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Neural Network Analysis of Factors Influencing Forgotten Financial Remittances in Yemen

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ABSTRACT

Remittances are vital for economic growth, especially in developing nations like Yemen. However, the phenomenon of forgotten financial remittances poses significant threats to Yemen's financial stability, as these unreceived transfers negatively impact its economy. Therefore, this study aims to identify the main causes of this phenomenon. These causes include logistical and economic factors of senders and beneficiaries, and features of banks and money exchange firms. The study surveyed 931 Yemeni respondents who experienced forgotten financial remittances, answering 15 possible reasons with "yes" or "no" in the questionnaire. Descriptive statistical measures were employed to characterize the sample, while neural network analysis (NNA) primarily identified the main factors contributing to forgotten financial transfers. The analysis revealed three key dimensions leading to this problem. The first dimension involves communication or access problems between the sender and recipient. The second dimension involves logistical obstacles that hinder remittance flows, including technological, financial, administrative, and bureaucratic challenges. These barriers can be associated with the senders, recipients, or exchange companies. The final dimension is related to the operations of money exchange companies and the uniformity of their rates. To ensure the stability of the results, Bootstrapping technique was utilized based on a random sample of size 500 observations from the original dataset. Thus, the results demonstrated stability and reliability for all samples larger than 30% of the original sample size.

ملخص

تعد الحوالات المالية عاملا حيويا للنمو الاقتصادي، خصوصا في البلدان النامية مثل اليمن. غير أن ظاهرة الحوالات المالية المنسية تمثل تهديدا كبيرا للاستقرار المالي في اليمن، حيث تؤثر هذه

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التحويلات غير المُستلمة سلبا على الاقتصاد. لذلك، تهدف هذه الدراسة إلى تحديد الأسباب الرئيسية لهذه الظاهرة، والتي تشمل العوامل اللوجستية والاقتصادية المرتبطة بالمرسلين والمستفيدين، إضافة إلى خصائص البنوك وشركات الصرافة. وقد استطلعت الدراسة آراء 931 مشاركا يمنيا ممن واجهوا حوالات مالية منسية، من خلال استبيان تضمن 15 سببا محتما للإجابة عليها بـ "نعم" أو "لا". وتم استخدام أساليب الإحصاء الوصفي لوصف العينة، بينما استخدم تحليل الشبكات العصبية لتحديد العوامل الرئيسة المسببة للحوالات المالية المنسية. وأظهرت النتائج ثلاثة أبعاد رئيسية لهذه المشكلة، وتمثل البعد الأول في مشكلات الاتصال أو الوصول بين المرسل والمستفيد. بينما يرتبط البعد الثاني بالعوائق اللوجستية التي تعيق تدفقات الحوالات، وتشمل التحديات التقنية والمالية والإدارية والبيروقراطية، والتي قد ترتبط بالمرسلين أو المستفيدين أو شركات الصرافة. ويتعلق البعد الأخير بعمليات شركات الصرافة وتوحيد أسعارها. ولضمان استقرار النتائج، تم استخدام تقنية Bootstrapping بالاعتماد على عينة عشوائية مكوّنة من 500 ملاحظة من البيانات الأصلية. وقد أظهرت النتائج استقرارا وموثوقية لجميع العينات التي تزيد عن 30% من حجم العينة الأصلي.

RÉSUMÉ

Les transferts de fonds sont essentiels à la croissance économique, en particulier dans les pays en développement comme le Yémen. Cependant, le phénomène des transferts financiers oubliés représente une menace importante pour la stabilité financière du Yémen, car ces transferts non reçus ont un impact négatif sur son économie. Cette étude vise donc à identifier les principales causes de ce phénomène. Ces causes comprennent des facteurs logistiques et économiques liés aux expéditeurs et aux bénéficiaires, ainsi que les caractéristiques des banques et des sociétés de change. L'étude a interrogé 931 Yéménites ayant été victimes de transferts financiers oubliés, qui ont répondu « oui » ou « non » à 15 raisons possibles dans le questionnaire. Des mesures statistiques descriptives ont été utilisées pour caractériser l'échantillon, tandis qu'une analyse par réseau neuronal (NNA) a principalement identifié les principaux facteurs contribuant aux transferts financiers oubliés. L'analyse a révélé trois dimensions clés à l'origine de ce problème. La première dimension concerne les problèmes de communication ou d'accès entre l'expéditeur et le destinataire. La deuxième dimension concerne les obstacles logistiques qui entravent les flux de transferts, notamment les défis technologiques, financiers, administratifs et bureaucratiques. Ces obstacles peuvent être liés aux expéditeurs, aux destinataires ou aux sociétés de change. La dernière dimension est liée au fonctionnement des sociétés de change et à l'uniformité de leurs taux. Afin de garantir la stabilité des résultats, la technique du bootstrapping a été utilisée sur un échantillon aléatoire de 500 observations issues de l'ensemble de données original. Les résultats ont ainsi démontré la stabilité et la fiabilité de tous les échantillons supérieurs à 30 % de la taille de l'échantillon original.

Key Words: Forgotten remittances, Yemeni financial system, Neural Networks Analysis, Exploratory factor analysis, Centrality measures, Bootstrap technique.

1. Introduction

Financial remittances play a prominent role in enhancing economic development and prosperity in many countries, particularly in developing nations like Yemen. These remittances, transferred between citizens and expatriates residing abroad, contribute to building foreign exchange reserves, thereby bolstering economic stability and mitigating poverty. However, a recent phenomenon known as forgotten financial remittances (FFR) has emerged in Yemen, indicating transfers that go unclaimed due to various factors. FFR has not been addressed before, it is a modern and emerging challenge that poses a significant threat to the Yemeni economy. So, no studies related to this topic directly, but it take about the factors that address key topics such as the behaviors of remittance users, challenges in documenting financial records, and the economic significance of remittances. Understanding the factors influencing FFR are crucial for policymakers and financial institutions to devise strategies and policies that enhance remittance flows and maximize their impact on the Yemeni economy. Accordingly, the significance of this study arises.

Reports obtained in our investigations indicate a gap or problem FFR in Yemen, underscoring the importance of investigating the reasons behind this phenomenon. This gap is believed to have led to a decline in the ability to track these funds and maintain transparency, and integrity in financial transactions in the country, thus impacting the state’s economy. For instance, according to these reports, the value of forgotten financial in just one Exchange Company over two years amounted to YER 2,038,862,547, approximately equivalent to SAR 13.6 million. Additionally, the total amount transferred in Saudi riyals during the same period exceeded SAR 6,881,820, while the total amount transferred in US dollars was $575,701, which is more than five hundred thousand US dollars.

The details of these amounts are without the data of the sender, recipient, and mobile number in order to maintain privacy[2]. According to the annual report of the Central Bank of Sanaa at the end of the year 2022, the number of licensed exchange companies and their branches reached (946) exchange companies[3]. In addition, according to the report issued by the Central Bank of Aden for the year 2023, the number of licensed exchange companies, establishments, and remittance agents reached (379) exchange companies[4].

