accounting	A2	0.8245	2.9465	0.8245	0.2186	0.7814	0.7769	0.7769	1
Sales	A3	0.3862	1.3803	0.3862	0.2186	0.7814	0.3640	0.3640	8
Customer service	A4	0.4458	1.5932	0.4458	0.2186	0.7814	0.4201	0.4201	7
Executive/upper management	A5	0.7097	2.5362	0.7097	0.2186	0.7814	0.6688	0.6688	3
Procurement	A6	0.4851	1.7338	0.4851	0.2186	0.7814	0.4572	0.4572	5
Administrative support	A7	0.6829	2.4406	0.6829	0.2186	0.7814	0.6436	0.6436	4
Finance	A8	0.7584	2.7103	0.7584	0.2186	0.7814	0.7147	0.7147	2
	AI	1.0000							

According to the results of the SWARA-MARCOS method, occupational fraud is most prevalent in accounting, followed by finance. Other affected departments include Executive/Senior Management, Administrative Support, Procurement, Operations, Customer Service, and Sales. Occupational fraud is least common in sales. Effective control of the accounting process and financial activities can significantly reduce occupational fraud. External audits, internal audits, forensic accounting, and auditing play a significant role in this. The impact of digitizing accounting and financial operations is also noteworthy. Ethical standards in accounting and finance are crucial.

CONCLUSION

Recently, occupational fraud has increasingly affected the performance of all entities. Therefore, researching it from different angles is highly challenging. This study evaluates occupational fraud in various industries and high-risk departments using the SWARA and MARCOS methods. The results indicate that the top five industries for occupational fraud include

construction, religious, charitable, or social services, government and public administration, health care, and education. Occupational fraud is most prevalent in the construction industry, while the information industry experiences the least fraud. Retail has a relatively low incidence of occupational fraud. The key question is how to suppress or minimize occupational fraud across various industries. This can be achieved through more effective control of collections, cash theft, cash-on-hand disbursements, unauthorized check and payment tampering, corruption, reimbursement fraud, financial statement fraud, cashless payments, payroll fraud, registered payments, and skimming. External audits, internal audits, state audits, and forensic accounting and auditing play significant roles. The digitization of entire business operations has a positive effect on fraud prevention. It is also necessary to foster ethical values among all participants in the value chain, which positively impacts the overall performance of entities.

According to the SWARA-MARCOS method, occupational fraud is most common in accounting, followed by finance. Other affected departments include Executive/Senior Management, Administrative Support, Procurement, Operations, Customer Service, and Sales. Occupational fraud is least prevalent in sales. Effective control of the accounting process and financial activities can significantly reduce occupational fraud. External audits, internal audits, forensic accounting, and auditing play crucial roles in this regard. The impact of digitizing accounting and financial operations is also noteworthy. Upholding ethical standards in accounting and finance is essential.

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Analiza profesionalnih prevara na osnovu SWARA i MARCOS metode

Rezime: U poslednje vreme, profesionalne prevare postale su izraženije, što njihovo istraživanje čini veoma izazovnim. Ova studija istražuje profesionalne prevare u različitim industrijama i visokorizičnim odeljenjima koristeći metode SWARA i MARCOS. Istraživanje je pokazalo da, prema rezultatima metode SWARA-MARCOS, pet sektora s najvećim brojem profesionalnih prevara uključuje građevinarstvo, verske, humanitarne ili socijalne službe, državnu i javnu administraciju, zdravstvenu zaštitu i obrazovanje. Profesionalne prevare su najzastupljenije u sektoru građevinarstva, dok ih u informacionoj industriji ima najmanje. U maloprodaji je stopa profesionalnih prevara relativno niska. Ključno pitanje je kako suzbiti ili minimizirati profesionalne prevare u različitim sektorima. To se može postići efikasnijom kontrolom naplata, krađe gotovine, isplata gotovine na ruke, neovlašćenih izmena čekova i plaćanja, korupcije, lažnih nadoknada troškova, prevara u finansijskim izveštajima, bezgotovinskih plaćanja, zloupotreba pri obračunu plata, registrovanih plaćanja i prisvajanja novca (skimming). Spoljne revizije, interne revizije, državne revizije, kao i forenzičko računovodstvo i revizija, igraju značajnu ulogu u sprečavanju prevara. Pored toga, digitalizacija celokupnog poslovanja ima pozitivan efekat na suzbijanje profesionalnih prevara. Neophodno je razvijati etičke vrednosti među svim učesnicima u lancu vrednosti. Što se tiče profesionalnih prevara u visokorizičnim odeljenjima, prema rezultatima metode SWARA-MARCOS, najveći nivo profesionalnih prevara prisutan je u računovodstvu, zatim u finansijama. Ostala pogođena odeljenja uključuju izvršno/starije rukovodstvo, administrativnu podršku, nabavku, operacije, korisničku službu i prodaju. Profesionalne prevare su najmanje zastupljene u sektoru prodaje. Efikasna kontrola računovodstvenih procesa i finansijskih aktivnosti može značajno smanjiti profesionalne prevare. Spoljna revizija, interna revizija, forenzičko računovodstvo i revizija imaju ključnu ulogu u tom procesu. Takođe, uticaj digitalizacije računovodstvenih i finansijskih operacija je značajan. Pored toga, održavanje visokih etičkih standarda u računovodstvu i finansijama od suštinskog je značaja.

Ključne reči: profesionalne prevare, industrija, odeljenja, SWARA, MARCOS