Evaluating the Critical Factors of Tax Evasion in Business Tax Using a Novel Network Decision Support Model

Received: 22 October 2022; Accepted: 20 August 2024.

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Abstract

This study developed an expert network evaluation framework to assess the critical factors contributing to tax evasion in business tax. First, the framework established a network comprising three perspectives and fifteen indicators through the modified Delphi method (MDM). Then, the analytic network process (ANP) was applied to determine the relative weights of the evaluative criteria. Finally, the application of the framework ranked the critical factors of tax evasion in business tax. As a result, tax authorities can utilize this novel framework to integrate key factors, set thresholds, and detect suspicious tax evasion activities, thereby promoting tax fairness. The proposed framework enhances the efficiency of authorities and governments in evaluating suspicious tax evasion cases. Academically, it addresses a gap in research by applying network concepts and methodologies to assess suspicious tax evasion activities. Commercially, the model aids in diagnosing and evaluating key factors influencing tax evasion in the business sector.

***Keywords*:** Business tax; Tax evasion; Critical factors; Analytic network process; Delphi method

JEL: H25, H26.

Tax revenue is critical for countries to sustain their economic and operational functions. This means that a shortage of tax revenue can reduce a nation's economic and operational efficiency. The most persistent and serious issue faced by tax authorities is “tax evasion” (Ma et al., 2021; Slemrod, 2007). According to Murphy (2011), the tax evasion scale affects 98% of the global gross domestic product (GDP) across 145 countries, causing a loss of USD 3.1 trillion. Additionally, Murphy (2011) revealed that tax evasion issues surpass GDP and health expenditures in these countries by 5% and 54.9%, respectively. Further evidence from Murphy (2019) shows that in 2015, the tax gap in the European Union (EU) due to significant domestic tax evasion amounted to nearly €830 billion. As a result, tax authorities have adopted compliance measures through enforcement and deterrence mechanisms as tax collection strategies to prevent or reduce tax evasion (Okafor & Farrar, 2021). According to the OECD classification, business tax (value-added tax) is one type of consumption tax. In Taiwan, business taxation is based on sales revenues, utilizing a knock-on articulation strategy and receipt characteristics to reduce tax evasion. Despite the implementation of multiple strategies to combat tax evasion, tax evasion cases in businesses have not significantly decreased in Taiwan. Therefore, addressing tax evasion more efficiently and reducing tax fraud has become an urgent priority for tax authorities to enhance tax equity and ensure the stability of public revenues. Previous research on tax evasion and tax fraud relied on statistical methods. However, Bevilacqua et al. (2008) highlighted that assumptions about data distribution prior to analysis in statistical models can influence evaluation outcomes. Furthermore, the selection and evaluation processes for business tax evasion are often based on the experiences of tax officials, which is highly dependent on experience and subjectivity. To address this, this study applied the modified Delphi method (MDM) and the analytic network process (ANP) algorithm, which are expert network analysis techniques, to identify critical tax evasion indicators for tax authorities.

This study consists of three additional sections. Section 2 describes the expert network analysis model. Section 3 presents the business tax case study and its findings. Section 4 provides the conclusion.

1. Literature Review

The key factors contributing to tax evasion for business tax evaluation in Taiwan are critical challenges in public finance. To address these issues, tax authorities have implemented enforcement and deterrence mechanisms as tax collection strategies to prevent and mitigate tax evasion. Although recent empirical studies have shown a decline in tax evasion, the rise of the digital and shadow economy, along with evolving business models, continues to pressure the government’s tax system. For example, the proportion of tax evasion was 4.2% (of the official GDP) in Poland, 1.9% in Germany, and 2.9% in the Czech Republic, which negatively affects tax compliance (Schneider et al., 2015; Robert-Aurelian & Popa, 2020; Etim et al., 2020). The classification of tax revenues, as outlined in the Organization for Economic Cooperation and Development (OECD) Interpretative Guide, has been in use since the 1970s and provides policymakers, academics, and researchers with a reference framework for the tax revenue system (OECD, 2020). According to this classification, tax revenues are categorized into three systems: income tax (profit-seeking enterprise income tax, individual income tax, and land value increment tax), consumption tax (customs and duties, commodity tax, tobacco, and alcohol tax, business tax, vehicle license tax, stamp tax, amusement tax, and tobacco health welfare surcharge), and property tax (estate tax, gift tax, securities transaction tax, futures transaction tax, land value tax, house tax, and deed tax) (OECD, 2021). The revenues and percentages of these tax systems from 2013 to 2020 are presented in Table 1 and Figure 1. Figure 1 shows that the largest contributors to tax revenues in Taiwan are income tax and consumption tax, accounting for nearly 90% of total tax revenue each year (Ministry of Finance, R.O.C, 2021a).

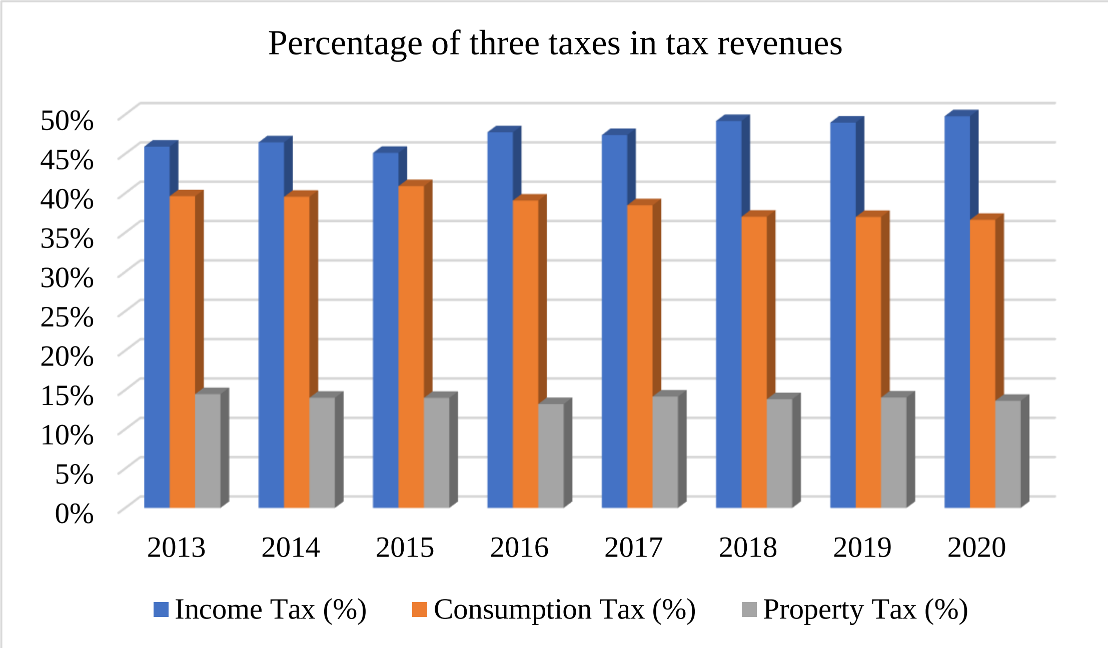

Figure 1. The percentages of three taxes in tax revenues

Source: Ministry of Finance, R.O.C. (2021a)

Tax authorities have implemented additional strategies to combat tax evasion, including analyzing statistical data from previous tax omission cases and punitive fines in Taiwan, as shown in Table 2. Between 2013 and 2020, the highest percentages of tax omission cases occurred in individual income tax, business tax, and vehicle license tax, while the highest average punitive fines were issued in profit-seeking enterprise income tax, individual income tax, and business tax. Additionally, tax omission cases and punitive fines related to business tax accounted for 40% of all penalties (see Table 3 and Figures 2) (Ministry of Finance, R.O.C., 2021a). Table 3 and Figure 2 demonstrate that the number of tax evasion cases has not significantly decreased in Taiwan. Therefore, improving tax equity and ensuring greater stability of public revenues have become urgent tasks for tax authorities, necessitating more efficient measures to combat tax evasion and reduce tax fraud (Grgić & Terzić, 2014; Ma et al., 2021).

