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Article

Topological components in a community currency network

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ABSTRACT

Transaction data from digital payment systems can be used to study economic processes in such detail that was not possible previously. Here, data from the Sarafu token network, a Community Inclusion Currency in Kenya, are analysed. During the Coronavirus Disease 2019 (COVID-19) emergency, Sarafu was distributed as part of a humanitarian aid project. In this work, the transactions are analysed using network science. A topological categorization is defined to identify cyclic and acyclic components. Furthermore, temporal aspects of the circulation that takes place within these components are considered. The significant presence of different types of strongly connected components compared to randomized null models shows the importance of cycles in this economic network. Especially, indicating their key role in currency recirculation. In some acyclic components, the most significant triad suggests the presence of a group of users collecting currency from accounts that are active only once, hinting at a possible misuse of the system. In some other acyclic components, small isolated groups of users were active only once, suggesting the presence of users only interested in trying the system out. The methods used in this article can answer specific questions related to user activities, currency design, and assessment of monetary interventions. The methodology provides a general quantitative tool to analyse the behaviour of users in a currency network.

KEYWORDS: directed networks; payment systems; community currency.

1. INTRODUCTION

The transactions in a payment system span a directed, weighted, temporal network, where the nodes are the subjects of the system and the timestamped directed weighted links correspond to those transactions. In this work, the transactions are temporally aggregated into weighted directed links to study the network topology. Nevertheless, some temporal aspects of circulation will be analysed by considering the time-stamped transactions.

This work focuses on the Sarafu token network, a digital community currency system used as a payment system in Kenya and organized by the non-profit organization Grassroots Economics [1]. Since the end of 2021, the Sarafu network has changed its structure and internal policies by also integrating a producer voucher credit system [2]. However, in this work, only data from the

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period when the Sarafu token network was used as part of an emergency cash transfer programme during the Coronavirus Disease 2019 (COVID-19) emergency are used [3]. This humanitarian aid campaign called *Community Inclusion Currency* was co-designed with the Kenyan Red Cross. A cash transfer programme is used in emergency contexts to transfer money or vouchers to people in need which allow them to buy goods and services. A *Community Inclusion Currency* is a specific type of local voucher system used for humanitarian cash transfer programmes, which can be used only in a predefined geographic region or within a local network of participants. In fact, it is argued that, once this local voucher is issued and its recirculation is bounded to a defined geographic area, it could also boost local development whenever the increase in demand for goods and services meets the unused productive capacity of the region [4]. However, a very limited number of quantitative studies analysed the effectiveness of local voucher systems in cash transfer programmes. Their effect on local economy is largely unexplored, but the digitization of voucher and currency systems opens new frontiers to this field of research.

Only in recent years has a limited number of studies attempted to assess the economic impact of digital community currency systems using network analysis. However, many aspects of the topology and the dynamics of payment systems are left to be explored. In this article, the topology of the network is analysed to investigate the usage of the currency. The currency network is studied by identifying cyclic and acyclic components and, therefore, also the recirculation in them. This technique can be used to distinguish users who interact with the system in different ways. For example, it is possible to identify users who were fully committed to using the system regularly by both buying and selling, and users who instead followed different strategies. In fact, users who do not engage as expected with the rest of the currency network are an important signal to be considered in assessing the system. Identifying these users and understanding their strategies is a vital aspect of the management of a currency system. Understanding user engagement is especially important in the assessment of *Community Inclusion Currency* systems, which are designed for cash transfer programmes. Finally, the methods developed in this article could also be extended for the evaluation of similar monetary interventions, whenever the transaction data are available in digital format.

A *Community Inclusion Currency* is a specific type of community currency system. A community currency system is a payment system that circulates in a limited geographic region in parallel to the official currency. In particular, a community currency is not enforced by the state but is based on agreements among members of the community [5–10]. Community currency systems have been explored as innovative methods for social and humanitarian interventions that could induce endogenous local development, empower local communities, and at the same time provide humanitarian aid [4, 7, 11–15]. Furthermore, their countercyclic (or macrostabilizer) effect may have an important role in enhancing the resilience of the local economy [12, 16–19].

Previous studies on digital community currencies used network science techniques for their characterization. One of the first studies focused on a convertible community currency Tomamaecho, which was active in Hokkaido for only 3 months [20]. Their findings confirmed that the transaction network was characterized by a power law decay of the degree distribution, dis-assortative behaviour, and a 'small world' feature. The authors found that the ratio of the exponents of in-degree to out-degree distributions decreases with the velocity of the currency. They also measure the *network centralization* [21] of the transaction graph defined as the 'ratio of the sum of actual difference between the degree centrality of the most central actor and that of all the other actors in the network and the theoretical maximum possible sum of differences in actor degree centrality' (from p. 282, note 15 [20]). One of their main findings is that network centralization is positively correlated with transaction volume. Regarding the Sarafu data used in this article, the power law decay and dis-assortative behaviour were already confirmed in a previous work [22]. In this work, the power law decay is only reported in the data description in Section 3 and the Supplementary Material (Document A, Section S4, Fig. S2 and Table S1).

In another work, network indicators were suggested to measure the performance of time banks [23]. A time banking system is a specific type of community currency system in which time is used as a unit of account and organized as a mutual credit group. In that work [23], two sets of performance indicators were applied to the case of Portland West Time Dollar Exchange in Portland, Maine. The first set reported the number of active members, new members joining each month, transaction volume, average transaction volume, and account balance per user. The second set reported the number of trading partners, the number of reciprocated links, the density of the ego networks, and the diversity of exchanged services. In particular, the second set of indicators aims at measuring reciprocity and resilience in such a time-based currency. Similarly, in this work, the identified topological components in the Sarafu network are analysed separately by looking at some network metrics that can be used to characterize their flow: number of weakly connected components (WCCs), number of nodes, number of directed links, number of transactions, and volume.

In another paper, network analysis was mainly focused on detecting central players and identifying a rich-club of prominent users in the RozLEŤSe system active in Brno, Czech Republic [24]. The identification of a rich-club was then used to study the resilience of the economic network by implementing a stress test using an experiment in which users have been removed from the system. A more recent work analysed a basic income community currency located in Berlin, called Circles UBI [25]. In that paper, the authors split the network into two periods by calculating the characteristic time through the causal fidelity index and studied how the structure of the network changed over time in terms of coreness and prominent users. In this work, the Sarafu data are temporally aggregated into a weighted directed network to study its topology. The identification of key players is not considered in this work. The purpose of this work is to identify groups of users who interact with the system in different ways.

Other works focused on the Sardex network, a business-to-business mutual credit system operating in Sardinia, Italy. In the most recent [26], the connectivity of the network is analysed over time by looking at the average directed path length, average degree, diameter, clustering coefficient, and average degree centrality. The authors concluded that the connectivity of the network increased with time. In another work on the Sardex network [27], it was found that a statistically significant presence of directed cyclic motifs is beneficial for that payment system. Moreover, they define prominent nodes based on their participation in directed cycles. The findings suggest that the most prominent nodes in fact have a better performance over time. However, their analysis is focused only on static directed simple cycles of lengths 2, 3, 4, and 5. Inspired by the importance of cycle motifs in a currency network, in this work, the functional role of cyclic components is explored (Section 4.1). In fact, a cyclic component can include many cycles of different lengths. Every node in a cyclic component can belong to many different cycles of different lengths, from cycles of length 2 to cycles with a length equal to the size of the component itself. In this work, the comparison between the cyclic and acyclic components is then carried out to show important behavioural differences between their users.

A recent work analysed the transaction network of a mutual credit system (Hanbat LETS) in Korea as a multiplex network [28]. The authors wanted to characterize the emergence of social capital through three main types of connections: bonding, bridging, and linking. In particular, they could distinguish by economic transactions, share of used goods, and provision of support. According to the authors, *bonding* can be related to dyadic reciprocity (i.e. cycles of length 2) and transitive closure (i.e. cycles of length 3). On the other hand, *bridging* can be related to formation of k-out-star and k-in-star. And finally, *linking* can be related to degree assortativity. In terms of the *bonding* process, the authors found that while transitive closure is significant in the transaction network, dyadic reciprocity is significant only from a multiplex perspective. In terms of *bridging* process, degree assortativity is significant at both the transactional and multiplex levels. The results suggest that different relational dimensions could complement each other and, therefore, a multiplex approach is advised in assessing the socioeconomic impact of similar projects. In another work [29, 30], the authors try to assess the socioeconomic impact of a disaster response emergency community currency in Japan. To do so, they try to estimate how the social network grows according to the individual perception of community resilience. The authors detected a disassortative mixing based on the heterogeneous perception of community resilience, the absence of homophily, and a high level of clustering. In other words, people who were positive about the resilience of the community played a key role in the formation of social networks. In this work, only the transaction network is analysed, and only from its economic interpretations. However, it may not be completely excluded that studies on topology and currency recirculation can also have implications for the literature on social capital and community resilience.

A triadic census analysis was also recently performed in the Sarafu token network, comparing it with two other decentralized socioeconomic networks, the NFT (Non-Fungible Tokens) market and Steemit ([31]). The authors analyse directed triads from a static and dynamic perspectives. As expected, dyadic reciprocity is higher in Sarafu (i.e. cycles of length 2), which also has a larger strongly connected component (SCC) and less chain-like structures than other online social networks. In particular, most of the open and closed triads that include a reciprocal dyad are significant. This is probably due to the fact that group accounts are included in the data, which are run by *Chamas* (i.e. rotating savings and credit groups). Finally, the authors report interesting statistics on the dynamics of the triadic closure process: on average, there are 283 new links per day and a peak-day of 1370; on average, there are also 540 closing triads per day with a peak-day of 7328; and finally, on average, there is a triad/link ratio of 1.73 and a peak of 15. The triad/link ratio started to grow in July 2020 with a peak in January 2021, and decreased after that. Finally, 23% of the closures happen in less than a day and 89% in <3 months. These results are an important starting point for the analyses carried out in this work. First, group accounts are excluded in this work because the focus is on economic processes and not on financial processes. In fact, dyadic reciprocity between groups and individuals can be easily confused by borrower-lender transactions. Second, a static triadic census analysis is considered only for acyclic components to detect anomalies in the economic behaviour of agents excluded from trading cycles.

Another recent quantitative study on the Sarafu network focused on an inverse estimation of transfer velocity and effective balance [32]. In their work, the inverse estimation of the transfer velocity is defined as the average holding time of the received funds and calculated on a 'first-in first-out' basis [33]. Its findings suggest a high level of geographic and temporal heterogeneity in the usage of the currency. In particular, transfer velocity and effective balance generally had a sharp increase in the first half of 2020, but with some variations between urban and rural areas. Another study on the Sarafu network analysed some aspects of currency circulation [22]. In particular, in that work, the Sarafu network appears to be characterized by three main factors: geographic localization, cycle motifs (of length 2, 3, 4, and 5), and structural correlations. Moreover, the authors detected key players using PageRank centrality: savings groups and faith leaders seem to play a key role in the circulation of Sarafu. In another work, the cooperative behaviour of savings groups is analysed over time using Sankey diagrams [34, 35]. In that work, the network was split into different periods according to the application of restrictions due to the emergency of COVID-19. The authors observed that the role of savings groups increased, especially when the strictest COVID-19 restrictions were implemented. The percentage of transactions from group accounts to users increased from 8% to 25%, the sectors of *food* and *shop* gained importance during the same period and finally, the geographical heterogeneity increased in terms of spending behaviour.