Estimates published on the World Bank's electronic platform indicate that financial remittances to low- and middle-income countries grew by about 3.8% in 2023, which is less than in previous years. The indicators show that the flow of migrant funds to their home countries reached approximately $669 billion by the end of 2023, compared to about $794 billion the previous year[5]. These inflows of migrant funds to their home countries, especially in developing countries like Yemen, highlight the existence of FFR, as mentioned earlier.

FFR pose risks and threats as they undermine the financial system. They indicate weaknesses in the financial system and financial monitoring, which may erode confidence in the Yemeni financial system and, consequently, reduce investments and capital flows.

Moreover, they have implications for economic growth, as the loss of a significant portion of remittance funds deprives the economy of resources for investment, financing development projects, and more. Furthermore, FFR affect the government's public budget and point to weaknesses in transparency and anti-corruption systems, which may increase corruption and undermine the role of the system and the law.

This study aims to identify the main reasons behind the occurrence of FFR in the Republic of Yemen. These reasons include the logistical and economic characteristics of remitters and beneficiaries, as well as some features specific to banks and exchange companies. The proposed reasons

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[2] https://github.com/salahalhagree/Forgotten-Remittance-in-the-Republic-of-Yemen.git

[3] https://centralbank.gov.ye/UpldImgAndFile/file/شركات%20الصرافة%20وفروعها%20المرخصة.pdf

[4] https://cby-ye.com/files/65427257edd05.pdf

[5] https://www.worldbank.org/en/news/press-release/2023/12/18/remittance-flows-grow-2023-slower-pace-migration-development-brief

were gathered from reliable and reputable sources and complemented by investigative studies and interviews conducted with remitters and beneficiaries. Insights gained from this analysis can guide policymakers, financial institutions, and remittance service providers in developing and improving the process, enhancing the ideal and secure system for financial remittances in Yemen.

The rest of the paper is organized as follows. Section 2 provides relevant studies in the field. Section 3 an overview of both factor analysis and neural networks is presented. Section 4 delineates the primary procedural steps involved in the practical application of FFR (Factor Analysis and Neural Networks), encompassing neural network analysis, exploratory factor analysis, stability assessment of results through Bootstrap network analysis. Lastly, Section 5 encapsulates the conclusions drawn from the analysis, along with accompanying recommendations and suggestions for future research endeavors.

2. Relevant studies

As previously mentioned, the phenomenon of Forgotten Financial Remittances (FFR) has not been directly addressed. Despite exhaustive research efforts, we encountered an absence of scholarly discourse addressing the phenomenon of "FFR", which remain unreceived. Surprisingly, no substantial studies have been conducted on this crucial issue, leaving a significant gap in the literature. The limited references available solely exist in occasional mentions within newspaper articles. This stark absence underscores the urgent need for comprehensive exploration and analysis of unclaimed remittances, their implications, and potential strategies for addressing this overlooked aspect of international financial transactions. Below are several related studies that primarily discuss the impact of financial remittances either on individuals personally or on the country as a whole.

Many studies have unanimously agreed on the role and impact of remittances, some of which have confirmed that remittances have a crucial role in reducing the unemployment rate in the country (Bunduchi et al., 2019) , and that remittance flows have a positive impact on the inflation rate in the developing countries (Narayan et al., 2011). Another study highlights the importance of financial remittances from immigrants to Arab economies as a major alternative to their external financing, and how they have an effective role in promoting economic development (Boutalbi et al., 2017). This study also focused on the challenges facing Arab countries in benefiting from remittances from their immigrant communities. At the Yemeni level, the flow of international aid and huge financial transfers from Yemeni expatriates contributed significantly to increasing the country's overall revenues (Fadel & Sacchetto, 2023). In the Arab world, it is not only Yemen that benefits from these remittances, as migrant remittances to Arab countries amounted to $49 billion in 2015, and Egypt ranked first in the Arab world and seventh internationally with approximately 40% of the total remittances of workers to the Arab region, (Amhamed et al., 2017).

Returning to the Yemeni issue, economic data showed that the Yemeni economy was heavily dependent on oil exports at the beginning of the twenty-first century, which made it clearly affected by the fluctuations of the global oil market. This reliance has contributed to achieving positive economic results for the country (Karanfil & Omgba, 2023) . However, since the start of the war, Yemen has suffered from many social issues, including high levels of unemployment, rapid population expansion, and widespread poverty (Mukashov et al., 2022). The war also led to long-term disasters and major humanitarian impacts. Due to this influence, Yemen needs financial resources to help rehabilitate its collapsed economy (Kimball & Jumaan, 2020). The flow of remittances is considered one of the most important sources of financing for the country, as it plays a pivotal role in restoring the economy and stability of Yemen by providing a large financial source for individuals and the national economy. It is worth noting here that Yemen includes a large number of expatriates spread across different countries, especially within the Gulf States (Moss, (2021). Remittances, which refer to money expatriates send home, can contribute significantly to Yemen's economic recovery.

The flow of remittances alleviates poverty and contributes to providing the country's foreign currency reserves. Some studies also indicated that remittances had a positive impact on financial growth and the level of banking services in both countries (sender and recipient). The continuation of these transfers in a safe, effective and transparent manner ensures and enables the construction of plans and strategies to maximize the benefit of these resources to alleviate poverty and promote economic growth, by enacting laws aimed at improving and supporting the security of remittance networks, and facilitating the transfer process to make it more flexible and smooth (Delgado, 2011; Pal, 2023; Guha, 2013).

At the Yemeni level, Delgado (2011) confirmed that financial transfers can directly reduce poverty and improve the living conditions of Yemeni families, including subsistence, medical care, and education, which contributes to building a more stable society. In addition, the flow of remittances has the ability to stimulate local economic activity, as recipients of remittances often invest their money within their communities, which leads to job creation and opportunities to establish local companies and small businesses, reconstruction, and strengthen the overall economy. And strengthen the country's infrastructure (Khan, 2023; Khan & Gunwant, 2023a; Dhawan & Zollmann, 2023)

Given this importance, emphasis should be placed on creating efficient, secure, and transparent remittances methods to reduce potential risks, such as misappropriation of funds (Alhannom & Mushabeb, 2021). Amhamed, Bazaria, and Ait Si Mammer (2017) confirmed that expatriate remittances are one of the most important lost sources of financing due to the absence of a scientific outlook to make the most of them as a fixed source for the current account that contributes to mitigating the impact of oil price fluctuations. In a recent study concerned with Yemeni affairs as a developing country, it aimed to predict financial remittance flows to Yemen for the period 2020-2026. The study relied on time series data on information about transfers to Yemen spanning the years 2000-2019, and the data for this study was collected from the World Bank. The researchers used the Box-Jenkins ARIMA technique, and the predictive ability of the model was verified using various methods. The results of their study revealed an expected increase in remittance flows to Yemen over the next six years, eventually reaching 36.83% of the country’s gross domestic product (GDP) (Khan & Gunwant, 2024).

3. Scientific Introduction

In this section, we will provide necessary information and definitions related to the study.

3.1. Factorial Analysis

Factor analysis is a powerful statistical tool widely used for studying the complex internal causes and factors influencing a phenomenon at a given time. Its primary aim is to reduce the number of these factors or causes DR (Data Reduction) and form what is known as a factor or dimension, providing a more comprehensive understanding of the factors affecting the phenomenon. Factor analysis directly addresses the phenomenon, making interpretation easier Tighza (2012) Mathematically, factor analysis is a statistical process that targets positive correlation coefficients with statistical significance (Stevens, 2012; Tabachnick, Fidell, & Ullman, 2013; Kirk, 1974).