Table 1. The revenues of the three tax systems from 2013-2020

Unit: Thousand

	Income Tax			Consumption Tax								Property Tax						
Year	PEIT	IIT	LVIT	CD	CT	TAT	BT	VLT	ST	AT	THWS	ET	GT	STT	FTT	LVT	HT	DT
102	389,168	382,379	82,861	98,900	170,722	49,296	319,768	57,411	9,495	1,688	29,800	16,280	6,980	96,363	5,953	67,851	63,581	12,099
103	387,711	382,379	95,259	97,900	170,722	49,296	319,768	57,725	9,695	1,516	29,800	16,406	8,837	87,117	3,680	68,821	63,364	12,501
104	392,747	382,379	101,042	110,000	174,137	43,713	363,899	59,315	9,999	1,517	31,500	15,449	10,302	94,027	2,249	70,675	66,374	12,427
105	443,510	458,960	96,797	114,300	178,226	45,643	377,054	60,375	10,028	1,526	30,500	15,420	10,400	88,818	2,862	78,057	68,856	11,937
106	443,381	486,204	90,057	115,300	186,148	45,643	376,827	62,037	10,163	1,526	30,000	16,085	10,720	97,700	4,004	91,954	72,706	11,332
107	538,574	499,287	90,244	115,000	170,451	68,943	395,845	63,475	10,433	1,470	23,300	19,187	13,918	99,156	4,004	93,458	75,226	12,089
108	618,517	458,676	90,323	120,000	181,168	65,133	415,145	64,556	10,967	1,554	23,000	19,187	13,918	112,900	6,150	91,070	78,798	12,611
109	639,743	472,236	91,293	119,741	178,333	64,650	419,018	65,195	11,726	1,598	24,500	20,411	14,731	106,475	5,145	91,353	78,211	12,673

Note: Profit-seeking Enterprise Income Tax (PEIT), Individual Income Tax (IIT), Land Value Increment Tax (LVIT), Customs and Duties (CD), Commodity Tax (CT), Tobacco and Alcohol Tax (TAT), Business Tax (BT), Vehicle License Tax (VLT), Stamp Tax (ST), Amusement Tax (AT), Tobacco Health Welfare Surcharge (THWS), Estate Tax (ET), Gift Tax (GT), Securities Transaction Tax (STT), Futures Transaction Tax (FTT), Land Value Tax (LVT), House Tax (HT), Deed Tax (DT)

Source: Ministry of Finance, R.O.C. (2021a)

Table 2. The cases of tax omission and punitive fines in Taiwan from 2013-2020

Tax items	Number of cases of tax omission (NCTO)	Average of NCTO (ANCTO)	Percentage of ANCTO (%)	Amounts of punitive fines (APF)	Average of APF (AAPF)	Percentage of AAPF (%)
PEIT	61,297	7,662	3.936%	12,226,412	1,528,302	**19.283%**
IIT	429,151	53,644	**27.557%**	13,425,365	1,678,171	**21.174%**
ET	1,581	198	0.102%	1,853,629	231,704	2.923%
GT	1,731	216	0.111%	1,236,239	154,530	1.950%
CT	776	97	0.050%	874,692	109,337	1.380%
STT	137	17	0.009%	14,363	1,795	0.023%
TAT	699	87	0.045%	1,066,063	133,258	1.681%
SSGST	3,247	406	0.208%	2,361,254	295,157	3.724%
BT	170,486	21,311	**10.947%**	25,127,605	3,140,951	**39.631%**
LVT	48,889	6,111	3.139%	651,659	81,457	1.028%
HT	1,408	176	0.090%	233,060	29,133	0.368%
VLT	595,679	74,460	**38.250%**	3,124,319	390,540	4.928%
DT	241,244	30,156	15.491%	1,121,670	140,209	1.769%
ST	497	62	0.032%	25,846	3,231	0.041%
AT	493	62	0.032%	62,323	7,790	0.098%

Note: Profit-seeking Enterprise Income Tax (PEIT), Individual Income Tax (IIT), Commodity Tax (CT), Tobacco and Alcohol Tax (TAT), Business Tax (BT), Vehicle License Tax (VLT), Stamp Tax (ST), Amusement Tax (AT), Estate Tax (ET), Gift Tax (GT), Securities Transaction Tax (STT), Land Value Tax (LVT), House Tax (HT), Deed Tax (DT), Specifically Selected Goods and Services Tax (SSGST)

Source: Ministry of Finance, R.O.C. (2021a)

Table 3. The percentage of ANCTO (%) and percentage of AAPF (%) of business tax from 2013 to 2020

Business tax	Percentage of ANCTO (%)	Percentage of AAPF (%)
2013	21,772 (13%)	2,308,541 (9%)
2014	22,240 (13%)	3,211,697 (13%)
2015	21,305 (12%)	3,806,331 (15%)
2016	21,014 (12%)	3,058,776 (12%)
2017	21,777 (13%)	3,586,859 (14%)
2018	22,057 (13%)	2,934,642 (12%)
2019	21,076 (12%)	4,139,200 (16%)
2020	19,245 (11%)	2,081,559 (8%)
Total	170,486(100%)	25,127,605 (100%)

Note: Average of number of cases of tax omission (ANCTO), and Average of amounts of punitive fines (AAPF)

Source: Ministry of Finance, R.O.C. (2021a)

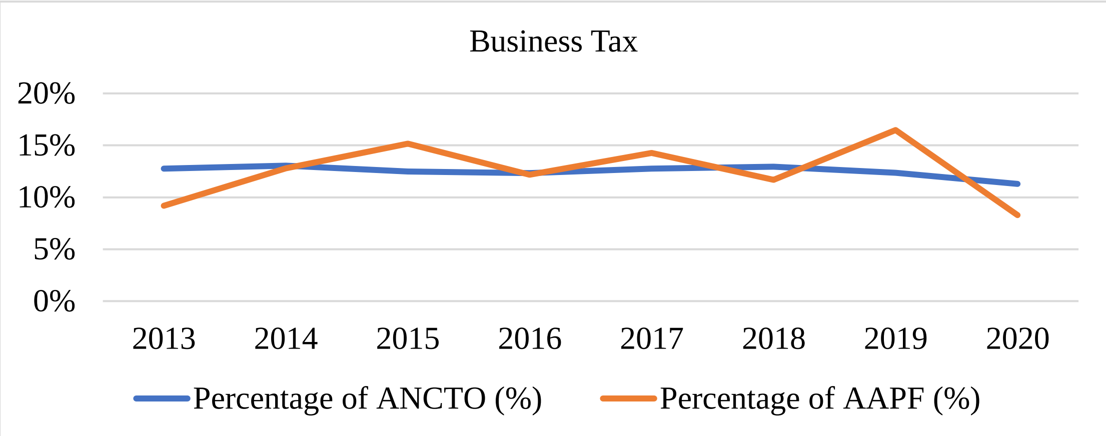

Figure 2. The percentage of ANCTO (%) and percentage of AAPF (%) of business tax from 2013 to 2020