Unlike, those previous works on the Sarafu token network, in this article, only the transactions among users are considered (i.e. group accounts are excluded). Instead of considering the velocity of circulation [32], the recirculation time is defined and calculated (Section 2.2). Furthermore, like the other aforementioned works [22, 34, 35], the analysis of circulation is made on a temporally aggregated network of the whole period. Moreover, in this work, three aspects are analysed for each topological component to identify different usage strategies (Section 2.1): users who made only one operation (Section 4.2), three-node motifs in acyclic components (Section 4.3), and recirculation time (Section 4.4). This is the main difference from previous works that focused on the activity of user and group accounts at the network level [22, 34, 35]. Finally, instead of focusing on cycle motifs (of lengths 2, 3, 4, and 5) as in previous work on Sarafu data [22], in this work, cyclic components are considered. As explained above, each cyclic component is defined here as an SCC, where every node can be involved in one or more cycles of different lengths.

From a theoretical point of view, the relation between topology and dynamics in economic and financial networks has already been suggested. In network game theory, degree centrality and sparseness of the network have been shown to be the main causes of inequality, keeping all other conditions fixed [36]. In an agent-based model simulation, nodes with a high level of betweenness centrality on specific trading paths imposed a *mark-up* on their transactions, and therefore affecting the formation of prices throughout the network [37]. In a recent theoretical discussion paper [38], the authors suggested that the presence of directed cycles in a payment system may be theoretically linked to a redistribution of economic power in it, where economic power is defined by degree and betweenness centrality. Cycle detection is used to reduce the need for liquidity in a payment system [39, 40]. This operation called 'cycle clearing' is one of the 'netting' techniques (or 'net settlement') used in the management of payment systems [41–48]. The same technique was also used to calculate the synergistic effect in an economic network [49]. In summary, the role of cycles in payment systems has been increasingly recognized for its structural functionality. For this reason, this work compares behavioural aspects related to users in cyclic and acyclic components. The findings suggest indeed that participation (or not) in cycles corresponds to different user strategies. In general, a user which is part of a directed a cycle is both buying and selling. This signals a full engagement with the economic network.

In conclusion, the main contributions of this work can be summarized as follows. First, a topological categorization for directed networks specifically related to payment systems is suggested (Section 4.1). In fact, categorization of cyclic and acyclic components can help identify some behavioural dynamics that were not seen in previous work on the structure of directed networks [50–53]. In fact, the presence of cycles in a payment system was already related to its performance in a previous work [27], while in this work, the user behaviour is successfully analysed by using a different but related topological categorization. Secondly, the effect of cycles in a payment system is studied without any arbitrary limit on their size. Previous studies on cycles in payment systems focused on the detection of cycles up to 5 [22, 27], but in this work, the integrity of the cyclic components is analysed. This means that each cyclic component can have cycles from size 2 to a size equal to the length of that component itself. Third, temporal aspects of circulation are analysed using different tools, which can help identify specific behavioural dynamics. For example, instead of focusing on estimating the transfer velocity of the system [32], in this work, the circulation is studied by categorizing each recirculation operation and classifying users according to it (Section 4.4). In addition, users who used the system only once can signal important aspects of currency circulation (Section 4.2). In the knowledge of the author, this approach has never been considered before to analyse currency networks.

Finally, this work is focused on studying the circulation in the economic network, while previous works also considered the financial network (e.g. borrowing, lending) of savings groups [22, 32], or exclusively their financial operations [35]. Beyond abstract monetary exchange for financial purposes, the analysis of pure economic exchange can reveal information about the flow of real goods and services. Moreover, in the period considered, while the creation of group accounts was somehow supervised by system administrators, the creation of user accounts was not. This means that single users could strategize around the creation of new accounts to obtain some benefit (Section 5). This is one of the key aspects behind the research questions tackled in this article. In fact, the main research questions unfolded throughout the article are listed below.

1. **RQ1**. *What are the most relevant topological components in the currency network?* A topological categorization is presented to uniquely assign nodes and edges to components based on their systemic functionalities.
2. **RQ2**. *How does circulation of currency differ among these topological components?* After having defined these topological components, their temporal behaviour is analysed. In particular, the recirculation of currency and its speed are analysed, along with one-time usage.
3. **RQ3**. *Is there a relationship between human behaviour and the topological components observed in the currency network?* Topological and circulation analyses can help identify different levels

of user engagement. For example, the significance of certain triads in some topological components can be related to specific behavioural strategies.

One of the main findings of this article is that the identified topological categories are shown to be relevant for the study of a payment system (Section 4.1). Some of those topological categories can be related to different user strategies. In fact, the temporal behaviour of users within these components reveals different types and levels of participation within the economic network (Sections 4.2 and 4.4). Moreover, the significance of some types of triads in acyclic components can confirm the existence of particular strategies (Section 4.3). The existence of these strategies also matches the findings of a recent qualitative study [54] (Section 5). Another important finding is about the relevance of cycle analysis. In fact, according to recent studies on the role of cycles in payment systems [22, 27], also in this work, the cyclic components are also found to be relevant for the circulation of currency. Finally, similarly to a previous study on savings groups in the Sarafu network [34, 35], it is possible to conclude that the Sarafu token network generally succeeded in engaging the majority of its users within its economic network.

The structure of the article is described below. In the next Section 2, the topological categorization adopted in this article is presented, also in relation to existing techniques. In Section 3, the data are described by providing also geographic and economic information about the transaction network. In Section 4, the topological and temporal analyses are presented (RQ1 and RQ2 are answered). In particular, in Section 4.1, the network is analysed in its predefined topological components providing information about their statistical significance. In Section 4.2, users who used the system only once are considered in relation to those topological components. In Section 4.3, the acyclic components are analysed using a triadic census. In Section 4.4, users are assigned to different temporal categories according to their speed of recirculation. Finally, in Section 5, the results are interpreted to describe possible user strategies, which are also reported in previous qualitative works (RQ3 is answered).

2. BACKGROUND

2.1. Network topology

The topological categorization of cyclic components, acyclic components, and single nodes is used in this work for behavioural investigations on the economic network. Previous studies have already analysed the inner structure of directed networks [50–53]. According to the existing literature, directed networks are generally characterized by a *bow-tie* structure with a largest *SCC* as the core, where nodes are mutually reachable from each other, a set of nodes which are only sending to the *SCC*, called *IN*-component, and a set of nodes which are only receiving from the *SCC*, called *OUT* component. Attached to the *IN*- and *OUT*-components, there are *tendrils* which can be either sets of nodes that (i) can be reached only from the *IN*-component, or (ii) sets of nodes which do not belong to the *SCC* but can reach nodes of the *OUT*-component. Other groups of nodes, called *tubes*, connect the *IN*-component with the *OUT*-component without passing through the *SCC*. Finally, isolated groups of nodes are just described as *disconnected* components. The *bow-tie* description was successfully applied to study the structure of directed graphs. In particular, it can be used to study some of their properties, such as their expected size, degree distributions, and resilience to random failures and targeted attacks [52, 55]. A subsequent work on the web graph reviewed the *bow-tie* structure suggesting a *daisy* shape, where the *IN*- and *OUT*- components are highly fragmented into many *petals*, which are chains of nodes connected with the same component of origin [51]. Finally, a more advanced version of the *bow-tie* [53] was recently introduced where *tendrils* and *tubes* are categorized based on their distance from the *IN*- and *OUT*- components. The results of these works also have important implications for the study of the resilience of directed networks. However, in this work, the main focus is on currency recirculation. For this reason, the entire topological categorization is based on the relation between cyclic components and other acyclic

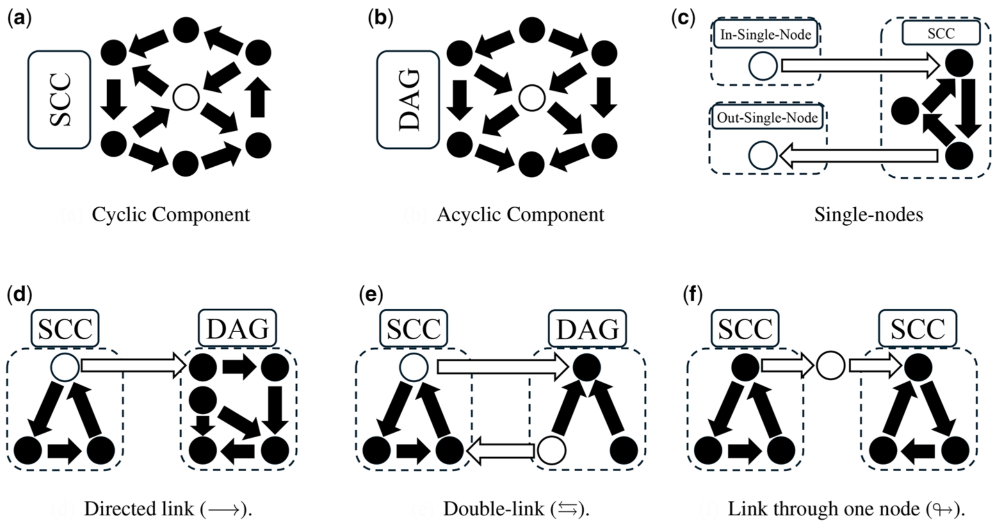


Figure 1. Objects and relations for the topological categorization. In figures (a–c), the considered objects are represented. In figures (d–f), the considered relations are represented.
Alt text: Illustration of objects and relations considered for the topological categorization. Cyclic component and SCC are used as synonyms. Acyclic component and DAG are used as synonym. Single-nodes are nodes that only either send or receive from an SCC. A first type of relation between an SCC and a DAG is an arrow from an SCC to a DAG, i.e. directed link. A second type of relation between an SCC and a DAG are two links in opposite direction, i.e. double-link. Finally, two SCCs can be linked through a node, i.e. link through a node.

components. The bow-tie categorization typically ignores this aspect which is fundamental for the study of transaction networks.

Contrary to the *bow-tie* description, the *core*, *IN*- and *OUT*- components, and relative connections are not considered in this work. Instead, the differentiation between cyclic and acyclic components is the key aspect considered here. A cyclic component is a portion of the network structured as an SCC, whereas an acyclic component is a portion of the network structured as a directed acyclic graph (DAG). To understand the difference between cyclic and acyclic components consider the Fig. 1a and b. In Fig. 1b, the white node in the centre of a DAG can move and leave its position but cannot return to it following the direction of the arrows. On the other hand, in Fig. 1a, the white node in the centre of an SCC can move and leave its position and return to it by following at least four different directed *paths* which do not cross the same node twice. These directed paths identify directed simple *cycles*, because they start and end at the same white node position. For this reason, in this article, the cyclic component and the SCC are used as synonyms. Similarly, the acyclic component and DAG are also used as synonyms. Since only cyclic and acyclic components are identified, their connectivity with the rest of the network characterizes the categorization procedure adopted in this article. In Table 1, the directed network is split into 14 different components: 11 including nodes and edges, plus 3 including only edges (see Table 1 for definitions). This is a comprehensive categorization which uniquely assigns each node and edge into one and only one of those categories, and therefore, one and only one related network component.