. Several conditions are necessary for apply factor analysis, including a large and representative sample of the target population, and the assumption that this population is normally distributed, which should be reflected in the sample collected.

3.1.1. Types of factor analysis:

There are several types of factor analysis; however, this study focuses on Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), which are briefly introduced below.

3.1.1.1. Exploratory factor analysis (EFA):

This type of analysis is used when the relationships influencing a phenomenon are unknown and aims to identify them from a large group of known factors or causes (as in our case). It restructures the variables based on their significance and combines them into a smaller number of dimensions without losing essential information from the original variables. Criteria such as KMO-Kaiser measures and the latent root greater than one criterion are used to identify dominant factors or dimensions of the phenomenon (Tighza, 2012; Stevens, 2012; Tabachnick, Fidell, & Ullman, 2013; Kirk. 1974). After factor identification, it may be necessary to rotate the factors to facilitate interpretation. Rotation can be done in two ways: orthogonally and obliquely. The aim is to obtain a simpler structure for a better understanding of the overall picture of the variables and the factors or dimensions derived from them, with the threshold for commonality usually set at 0.3 in absolute value (Field, 2013).

. The statement that the prevalence is estimated at 0.3 means that the variable under study is present in about 30% of the sample. This indicates that it is a rather average occurrence that is neither very common nor very rare. This numerical value helps researchers to understand the prevalence of the variant in the target population.

3.1.1.2.Confirmatory factor analysis (CFA).

It is used to confirm or reject hypotheses about the existence of certain relationships between variables and latent factors (eigenvalue). It is also used to check the compatibility of the data with the previously defined theoretical structure (Al-Nuaimi, 2020) . It is also used to check model validity and for path analyzes (Russell, 2002).

3.1.2 Methods of factor analysis:

There are several methods for factor analysis, such as the principal component method (which was used in our study), the diagonal method and the centroid method. Each method has its advantages and disadvantages. Details of these methods can be found in Tighza (2012) and Gorsuch (2014).

3.2. Neural network

Neural networks are very popular in various fields because they are able to model complex patterns and relationships within data by using machine learning technologies. A neural network is an application of artificial intelligence, it is a processing model that mimics the way the human brain processes information. A neural network represents an interconnected system made up of small units called nodes or neurons, and these units interact with each other through what are called *edges* to perform specific tasks. It is a strong tool due to many aspects, it can be used in all types of measurement levels, it has high diagnostic power for factors, stronger than other tools and it gives a visual representation or map of the network of relationships and their interaction between nodes, making them a suitable choice for our study

3.2.1. Network architecture

In simple terms, a neural network consists of successive layers of nodes, where the first layer receives input, while the hidden intermediate layers contain many nodes and process information, and finally the last layer is the output layer. There are connection weights between the nodes to increase or decrease a certain effect, and these weights are determined during the learning process, and the intensity of the neural connections between the neurons is used to store the acquired knowledge, Figure 1-a.

Figure 1-b shows a simplified scientific structure of an artificial neural network, where $x_1, x_2, \dots, x_n$ represent the inputs to the neural cell, while $w_1, w_2, \dots, w_n$ represent the weights, which are real values used to improve performance and form connections within the neural network. Σ represents the weighted sum, f is called the operation function, and y represents the output of the neuron. It is worth to be mentioned, weight can be positive, indicating a positive correlation (represented by blue or green lines), negative, indicating a negative correlation (represented by red lines), thick, indicating a strong correlation, or thin, indicating a weak correlation. Figure 1-c. Based on the method of communication between neurons, the communication pattern can be divided into two categories:

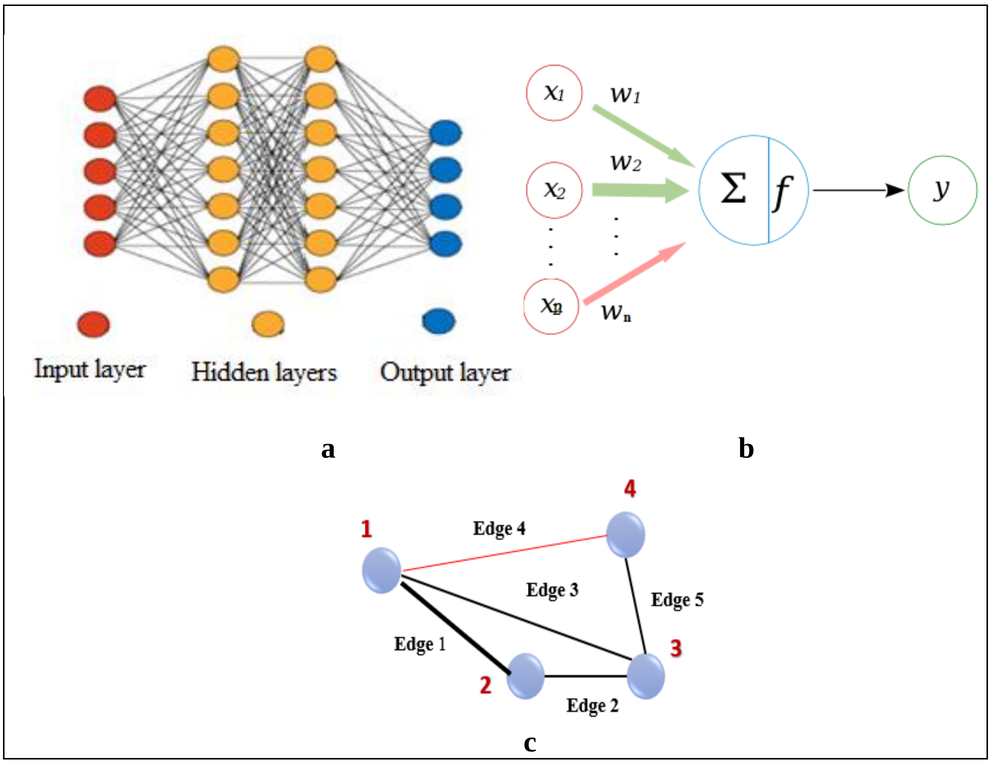
- Feedforward Neural Networks (FNNs): It is a fixed network that produces only one output from a given input, and its response to an input is independent of the previous network state.

- Recurrent Neural Networks (RNNs): The main idea here is to use a feedback cycle where previous outputs can be part of the current input. In this way, the neural network can interact with information that may be important in a temporal context, such as timelines and texts.

In computer science, the process of providing inputs to the network, processing them, and obtaining outputs is commonly referred to as training the network.

Neural networks are used in a variety of applications, including machine learning, computer vision, data analysis and forecasting. They are considered an important part of the field of artificial intelligence and offer unique opportunities to learn from data and adapt to continuous change (Wu & Feng, 2018; Abiodun et al., 2018; Gupta, 2013).