Source: Ministry of Finance, R.O.C. (2021a)

In accordance with the Ministry of Finance, R.O.C. (2021b), when enterprises sell commodities or services, the cost must include a 5% business tax, which is paid to the government during the levy process (Ministry of Finance, R.O.C., 2021b). Hence, the business tax in Taiwan is a form of indirect taxation borne by the end customer, meaning the tax collection and payment are conducted on the customer's behalf. For example, if a company sells a profit-earning service for 1,000 NTD, the final price would be 1050 NTD, which includes 50 NTD for business tax. The company then remits the 50 NTD to the government . However, tax evasion has become more prevalent in increasingly complex structures, differing tax rates across countries, and the globalization of operations (Vanhoeyveld et al., 2020). Despite the business tax system requiring collection and payment of taxes on behalf of the end customer, fraud and abuse are rampant. These include failure to register, misclassification of commodities, collusion between agents, exaggerating purchases, under-declaring sales, restricting payable tax, and falsifying receipts (Smith & Keen, 2006; Vanhoeyveld et al., 2020). Figure 3 illustrates a simple case of business tax evasion in the declaration system. A single company can act as both buyer and seller, such as Company A, Company B, and Company C. The dotted line represents sales declarations, while the solid lines represent purchase declarations. As shown, the declarations of Company A and Company B align within the network. However, discrepancies exist between companies (i.e., Companies C, D, E). The declarations of Company B and C differ, indicating that Company B does not report any purchases from D and E. However, Companies D and E declare sales to B (González-Martel et al., 2021).

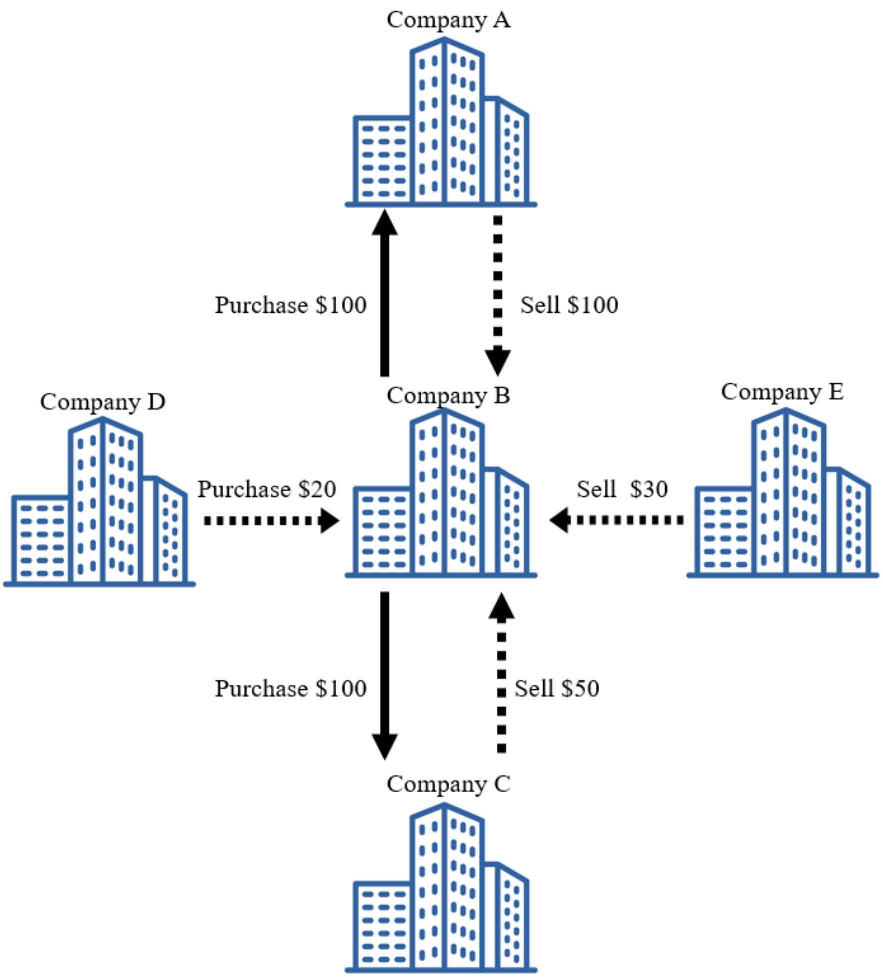

Figure 3. The simple concept of a tax evasion network

Source: González-Martel et al., (2021)

The time costs and efficiency associated with the selection and evaluation of business tax evasion are critical issues for tax authorities in the highly complex ecosystem of business tax evasion. Additionally, the selection and evaluation process is largely based on the experiences of tax officials when establishing guidelines, which can reduce the risk of adverse selection. However, this process relies on individual judgment, which may result in inconsistencies across evaluators. Moreover, the dependence on experience and subjectivity increases the risk of adverse selection and makes it challenging for novice tax officers to effectively perform their duties. To address these limitations and introduce a more objective, expert-driven approach, this study implements the MDM and the ANP to achieve expert consensus. These methodologies offer several key advantages, such as improved decision quality (Djordjević et al., 2023), reduced complexity in decision-making (Bajo Marcos et al., 2023; Kattirtzi and Winskel, 2020), reduced subjectivity (Walters et al., 2021; Mukherjee et al., 2015), and better handling of qualitative and quantitative data (Suominen et al., 2022). Additionally, the ANP algorithm facilitates the integration of complex interdependencies and feedback loops among elements within a decision hierarchy, providing a more comprehensive representation of real-world decision scenarios (Farias et al., 2019; Tadic et al., 2014). Based on these factors, this study aims to construct a tax evader detection model that is focused on business taxes using the expert network analysis approach, including the MDM and the ANP algorithm. The proposed expert network analysis model can assist tax officers in identifying critical criteria and establishing selection guidelines to address business tax evasion.

Previous research on tax evasion and tax fraud has primarily focused on statistical methods. For instance, Levin and Widell (2014) employed regression analysis to evaluate discrepancies in reported trade flows between Kenya and Tanzania, correlating those discrepancies with tax rates. Alm et al. (2016) proposed a regression model to examine how the potential for bribery among tax officials influences a firm's tax evasion decisions. Their findings indicated that corruption and tax evasion within firms can become mutually reinforcing. Abdixhiku et al. (2017) used regression analysis to investigate the relationship between business tax evasion, tax burden, and transition economies. Their results showed that higher tax burdens were positively associated with business tax evasion and that institutional factors significantly impacted firms' tax evasion behavior in transition economies. Immordino and Russo (2018) analyzed European data using statistical methods to explore whether cashless payments reduce tax evasion behavior. Khalil and Sidani (2020) utilized regression models to identify key factors of tax evasion, revealing that income was a significant predictor. Sun (2021) developed a regression model to explore the relationship between government corruption and corporate tax avoidance in China, finding a positive correlation between government corruption and tax avoidance. Their study also suggested that corporate tax avoidance increases by 6% for every standard deviation rise in government corruption.