The logic of this categorization is explained in Figs 1–3. In Fig. 1, the objects and the relations among them are defined. The objects can be either a cyclic component (SCC, ⭮) (Fig. 1a), an acyclic component (DAG, ⟨↕⟩) (Fig. 1b), or a single-node (◯) (Fig. 1c). Every pair of objects can have three types of relation with each other. Please note that each relation considered here between each pair of objects cannot change the nature of the object itself. For instance, a cyclic component

Table 1. Description of topological categories for edges and nodes[a]

Node	Edge	Definition
sccTmix	=	SCC sending to and receiving from a DAG, an in-single-node, and/or an out-single-node.
sccTin	=	SCC receiving from a DAG or an in-single-node.
sccTout	=	SCC sending to a DAG or an out-single-node.
scc0	=	SCC not connected neither with a DAG, an in-single-node, nor an out-single-node.
dagTmix	=	DAG sending to and receiving from an SCC.
dagTin	=	DAG sending to an SCC.
dagTout	=	DAG receiving from an SCC.
dag0	=	Isolated DAG.
out-single-node	=	Single-node receiving from an SCC.
in-single-node	=	Single-node sending to an SCC.
bridge_scc	=	Single-node connecting two or more SCCs.
–	edge_dag2scc	Link from a DAG to an SCC.
–	edge_scc2dag	Link from an SCC to a DAG.
–	edge_scc2scc	Link connecting two SCCs.

[a] *SCC* is used as the abbreviation for a strongly connected component. *DAG* is used as the abbreviation of the directed acyclic component. Note that *edge_dag2scc*, *edge_scc2dag*, and *edge_scc2scc* do not have a corresponding node because their nodes are already assigned to different components. For example, one *edge_scc2dag* is made of one sender in an *SCC* and one receiver in a DAG. Similarly, *bridge_scc* is only one single-node that receives from one SCC and sends to another SCC. However, if there is a chain of nodes where the first node receives from an SCC and sends to another SCC through its last node, this is considered as *dagTmix*.

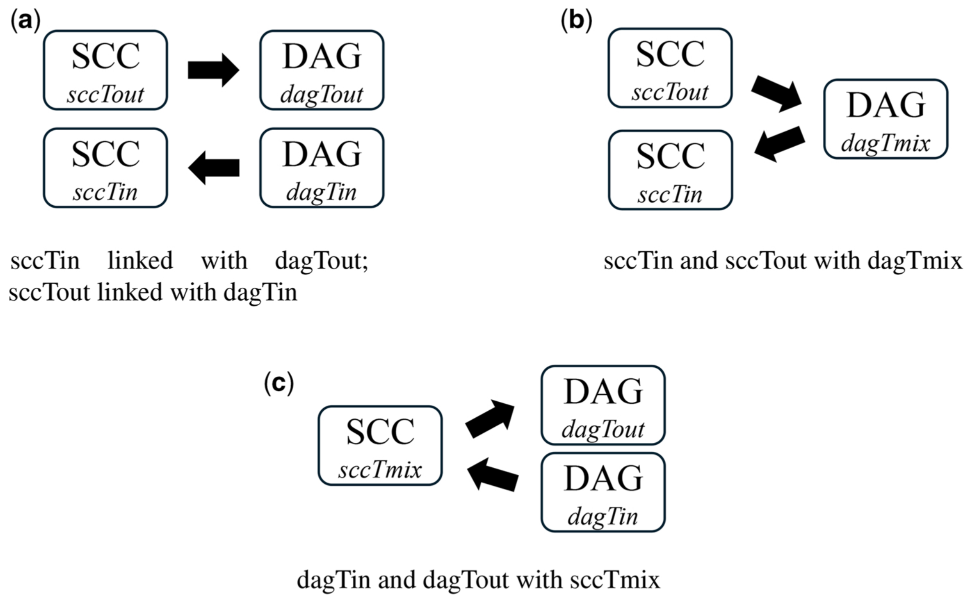


Figure 2. Categorization of SCCs and DAGs based on their connections. The arrow indicates a direct link between two components. On the top of figure (a), an arrow links from an SCC to a DAG symbolizing an *edge_scc2dag*. On the bottom of figure (a), an arrow links from a DAG to an SCC symbolizing an *edge_dag2scc*. In figure (b and c), both an *edge_scc2dag* and an *edge_dag2scc* are present.
Alt text: Illustration comparing different types of categorization of SCCs and DAGs based on their connections. If an SCC is receiving from another DAG, this connection identifies an sccTout and a dagTout. If a DAG is both receiving from and giving to more SCCs, then it identified as a dagTmix. If an SCC is both receiving from and giving to one or more DAGs, it is identified as an sccTmix.

cannot become an acyclic component by adding any of the relations considered between them. The first type of relation considered here is a directed link ($\longrightarrow$) from one object to another (Fig. 1d). A directed link corresponds to one or more transactions (flow of currency) from one object to another following the direction of that link. The second type of relation ($\leftrightarrows$) is a connection between two objects which includes links in the opposite direction, but without creating a cycle which involves nodes from both objects. This type of relation is illustrated in Fig. 1e, where it is possible to imagine that the white nodes can move and jump into the opposite component following their white arrows but eventually cannot return to their original position following the direction of the arrows. Obviously, this also implies that any two nodes from two different components cannot exchange back and forth; otherwise, they would create a cycle of length 2. Finally, a third type of relation is a connection between two components that involves one node only ($\looparrowright$). In other words, one node is receiving from one component and sending to another component (see Fig. 1f). For the last case, note the difference between Fig. 1c–f. In Fig. 1d, one node connects an SCC to a DAG (i.e. a chain of nodes is part of the DAG); in Fig. 1f, one node receives from one SCC and sends to another; finally, in Fig. 1c, a node is sending or receiving from an SCC. Obviously, a single-node sending to or receiving from another node in a DAG is part of that DAG itself. Similarly, a single-node sending or receiving from another single node is a pair which constitutes a DAG. The categorization procedure is explained in further detail in Fig. 3. In Fig. 2, the directed links between SCC and DAG components are illustrated.

In the previous paragraph, objects and relations for the topological categorization were introduced. In this paragraph, each object is categorized based on its relation to another object. In Fig. 3, the logic of this categorization is explained by showing eight simple cases, where there are only two

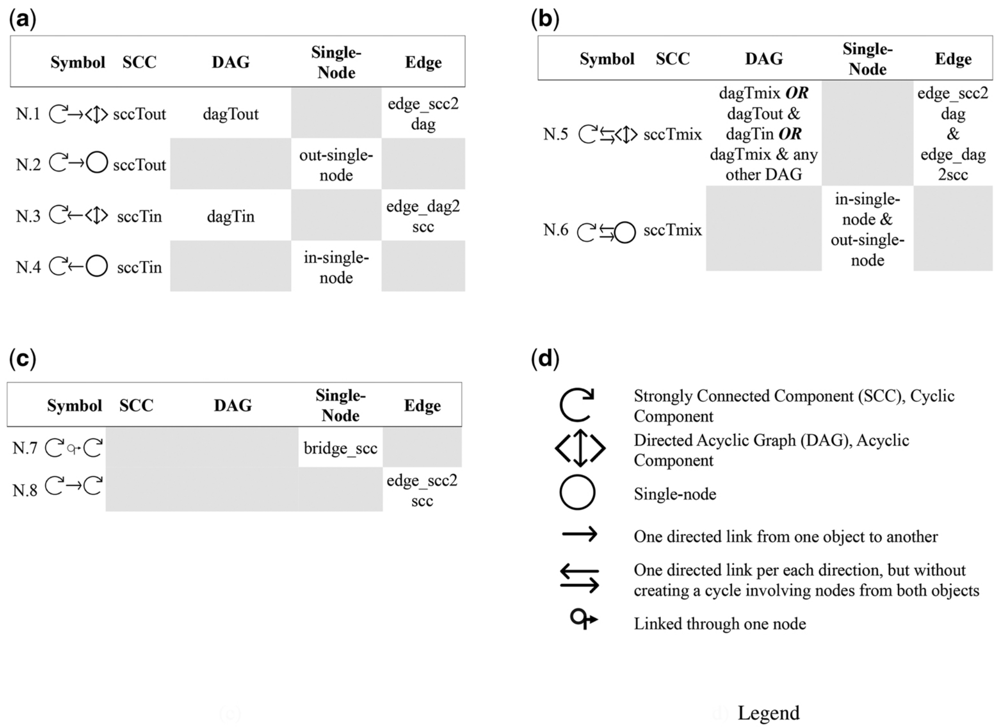


Figure 3. Label per each topological component. The logic of this categorization procedure is explained by showing eight cases in figures (a–c). In each case, there are only two objects in relation to each other. The objects can be either a cyclic component (SCC, ↻), an acyclic component (DAG, ⟨↕⟩), or a single-node (◯). Each pair of objects can have three types of relation exclusively. The first type of relation is a directed link (⟶) from one object to another. The second type of relation (⇆) is a connection which includes links in opposite direction between two objects (without creating a cycle). The third type of relation is a connection between two objects which involves one node only, which is receiving from one component and sending to another one (↬). In reality, there is often a combination of these eight cases represented above. For example, a strongly connected component can receive from a DAG and send to a single-node, and therefore, being identified as a *sccTmix*. Finally, consider also that a *bridge_scc* is a node receiving from an SCC and sending to another SCC, a behaviour which is described by the relation ↬. As already mentioned, it is important to point out that a single-node sending to or receiving from another node in a DAG is part of that DAG itself, and one single-node sending or receiving from another single-node is a pair which constitutes a DAG.

Alt text: The logic of this categorization procedure is explained by showing eight cases. The objects can be either a cyclic component (SCC), an acyclic component (DAG), or a single-node. Each pair of objects can have three types of relation exclusively. The first type of relation is a directed link from one object to another. The second type of relation is a connection which includes links in opposite direction between two objects (without creating a cycle). The third type of relation is a connection between two objects which involves one node only, which is receiving from one component and sending to another one. These eight cases identify all the categories described in Table 1.

objects in relation to each other. First, four types of cyclic components are defined: *sccTin*, *sccTout*, *sccTmix*, and *scc0*. Although *scc0* is simply an SCC only connected to other SCCs or isolated, the other categories can emerge in one of the cases represented in Fig. 3a and b (see also 2). A *sccTout* component emerges if an SCC sends to a DAG or single-node (N.1 and N.2, Fig. 3a; see also the top of Fig. 2a). A *sccTin* component emerges if an SCC receives from a DAG or single-node (N.3 and

N.4, Fig. 3a; see also the bottom of Fig. 2a). A *sccTmix* component emerges if an SCC sends to and receives from a DAG and/or a single-node (N.5 and N.6, Fig. 3b; see also Fig. 2c).

Secondly, the typology for the acyclic components is also categorized as: *dagTin*, *dagTout*, *dagTmix*, and *dag0*. In this case, *dag0* is an isolated acyclic component, while the other categories can also emerge in one of the cases represented in Fig. 3a and b. A *dagTout* component emerges if a DAG receives from an SCC (N.1, Fig. 3a; see also Fig. 2a and c). A *dagTin* component emerges if a DAG sends to an SCC (N.3, Fig. 3a; see also Fig. 2a and c). A *dagTmix* component emerges if a DAG sends to and receives from an SCC (N.5, Fig. 3b; see also Fig. 2b), obviously without creating a cycle with it (or them).

The edges between SCC and DAG are considered as a separate category: from cyclic component to an acyclic component (*edge_scc2dag* in N.1 and N.5 in Fig. 3a and b) and from an acyclic component to a cyclic component (*edge_dag2scc* in N.3 and N.5 in Fig. 3a and b). See also the cases represented in Fig. 2. Similarly, the edges between different SCCs (*edge_scc2scc*) are also considered separately (N.8 in Fig. 3c).

