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Cooperative behavior in blockchain-based complementary currency networks through time: The Sarafu case study

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A B S T R A C T

The effort to reach the 17 Sustainable Development Goals by the United Nations has incentivized the adoption of IT solutions in many fields. Many systems for sustainable economic development are now relying on a digital form making them more accessible and provides the access to new functionalities. A very interesting example of such systems are complementary currencies i.e. cooperative currency systems that support national economies to provide humanitarian aid and promote sustainable development. While there are many studies on the principles and case studies of successful complementary currencies, many aspects are still unexplored, especially regarding cooperative behavior. Cooperative behavior in these systems is a key aspect, as complementary currencies are often born out of cooperation among members that face a period of crisis or they usually have the objective of creating bonds of reciprocity and integrating social networks between people, which should lead to increased cooperation. However, there is a lack of studies on many aspects of cooperative behavior in complementary currencies, such as how such behavior changes over time, especially in times of a crisis like the COVID-19 pandemic. Moreover how cooperation behavior is affected by time and different geographical locations is still unclear. In this work, we analyze Sarafu, a complementary currency that went digital and now relies on blockchain technology. Sarafu is a successful case of a complementary currency that was used for humanitarian aid during the COVID-19 pandemic. Moreover, Sarafu is a perfect case study for the study of cooperative behavior, as it implements a special type of account, the *group account*, to support cooperation groups. This feature supports the study of group dynamics and behavior. What we find is that Sarafu users exhibit strong reliance on cooperation groups; we also observe that the interaction of users and cooperation groups is influenced by both time and geographical location. The study of group accounts and in general mechanisms that promote cooperation can be useful for other humanitarian or community development projects. Moreover, similar cooperation enhancers could have an important role in other social development projects, and in general, in any setting where there is a strong need to foster cooperation for reaching social good.

1. Introduction

The Sustainable Development Goals by the United Nations [1] have incentivized the good use of ICT and emerging technologies in many fields and scenarios. Many systems for sustainable economic development are now relying on a digital form that makes them more accessible and providing the access to new functionalities. A very interesting example of such systems is complementary currencies (CCs), i.e. cooperative currency systems that support national economies [2], and studies show that they actually boost local economies [3], address the issues of national currencies [4] or promoting the growth of industries [5]; moreover, they may achieve a positive impact on social sustainability as well, by increasing trust, expanding social networks and fostering social inclusion [6]. One of the most recent interesting uses, which attracted a lot of attention due to recent economical and social shocks, was the use of CCs in the field of humanitarian aid. While there are qualitative studies on the design principles and impact [6–8] of CCs for humanitarian aid, data-driven, and quantitative investigations are limited and many aspects are still unexplored. For example, cooperative behavior in these systems is a key factor, as CCs are often born out of cooperation among members that face a period of crisis, and communities use them to sustain themselves and support members in need during periods of crisis or instability [6]. And often, CCs have the objective of creating bonds of reciprocity and fostering social integration and inclusion [7], which should lead to increased cooperation. And yet, there are still key aspects of cooperative behavior, that

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are still unexplored: for instance, understanding how cooperative behavior is affected by other external factors, such as changes over time and geographical location. Another understudied aspect is the role of CCs during a period of crisis like the COVID-19 pandemic. And finally, there is a lack of studies on cooperative behavior. While we have a few works highlighting scenarios where CCs have been useful in times of economic crisis [6], only a few cover CCs activity in the pandemic period: a few examples are studies on a Polish CC [9], or in Brazil [10] and Kenya [4].

In this work, we study different aspects of cooperative behavior by focusing on group accounts to understand currency movements and cooperation patterns. We also examine how cooperative behavior is influenced by different external factors such as the COVID-19 pandemic and how geographical location can influence cooperation patterns. As a case study, we focus on the Kenyan CC Sarafu [11] to investigate these aspects. Sarafu is a noteworthy example of a CC that went digital to address several needs, become more accessible and improve the system with new features. Sarafu has some very interesting characteristics: (i) it is one of the first blockchain-based CC projects, that, like other Blockchain for Good projects, relies on blockchain technology for transaction processing, (ii) it is a CC that was relied upon by Red cross Kenya to successfully deliver humanitarian aid during the COVID-19 pandemic [4], and (iii) Sarafu further enhances the cooperation of organized groups of individuals, by implementing a special type of account, namely *group account*: this type of account is handled by a group of users to save money and help members in need. Group accounts are an innovative feature, unique to this CC system, that makes Sarafu the best case study for the analysis of cooperation. We conduct our analysis on a dataset of currency transactions [12] during the COVID-19 pandemic. We analyze monetary flows in the transactions network, to monitor the following aspects: *(RQ1)* the impact of cooperation groups and how it changes over time as we consider different pandemic situations and restrictions, *(RQ2)* how cooperation groups allocate and redistribute resources, considering their *business types* (such as "food", "farming", etc.), *(RQ3)* the impact of geographical location in cooperative behavior, and *(RQ4)* the interplay between the geographical location and how users or cooperation groups allocate and redistribute resources.