Countries with well-developed legal and policing systems, such as the United States, may be better equipped to combat business tax evasion due to several key factors. These include advanced detection methodologies, strong enforcement mechanisms, and comprehensive legal frameworks that facilitate the prosecution of tax evaders (Alm et al., 2016; Lederman, 2020). For instance, the United States' use of information reporting and withholding systems has significantly enhanced tax compliance (Lederman, 2020). Additionally, Ermasova et al. (2021) argued that social stigmatization penalties are effective in promoting tax compliance in the United States. This aligns with earlier findings by Porcano and Price (1993), who demonstrated that social stigmatization techniques, such as publicizing tax violations in newspapers, strongly deter hypothetical tax evasion behaviors. Empirical evidence supports this assertion, with several U.S. states successfully curbing tax evasion through the use of social stigmatization programs (Herman, 2004a, 2004b). However, even countries with advanced legal frameworks continue to face challenges in addressing evolving tax evasion strategies, particularly in the context of globalization and digital economies (Adigamova & Tufetulov, 2014).

Recent studies on tax evasion have identified several key factors influencing corporate taxpayers' involvement in tax avoidance and evasion. Hossain et al. (2024) highlighted that profitability, corporate governance, and financial restrictions are critical determinants of tax avoidance. Applying institutional theory, Bani-Mustafa et al. (2024) demonstrated that government efficiency, ethical standards, and the control of corruption significantly reduce tax evasion, both independently and through mediating relationships. Khaltar (2024) examined the role of governance quality and the adoption of open government partnership adoption in combatting trade-related tax evasion in developing countries. Their study found that government effectiveness, regulatory quality, control of corruption, and open government initiatives are key contributors to reducing tax evasion. Dragojlović and Đuričić (2023) emphasized the importance of actual detection and prosecution by legislative and executive authorities in reducing tax evasion. Additionally, Yamen et al. (2023) suggested that digitalization can significantly reduce tax evasion, with its impact particularly pronounced in low-corruption countries compared to those with high corruption levels. This finding highlights the interaction between technological advancements and institutional integrity in shaping tax compliance behaviors.

While previous studies have proposed evaluation models for detecting tax evasion using statistics tools, Dangeti (2017) noted that these models must assume the data distribution before analysis. Bevilacqua et al. (2008) illustrated that the assumption of data distribution prior to analysis can significantly affect the evaluation results. Furthermore, the selection and evaluation process for business tax evasion relies heavily on the experiences of tax officials in establishing guidelines, which is highly dependent on experience and subjectivity. As a result, some studies have integrated expert opinions into the construction of tax evasion measurement models. For instance, Diakomihalis (2020) developed an analytic hierarchy process (AHP) model to examine critical factors contributing to tax evasion in Greece, identifying excessive taxation and impunity as key issues. Similarly, Ahmadi et al. (2021) ranked tax evasion factors using the AHP method, revealing that instability preferences, loss avoidance, and ambiguity avoidance are significant drivers of tax evasion in Iran. Given these considerations, the development of selection and evaluation guidelines for business tax evasion emerges as an optimal alternative and a critical evaluation issue. The AHP technique effectively addresses optimal alternatives and the evaluation of critical features (Baidya et al., 2018; Kamaruzzaman et al., 2018; Ho & Ma, 2018). Additionally, the AHP method is widely used across various industries to identify critical factor evaluation issues and derive optimal solutions (Khanzode et al., 2021; Achu et al., 2020; Kilic & Ucler, 2019). However, AHP assumes that the levels and criteria are independent in decision evaluation; thus, subsequent studies have sought to overcome this limitation by introducing network concepts to improve evaluation efficiency. Saaty (1996) proposed the ANP to address the independence assumptions of AHP, making it widely applicable (Lin & Lin, 2018; Hsueh & Lin, 2015; Kheybari et al., 2020). In many decision-making problems, the interdependent and nonlinear nature of the relationships cannot be effectively expressed in a hierarchical manner. Therefore, the advantages of ANP include its ability to manage feedback characteristics, define the relationships within a network model, and address dependence among criteria or sub-criteria (Saaty 1996).

Previous studies have also utilized the ANP algorithm to construct evaluation models aimed at identifying optimal solutions and critical factors. For example, Raut et al. (2021) implemented the ANP method to develop an evaluation network framework that addresses the barriers to big data analytics. Similarly, Dubey and Tanksale (2022) applied both DEMATEL and ANP to measure the barriers to the adoption and growth of food banks in India. Esfandi et al. (2022) employed ANP to assess the energy resilience of urban spatial structures. The ANP framework is effective for evaluating optimal alternatives and critical factors within the expert network analysis model, enabling the collection of relevant factors and the development of an evaluation framework to identify critical features (Lin, 2020; Hamdan & Cheaitou, 2017; Lin, 2017). Thus, this study implemented MDM and the ANP algorithm, both of which are expert network analysis techniques designed to establish critical tax evasion indicators for business tax authorities.

The proposed expert network analysis model effectively identifies critical tax evasion factors for business tax enforcement agencies. Academically, this expert network model addresses a significant research gap in evaluating suspicious tax evasion by leveraging network concepts and methodologies. It offers a novel approach to understanding the interdependent nature of tax evasion factors and their relative importance. From a commercial perspective, the detection model serves as an evaluation tool for tax authorities to analyze suspicious tax evasion and establish thresholds based on key factors more effectively. Highlighting key impact factors in the business tax field allows for more targeted and efficient auditing processes.

2. Expert Network Decision Support Model

The MDM and ANP were employed to construct a framework for assessing the critical factors of tax evasion, using business tax as an example. The expert network analysis processes are outlined as follows:

2.1 Modified Delphi Method

MDM involves collecting and analyzing the opinions of anonymous experts who communicate through writing, discussion, and feedback on specific issues. These experts share their knowledge, skills, expertise, and opinions until they achieve mutual consensus (Sung 2001). The procedure of the Delphi method consists of the following steps (Wu et al. 2007):

A. Select anonymous experts.
B. Conduct the first round of the survey.
C. Conduct the second round of the questionnaire survey.
D. Conduct the third round of the questionnaire survey.
E. Integrate expert opinions and reach a consensus.

Steps C and D are repeated until the experts reach a consensus. The number of experts should be limited to between five and nine (Sung, 2001; Hasson & Keeney, 2011). The MDM is suitable for various industries to analyze optimal alternatives and critical factor evaluation problems, as demonstrated in studies by Lin (2017), Lin et al. (2020), Lin (2020), and Pathak et al. (2022). Therefore, this study applied the MDM to establish quality evaluation criteria for measuring business tax evasion and its critical features.