Splitting a directed network only into cyclic and acyclic components (and link between them) is not sufficient to identify a comprehensive and unique categorization for each node and edge in the network. Indeed, the inclusion of single-nodes should complete its description. A single-node receiving from one SCC and sending to another SCC is called *bridge_scc* (N.7 in Figs 1f and 3). A single-node only sending to SCCs is called *in-single-node* (N.4 in Figs 1c and 3). A single-node receiving only from SCCs is called *out-single node* (N.2 in Figs 1c and 3). Any connection to a DAG would categorize the single-node as a part of that DAG itself. A single-node connected to another single-node with only one directed link obviously creates a DAG. In Table 3, an analytical description of these categories is reported. Since each category corresponds to a uniquely identified network component, the sum of the volume of each component corresponds to the total volume of the network. For this reason, it is possible to conclude that this topological categorization completely and successfully describes the whole network under examination. However, future studies may find a better way to improve this technique and adapt it to different contexts and purposes.

2.2. Recirculation

In this article, the characterization of the dynamics of the network is carried out by using the recirculation time. The velocity of circulation transfer was used in a recent work to describe the circulation of Sarafu using these data [32]. In that work, the authors were interested in the time between one incoming operation and the first outgoing operation ('first-in, first-out' [33]), and then averaging this quantity to define the 'holding time' per each user. The authors then analyse the 'holding time' in relation to business sectors and geographic areas. As described in Fig. 4, the recirculation time is here measured as the time difference between the first of all the incoming operations and the last of all the outgoing operations before another incoming operation arrives. Moreover, the recirculation time is not aggregated (or averaged) per user. Indeed, each individual is assigned to one or more temporal categories, according to the speed of their recirculation operations (Section 4.4). Instead of focusing on circulation in business sectors and geographic areas, the recirculation time is then analysed in relation to these predefined topological categories.

The speed of recirculation is therefore defined as the time difference between the first incoming operation (at time t in Fig. 4) and the last outgoing operation (at time $t + 3$ in Fig. 4). In the example of Fig. 4, the speed is equal to 3. This value is then used to categorize recirculating operations from low to high speed. The distribution of recirculation speed is left-skewed, because most of the recirculating operations (or recirculations) occur in a very short time. The distribution of recirculation speed per each operation is first ordered in ascending order, then its quartiles are detected. The operations are therefore divided into four sets based on the quartiles of the speed distribution.

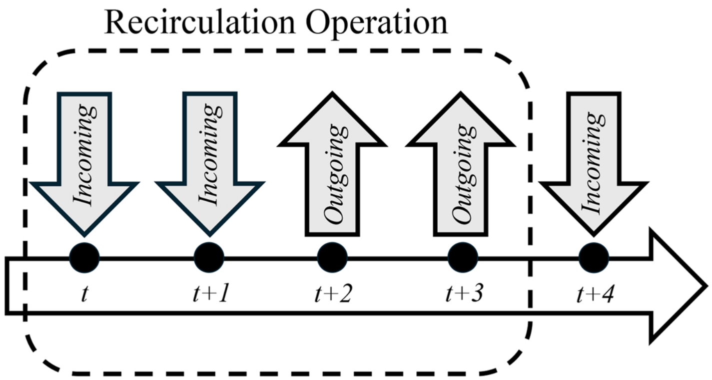


Figure 4. Illustration of a recirculation operation as defined in this article. One recirculation operation includes many incoming and outgoing operations. The node in the figure receives two incoming transactions at time *t* and *t* + *1*. After that, it sends currency twice at *t* + *2* and *t* + *3*. At *t* + *4*, it receives again some currency, so the recirculation operation closes.
Alt text: Illustration of a recirculation operation. The figure illustrates a timeline of transactions which involved a node N, from time t until time t+4. The node N is receiving two incoming transactions, at time t and t+1. At time t+2 and t+3, the Node N is making two outgoing transactions. At t+4, the Node N again receives an incoming transaction, and therefore, the recirculation operation closes. In this case, the recirculation operation only includes the two incoming transactions (at time t and t+1) and the two outgoing transactions (at time t+2 and t+3).

The acronym *HS* stands for *high speed*. The acronym *LS* stands for *low speed*. The suffices *Q1*, *Q2*, and *Q3* indicate the interquartile ranges considered in each category. Q1 for operations in the first quarter of the distribution (interquartile range 0–25%). Q2 for operations in the second quarter (interquartile range 25–50%). *High speed* Q3 (HSQ3) for operations in the third quarter (interquartile range 50–75%). And finally, *low speed* Q3 (LS3) for operations in the last quarter of the distribution (interquartile range >75%).

3. DATA

The data used in this work are time-stamped transactions from the Sarafu system in Kenya between 25 January 2020 and 15 June 2021 [3]. More user information is available in the data: geographical location, business sector, and gender. In this period, the currency was used as part of a COVID-19 disaster response intervention in the Mukuru kwa Njenga slum, Nairobi, and Kisauni, Mombasa, in collaboration with the Kenyan Red Cross [1]. The Sarafu token was used as a cash transfer programme in local vouchers. This means that each user could spend the Sarafu token only in local businesses. Furthermore, local businesses could reuse the Sarafu token among each other, as long as everyone had joined the network. For a limited period of time, some donors supported the initial fund, so cash withdrawal in Kenyan Shillings was limited for that short time to users and vendors through savings groups (or *Chamas*), under certain conditions.

It is also important to mention that since 2017 the Kinango area (Kwale county) has been targeted by Grassroots Economics for specific development interventions: donations have been collected to build community-owned assets with the purpose of enhancing community socioeconomic resilience (e.g. maize milling, refrigeration, water storage equipment, etc.) [1]. In fact, in the data, Kinango, Mukuru kwa Njenga slum, and Kisauni are the most active geographic areas. However, about 86% of the users come from one of these treated areas, so any comparison with the untreated areas would be unbalanced.

Chamas, informal cooperative groups common in East Africa, are used to pool and invest savings. They play a significant role in the Sarafu network [1, 22, 34, 35, 56]. In the data, they are identifiable

Table 2. Split of recirculation time distribution along quartiles[a]

Recirc.	From	To	Mode	
HSQ1	$\sim$ 1 s	19.0 min, 39.0 s	104 s (158 times)	0–25%
HSQ2	19.0 min, 40.0 s	10.0 h, 3.0 min	28 min, 20 s (12 times)	25–50%
HSQ3	10.0 h, 3.0 min	1.0 day, 21.0 h	(6 times) (6 times)	50–75%
LS3	1.0 day, 21.0 h	50.0 weeks, 6.0 days	1 day, 22 h (3 times)	75–100%

[a]The time of recirculation shows a tendency to recirculate within a day. In fact, 75% of recirculations are happening before 1 day and 21.0 h (Q3).

as *group accounts* (formal savings group) or *savings* business accounts (informal savings groups) but are excluded in the analyses carried out in this article. In fact, this article is only focused on user accounts because the main objective is to identify an individual strategy for engaging with the Sarafu economic network.

The resulting transaction network contains 39 433 users, 360 117 transactions, and a total volume of 182 605 612.73 Sarafu (in parity with Kenyan Shillings). In this network of individual users, 28 709 009.6 Sarafu were distributed mainly to new members and to reward existing members (see Section 5 for details). The users are grouped into 10 main geographic areas: Kilifi, Kinango (Kwale County), Kisauni (Mombasa County), Mombasa, Nairobi, Rural Counties, Mukuru (Nairobi County), Nyanza County, Turkana County, and other/unknown. See Supplementary Material (Document A, Section S4) for further information on geographic areas and business sectors.

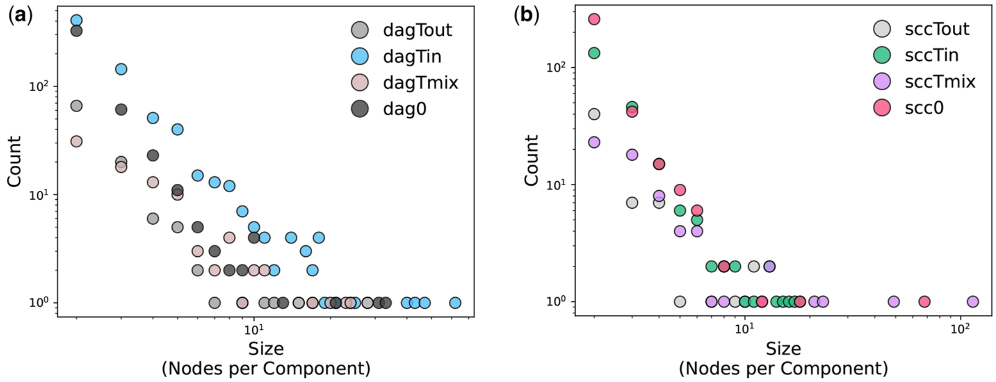
As described in a previous work [22], the degree distributions of this network are heavy-tailed. The degree distributions are built by aggregating all the transactions that happen between each pair of nodes and preserving their directionality. The in-degree and out-degree distributions can be well approximated by power-laws, respectively, with exponents 1.53 and 1.47 (see Supplementary Material, Document A, Section S4). Similarly, the distribution of the number of transactions per link also behaves as a power law with an exponent of 1.44. This means that a very high number of links have one or few transactions happening on them, while a few links are responsible for a very high number of transactions. The distribution of volume per link is also well approximated by a power law distribution with exponent 1.85. The Pearson correlation between the distribution of the number of transactions and the total weight per edge is equal to 0.58 significant at 1% (P-value $< .01$).

In Table 2, the categories for the speed of recirculation are reported. The first quartile of *19 min, 39 s* defines the temporal category *HSQ1*; its most frequent value (or *Mode*) is *104 s* and is also the mode of the entire distribution of the speed of recirculation. Approximately half of those operations occur within about 10 h (*HSQ2*) and 75% of them in <2 days (*HSQ3*). Users can be assigned to one or more temporal categories based on the speed of their recirculation operations. For example, if a user performs one recirculation in 5 s and then another recirculation operation in 5 days, then the user is classified as *HSQ1-LS3*. In Section 4.4, the result of this type of analysis on users is shown.

4. RESULTS

4.1. Network topology

In this section, the results of the topological analysis are reported, and the empirical values are compared with null models to test their statistical significance. The topological categorization is used to distinguish between cyclic components (i.e. *SCCs*), acyclic components (i.e. *DAGs*) and single-nodes. The complete topological categorization used in this article is explained in Section 2.1. In Table 1, a short definition for each category is reported. In Fig. 6, a randomly sampled



DAGs SCCs

Figure 5. Size of SCCs and DAGs as weakly connected components, in terms of number of nodes. The largest strongly connected component (LSCC) is excluded from this plot, which has 19 737 nodes, 315 602 transactions, and a volume of 174 919 583.45 Sarafu. After removing the LSCC, the network is left with 19 696 nodes and 15 663 transactions, and a volume of 2 511 366 Sarafu. The weakly connected components are detected after removing the LSCC. Note that the sum of LSCC and not-LSCC is not equal to the total sum of whole network. Since weakly connected components within to the two are considered, the connections between them are excluded from the calculation.
Alt text: The plot on the left reports the size of DAGs on the x-axis and the number of DAG components on the y-axis. The scatter plot shows a negative relation between size and number of components. The presence of dagTin and dag0 dominates the other DAG categories. The plot on the right reports a similar pattern for SCCs. In this case, the presence of scc0, sccTmix, and sccTin dominates other SCC categories. The largest strongly connected component (sccTmix category) is excluded from this plot.

subgraph illustrates the network of users coloured by their topological category. Figure 6 is a quick representation of the main findings discussed in this section.