Figure 1: (a) A simplified representation of a neural network, (b) a representation of the basics of a neural network and (c) A network with 4 nodes and 5 edges



In another way, a network of n nodes can be conceptualized as a graph, represented by the matrix g in the space $\mathbb{R}^{n*n}$, The connections between nodes are represented by edges Figure (1c). Edges refer to the statistical correlations between the nodes in a network. These relationships can be modified through what are known as weights. For any two nods i and j, where $i, j = 1,2 \ldots n, i \neq j$, if the element $g_{ij} \neq 0$, that means there's a link (edge) between nodes i and j , otherwise, it implies no edge between them (Bloch, Jackson & Tebaldi,2023)..

The node degree of a node , $d_i(g)$ in many cases of networks is the count of edges connected to the node i.

$$d_i(g) = \left|\{j: g_{ij} \neq 0\}, j = 1,2, \ldots n\right| \tag{1}$$

The *distance* between nodes i and j, denoted as $P_g(i, j)$, represents the total number of edges along the shortest path (geodesic) connecting nodes

i and j within the network. If no such path exists, the distance is considered to be infinite ∞. The relationships between the nodes are graphically represented using variations in color and thickness, as demonstrated in the application aspect below. These visualizations reflect internal computational processes performed by the software and are displayed as gradients in the thickness of the connection lines between nodes.

3.2.2. Centrality measures of the neural network

Centrality measures are important tools for understanding networks because they use graph-theoretic algorithms to calculate the importance of each node in the network and show which parts of the network need attention ,but they all work differently. Each metric has its own definition of "importance". So you need to understand how it works to find the best metric for your graph visualization applications (Elmezain., Othman., & Ibrahim. 2021; Agryzkov et al., 2019). In our study, we used more than one central measure to identify the nodes with the highest closeness or that are most interconnected to each other. In the following some necessary definitions.

Let $G(n)$ denote the set of all possible networks of n nodes. A centrality measure is a metric, or function $c : G(n) \rightarrow \mathbb{R}^n$, where $c_i(g)$ represents the centrality of the node i in the network g (Borgatti, 2005; Jackson,2008).

3.2.2.1. Degree Centrality:

A node's degree centrality corresponds to the number of connections it has. For instance, a node with 5 edges would exhibit a degree centrality of 5, whereas a node linked by just one edge would have a degree centrality of 1. A degree centrality for a node i, denoted by $d_i(g)$, higher values indicate more importance of this node. If we divided by $n-1$, we get the normalize degree is on between 0 and 1.

$$c_i^{deg}(g) = \frac{d_i(g)}{n-1} \tag{2}$$

Where $n-1$ is the maximum possible number of edges a node can have (Sabidussi, 1966)

3.2.2.1.1. Closeness centrality measure:

We relied heavily on this scale in our study, in addition to other scales such as Betweenness, Closeness and Strength.
Closeness centrality evaluates each node's proximity to all other nodes within the network. This measure computes the shortest paths between every pair of nodes, then assigns a score to each node based on the sum $\sum_j P_g(i,j)$, $\mathrm{i,j} = 1,2,\ldots \mathrm{n}$ of these shortest paths (Elmezain., Othman., & Ibrahim, 2021; Agryzkov et al., 2019). In this measure a higher score suggests reduced centrality (Sabidussi, 1966; Bavelas. 1950). There is another definition for this measure, harmonic centrality (Rochat, 2009; Garg, 2009). Distances they suggest the sum of all inverses, that is $\sum_j \frac{1}{P_g(i,j)}$, $\mathrm{i,j} = 1,2,\ldots \mathrm{n}$. This form prevents the scenario where a small number of nodes have a significant or infinite distance, which could skew the measurement. Here, a higher score suggests a higher centrality. The normalized form can be written as

$$c_i^{cls}(g) = \frac{n-1}{\sum_{j \neq i} P_g(i,j)}, i = 1,2,\ldots n \quad (3)$$

3.2.2.1.2. Strength centrality measure:

Strength centrality is a measure that clarifies which node is more connected to others in the network. It is the sum of the edges' weights to or from a node. It represents the collective impact of the connections involving that node. Higher values indicate higher centrality (Barcaccia et al., 2020). In network theory, the concept of "node strength" refers to the importance or influence of a node within a network. It reflects the node's ability to activate or influence other nodes.

3.2.2.1.3. Betweenness centrality measure

The betweenness centrality measure evaluates all shortest paths between nodes j and k that traverse through node i, where $i \neq j$ and $i \neq k$ (distinct from j and k). When a node is connected to a large number of other nodes within a network, it exhibits high betweenness centrality. Hence, this measure identifies nodes that act as intermediaries in information transmission within the network (Freeman, 1977). It is needed to keep track of the fraction of geodesic paths passing through i, $v_g(i : j,k)/v_g(j,k)$, in other word, betweenness centrality of a node i is the sum of fraction of all pairs shortest paths that pass through

$$\sum_{(j,k),j\neq i,k\neq i}\frac{v_g(i:j,k)}{v_g(j,k)}, i,j,k = 1,2,\ldots n \quad (4)$$

And the normalize form can be shown as

$$c_i^{bet}(g) = \frac{2}{(n-1)(n-2)}\sum_{(j,k),j\neq i,k\neq i}\frac{v_g(i:j,k)}{v_g(j,k)}, i,j,k = 1,2,\ldots,n \quad (5)$$

Betweenness centrality assigns equal weight to all shortest paths, regardless of the distance or number of alternative routes between nodes j and k. Other definitions can be read in (Jackson, 2020).

3.2.3. Expected influence

Bridge expected influence, akin to bridge strength, signifies the cumulative connectivity of a node with other disorders. Unlike bridge strength, however, bridge expected influence doesn't involve taking the absolute value of edges before summing them.

$$BEI(i) = \sum_{j\neq i}\omega_{ij} \quad (6)$$

It is worth to be mentioned, centrality measures are typically standardized, with a mean of 0, a variance of 1, and no units of measurement.

3.2.4. Weight matrix

The weight matrix of a neural network is a diagonal matrix that stores the weights of the network and expresses the strength or weight assigned to each link between the nodes in the connected layers. It plays a vital role. The weight matrix in neural networks serves as a pivotal component, these weights are employed for diverse functions, including updating during training, maintaining stability, and improving learning in specific tasks (Sivakumar, & Sivakumar, 2017).

4. The Practical Application on FFR

Descriptive statistics of the data.

The study is based on a number of 931 respondents from all over Yemen who had forgotten money transfers and dealt with the relevant exchange offices. Those whose responses were complete on all scales were selected, while any respondent who did not answer the scale completely was excluded to ensure more accurate results and our commitment to accuracy and transparency in the research process, and to provide results worthy of advanced scientific analysis. The scale items are listed in Table 1, which include a “yes” or “no” response for 15 factors (simple/variable). These factors will represent the nodes in the network analysis section of the study.

Table 1: The possible factors causing forgotten financial transfers in the Republic of Yemen and the codes associated with each reason (R1-R15).