2.2 AHP

The AHP method, proposed by Saaty (1980), is a method that addresses complex decision problems through expert opinion. The steps involved in AHP are as follows:

Step 1: Construction of pairwise comparison matrix A

Let C_1, C_2, ..., C_n represent the set of factors, while a_{ij} indicates a quantified judgment on the pair of factors C_i and C_j. The relative importance of the two elements is rated using a scale with values of 1, 3, 5, 7, and 9, where 1 denotes 'equally important,' 3 denotes 'slightly more important,' 5 denotes 'strongly more important,' 7 denotes ‘demonstrably more important,’ and 9 denotes ‘absolutely more important.’ This yields an n-by-n matrix A, as follows:

$$A=\left[a_{ij}\right]=\begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array}\begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{n2} & \cdots & 1 \end{bmatrix} \end{array} \tag{1}$$

Step 2: Calculation of eigenvalue

According to Saaty (1990), the largest eigenvalue λ max can be computed as follows:

$$\lambda_{\max}=\sum_{j=1}^{n} a_{ij}\frac{W_j}{Wi} \tag{2}$$

If A is a consistency matrix, the eigenvector X can be calculated by solving:

$$(A-\lambda_{\max} I)x=0 \tag{3}$$

To verify the consistency of the comparison matrix, Saaty (1990) proposed utilizing the consistency index (CI) and consistency ratio (CR). CI and random index (RI) are defined as follows:

$$CI=(\lambda_{\max}-n)/(n-1) \tag{4}$$

$$CR=CI/RI \tag{5}$$

where RI represents the average CI over numerous random entries of same-order reciprocal matrices. If $CR\leq 0.1$, the estimate is accepted; otherwise, a new comparison matrix is solicited until $CR\leq 0.1$.

2.3 ANP

Saaty (1996) proposed ANP, which incorporates a feedback mechanism and relationships into the AHP, to address the dependencies among criteria. Given that these criteria are mutually affected and interdependent, as well as non-linear, the complex relationships in many problems decision-related problems cannot be adequately expressed in a hierarchical manner, which is similar to a network structure (Atmaca & Basar, 2012; Keramati & Salehi, 2013; Saaty, 1996), as illustrated in Fig. 4. The ANP comprises four steps, as shown below:

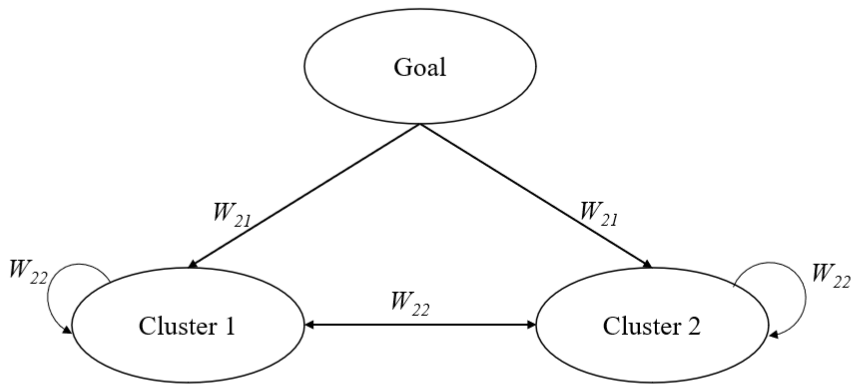

Figure 4. The network relationship model

Step 1. Model construction and problem establishment

To determine the targets based on the characteristics of the problems, it is essential to identify the decision factors, including the sub-factors contained within all factor clusters, as well as the mutual influence among all factors. If mutual influence exists among different clusters, it is referred to as outer dependence; conversely, if the sub-factors within the same criterion clusters influence each other, it is termed inner dependence. Finally, the overall network structure of the decision problem is illustrated.

Step 2. Pairwise comparison matrix structuring and eigenvector calculation

Pairwise comparisons are conducted between two factors and are divided into two parts: pairwise comparisons between all clusters and those between the sub-factors within clusters. Pairwise comparisons among sub-factors can also classified as either intra-cluster (within the same cluster) or inter-cluster (between different clusters). The measurement scale applied for comparative evaluation aligns with that of the AHP, allowing all comparative matrices to be utilized to obtain the eigenvectors that represent the values of the supermatrices. This process illustrates the dependence relationships and relative importance of the clusters. Eq. (6) can be used to derive the relative importance scores among all criteria in this step.

$$Aw = \lambda \max W \tag{6}$$

$$\lambda \max = \sum_{j=1}^{n} \alpha_{ij} \frac{W_j}{W_i}$$

where A represents the pairwise comparison matrix of clusters and criteria, w denotes an eigenvector, and $\lambda \max$ refers to the maximum eigenvalue.

Step 3. Supermatrix structuring

A supermatrix comprises all decision factors, as depicted in Figure 5. The values within a supermatrix are composed of small matrices, including the comparisons between all factors and dependent factors. The number of clusters without feedback influence or factors is denoted as 0, as shown in Eq. (7).

$$
\begin{array}{ccc}
 & & \begin{array}{ccccccccccc} & C_1 & & \cdots & & C_k & & \cdots & & C_N & \\ e_{11} & \cdots & e_{1n_1} & \cdots & e_{k1} & \cdots & e_{kn_k} & \cdots & e_{N1} & \cdots & e_{Nn_N} \end{array} \\
W = & \begin{array}{cc} & e_{11} \\ C_1 & \vdots \\ & e_{1n_1} \\ \vdots & \vdots \\ & e_{k1} \\ C_k & \vdots \\ & e_{kn_k} \\ \vdots & \vdots \\ & e_{N1} \\ C_N & \vdots \\ & e_{Nn_N} \end{array} & \begin{bmatrix} W_{11} & \cdots & W_{1k} & \cdots & W_{1N} \\ \vdots & & \vdots & \ddots & \vdots \\ W_{k1} & \cdots & W_{kk} & \cdots & W_{kN} \\ \vdots & & \vdots & \ddots & \vdots \\ W_{N1} & \cdots & W_{Nk} & \cdots & W_{NN} \end{bmatrix},
\end{array}
$$

Figure 5. Supermatrix

Source: Saaty (1996)

$$w_x = \begin{bmatrix} 0 & 0 & 0 \\ W_{21} & W_{22} & 0 \\ 0 & W_{32} & I \end{bmatrix} \quad (7)$$

The calculation procedure of the ANP consists of three matrices: an unweighted supermatrix, a weighted supermatrix, and a limited supermatrix. An unweighted supermatrix is derived from the weights of the original pairwise comparisons, while a weighted supermatrix refers to the multiplication of the weights of the same factors in the unweighted supermatrix by the weights of the relevant clusters. A limited supermatrix is obtained by repeatedly multiplying the weighted matrix by itself until the values in all columns are equal. If supermatrix W is irreducible during the calculation of the analytic network, as proposed by Saaty, all columns in the matrix will converge to the same vector, indicating that convergence has been achieved. Eq. (8) can be used to obtain the final weights of the convergence process.

$$\lim_{n->\infty} W^n \quad (8)$$

Step 4. Rank the alternatives

Once the analytic network architecture has been verified, the unweighted supermatrix, weighted supermatrix, and limited supermatrix will yield the final weights of all alternative solutions and criteria. These final weights can then be ranked to determine the optimal solution.