In Fig. 5, the size of the detected SCC and DAG (as WCCs) is calculated after the largest SCC is removed from the network. The largest SCC has 19 737 nodes, 315 602 transactions and a volume of 174 919 583.45 Sarafu. The size of DAGs ranges from 2 to 62 nodes, while the size of SCC ranges from 2 to 114 nodes. In Table 3, the network features per each type of component is reported. The biggest category is *sccTmix* which also includes the largest SCC. The second largest category is the one of *in-single-node* nodes, namely nodes that are sending currency to another node in an *SCC* (see Fig. 6, as an example).

The network features presented in Table 3 are then compared with three types of null models (more details in Supplementary Material, Document A, Section S3). In the first type of null models, only the targets are swapped ('target-swap'), in the second only, the sources ('source-swap'), and in the third either the source or target is swapped with a chance sampled from a uniform distribution ('both-swap'). When swapped, each directed link between two nodes carries with it all the transactions (and related data) between those two nodes. The comparison is carried out by using Z-score and Robust Z-score (for further details see Supplementary Material, Document A, Section S3). The Z-score represents the distance between the empirical value and the average value of the null models but expressed in the number of standard deviations. While the Robust Z-score represents the distance between the empirical value and the median of the null models but expressed in number of interquartile ranges. Generally, the Robust Z-score is considered when the normality assumption (necessary for the ordinary Z-score) is rejected by the Anderson–Darling normality test [57]. The results of this comparison with the null models are reported in Fig. 7.).

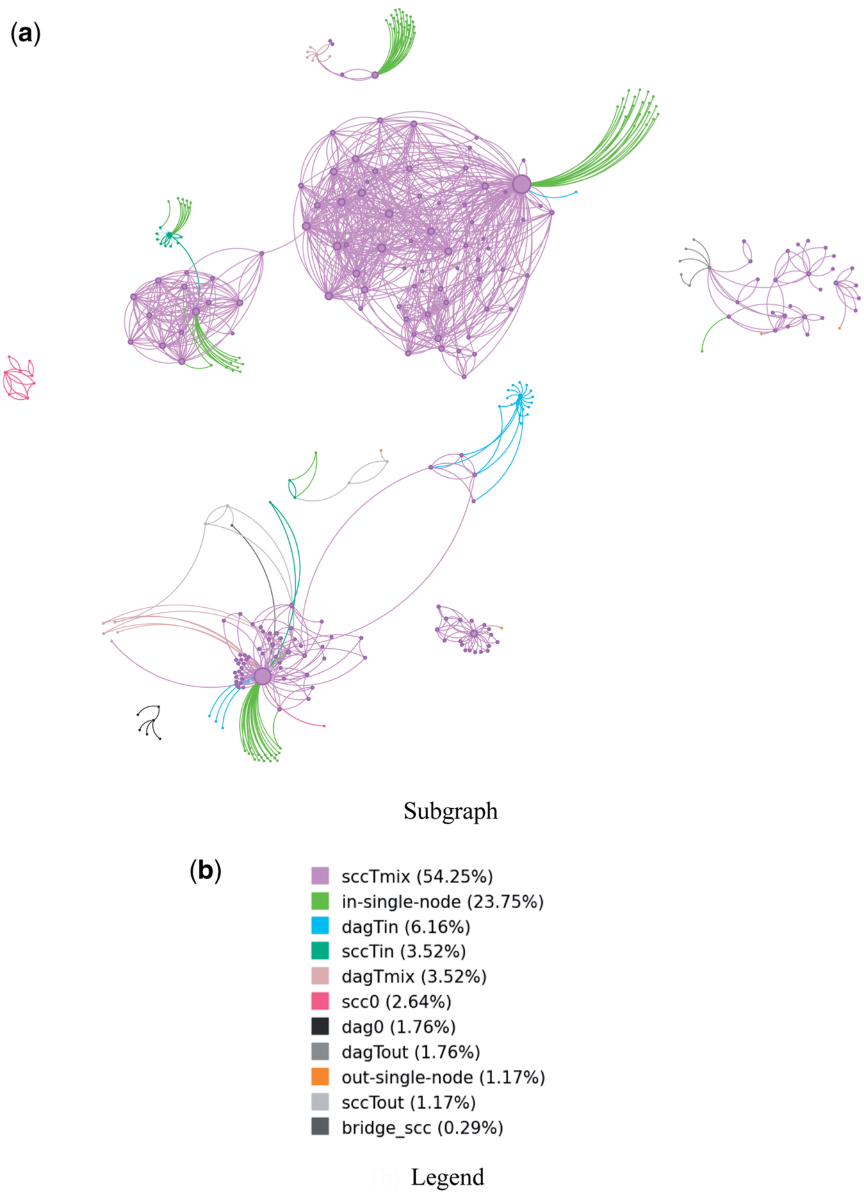
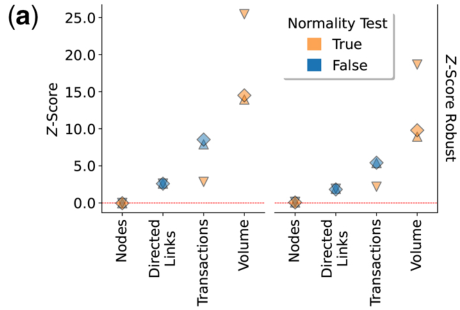


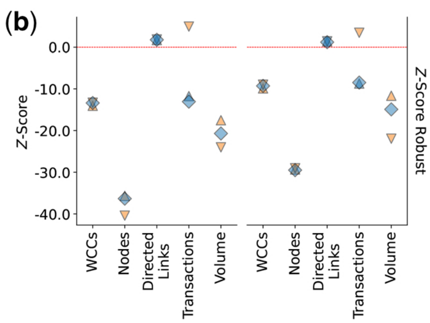
Figure 6. Subgraph of 341 nodes and 1060 directed links. The subgraph is created by merging ego graphs at depth 1, 2, and 3 of 11 nodes, one random node per each topological category. The *in-single-nodes* are all connected to a few hubs of *sccTmix* components . Similarly, one central node in a *dagTin* component is collecting from other nodes and then sending to other not central *sccTmix* nodes. Furthermore, *dagTmix* (bottom left) and *dagTout* (top right) can also be observed attached to two different *sccTmix* components. The *dagTout* is made of one hub receiving from other (*sccTmix* and *dagTout*) nodes, while *dagTmix* is made of dyads. Finally, on the left side there are isolated *dag0* (on the bottom) and *scc0* (on the top) components. This plot is made out of a sample of ego graphs, hence, it is very likely that some connections are missing within the same components. In the legend, the proportion of users per each category in parenthesis.
Alt text: This plot shows a subgraph of 341 nodes and 1060 directed links. The scope of this illustration is to show how the topological categories described in this section look in the real graph. For example, at least one node in each sccTmix component have many in-single-nodes attached to it.

Table 3. Size for each topological category

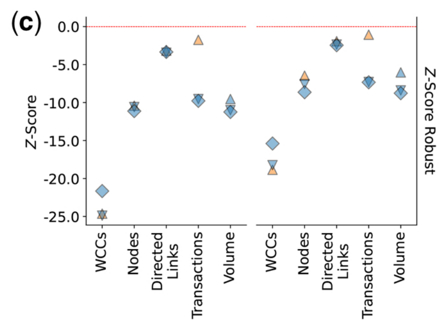
Node label	Edge label	SCCs	WCCs	Nodes	Dir.Links	TX	Volume
sccTmix	=	67	67	20 173	107 067	318 567	175 590 852.21
sccTin	=	220	220	699	1165	3688	634 183.02
sccTout	=	62	62	198	350	937	49 513.0
scc0	=	336	336	899	1159	1825	161 622.65
dagTmix	=	–	92	460	389	502	99 747.96
dagTin	=	–	723	2642	1947	2300	411 191.95
dagTout	=	–	104	309	207	280	30 067.0
dag0	=	–	441	1205	766	906	124 367.0
out-single-node	=	–	534	1749	1224	1620	98 822.03
in-single-node	=	–	1520	14 889	15 613	24 062	4 203 649.49
bridge_scc	=	–	20	75	57	78	21 280.0
–	edge_dag2scc	–	415	2248	2008	3272	709 891.184
–	edge_scc2dag	–	178	622	490	777	126 142.14
–	edge_scc2scc	–	256	1112	894	1303	344 283.09



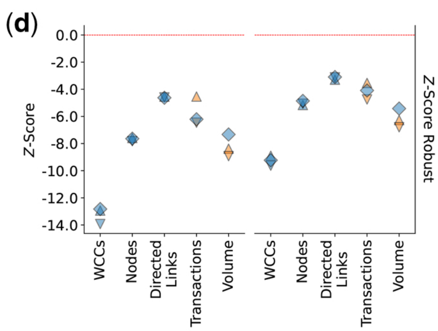
Statistical significance for the **sccTmix** category.



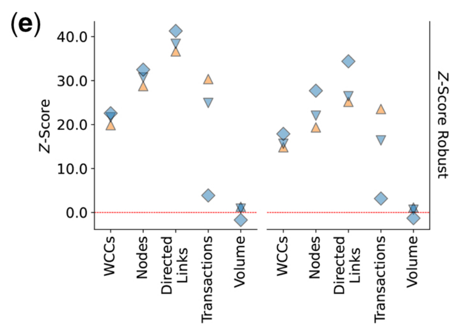
Statistical significance for the **in-single-node** category.



Statistical significance for the **out-single-node** category.



Statistical significance for the **dagTin** category.



Statistical significance for the **dag0** category.

Figure 7. Statistical significance for sccTmix, in-single-node, out-single-node, dagTin, and dag0 categories. Every feature has three markers, one per each null model used: 'targets-swap' (downward triangle), 'sources-swap', (upward triangle), and 'both-swap' (rotated square). Both plots report the Z-score and Z-score robust (for further details see also Supplementary Material, Document A, Section S3). The feature 'WCCs' indicates the number of weakly connected components. The normality test is carried out by the Anderson–Darling test [57]: 'yellow' markers represent values for which the P-value is $<5\%$ (and therefore the normality hypothesis cannot be rejected

Alt text: The figure illustrates the statistical significance of some features for the mentioned topological categories. The features considered are the number of nodes, the directed links, the number of transactions, and the volume. Each marker has a different shape which reflects a different type of null model, and the colour of the marker reflects its normality test. Each plot reports the values for the Z-score and the Z-score robust.

In this empirical network, there are 62 *sccTmix* components. The largest SCC falls into the category of *sccTmix*. In the null models, a large SCC *sccTmix* emerged; it is also the only SCC. In other words, while in the empirical network, there are 62 *sccTmix* components, in null models, there is only one which is also the largest. This result is not reported in Fig. 7a for obvious reasons: since the standard deviation and the interquartile ranges of the number of components (WCCs) are equal to zero, both the Z-scores and the Robust Z-scores cannot be defined.