N	Factors	Code
1	I have not received an SMS	R1
2	The recipient's cell phone has changed	R2
3	The sender has not contacted me	R3
4	Loss of cell phone or change of number	R4
5	The receipt was postponed to another day and the transfer was forgotten	R5
6	The cost of traveling to the exchange company is ineffective	R6
7	There are spelling mistakes in the name	R7
8	The sender wants to document a receipt to prove their rights	R8
9	The transfer was of equal value from other parties and we did not know about it	R9
10	Multiple networks of exchange offices leading to the loss of the transfer	R10
11	There is no proof of identity or the card has been lost	R11
12	Do you have a transfer and it has been withdrawn by others?	R12
13	Are you satisfied with the operations of the bureau de change in Yemen?	R13
14	Would you like any transfer in the future to be made without intermediaries?	R14
15	Is the exchange rate uniform at all exchange offices?	R15

Table 2 shows the percentage presence of each factor in the responding sample, where the reasons (The sender has not contacted me “R3”), (the recipient wanted to make the transfer without an intermediary in the future “R14”) and (I have not received an SMS “R1”) having the highest percentages. In the sample, the rates are between 82% and 88%. While the reason (There is no proof of identity or the card is missing “R11”) has the lowest attendance rate among the items at 38% according to the sample used. Both (Did you have a transfer and it was deducted from others “R12”) and (Is the exchange rate consistent) have the same percentage of presence, “R15” has an attendance rate of 44%. As for the other reasons, one part is between 50% and 60% and the other between 66% and 78%. Figure 2 shows a visual representation of these percentages.

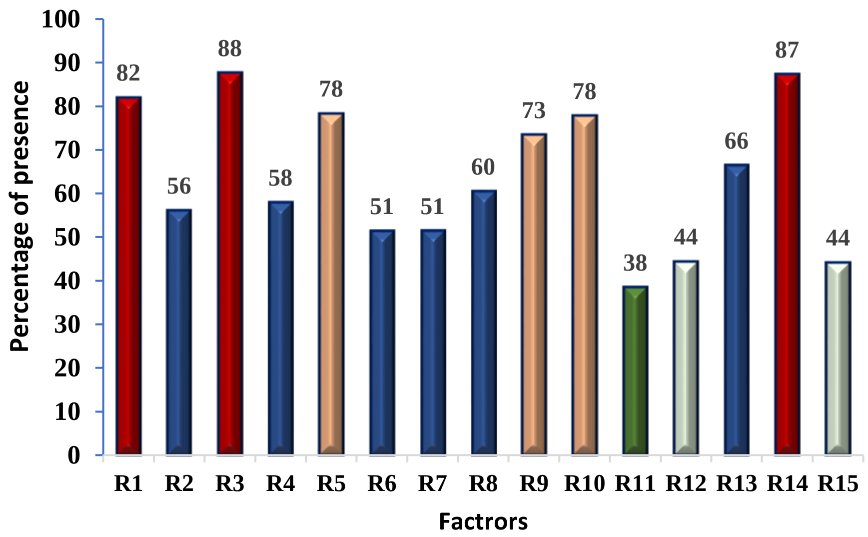
The results in Table 2 also show the lack of moderation of the study variables in the column of the normality test (Shapiro-Wilk test) as well as in the columns (skewness and kurtosis), as all significance coefficients (sig) were below the default significance level of 0.05.

Table 2: Descriptive Statistics and Tests of Normality

Items	Valid	Missing	Skewness	Kurtosis	Shapiro-Wilk	P-value of Shapiro-Wilk	Sum	Percentage %
R1	931	0	-1.665	0.772	0.467	< .001	763	82
R2	931	0	-0.245	-1.944	0.631	< .001	522	56
R3	931	0	-2.292	3.261	0.385	< .001	816	88
R4	931	0	-0.32	-1.901	0.627	< .001	539	58
R5	931	0	-1.376	-0.108	0.508	< .001	729	78
R6	931	0	-0.054	-2.001	0.636	< .001	478	51
R7	931	0	-0.058	-2.001	0.636	< .001	479	51
R8	931	0	-0.429	-1.82	0.62	< .001	563	60
R9	931	0	-1.059	-0.881	0.552	< .001	683	73
R10	931	0	-1.338	-0.211	0.513	< .001	724	78
R11	931	0	0.475	-1.778	0.617	< .001	358	38
R12	931	0	0.227	-1.952	0.632	< .001	413	44
R13	931	0	-0.695	-1.521	0.596	< .001	618	66
R14	931	0	-2.247	3.058	0.39	< .001	813	87
R15	931	0	0.236	-1.948	0.632	< .001	411	44

Figure 2: Relative frequency of data

In addition, the skewness coefficients were negative, indicating skewness from the normal distribution to the left, and positive values, indicating skewness from the normal distribution to the right, which means that the data/variables are not normally distributed. The same result is provided by the kurtosis measure, which provides negative values for a distribution with a strong peak compared to the normal distribution or positive values for low peaks compared to the normal distribution. Furthermore, the data in its hidden structure is a mixture of nominal and continuous data, so the conditions for a factor analysis are not met. This is one of the key justifications for using network analysis, as it does not require the same conditions or assumptions as other analytical methods. Nevertheless, we will do so and keep the results of the exploratory factor analysis for comparison with neural network analysis, which is not subject to the same limitations.



4.1. Exploratory factor analysis:

Exploratory Factor Analysis (EFA) was applied to the collected sample, enabling the identification of key dimensions and underlying factors contributing to the phenomenon of Forgotten Financial Remittances (FFR).

Principal component analysis (PC) and oblique rotation (Promax) methods were applied because the results in Table 3 indicate the adequacy of the sample and the possibility of adopting its results, where the value of the KMO measure indicates the strength of the partial correlation between the variables and the statistics of the measure to the value (0.815) is considered a good value, and the value of the Bartlett test statistic is 2405.366, which means a significance level of less than 0.0001, which indicates that these results are highly statistically significant and that the results of the sample can be relied upon due to their reasonableness and statistical significance. We can also be confident that the variables interact with each other well and statistically significantly.

Table 3: Kaiser-Meyer -Olkin (KMO) test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.815
Bartletts Test of Sphericity	Approx. Chi-Square	2405.366
	Df	105
	Sig.	.000

Table 4 also shows the main dimensions or factors suggested by the exploratory factor analysis based on the degree of satiety, namely: The first dimension: includes (R7-R9, R11, R12), the second dimension: includes R2, R4, the third dimension includes: (R5, R6, R10), the fourth dimension includes: (R13, R15), and the fifth dimension: includes (R1, R3). It is also clear that R14 is not saturated at any dimension. In the last column shows the ability of each reason to explain or account for the total variance of the data in a different percentage depending on the reason. For example, “R2:The recipient’s cell phone was changed” can explain or account for 75.4% of the total variance in the data after principal components analysis, and “R4: Losing a cell phone or changing the number explains 74.5% of this variance. Worth mentioning, we set the commonality threshold at 0.3 in absolute value, which is typically used in statistical analyses [22] to retain factors that have a reasonable level of shared variance without removing too many factors especially when the factors are not many.

In what follows, we will continue analyzing the factors that affect forgotten financial transfers using neural network analysis, on which we will focus more because it does not impose specific conditions for its application and it is an effective tool, as we will see below.