To answer our research questions, we model currency transactions as a temporal network, that is able to represent the economic ties between users. In addition to transaction networks, we rely on Sankey diagrams to study monetary flows between users and their consumption profiles [13] based on user information, i.e. types of accounts, their *business type*s, or geographical location.

Our analysis has highlighted some interesting findings. First, group accounts have a crucial role, as they are few (0.38%) and yet handle a significant amount of transactions (36%); moreover, their importance even increases over time, as the amount of money spent by these accounts increases significantly over the observation period (*RQ1*). Second, we also found that the allocation of resources by cooperation groups changes the observation period, as we observed variations over the categories of products of interest (*RQ2*). Third, we observed that while cooperation is important across different geographic locations, not all areas relied immediately on group accounts (*RQ3*). Fourth, we found an interesting interplay between geographic areas and the allocation of resources: geographical areas are characterized by their own categories of interest, with urban and periurban areas showing some similarities; and in some areas, the spending/funding of group accounts is much more significant compared to other categories (*RQ4*).

The paper is organized as follows. Section 2 provides a brief introduction to blockchain for good, complementary currencies, and Sarafu—the main subject of our study. In Section 3 we introduce the main research questions we focus on. In Section 4 we describe the Sarafu dataset and its preprocessing. The approach for modeling, extracting and analyzing the transaction networks and their projections are presented in Section 5. Section 6 report the main findings on the role of group accounts in supporting cooperation, the changes in the usage of Sarafu during the pandemic period and the impact of geographical location on cooperative behavior. Finally, Section 7 concludes the paper, pointing out possible future works.

2. Background

Sustainable development and blockchain for good. At the start of the decade, the United Nations changed the global development goals to emphasize the necessity of sustainable growth and social good [14]. The now 17 Sustainable Development Goals by the United Nations (UN Agenda 2030 for Sustainable Development [1]) have incentivized the good use of ICT and emerging technologies in many fields and scenarios. At the same time, we have seen the emergence of novel paradigms which are trying to reduce the over-centralization around a few big platforms and tech companies, a trend that has been very noticeable in different fields, like in finance [15] and in online social media [16,17]. In this scenario, one of the paradigms gaining momentum is Web3, i.e. the design of platforms and software systems built on blockchain technology has emerged as an effective solution for decentralized financial and industrial services [18]. The overlap of the need for more ICT for Good and the emergence of blockchain-based solutions has led to the concept of "Blockchain for Good" [19]. With this term, we refer to the many projects that have been developing over the years, focused on the application of blockchain technology's main features, including cryptocurrencies and smart contracts, to help humanity and the environment [20].

For example, there are blockchain-based solutions utilized to combat corruption and gender inequality [21], to the creation of transparent and sustainable supply chains [22], promoting financial inclusion [19] and social collaboration [23]. Moreover, several publications have examined the possibilities and limitations of blockchain for sustainable development, such as [20, 24]. And even the United Nations organization has promoted different blockchain-based programs [25] to help refugees, fund non-governmental organizations, and promote the collaboration and coordination of humanitarian aid and social development initiatives. Furthermore, blockchain technology has been utilized to promote social development and local economies [4].

Complementary currencies. Complementary currencies (CCs) are currencies that originate in various geographic situations to supplement the official national currency [2]. CCs can also be viewed as a fungible "voucher" or credit obligation redeemable for products and services, [4]. There are many instances of CC systems all around the world, with an estimated 3500 to 4500 CC initiatives in more than 50 nations since the 1980s [3,6]. In fact, they can be often referred to by many different names such as local currencies, alternative currencies, parallel currencies, community currencies [6], or community inclusion currencies [26] in the literature. While several studies have been conducted on the economical and social principles as well as the analysis of some case studies, there are presently few studies that focus on the impact of CCs during the COVID-19 epidemic. Gonzalez et al. [10] investigated the success of a Brazilian CC named Mumbuca E-Dinheiro during the epidemic. Stepnicka et al. [9] investigated the Zielony CC in Poland, claiming that the CC was not as successful during the epidemic as it was during times of true financial crises. While Ussher et al. [4] investigated Sarafu [12], a Kenyan CC that transformed into an improvised COVID-19 response system: during the crisis, Sarafu has proven to be quite beneficial in assisting the local population.

Sarafu, complementary currency on a blockchain. Sarafu[1] is a digital CC token created by the Grassroots Economics (GE) Foundation [27], a humanitarian aid foundation. Sarafu users may perform payments using mobile phones, transferring Sarafu digital tokens to other registered users. As described in Ussher et al. [4] the Kenyan Red Cross relied on Sarafu tokens to provide humanitarian aid during the COVID-19 pandemic: users registering were given free Sarafu tokens, backed by donors' money, to maintain the system running.