Generally, the size of the largest SCC in null models is the same as that of the empirical one in terms of the number of nodes. In fact, in Fig. 7a, the Z-score of the number of nodes is equal to zero. The number of directed links and transactions in the *sccTmix* components does not have a significant difference from the null models. In fact, the Robust Z-score shows a value only between 2 and 6 times (of interquartile range) higher than the median value in null models. However, the volume shows a much higher positive significance and the Z-score is 14 to 25 times (i.e. standard deviations) higher than the average value of null models. In summary, the presence of *sccTmix* components in the empirical network is only significant (i.e. over-represented with respect to the null models) for its fragmentation into many different groups (WCCs) and for its volume.

The other types of SCCs (*scc0*, *sccTin*, *sccTout*) are generally absent in the null models. This means that the presence of these types of SCCs cannot be explained only by randomness. The cyclic structures of these components may play a significant role in this economic network. The edges (*edge_scc2scc*) and nodes (*bridge_scc*) connecting different SCCs are also generally absent in the null models. This means that these particular topological components may reflect a significant functionality in this empirical network. As explained above, this could be related to the particular role that cycles play in real transaction networks for currency recirculation.

In Fig. 7e, the volume of *dag0* components is not significant. The reason for this behaviour is partially explained in Section 4.3. In short, these components are mainly made of dyads and 'collector' triads, where one user is collecting from two other ones. In fact, their composition could indicate trials among users not really interested in fully engaging with the rest of the network, and therefore the exchanged volume is not more than random (more details in Section 5). Despite this, all other characteristics of the *dag0* components are positively significant. Since the normality assumption is rejected (except for 'source-swap' models), the Robust Z-score is generally more reliable for testing the statistical significance in this case. The number of components (WCCs) for *dag0* is 15–20 times (i.e. interquartile ranges) higher in the empirical network than the median value of the null models. The number of nodes in *dag0* is 20–25 times higher in the empirical network than the median value of the null models. The number of links is 25–30 times higher in the empirical network than the median value of the null models. The number of transactions has a large variability between different types of null models, which may explain the low significance of volume. In summary, the number of *dag0* components and their size (in terms of nodes and links) is higher than expected in a random setting. This means that they may reflect a specific type of behaviour which characterizes this network. However, the number of transactions and their volume are generally not more than expected from a random setting.

The presence of *dagTin* (Fig. 7d), *out-single-nodes* (Fig. 7c), and *in-single-nodes* (Fig. 7b) components in the empirical network seems generally less than expected from the null models. In fact, the Z-score has either a very high negative value or close to zero. A high negative value means that there is a statistically significant under-representation in the empirical network with respect to a random setting.

For the *in-single-node* category, the normality hypothesis cannot be rejected for the 'source-swap' and 'target-swap' models, therefore the Z-score is considered. The Z-score of the number of components (WCCs) and transactions is about 15 standard deviations less than expected on average in a random setting. The number of nodes is about 40 times less than expected and the volume about 20 times less. The other features do not seem significant.

In the *out-single-node* category, only for the 'source-swap' model, the normality hypothesis cannot be rejected. For this reason, the Robust Z-score is considered. The number of components (WCCs) is about 15–20 interquartile ranges less than the median of the random setting. The number of nodes

Table 4. Users who took part only in one operation (one-time users), either as a receiver or a sender only

Topological category category	Users with one outgoing transaction	Users with one incoming transaction	Outgoing volume	Incoming volume
in-single-node	7011	–	1 886 274.21	–
dagTin	1109	70	241 881.0	5542.0
dag0	619	327	53 439.0	42 820.0
out-single-node	–	746	–	39 789.03
dagTmix	132	10	35 161.0	486.0
dagTout	113	26	14 601.0	3647.0
Total	8984	1179	2 231 356.21	92 284.03

and the volume is 5–10 times less than the median value of the null models. Other network features do not show strong significance.

For the *dagTin* components, the normality hypothesis cannot be rejected for three features (i.e. WCCs, number of nodes and directed links), so the Robust Z-score is considered for those. The number of nodes is 10 times less than the median of a random setting, while the number of nodes and directed links is about five times. For the number of transactions and the exchanged volume, the normality hypothesis cannot be rejected for the 'source-swap' and 'target-swap' models. The number of transactions is about five times less than the median value, while the volume is about nine times less.

In summary, the presence of *dagTin*, *out-single-nodes*, and *in-single-nodes* in terms of the number of components and nodes involved is surely less than expected in a random setting. This means that on a randomized network it is very likely to find more of those components, and with a larger size. This result complements the previous finding on the presence of SCCs. In other words, a randomization is expected to destroy cyclic structures and create more acyclic components and even single-nodes.

In conclusion, the result suggests that the hypothesis on the particular role played by cyclic structures made in previous studies [22, 27] could be confirmed by the statistically significant relative presence of SCCs and the significant relative absence of *dagTin*, *in-single-node*, and *out-single-node*. The significant absence of other acyclic components is also reported in the Supplementary Material (Document A, Section S5, Fig. S4). In Section 5, the presence of *in-single-nodes* could be hypothetically associated to the creation of 'fake' accounts. Surprisingly, the large positive Z-scores (or over-representation) for *dag0* may indicate another type of behaviour, where small groups of people are either trying the system or collecting Sarafu from each other without further involvement with the economic network (see Section 5 for more details). In the next two Sections 4.2 and 4.3, it is explained how the relative significant presence of *dag0* and the relative significant absence of *dagTin*, *out-single-node*, and *in-single-nodes* can be indeed associated with specific behaviours. For example, these components are strongly associated with one-time users (see Section 4.2). Furthermore, *dag0* and *dagTin* are related to the presence of dyads and 'collector' triads (i.e. one user collecting from two other users) (see Section 4.3). These findings will also be compared to a recent qualitative study [54] and discussed in Section 5.

4.2. One-time users

Many users made only one transaction during the observation period. The findings suggest that this phenomenon is closely related to the topological categories presented in the previous Section 4.1. In Table 4, such *One-Time* users are grouped by topological categories. Since they were involved in one operation in only one direction (receiving or sending), these users can belong only to acyclic components (DAGs) or single-nodes. In particular, 47% of *in-single-nodes*, 44.6% of *dagTin* users, 78.5% of *dag0* users, and 61.9% of *out-single-nodes* took part only in one operation, as receivers or senders (see Table 3 for comparison). More details on the characteristics of one-time users are provided in the Supplementary Material (Document A, Section S7, Fig. S7).

One of the criticisms that Sarafu received in this period was its use of rewards for bringing/recommending a new user [54] (more details in Section 5). An 'old' user could recommend a 'new' user's phone number to get a bonus after its registration. If the 'old' and the 'new' users agreed upon it, the 'old' user could also forward to its account the initial disbursement that the 'new' user received from Grassroots Economics. In fact, no previous agreement between the 'old' and the 'new' users was necessary, as far as the 'old' user had access to that phone number the operation would have been successful. In simple words, this means that some existing users could get the reward and the initial disbursements by recommending and then registering 'fake' accounts using phone numbers of other people, consensually or not. Analysing the transaction network, this operation would be recorded as an operation involving one-time users sending Sarafu only once to transfer this initial disbursement (or part of it) to at least one other user (i.e. the 'old' user). In fact, these one-time users that sent Sarafu and then stopped are 22.7% of the total number of registered users, but their transactions correspond only to 1.2% of the total volume. It is not possible to accurately estimate the size of this phenomenon, but at least it is possible to define its boundaries broadly.

The presence of one-time users seems to strengthen the suspicion of the use of multiple 'fake' accounts, but many other scenarios can be imagined (e.g. technical issues). However, the main topological groups corresponding to this type of activity would be identified mainly as *in-single-nodes* and *dagTin* (in Fig. 6, moderate green and soft blue nodes, respectively). In both these categories, one node is present in a *sccTmix* component that receives from one or more nodes outside of that component. The node sending can be isolated (*in-single-node*) or connected to other nodes (*dagTin*). For instance, the DAG could include one node collecting from other nodes, or a chain of nodes transferring to each other. One-time users falling into the category of *in-single-nodes* exchanged an amount of volume equals to 1% of the total. One-time users in the category of *dagTin* exchanged an amount of volume equal to 0.1% of the total. Therefore, even though the phenomenon can be observed in the data, its size may still be negligible.

Another important result to remark is that the majority of *dag0* users (78.5%) sent or received only one transaction. Moreover, there are 289 transactions that were made by a one-time sender towards a one-time receiver, these transactions are happening within *dag0* components and are equal to 31.9% of the total number of *dag0* transactions. In the previous section, it was observed that the presence of *dag0* components is more than random. This reinforces the assumption that this category may indicate mostly isolated pairs or a group of users simply trying out or testing the system without really engaging with the rest of the network. This behaviour is expected in an expanding phase of a novel complementary digital currency.

In conclusion, in the previous section, it was observed that the presence of *dagTin*, *in-single-nodes*, and *out-single-nodes* is generally less random. In this section, it is observed that about half of the users falling into these categories used the system only once. In particular, users in *dagTin* and *in-single-nodes* could be related to 'fake' accounts used to collect currency. However, this phenomenon described also in a recent qualitative study [54] has a negligible size (see Section 5 for more details). Furthermore, in the previous section, it was observed that the presence of *dag0* components is positively significant, but the majority of their users used the system only once. This reinforces the suspicion that users in *dag0* components were only trying out the system. In the next section, the three-node motifs that occur in the acyclic components (DAGs) are analysed with a particular focus on *dag0* and *dagTin* components.

4.3. Triads

In this section, a triadic census analysis of acyclic components (DAGs) is provided. It is possible to observe that 90.6% of DAGs have a size between 2 and 5 (see Table S2 in the Supplementary Material, Document A, Section S5). Excluding the DAGs made by one-time users, the rest of them counted 1571 nodes with 1115 directed links, 3345 transactions and a total volume of 510 945.13 Sarafu (0.2% of the total volume). In acyclic components, most transactions among users who used the system more than once belong to the *dagTin* category (see Fig. 5a).

Since most DAGs are dyads and triads, in this section, a triadic census analysis is implemented using one of the most common existing nomenclatures [58]. However, only 4 of those 16 types of triads are found to have a statistically significant presence in this network: 012, 021C, 021U, and 021D. The dyadic triad 012 is a simple dyad (from A to B). The triad 021C is a 'brokerage' interaction (from A to C through B—where B is the 'broker'). The triad 021U represents one central user collecting the currency of the other two (from A to B, from C to B; where B is the 'collector'). The triad 021D represents one central user sending to two other users (from B to A, from B to C—where B is the 'distributor').

The 021U 'collector' triad is the most significant type of triad in all DAGs (see Fig. 8). For *dag0*, the Robust Z-score is up to 700 times higher than the median value in null models. For *dagTin*, the Z-score is up to 200 times higher than the average value in null models. *DagTin* components have at least one user sending to an SCC, *dag0* components are isolated. This means that the 'collector' user in a *dag0* component was simply hoarding the currency.

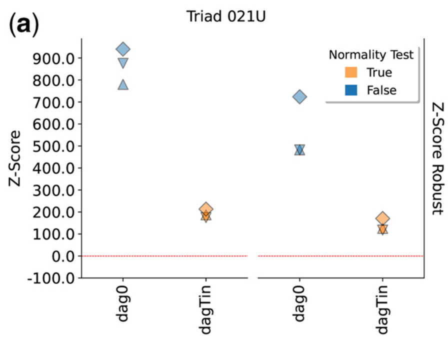
It is worth mentioning the statistical significance of the triads 021C, 012, and 021D in the *dag0* components. Their presence seems to be significant in *dag0* components, especially isolated dyads 012 which are 100 times more than expected in a random setting. Since the majority of *dag0* are one-time users, it is fair to assume that these are pairs of people simply trying out the system or not engaging further due to technical difficulties. Even if statistically significant the size of these phenomena is not so relevant to compromise the whole system. In fact, the volume of *dag0* is only 0. 002% of the total volume of Sarafu (see Table 3). Finally, the other triads in *dagTin*, *dagTout*, and *dagTmix* have a very low or negative Z-scores. This means that there is no triad formation that plays a meaningful role in those topological categories, except for 021U (the 'collector' triad).