Table 4 The results of the exploratory factor analysis of the main dimensions

The possible factors	Factors / dimensions					Communalities
	1	2	3	4	5	
R12	.571					.613
R7	.525					.520
R11	.485					.510
R8	.480					.504
R9	.340					.415
R5			.519			.505
R6			.457			.469
R10			.351			.544
R2		.752				.754
R4		.707				.745
R15				.667		.662
R13				.575		.687
R3					.528	.584
R1					.372	.589

4.3. Neural network analysis

In the introduction, we highlighted the importance of understanding the factors contributing to Forgotten Financial Remittances (FFR). Neural network analysis offers a significant advantage by avoiding the restrictive assumptions imposed by traditional methods, such as the moderation condition, enabling a more flexible modeling process, as demonstrated in this section. Network analysis is a relatively new technique for modeling interactions between a large number of variables in which the relationship between all variables is directly estimated.

In the following subsections, we will list an analysis of neural networks between variables using JASP, as we rely on most of the analyzes presented using the “bootnet” package in the R programming language Epskamp, Borsboom & Fried, 2018) while network graphs depend on the” qgraph” package in R (Epskamp et al., 2012).

4.3.1. Factor Analysis

To analyze the factors and their connections through some measures, like centrality measures and weights matrix, as follows:

4.3.1.1. Centrality measures

By using centrality measures per variable, we can gain a deeper insight into the distribution of influence in the data or network. These measures can include the degree of betweenness centrality, the degree of closeness centrality, and the strength of agency, each reflecting a different aspect of influence and interaction within the network and providing a deeper understanding of the structure and internal dynamics of the system under study, contributing to a better understanding of the role of each variable in the overall context.

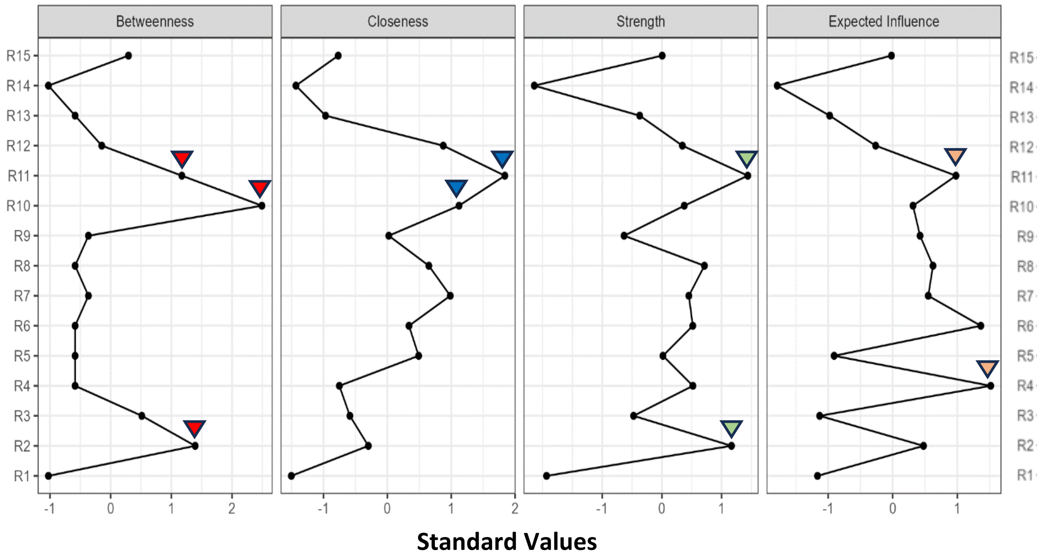
Table 5, which presents the centrality measures per variable, shows the elements with the highest betweenness centrality are R10, followed by R2 and R11. These nodes have the most role to active the rest nodes. The highest closeness nodes, namely R11 and R10, may possess a greater capacity to access information, communicate effectively, or exert influence within the network compared to other nodes. For the strongest nodes, it was R11, then R2 then R8, which means they have the strongest correlation . The expected influence within the network was greatest for elements R4, followed by R6 and R11. Figure 3 also illustrates these relationships visually.

Table 5: Centrality measures per variable

Variable	Betweenness	Closeness	Strength	Expected influence
R1	-1.027	-1.504	-1.932	-1.165
R2	1.393	-0.299	1.166	0.478
R3	0.513	-0.588	-0.474	-1.131
R4	-0.587	-0.753	0.519	1.518
R5	-0.587	0.489	0.018	-0.907
R6	-0.587	0.338	0.518	1.364
R7	-0.367	0.985	0.452	0.550
R8	-0.587	0.649	0.713	0.624
R9	-0.367	0.022	-0.633	0.423
R10	2.493	1.121	0.375	0.314
R11	1.173	1.839	1.439	0.979
R12	-0.147	0.875	0.344	-0.264
R13	-0.587	-0.969	-0.372	-0.976
R14	-1.027	-1.433	-2.137	-1.788
R15	0.293	-0.771	0.005	-0.019

In the following, Figure (3) presents those numbers graphetically in standard form.

Figure 3: Centrality measures of the neural network



Note: The centrality values and plots displays the standardized z-scores of all nodes for the three centrality measures: betweenness, closeness, and strength that are take values between -3 and 3.

4.3.1.2. Weights matrix

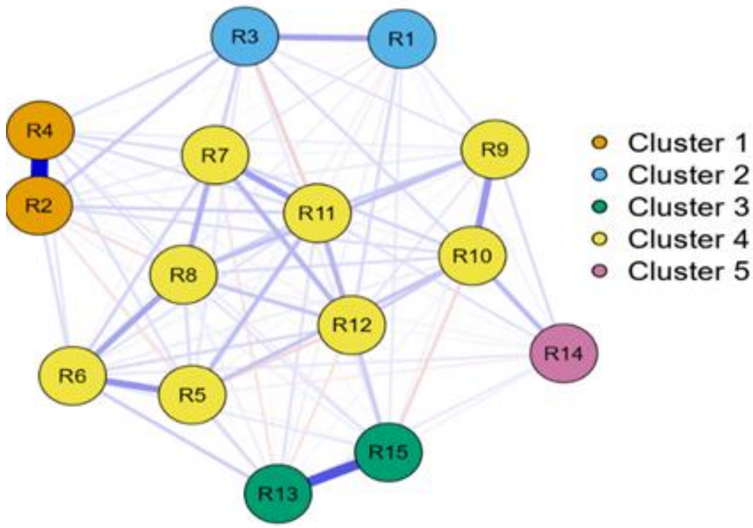
The weight matrix in neural networks assigns strengths to links between nodes, adjusted during training to enhance model performance. Based on the partial correlation between the variables in Table 6, which allows the actual relationship between two variables to be estimated without the influence of other variables, the relationships are generally weak, with the exception of R2, which is somewhat strongly related to R4, and R13 is somewhat strongly related to R15. Relying solely on the weight matrix is insufficient, as it reflects only one aspect of the network. Therefore, we used previously multiple tools like centrality measures to enhance, refine, and make the results more comprehensive. This approach will help ensure a more thorough and reliable analysis by combining various methods for the most correct result and the best mode. Based on these links, this network was proposed to represent the clusters of factors/causes affecting forgotten financial transfers and their association and proximity to each other. All nodes with strong correlations will be in the same cluster and maybe measure the same things.

Figure 4 shows the network of partial correlations depicted in Table 6, where the blue lines represent a positive correlation, the red lines a negative correlation and the thick lines a strong correlation, and the thinner the line, the weaker the relationship, whether negative or positive. If we see the row of R14 we can note all correlation approximately zero.