3. Case Study

This study aimed to develop an expert network analysis model for evaluating critical tax evasion factors, using business tax as an example. The research framework is illustrated in Figure 6, and the expert network analysis processes, dimensions, and factors are defined as follows:

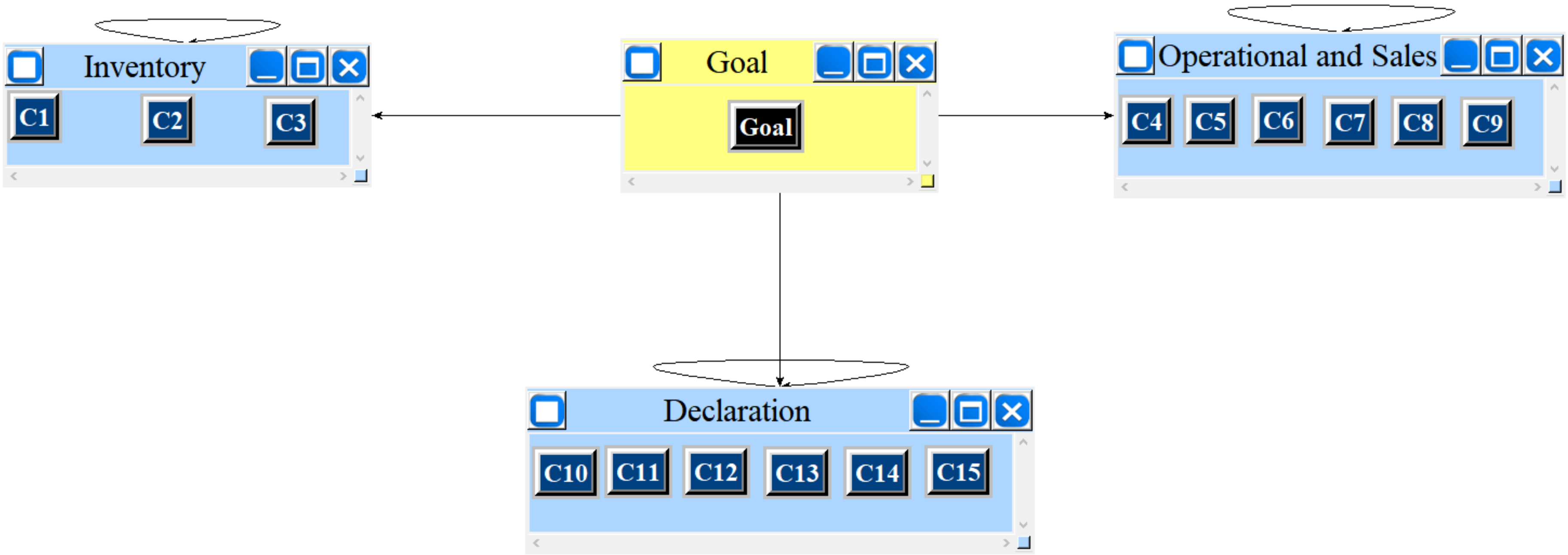

Figure 6. The expert network analysis framework

Step 1. Model construction and problem establishment

This study applied the Delphi method to identify the evaluation sub-criteria. Based on these sub-criteria, interviews were conducted with nine experts, adhering to the recommended number of participants between five and nine (Sung, 2001; Hasson & Keeney, 2011). All participants in the expert panel were senior-level managers from the business tax sector within governmental tax authorities. The Delphi method involves several rounds of inquiry, feedback, and consideration of previous responses during the expert interviews. The topics may evolve, and the responses remain anonymous (Linstone and Turoff, 1976). This method is particularly suitable for explorative studies when changes in the relationships between key variables are intuitively expected, respondents are geographically distant, and no single individual dominates the discussion (Tapio, 2003; Nowack et al., 2011). The results obtained through this study using the Delphi method are statistically valid.

This study collected the sub-criteria through a literature review and expert interviews, utilizing a 5-point Likert scale for scoring, ranging from "very important" (5) to "very unimportant" (1). After obtaining the scores, a consistency test was conducted using quartile deviation to sort the criteria. The criteria with a score of 3.00 or below and a quartile deviation (QD) of below 1.00 were excluded; otherwise, they were retained (see Figure 7).

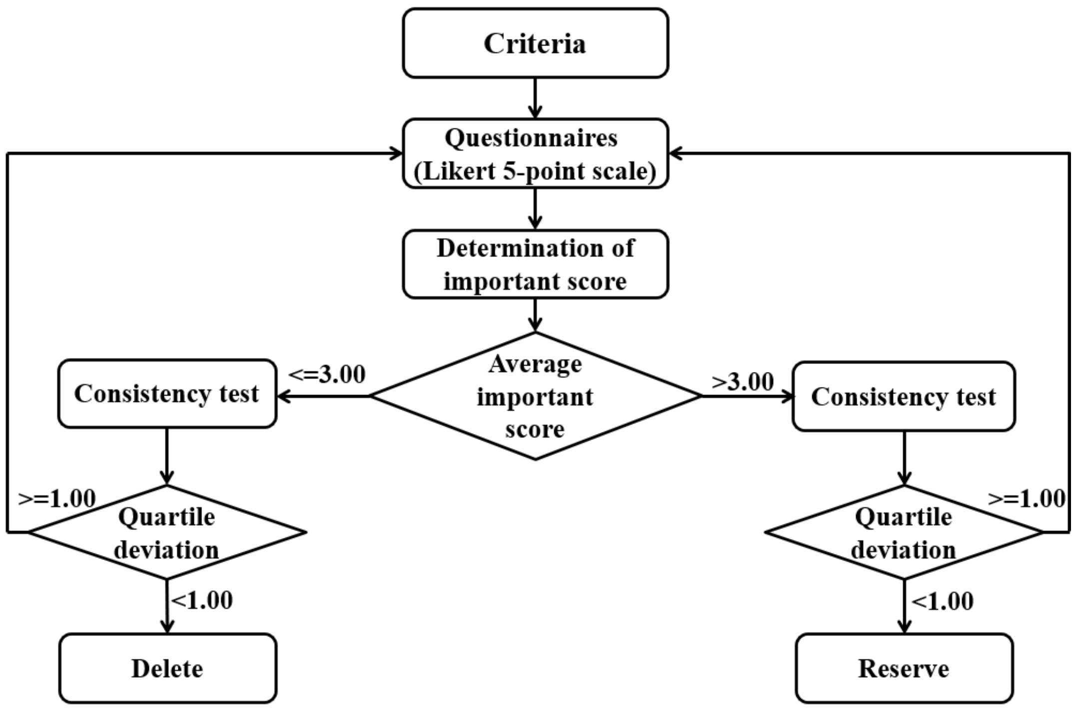

Figure 7. The MDM process

Due to the extensive volume of data, unfiled input tax credit (C10) was used as an example to illustrate the details. The results related to the unfiled input tax credit are presented in Figure 8.

Unfiled input tax credit	Very unimportant	unimportant	No preferred	Important	Very important
Expert 1					V
Expert 2				V	
Expert 3					V
Expert 4					V
Expert 5					V
Expert 6					V
Expert 7				V	
Expert 8					V
Expert 9					V

Figure 8. The sample of unfiled input tax credit criterion survey

The Delphi survey scores for Experts 1 through 9 are as follows: 5, 4, 5, 5, 5, 5, 4, 5, and 5, respectively. The process is detailed below:

Step 1: Calculate the average important index (IIN).

$$IIN = \frac{5+4+5+5+5+5+4+5+5}{9} = 4.778, > 3.000$$

Step 2: Rank the series.

The ranked series is: 4, 4, 5, 5, 5, 5, 5, 5, and 5.

Step 3: Calculate Q1 and Q3

$$Q1 = \frac{9+1}{4} = 2.$$

$$5 \fallingdotseq 3, value = 5$$

$$Q3 = \frac{3(9+1)}{4} = 7.5 \fallingdotseq 8, value = 5$$

Step 3: Determine the QD results.

$$QD = \frac{5-5}{2} = 0$$

The result of the QD for the unfiled input tax credit criteria is 0. Therefore, the unfiled input tax credit criterion is retained in the ANP model.