In conclusion, the presence of 'collectors' is highly significant in acyclic components and is identifiable by the triad 021U. As expected, most of the 'collectors' lay in *dag0* and *dagTin* components, where 44.6% of *dagTin* accounts and 78. 5% of the *dag0* accounts were used only once. This evidence increases the suspicion that *dagTin* identify users collecting Sarafu from 'fake' accounts in at least half of the cases, while *dag0* identify users simply trying out the system in the majority of the cases. In the next section, the dynamics of circulation is explored. The purpose is to observe differences in circulation between cyclic components (SCCs) and acyclic components (DAGs), which are in line with the previous findings.

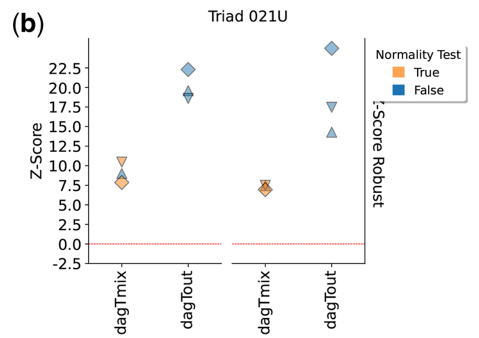
4.4. Recirculation

In this section, circulation is described using a temporal metric, the *speed of recirculation*. A recirculation operation is the time difference between the first of all incoming transactions and the last of all outgoing transactions, before the next incoming transaction arrives. In Fig. 4, the concept of recirculation operation is explained. All transactions that occur between time t and time $t+3$ are included in the recirculation operation. As soon as an outgoing transaction is followed by another incoming transaction (at time $t+4$), the recirculation operation closes. This implies that the same node can have many recirculation operations. In other words, for each set of incoming transactions followed by a set of outgoing transactions, a recirculation operation is recorded for that particular user.

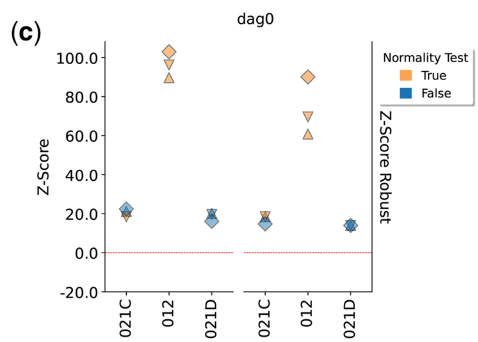
In total, there were 123 741 recirculation operations. The total amount of transactions included in these operations was 328 191 transactions, which is equal to 91.1% of the total number of transactions and 94% of the total volume. As described above, a recirculation operation can be made of several outgoing and incoming transactions. Almost half (49.4%) of those transactions took place among recirculating users. In other words, the outgoing transaction of one recirculating user became the incoming transaction of another user who recirculated afterwards in almost half of the cases. There were 9984 recirculating users (25.31% of the total), but they involved up to 23 488 other non-recirculating users, either as only-senders or only-receivers of these recirculating operations. In short, it is remarkable to observe that 25.31% of the users were responsible for 91.1% of the transactions (94% of the total volume) and recirculating almost half of the transactions between



Statistical significance of triad 021U for **dag0** and **dagTin**.



Statistical significance of triad 021U for **dagT-mix** and **dagTout**.



Statistical significance of triads 021C, 012, 021D for **dag0**.

Figure 8. On the top, the statistical significance of triad 021U for each type of DAG. The triad 021U represents one central user collecting the currency of other two. On the bottom, the statistical significance for triads 021C, 012, and 021D for 'dag0' components. The normality test is carried out by the Anderson–Darling test [57]: 'yellow' dots represent values for which the P-value is <5% and therefore the normality hypothesis cannot be rejected. The three markers correspond to one of the of null models used for this test: 'targets-swap' (downward triangle), 'sources-swap', (upward triangle), and 'both-swap' (rotated square)—for further details see also Supplementary Material, Document A, Section S3.
Alt text: The plot shows the statistical significance (positive Z-score and Z-score robust) of the triads 021U in dag0, dagTin, dagTmix, and dagTout. The triads 021C, 012, and 021D are also significant (positive Z-score and Z-score robust) in dag0 components. Each marker has a different shape which reflects a different type of null model. The colour of the marker reflect whether the normality test gave a positive or a negative result.

them (49.4%). Additional information on the statistical significance of recirculation is provided in Supplementary Material (Document A, Section S6).

In terms of recirculation operations, it is notable to observe the role played by *in-single-nodes* (Table 5). The *in-single-nodes* are the second biggest category of users who initiated recirculation operations. This means that 5.8% of the total transactions involved in the recirculation operations were initiated by single-nodes that sent to SCCs. Note also that this is true across all temporal categories, but decreases from the slowest (LS3) to the fastest (HSQ1). This means that the role of users in *in-single-nodes* was that of providing liquidity to other users in SCCs (*sccTmix* and *sccTin*) which eventually recirculated it after a few days (the majority) or a few seconds. This may confirm the suspicion that *in-single-nodes* were mostly made of 'fake' accounts created with the purpose

Table 5. Number of transactions involved in recirculation operations[a]

	HSQ1	HSQ2	HSQ3	LS3	Tot.Top.Cat.
sccTmix	64 096	100 646	109 976	128 947	403 665
sccTin	933	1172	954	1043	4102
sccTout	181	139	182	490	992
scc0	323	174	250	514	1261
in_single_node	439	2548	3247	14 746	20 980
edge_dag2scc	79	333	461	2143	3016
edge_scc2scc	48	129	187	938	1302
Tot.Freq.Cat.	66 283	105 474	115 462	149 533	436 752

[a]Note that the total is >328 191. This is due to the fact that 108 561 were transactions from and to recirculating users. For this reason, they are counted twice (i.e. first, as 'incoming', and then, as 'outgoing'). The table only reports the results for the first seven biggest topological groups.

Table 6. Number of users involved in recirculation operations[a]

	scc0	sccTin	sccTout	sccTmix	dagTin Cat.	Tot.Freq.
HSQ1	70	46	12	967	13	1113
LS3	47	108	20	1682	46	1926
*__All__	6	22	8	2092	0	2128
Tot.Top. Cat.	216	334	82	9185	120	9984

[a]The users are counted only for the main topological group and the three largest temporal categories (HSQ1, LS3, and All). The percentages per each topological group represent the share of users for each temporal category. The category 'All' reports users who were active in all of the considered temporal categories (HSQ1, HSQ2, HSQ3, and LS3).

of collecting Sarafu to reuse it afterward. Especially considering that half of them made only one operation, as explained in Section 4.2.

In Table 6, the distribution of users for the main topological groups in the largest temporal categories is reported. The temporal categories are defined in Section 2. Most recirculation operations are concentrated in three main temporal categories: users with only recirculation activity for more than a day (LS3), users with recirculation activity <20 min (HSQ1), and users with recirculation activity across all temporal categories (HSQ1, HSQ2, HSQ3, LS3). Users belonging to SCCs have the most diverse temporal behaviour, and most recirculation occurs within SCCs: 91.99% of the recirculating users belong to *sccTmix* components, 2.28% to *sccTin*, 1.49% to *scc0*, and 0.5% to *sccTout* components. This also confirms the role of cyclic structures in the recirculation of a currency system. On the other hand, most of users in DAGs do not report such temporal diversity, and they report mostly either very high speed of recirculation (HSQ1) or very low (LS3).

Concluding, recirculation took place among 25.31% of users who were responsible for 91.1% of transactions (94% of the total volume). Almost half of those transactions were recirculating only among recirculating users (49.4%). Moreover, 75% of these transactions was recirculated in less than 2 days. The majority of recirculating users belong to SCCs, 91.99% only to *sccTmix* components. Furthermore, *in-single-nodes* played an important role in initiating about 5.8% of recirculating operations. Since almost half of those accounts was used only once, this means that *in-single-nodes* may indeed identify accounts which were used only to collect Sarafu. This liquidity was eventually injected and recirculated in the rest of the economy through SCCs. In the next Section 5, the results are summarized and analysed to appreciate the complete picture of these findings.

5. DISCUSSION

A study on the Sarafu network argued that the adoption of a community currency system is more efficient and effective than the usual cash transfer programme using fiat currency [4]. In that paper, it is argued that the use of local currency stimulates the local economy while providing humanitarian aid. However, the use of the 'Sarafu token', as a cash transfer programme that was in place between 2020 and 2021, has recently also received some criticism [54, 56]. Some of those criticisms are discussed in this section. In the most recent qualitative study [54], the findings of 31 interviews and 6 focus groups (of 8–12 participants) suggested that some users may have tried to 'game' the system by taking advantage of its rewards and cash-out programmes. In that work, the size of the phenomenon has not been further investigated, but four different *gaming strategies* are described and reported (see below).

- **Strategy N.1**. An existing account could register more than one phone number. Every new phone number is associated with a new account, which automatically gets an initial disbursement. In principle, by having direct physical access to this new phone number, a first user could send this initial disbursement to itself to accumulate more Sarafu. Moreover, from this new phone number, it would be possible to communicate the phone number of someone else from whom it was invited to join the system (i.e. recommendation system). In this way, the first user could also get a reward (in Sarafu) for having brought this new member to the network. This recommendation system is also described in a data descriptor paper [1].
- **Strategy N.2**. Similarly to *Strategy N.1*, an existing user could register the phone number of other people in a non-consensual way. The user, who had access to someone else's phone for enough time, could obtain all the benefits described in *Strategy N.1*.
- **Strategy N.3**. Users could fake transactions to get some promotional bonus and avoid the (weekly and then monthly) holding fee. The holding fee (or *demurrage* charge) is also described in the data descriptor paper [1]. However, the functioning of the promotional bonus is not officially described. The disbursement of the promotional bonus took place four times in the analysis period [1]. The qualitative study [54] reports a specific promotional strategy that seems to be connected to a reward for triad formation: 'A buys from B, C and D, who in turn trade with E, F and G' (p. 44 [54]), and 'I send him, he sends to her and she sends to me' (p. 46 [54]). The first triad formation strategy seems to describe a 'brokerage' triad (021C). The second triad formation strategy seems to describe a cycle of length 3 (030C).
- **Strategy N.4**. Every saving group (or *Chama*) registered in the Sarafu system was entitled to a partial/limited cash out (i.e. exchange Sarafu for Kenyan Shillings). A user who wanted to exchange its own Sarafu for Kenyan Shilling could potentially register in many different savings groups to escape cash-out limitations.

In this section, the first three *gaming strategies* are analysed considering the transaction data for the same period. In fact, the integration of qualitative and quantitative methods could help reconstruct a complete picture of this phenomenon. In the next paragraphs, the quantitative findings presented in this article are matched with the description of these 'gaming' strategies just mentioned.