Table 6: Weights matrix

	Network nodes														
Variable	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**	**R15**
R1	**0.000**														
R2	0.012	**0.000**													
R3	0.194	0.108	**0.000**												
R4	0.012	**0.534**	0.080	**0.000**											
R5	0.025	-0.050	0.046	0.063	**0.000**										
R6	0.030	0.070	-0.020	0.050	0.223	**0.000**									
R7	0.045	0.043	0.088	0.076	-0.012	0.089	**0.000**								
R8	-0.004	-0.070	-0.042	0.058	0.070	0.184	0.162	**0.000**							
R9	0.057	0.042	0.056	0.037	0.012	0.024	0.019	0.127	**0.000**						
R10	-0.005	0.069	0.072	-0.004	0.120	0.038	0.088	0.072	0.213	**0.000**					
R11	-0.030	0.092	-0.093	0.071	0.133	0.058	0.199	0.084	0.104	-0.028	**0.000**				
R12	0.073	0.019	-0.013	0.028	-0.083	0.079	0.146	0.117	0.049	0.098	0.149	**0.000**			
R13	0.029	-0.049	-0.013	0.004	0.072	0.100	-0.054	0.036	-0.004	0.016	0.059	-0.055	**0.000**		
R14	0.024	-0.006	0.006	0.014	-0.038	0.051	-0.019	0.026	0.068	0.138	0.061	-0.020	0.045	**0.000**	
R15	0.044	0.030	0.041	0.037	-0.022	0.051	-0.013	0.054	0.026	-0.077	0.086	0.103	**0.356**	0.025	**0.000**

Figure 4: Partial link network



Through this network, we can point to five factors/dimensions:

- The first: Includes (R2 and R4), which relate to the change or loss of the recipient's cell phone.
- The second: It includes (R1 and R3) and is related to the lack of communication between the sender and the recipient.
- Third: It includes (R13, and R15) and is related to dealing with exchange offices and standardizing the exchange rate in these companies.
- Fourth: It includes (R5-R12), which relates to the postponement of receiving and traveling expenses, the existence of spelling or technical errors such as an equivalent transfer from other parties, and matters related to documentation and proof of sender or receiver.
- Fifth: it includes R14 and can be ignored as it is somewhat removed from the other factors. It is related to the recipient's desire not to have a third party, but to receive directly from the sender. It can also be considered as an orientation or aspiration of the respondent rather than a factor.

At this point, it is striking how similar the results of neural network analysis are to (EFA), although they do not fulfil some requirements such as moderation and data connectivity.

4.3.2. Reduction of the factors

If we reduce the factors to 4 instead of 5 by deleting R14 to isolate it from the remaining factors (Remember that, this factor was not saturated on any dimension in the exploratory factor analysis) and retrain the network, we obtain the results shown in Table 7.

Table 7: Centrality measures per variable after excluding R14

Variable	Betweenness	Closeness	Strength	Expected influence
R1	-0.808	-1.732	-1.742	-1.742
R2	0.190	-0.129	0.737	0.737
R3	-0.143	-1.509	-1.301	-1.301
R4	2.186	0.172	1.383	1.383
R5	-1.141	-0.036	-0.964	-0.964
R6	1.521	0.910	1.144	1.144
R7	-0.143	1.218	0.751	0.751
R8	-0.143	0.752	0.655	0.655
R9	-0.475	0.221	-0.039	-0.039
R10	-0.475	0.069	-0.217	-0.217
R11	1.188	1.553	1.061	1.061
R12	-1.141	0.521	0.013	0.013
R13	-0.808	-1.146	-1.137	-1.137
R15	0.190	-0.866	-0.344	-0.344

After deleting item number 14 and training the network again, we obtained a similar result as shown in Figure 5.

Figure 5: Partial correlation network after excluding item 14

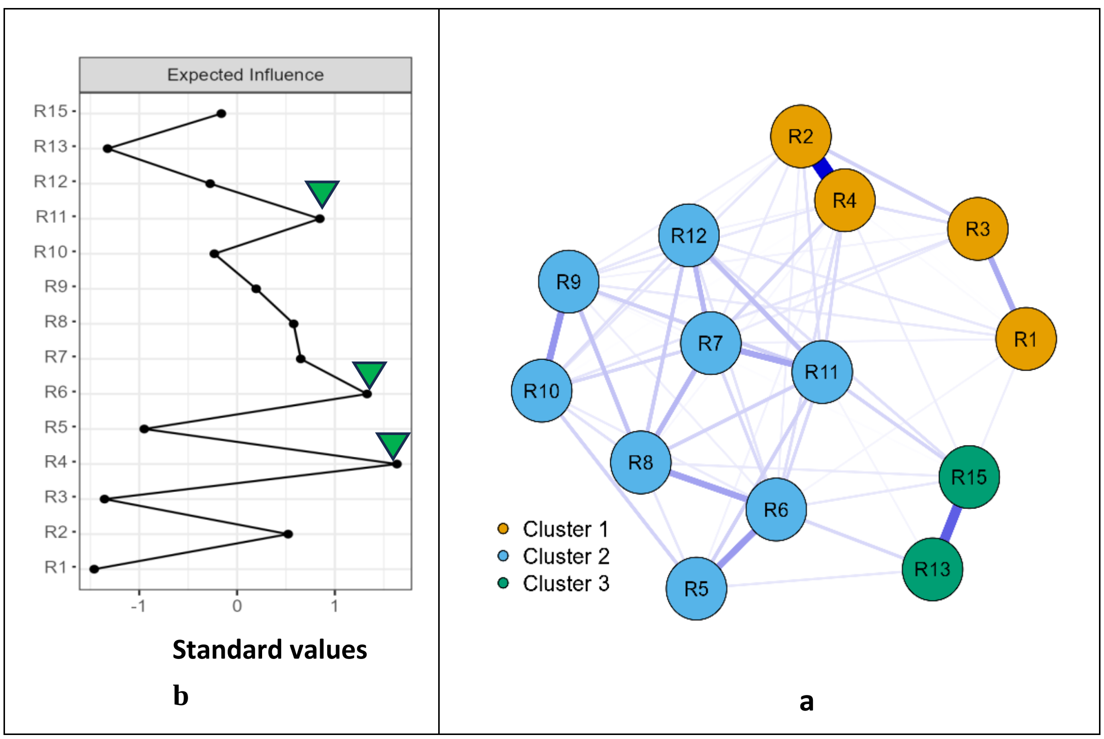


Figure 5 shows that the factors influencing FFR can be assigned to three dimensions/factors:

The first dimension (R1-R4): It can be summarized as “communication or access problems",” whether on the part of the sender or the recipient, or a deficiency that prevents this.

The second dimension (R5-R12): It can be summarized as financial, technical, evidential, or administrative obstacles.

The third dimension (R13, R15): Refers to the interaction and cooperation of exchange offices and the standardization of their exchange rates.

4.3.3. Independent variable importance

In order to check the relative importance of the factors (R5-R12) and the extent of their importance for factor R2 after deleting R14, we used the SPSS-26 program to obtain the results in Table 8 shows that all nodes introduce the same contribution, with the exception of R5, which predominates by a small percentage.