When establishing a study framework, it is crucial that the evaluation dimensions are agreed upon by experts (Ali-Yrkko et al., 2011; Linden et al., 2009). Therefore, the dimensions and factors for this study were collected through a literature review and expert questionnaires, followed by the application of the MDM to reach a consensus. The critical tax evasion factors for business tax were then evaluated to determine the dimensions, factor definitions, and contents as follows:

1. Inventory: This dimension includes the ending inventory, inventory turnover, and the proportion of inventory in sales revenue.
   1.1 Ending Inventory (C1): The value of remaining products and materials at the end of an accounting period
   1.2 Inventory Turnover (C2): The speed at which inventory is sold and replaced, indicating the firm's marketing capability and operational performance
   1.3 Proportion of Inventory in Sales Revenue (C3): The ratio of inventory value to sales revenue
2. Operation and Sales: This dimension includes operating revenues, the total annual revenue of sales, the average revenues in duplicate uniform invoices, total revenues of invoices in emptor for non-business entities, the amount of returns in credit card transactions, and the inconsistency of sales and purchases.
   2.1 Operating Revenue (C4): The revenue generated from the sale of products or the provision of services by the enterprise
   2.2 Total Annual Revenue of Sales (C5): The total revenue generated from sales during a fiscal year.
   2.3 Average Revenues in Duplicate Uniform Invoices (C6): The average revenue amount reflected in duplicate uniform invoices
   2.4 Total Revenues of Invoice in Emptor for Non-business Entity (C7): The revenue amounts from invoices issued to a non-business entity
   2.5 Amounts of Return in Credit Card Transaction (C8): The total returns associated with credit card transactions in a fiscal year.
   2.6 Inconsistency of Sales and Purchases (C9): Instances where sales records exist without corresponding purchase records
3. Declarations: This dimension includes unfiled input tax credits, accumulation in the offset against business tax payable, annual ratio of value-added tax, continuing to operate in declaration loss the year round, actual tax in a year, and the different amounts between an account of input documentary evidence

and a declaration of input documentary evidence credit.

3.1 Unfiled Input Tax Credit (C10): Input tax credits that have not been filed by the taxpayer for purchases or other value-add taxes

3.2 Accumulation in Offset Against Business Tax Payable (C11): The accumulation of output tax minus input tax for a business

3.3 Annual Ratio of Value-added Tax (C12): The ratio of sales amounts minus purchase amounts relative to sales amounts

3.4 Continue to Operate in Declaration Loss on All the Year Round (C13): A situation where a business reports a performance loss but continues to operate

3.5 Actual Tax in Year (C14): The total amount of business tax paid for a fiscal year

3.6 The Different Amounts Between Account of Input Documentary Evidence and Declaration of Input Documentary Evidence Credit (C15): The discrepancies between the amounts recorded in input documentary evidence and the amounts declared for input documentary evidence credits

Step 2. Pairwise comparison matrix structuring and eigenvector calculation

The pairwise comparison matrix of AHP was utilized to compute the eigenvectors of all perspectives and criteria, including those related to dependence. This study's framework comprises dimensions such as Inventory, Operation and Sales, and Declaration, along with factors including Ending Inventory, Inventory Turnover, the Proportion of Inventory in Sales Revenue, Operating Revenue, the Total Annual Revenue of Sales, the Average Revenues in Duplicate Uniform Invoices, Total Revenues of Invoice in Emptor for Non-business Entity, the Amounts of Returns in Credit Card Transactions, Inconsistency of Sales and Purchases, Unfiled Input Tax Credit, Accumulation in Offset Against Business Tax Payable, Annual Ratio of Value-added Tax, Continue to Operate in Declaration Loss on All the Year Round, Actual Tax in Year, and Different Amounts Between Account of Input Documentary Evidence and Declaration of Input Documentary Evidence Credit). The geometric mean method was employed to calculate the relative scores provided by the expert group for summarization. Table 4 presents the eigenvectors of the three dimensions (clusters), while Table 5 displays the eigenvectors of the 15 factors.

Table 4 The eigenvectors of the three dimensions

	Inventory	Operational and Sales	Declaration	Eigenvectors
Inventory	1.000	0.389	0.316	0.142

Operational and Sales	2.574	1.000	0.371	0.279
Declaration	3.163	2.697	1.000	0.579
		C.R.=0.066		

Table 5 the comparisons and eigenvectors of the 15 factors

Inventory							
	C1	C2	C3				Eigenvectors
C1	1.000	0.167	1.743				0.162
C2	5.976	1.000	4.193				0.713
C3	0.574	0.238	1.000				0.125
C.R.=0.089							
Operational and Sales							
	C4	C5	C6	C7	C8	C9	Eigenvectors
C4	1.000	0.705	0.415	0.646	0.233	0.252	0.071
C5	1.419	1.000	0.590	0.917	0.431	0.722	0.117
C6	2.407	1.696	1.000	1.556	0.732	1.225	0.198
C7	1.547	1.090	0.643	1.000	0.470	0.787	0.127
C8	4.291	2.319	1.367	2.128	1.000	2.674	0.313
C9	3.965	1.385	0.816	1.271	0.374	1.000	0.174
C.R.=0.014							
Declaration							
	C10	C11	C12	C13	C14	C15	Eigenvectors
C10	1.000	4.071	1.113	1.367	1.846	3.338	0.302
C11	0.246	1.000	2.039	1.277	3.724	3.118	0.214
C12	0.898	0.490	1.000	1.229	2.659	2.913	0.181
C13	0.732	0.783	0.814	1.000	1.349	2.441	0.148
C14	0.542	0.269	0.376	0.741	1.000	1.809	0.093
C15	0.300	0.321	0.343	0.410	0.553	1.000	0.062
C.R.=0.074							

Step 3. Supermatrix structuring

Based on the recommendations of the expert group and the results from the questionnaire, the inner dependence and outer dependence relations of the network models for critical tax evasion factors in business tax were outlined. An unweighted supermatrix and a weighted supermatrix were constructed using the eigenvector results. Subsequently, a limited supermatrix was derived from the weighted supermatrix, as illustrated in Tables 6 and 7.