The strategies **N.1** and **N.2** are easy to detect by looking at the topology of the transaction network. The above-mentioned behaviours imply the presence of one existing account connected with other accounts which only send Sarafu to it and then stay mostly inactive. As observed in Section 4.2, about half of the users falling in the categories of *in-single-node* and *dagTin* used the system only once, while the majority of users in *dag0* used the system only once. In *dagTin*, there is also a significant presence of 'collectors' (Section 4.3). Strategies **N.1** and **N.2** can be therefore confirmed by the data. However, one-time users in *in-single-nodes*, *dag0*, and *dagTin* moved overall only 1.19% of the total volume (see Table 4). More details on the characteristics of one-time users are provided in the Supplementary Material (Document A, Section S7, Fig. S7). In summary, the quantitative analysis confirms the strategies **N.1** and **N.2** described above, but the size of the phenomenon does not seem large enough to compromise the rest of the system.

The strategy **N.3** describes triad formation through 'fake' transactions with the only intention of accumulating Sarafu and eventually cashing them out (strategy **N.4**). According to the same qualitative study (pp. 46–47 [54]), some users were meeting regularly with the intention of 'faking' transactions to escape the holding fee and trying to unlock some promotional bonus. If the intention was to acquire Sarafu and sell it to Kenyan Shillings (Strategy **N.4**), then this behaviour would be observed in DAG. However, if the intention was to get Sarafu to eventually participate in the economic network, this behaviour would be observed in SCCs. Nevertheless, while 'faking' for cashing-out was an unintended consequence of the currency design, the second type of behaviour was somehow intended in the currency design and indistinguishable from ordinary transactions happening in the Sarafu economic network (or SCCs).

The exploration of strategy **N.3** in DAGs leads us to the results presented in Section 4.3, where a triadic census analysis of DAGs was carried out. The results suggest a significant presence of dyads (012) and other different types of triads in *dag0* components. However, since 78.5% of the users in these components made only one transaction, it is difficult to relate *dag0* with this type of strategy. On the other hand, 55.4% of the users in *dagTin* made more than one transaction, and the 'collector' triad (021U) is the most significant one there. This means that *dagTin* components are a good candidate for the description of strategy **N.3**, if the formation of the triads does not imply a cycle. Excluding the volume of one-time users operations, the resulting amount of currency exchanged in *dagTin* components is equal to about 0.01% of the total volume.

The exploration of strategy **N.3** in SCCs can also be addressed by the results in 4.4. In that section, it is reported that 91.1% of the recirculating operations occurred within *sccTmix* components. However, 15.8% of the transactions in *sccTmix* components composing those recirculating operations were carried out within about 20 min (HSQ1) (Table 5). In addition, 11.15% of the users engaged only in high-speed operations (HSQ1) and the majority of them (86.9%) are located in *sccTmix* components (Table 6). In other words, there is indeed the suspicion that high-speed recirculating operations (HSQ1) occurred with the purpose of unlocking some reward or escaping the holding fee, as described by strategy **N.3**. However, these rewards were also later spent on the Sarafu economic network (or SCCs), as originally planned by the currency designers.

Concluding, the strategies **N.1**, **N.2** and **N.3** can be identified in fact by analysing the behaviour of users in *dag0*, *dagTin*, *in-single-node*, and *sccTmix* components. Strategies **N.1** and **N.2** can be related to one-time users in *in-single-nodes*, *dag0*, and *dagTin* who moved overall 1.19% of the total volume. Strategy **N.3** can be related to triad formation. If the triad formation was happening with the intention of unlocking rewards to cash-out later, then a significant presence of triads in DAGs would be observed. Otherwise, if the triad formation was occurring with the intention of unlocking rewards to engage with the rest of the economy, then a significant presence of triads in SCCs would be observed. In the first case, the presence of 'collector' triads *dagTin* components could indeed confirm this behaviour (0.01% of the total volume). In the second case, it was observed that 11.15% of users were engaging only in high speed operations (*HSQ1*, <20 min) and the majority (86.9%) of them are part of the *sccTmix* components. However, a triadic census on SCCs cannot reveal further details since these users were embedded with the rest of the economy.

These findings also answer the research questions presented at the beginning of this article. The identified topological categories are shown to be relevant for the study of a payment system (**RQ1**). Since they are related to currency circulation, these topological categories succeeded in identifying different temporal behaviours within the Sarafu economic network (**RQ2**). In addition, these techniques were also used to describe different levels of engagement in a transaction network (**RQ3**). This shows the importance of studying the structure and the dynamics of an economic network to minimize the risk of unexpected outcomes in monetary interventions. This work also added additional nuances to the study of recirculation in currency networks. In particular, the role of cyclic structures presented in previous works [22, 27] is confirmed by the significant differentiation between cyclic components (SCCs) and acyclic components (DAGs and single-nodes). Finally, as observed in a previous quantitative analysis of these data [34, 35], the Sarafu token network generally succeeded in stimulating the local economy during the COVID-19 emergency by engaging the majority of its users within the local economic network.

It is important to clarify that one-time usage is a phenomenon that can have many different explanations. In this work, the focus was on strategies described in detail in a recent qualitative study [54]. However, this abrupt disengagement can also be explained by the emergence of technical issues, loss of interest, etc. For these reasons, the strategies discussed in this section cannot be considered exhaustive.

6. CONCLUSION

In this work, the Sarafu token network, a digital community currency system used in Kenya, is analysed. During the emergency of COVID-19, this complementary payment system was used as part of a humanitarian cash transfer programme. Since Sarafu could only circulate locally, it is argued that it could potentially boost local development whenever the increase in demand for goods and services meets the unused productive capacity of the region [4]. The paper unfolds through three research questions with the scope of investigating behavioural strategies in the use of Sarafu. The first question is about the most significant topological categories in the network (**RQ1**). The second question is about the recirculation activity in the network (**RQ2**). And finally, the third question is about inferring human behaviours that match previous qualitative studies with these results (**RQ3**). To answer such questions, a topological categorization was introduced in Section 2.1 and a recirculation analysis was presented in Section 2.2.

The main results can be summarized as follows. First, the presence of *in-single-node*s is less than expected in a random setting; 47% of them were active only once and moved a volume equal to 1% of the total. Moreover, 5.8% of the transactions in recirculation operations were initiated by *in-single-node*s. This phenomenon could possibly be related to users who were opening many new accounts to collect the initial disbursements after registering and to get rewards (see Section 5, strategy N.1 and N.2), as reported in a recent study [54].

Second, the presence of *dagTin* components is less than expected in a random setting, 44.6% of them were active only once and moved a volume equal to 0.1% of the total. Moreover, in these components we find the second highest positive Z-score for the 'collector' triad 021U. Similarly to the strategy defined above, this phenomenon could also probably be related to users who were opening many accounts to collect Sarafu or getting rewards, but without the intention of further engaging with the network (if not simply cashing out later on)(see Section 5, strategy N.3).

Third, the number of *dag0* components is more than expected in a random setting, 78.5% of them were active only once, 31.9% of transactions only between one-time users. Moreover, in the *dag0* components, there is the highest positive Z-score for the 'collector' triad 021U. In addition, in the same category, the highest positive Z-scores (in order of magnitude) for the dyads (012), the 'brokerage' triad (021C), and the 'distributor' triad (021D) are observed. This category probably reflects simply users trying out the system without further engaging with it.

In general, one-time usage (in *in-single-node*s, in *dagTin*, and in *dag0*) can be explained in many different ways. For example, it can also be caused by technical difficulties, loss of interest, etc. This comparison with some strategies described in a recent study [54] does not aim to provide a comprehensive explanation of the phenomenon.

Fourth, the presence of *sccTmix* components is more than expected in a random setting, only for its number of transactions and volume. In there, 76 448 *occasional dyads* equivalent to 24% of all transactions are observed. The majority of recirculating users (91.99%) belongs to *sccTmix* components. In addition, it is worth noting the absence of some types of SCCs (and related connections) in null models: *sccTin*, *sccTout*, *scc0*, *bridge_scc*, and *edge_scc2scc*. For these reasons, this category reflects the real economic exchange that is happening in the network. The size and significance of such category is strong evidence of a positive economic impact due to the high level of recirculation occurring in it.

The positive economic impact suggested by the findings mentioned above is confirmed by the analysis of one-time usage and recirculation dynamics. In terms of one-time usage, it is worth adding that the *one-time* users are equal to 22.7% of the total (1.2% of the total volume). In terms of recirculation, 25.31% of the users were responsible for 91.1% of the transactions (94% of the total volume) and recirculated almost half (49.4%) of the transactions between them. This high level of recirculation is also a sign of the successful participation of Sarafu users.

In conclusion, the adoption of Sarafu as a local voucher system for a humanitarian cash transfer programme appears to have been successful. However, some observations are necessary about generalizability, policy recommendations, and limitations. First, the socio-economic context of its implementation and the particular conditions given by the COVID-19 emergency constrain the generalizability of these results. In fact, in the same period several restrictions (partial and full lockdown) affected Sarafu's usage, as reported by a recent study [34, 35]. In this context, many users lost their income (from the formal or informal sectors), and, in the absence of an adequate social welfare system, the cash transfer programme was one of the few ways to survive.

In second place, future replications of a similar cash transfer programme should consider the emergence of possible 'gaming' strategies [54], as noted in Section 5. In fact, users may interact with the system in unexpected ways, which can potentially be detrimental to the achievement of the desired goals. In this paper, some of these strategies were quantitatively identified. The analytical tools introduced in this article can be used by organizers and policy evaluators to test and monitor the transaction network of a cash transfer programme. In this way, appropriate interventions can be designed and implemented in a timely manner to achieve the desired goals of a local development and humanitarian intervention. For this purpose, a technique described in this work was further developed in a recent study [59].

Finally, a different design principle is currently under experimentation. Since 2023, Grassroots Economics has implemented a different community resource coordination mechanism, which is based on entirely different logic [2, 60]. This type of system is still successfully adopted by local savings groups and is based on an old local tradition called *mweria*. Each member can promise a certain amount of supply to the rest of the group (which is called a 'commitment'). These commitments are then issued as temporary vouchers and used as credits among group members. This innovative design for local voucher systems does not include a rewards scheme, and therefore the incentives for 'gaming' should be lower. This system is entirely recorded on a CELO blockchain, and therefore its transaction network can be analysed. Surely more research is needed to study these promising innovations and their socioeconomic impact, especially in times of economic and financial crises.

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SUPPLEMENTARY MATERIAL

Supplementary Material Document A is available at *COMNET Journal* online. The Supplementary Material Document B can be downloaded from the GitHub repository (https://github.com/TeodoroCriscione/Component_Currency_Network_GitHub.git).

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DATA AVAILABILITY

The Sarafu data 2020–2021 [3] are available for download on UK Data Service (UKDS) under End User Licence (https://reshare.ukdataservice.ac.uk/855142/) after registration. A data description paper is also available for download [1].

SOFTWARE AVAILABILITY

All software used in this study is available under an open source licence:

- networkx v.3.1. [61]
- scipy v.1.9.1. [62]
- numpy v.1.23.0 [63]
- powerlaw v.1.5 [64]
- seaborn v.0.11.2 [65]
- matplotlib v.3.5.2 [66]
- pandas v.1.4.4. [67]
- pycirclize v.1.4.0 [68]
- gephi v.0.10 [69]

CODE AVAILABILITY

The code required to construct, randomize, and analyse the network is included the Supplementary Material Document B. The Supplementary Material Document B can be downloaded from the GitHub repository (https://github.com/TeodoroCriscione/_Component_Currency_Network_GitHub.git).

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