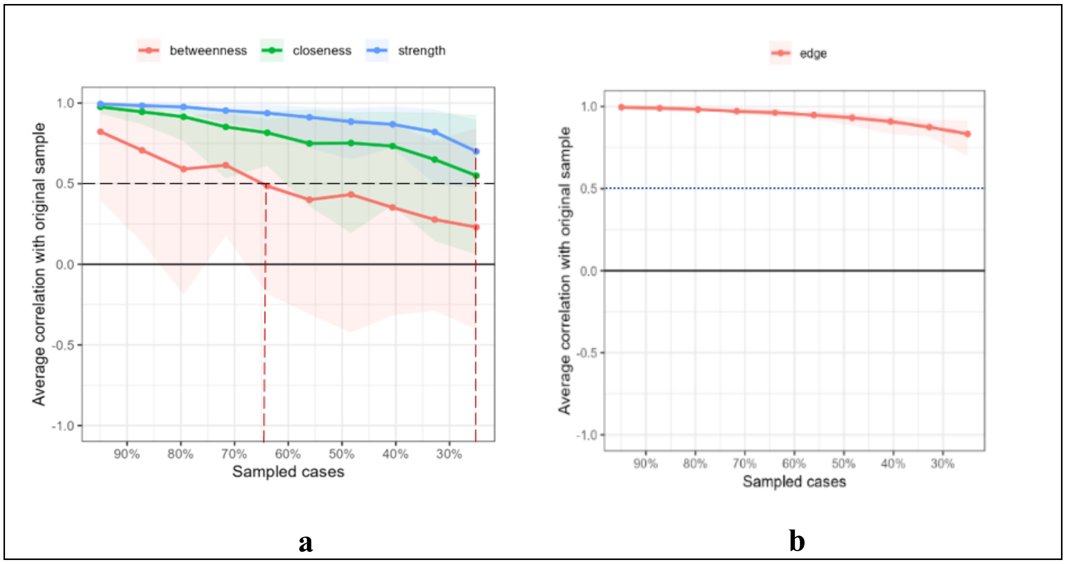
Table 8: Natural significance of the nods (R5-R12) after deletion of R15

Independent Variable Importance		
	Importance	Normalized Importance
R5	.129	100.0%
R6	.125	96.2%
R7	.124	95.9%
R8	.125	96.3%
R9	.124	96.0%
R10	.124	95.7%
R11	.125	96.5%
R12	.124	95.8%

4.4. Stability of results using Bootstrap network analysis

To support of other evidence for comparisons, and to enhance the depth and credibility of the analysis. In this section, we will employ Bootstrapping technique, a non-parametric method to assess the stability of results derived from a sample size of 931 individuals. The analysis involves generating 500 additional samples from the original random sample and measuring the results obtained from these samples. The results are presented in Figure 6 to demonstrate the stability of the conclusions we have reached.

Figure 6: Stability results in the original sample and subsamples in the bootstrap methodology



Results in Figure (6a) show the stability of the central measures of the network. According to this plot, we find that the results for both item closeness and strength stabilize at the level of the original sample for all samples that exceed 30% of the original sample. For the betweenness measure that is more affected by the sample size, stability is shown when the samples account for more than 64% of the original sample. Smaller samples do not show the same degree of stability in the analysis results. Figure (6b) shows the stability of the results for all samples whose size is more than 30 % of the original sample, i.e. all samples whose size is more than 280 individuals give us the same results. The red line represents the average correlation between the strength in the original sample and the subsamples (Wei et al., 2020) , which all show strong correlations of above 0.75 for all samples whose size is more than 30% (280 individuals) of the original sample, corroborating the results drawn from the original sample.

5. Conclusions and recommendations

5.1. Conclusions

Given the importance of financial transfers in promoting the economic development and well-being of many countries, especially developing countries such as the Republic of Yemen, this paper aims to analyze the factors that led to the emergence of forgotten financial transfers in Yemen, which plays a negative role on the country's economy and in companies trust. The article examines 15 possible causes of forgotten financial transfers, including logistical and economic characteristics of senders and recipients of transfers, as well as some specific characteristics of banks and exchange companies. The study involved 931 Yemeni respondents who experienced forgotten money transfers and were engaging with relevant exchange companies. Exploratory factor analysis has been applied even though some of its conditions are not met, then the neural networks analysis has been used mainly to identify and reduce the main reasons leading to the presence of forgotten financial transfers from among the 15 possible reasons initially proposed. The results showed firstly, great similarity with the results of the exploratory factor analysis and the results of the neural network analysis, secondly, The networks analysis has revealed three key dimensions leading to this problem. The first dimension involves communication or access problems between the sender and recipient. The second dimension involves logistical obstacles that hinder remittance flows, including technological, financial, administrative, and bureaucratic challenges. These barriers can be associated with the senders, recipients, or exchange companies. The final dimension is related to the operations of money exchange companies and the uniformity of their rates. To test the stability of the results, Bootstrapping technique has been utilized based on a random sample of size 500 observations from the original dataset. Thus, the results have demonstrated stability and reliability for all samples larger than 30% of the original sample size.

5.2. Recommendations

1. Governments and policymakers should establish and support a dedicated committee or ministry to address financial fraud issues, including those related to the problem under study. The tasks of such a committee could include accurate automated verification of sender and recipient details, implementation of a centrally coordinated messaging system, determining how long a remittance should be considered forgotten, and development of an application and website to facilitate tracking and monitoring of financial remittances These measures could work, supported by political oversight to reduce financial fraud incidents and address them proactively.
2. Policymakers must create stringent laws to safeguard citizens' money and solve this issue. Regulating the conditions around the issue and the parties engaged will improve transparency and access to quality service and fair financial transactions.
3. From a research point of view, we recommend adding a response variable or a dependent variable to the experimental design: Incorporating a response variable into experimental designs allows us to measure the effects of different variables independently or in combination with other variables on the response variable. This approach can help develop an optimal model to reduce the likelihood of forgetting financial transfers. Improve financial control systems. Governments must support oversight institutions (e.g. anti-corruption agencies, financial regulators) to allow independent operation and thereby integrity of financial operations.
4. Raising the salaries of bank and exchange office workers to the extent that makes them completely financially self-sufficient, which makes them more honest and able of preserving other people's money
5. Enhancing financial training and awareness: This recommendation suggests investing in training programs to educate citizens on the one hand and employees

on the other hand to improve the capabilities of financial regulatory bodies. Here comes the role of the government in directing the media to play an awareness role through programs, flashes, field campaigns, etc.

6. Conducting more research and studies: conducting more research to identify and studying the root causes of FFR, is very important issue. . Understanding those factors is crucial for implementing effective prevention measures. In this regard, governments and private institutions should support researchers financially and give them the time needed to conduct such research and overcome all difficulties.

List of Abbreviations	
Abbreviation	**Definition**
FFR	*Forgotten Financial Remittances*
DR	*Data Reduction*
EFA	*Exploratory factor analysis*
GDP	*Gross Domestic Product*
ARIMA	*Auto Regressive Integrated Moving Average*
CFA	*Confirmatory Factor Analysis*
NNA	*Neural network Analysis*
FNNs	*Feedforward Neural Networks*
RNNs	*Recurrent Neural Networks*
PC	*Principal component*

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