Table 6 Inner dependence matrix of 15 factors

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
C1	0.000	0.667	0.800	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C2	0.800	0.000	0.200	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C3	0.200	0.333	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C4	0.000	0.000	0.000	0.000	0.042	0.151	0.066	0.121	0.115	0.000	0.000	0.000	0.000	0.000	0.000
C5	0.000	0.000	0.000	0.074	0.000	0.097	0.054	0.111	0.057	0.000	0.000	0.000	0.000	0.000	0.000
C6	0.000	0.000	0.000	0.285	0.284	0.000	0.168	0.387	0.413	0.000	0.000	0.000	0.000	0.000	0.000
C7	0.000	0.000	0.000	0.057	0.067	0.074	0.000	0.079	0.088	0.000	0.000	0.000	0.000	0.000	0.000
C8	0.000	0.000	0.000	0.043	0.469	0.414	0.449	0.000	0.328	0.000	0.000	0.000	0.000	0.000	0.000
C9	0.000	0.000	0.000	0.156	0.137	0.264	0.262	0.302	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.461	0.252	0.309	0.248	0.239
C11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.546	0.000	0.504	0.466	0.496	0.483
C12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.125	0.132	0.000	0.134	0.073	0.114
C13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.234	0.297	0.158	0.000	0.141	0.122
C14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.054	0.069	0.043	0.047	0.000	0.042
C15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.040	0.041	0.044	0.044	0.043	0.000

Table 7 The limited supermatrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
C1	0.417	0.417	0.417	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C2	0.375	0.375	0.375	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C3	0.208	0.208	0.208	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
C4	0.000	0.000	0.000	0.104	0.104	0.104	0.104	0.104	0.104	0.000	0.000	0.000	0.000	0.000	0.000
C5	0.000	0.000	0.000	0.080	0.080	0.080	0.080	0.080	0.080	0.000	0.000	0.000	0.000	0.000	0.000
C6	0.000	0.000	0.000	0.258	0.258	0.258	0.258	0.258	0.258	0.000	0.000	0.000	0.000	0.000	0.000
C7	0.000	0.000	0.000	0.071	0.071	0.071	0.071	0.071	0.071	0.000	0.000	0.000	0.000	0.000	0.000
C8	0.000	0.000	0.000	0.287	0.287	0.287	0.287	0.287	0.287	0.000	0.000	0.000	0.000	0.000	0.000
C9	0.000	0.000	0.000	0.201	0.201	0.201	0.201	0.201	0.201	0.000	0.000	0.000	0.000	0.000	0.000
C10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.266	0.266	0.266	0.266	0.266	0.266
C11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.337	0.337	0.337	0.337	0.337	0.337
C12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.112	0.112	0.112	0.112	0.112	0.112
C13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.192	0.192	0.192	0.192	0.192	0.192
C14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.053	0.053	0.053	0.053	0.053	0.053
C15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.040	0.040	0.040	0.040	0.040	0.040

Step 4. Rank the alternatives

After calculating the above supermatrix, the weights of the dependence relations for all evaluation factors were obtained, as shown in Table 8. The comprehensive weights were used for ranking, resulting in the following order of evaluation factors is C11 (0.195) > C10 (0.154) > C13 (0.111) > C8 (0.080) > C6 (0.072) > C12 > (0.065) > C1 (0.059) > C9 (0.056) > C2 (0.053) > C14 (0.031) > C3 (0.029) > C4 (0.029) > C15 (0.023) > C5 (0.022) > C7 (0.020). These results indicate that the critical factors influencing suspicious tax evasion in business tax are "Accumulation in the offset against business tax payable," "Unfiled input tax credit," and "Continue to operate in declaration loss all the year round."

Table 8 The limited supermatrix

Factors	Normalized	Limiting	Rank
C1	0.417	0.059	7
C2	0.375	0.053	9
C3	0.208	0.029	11
C4	0.104	0.029	11
C5	0.08	0.022	14
C6	0.258	0.072	5
C7	0.071	0.02	15
C8	0.287	0.08	4
C9	0.201	0.056	8
C10	**0.266**	**0.154**	**2**
C11	**0.337**	**0.195**	**1**
C12	0.112	0.065	6
C13	**0.192**	**0.111**	**3**
C14	0.053	0.031	10
C15	0.04	0.023	13

4. Conclusion

Tax revenue is critical for countries to address economic and operational issues. Shortages in tax revenue can decrease the economic and operational efficiency of various nations; thus, the most challenging and significant problem for tax authorities is tax evasion. Although tax authorities have implemented various strategies to combat tax evasion, business tax evasion still presents the highest percentage of tax omission cases in Taiwan. Therefore, addressing business tax evasion more efficiently and reducing tax fraud has become an urgent priority for tax authorities to enhance tax equity and achieve greater stability in public revenues. This study aims to establish a tax evasion detection model and identify critical tax evasion factors in business tax using the expert network analysis concept, which includes the MDM and the ANP algorithms. This study focuses on how tax authorities can identify critical tax evasion factors from various perspectives. Additionally, a network analysis model was constructed to identify the key factors of tax evasion based on expert decision science and network architecture.

The results of this study indicate that the critical impact factors are “Accumulation in the offset against business tax payable,” “Unfiled input tax credit,” and “Continue to operate in declaration loss all the year round.” Based on these findings, this study proposes the following practical policy recommendations for tax authorities to enhance their efforts in combating business tax evasion:

1. Prioritize monitoring of accumulation in offset against business tax payable: Given that the most critical factor identified is C11 (weight 0.195), tax authorities should consider integrating advanced analytics detection models to identify businesses exhibiting anomalous patterns in their tax payable offsets. This approach could involve establishing empirically derived thresholds for acceptable levels of accumulation and implementing automated alert systems for cases that exceed these predetermined limits.
2. Enhance input tax credit verification processes: Given the significant weighting of “unfiled input tax credits” (C10, weight 0.154), tax authorities should consider implementing a real-time or near-real-time verification system for input tax credit claims. This approach could involve two key components: (1) cross-referencing claims against a centralized database of legitimate transactions and (2) instituting a tiered documentation requirement system wherein claims exceeding predetermined thresholds require the submission of additional substantiating evidence.
3. Develop predictive models for long-term loss declaration: The substantial weighting of the factor “Continue to operate in declaration losses on all the year round” (C13, weight 0.111) underscores the necessity for longitudinal analysis of business performance trajectories. To address this, tax authorities could develop and implement artificial intelligence-driven predictive models. These models would be designed to identify and detect businesses that consistently report operational losses while maintaining active operations, potentially indicating undisclosed revenue streams or systematic misreporting of financial data.

Overall, these critical impact factors suggest that firms may experience a scenario in which purchases exceed sales. This situation indicates a high probability of missing invoices or falsely reported input tax when firms maintain high purchase levels coupled with low sales over their long-term operations. However, if a scenario of higher purchases than sales occurs sporadically, it may suggest a high-cost purchase related to notable transactions. Generally, since enterprises can sell these inventories in future operations, such cases do not typically indicate suspicious tax evasion activities. Therefore, tax authorities can utilize the “Continue to operate in declaration loss all year round” factor to assess the long-term balance of purchases and sales in business operations. A high probability of tax evasion can be identified when firms consistently have purchases greater than sales over an extended period. Additionally, businesses may fail to purchase invoices to reduce their accumulated tax liability and conceal their tax evasion behavior. Hence, tax authorities should integrate these critical factors into a comprehensive framework for detecting suspicious tax evasion activities to promote tax equity. This framework should incorporate adaptive thresholds, refined through an iterative process utilizing artificial intelligence (AI) detection systems in collaboration with tax officials. By implementing this data-driven approach, tax authorities can leverage the insights derived from this study to develop more effective strategies for identifying and mitigating business tax evasion. This methodology enhances the efficiency and accuracy of tax collection efforts while fostering a more equitable business environment.

Using critical tax evasion factors of business tax as an example, this study proposes an expert network analysis model to identify the hierarchy of these factors. The proposed model can assist authorities and governments in obtaining vital information about tax evasion factors, thereby improving the efficiency of evaluating suspicious tax evasion cases. Academically, this expert network model addresses the research gap in evaluating suspicious tax evasion by employing network concepts and methodologies. Commercially, the detection model aids in diagnosing and evaluating suspicious tax evasion cases and identifying the critical impact factors within the business tax sector.

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