The use of blockchain technology is a key component of Sarafu. While the Sarafu project has not used blockchain technology from its inception, it has used it to solve several important issues [4]. Among the motivations, we have enhanced transparency, as transaction data allows contributors to fully disclose the impact of their donations. Furthermore, data analysis can lead to more informed decision-making processes regarding, for example, future investments and project functioning, while it also helps the GE Foundation to find ways to improve user welfare and minimize potential misuse. The system first moved to a blockchain maintained privately called *POA*. The name is derived from its consensus protocol, Proof of Authority [28], PoA in short. The project then switched to a public blockchain named xDai blockchain in 2020 to lower transaction costs [4]. Finally, in May 2022, the project transitioned to a new blockchain built by the GE Foundation to better meet its objectives. Kitabu ("Ledger" or "Book" in Kiswahili) is the name of the new blockchain, which is based on the Proof of Authority consensus protocol.

Sarafu and its impact are described in a few works in the literature. The GE Foundation provided an anonymized dataset for researchers [12], that covers a year and a half of user transactions. Mattsson et al. [11] have released a dataset paper, providing important context and background on Sarafu. The dataset has been used to study the program's success: Ussher et al. [4] presented an accurate description of CCs, the Sarafu project history, and an analysis of the dataset. Mqamelo [29] investigated the impact on people's welfare and local economic engagement, while Mattsson et al. [30] proposed an analysis modeling the entire dataset through a static network structure: their analysis highlights that money circulation is highly modular, geographically localized and occurring among users with diverse jobs. Clark et al. [26] rely on user information to perform simulations of the performance of the economic system using network-based complex systems model of subpopulation interactions. While in our previous work [31], we conducted a preliminary analysis focused on cooperation behavior, where we highlighted the presence of cooperation patterns and the importance of group accounts. In this article, we extend our previous study on the analysis of cooperative behavior by leveraging the geographic information available. More precisely, the main extensions focus on:

- how cooperative behavior impacts the allocation and redistribution of resources;
- the impact of geographical location on cooperative behavior; and
- the interplay between the geographical location and the allocation and redistribution of resources.

Cooperative behavior in Sarafu: group accounts. In Kenya, persons in need would frequently turn to informal saving organizations known as *chamas*[2] for assistance [4]. *Chamas* are savings groups usually composed of 15–30 people, often defined by a neighborhood, a shared occupation, or friendship and family ties [11]. Group members gather regularly at a fixed time of the day to pool their savings together and discuss the possibility of loans to other fellow members [32]. Essentially, it is a saving and lending scheme with no or small interest rate [33]. To facilitate the actions of these cooperation groups, the Sarafu system implements a particular type of account called *group account*. These *group accounts* were given to *chamas*, allowing them to save and lend Sarafu tokens like they would for the standard currency. Therefore, *group accounts* are the most crucial part of the analysis: the higher the amount of currency managed by group accounts in Sarafu, the higher the amount of group saving and lending, and consequently, we have higher the cooperation. As a result, *group accounts* enable an effective examination of cooperation patterns since they support and highlight cooperative behavior that could not be properly evaluated in other CC systems.

3. Research questions

In Sarafu, the GE Foundation assigns a group account to each cooperation group: these officially recognized accounts are leveraged to save money and assist members of the community in need [4]. As stated in Section 2, we can focus on the impact of *group accounts* to better understand user cooperative behavior.

The essential feature of cooperative behavior that we investigate is *how cooperation behavior is impacted by a crisis*, such as the COVID-19 pandemic, and to what extent cooperative behavior is influenced by other factors, such as geographic location. We can summarize the key aspects that we aim to investigate through the following research questions:

Research question 1 (RQ1): To what extent are cooperation groups used as a supporting tool for Sarafu participants? To what extent do the COVID-19 pandemic and the pandemic mitigation strategies impact the importance of cooperation groups?

Research question 2 (RQ2): How do cooperation groups allocate and redistribute resources? Does the allocation of resources by cooperation groups change over time?

Research question 3 (RQ3): What is the role of geographical location on the redistribution of resources? How does the geographical area impact cooperation groups?

Research question 4 (RQ4): Is there any interplay between the behavior of users and cooperation groups and the geographical location?

4. Dataset

The Sarafu dataset includes detailed and anonymized information on token transactions, along with a rich set of user features. The data spans the period from January 2020 to June 2021, totaling 930,161 economic transactions involving around 55,000 users. In the following, we fully describe transactions and users' data.

User information. Every user is mainly described by the following attributes:

- **held roles**: the role of the user. *Beneficiary*, which stands for a standard user, is the most prevalent. Another important role is the *group accounts*, i.e. accounts representing cooperation groups. Moreover, there are accounts used by management (*Token Agent*, *Vendor*, *Admin*) described in detail in [11];
- **business type**: standardized category of economic activity generated from the occupation information provided by users. Examples of possible values include *labor, food, farming, shop, fuel/energy* and so on (see Table 1);

[1] Sarafu means "currency" in Kiswahili.

[2] "Chama" is the Kiswahili word for "group".

Table 1
Description of user's *business types*, derived from the additional information provided with the dataset in [12].

Business type	Description
Labour	Non-farm workers of any kind. Carpenters, bakers, electricians, tailors, chefs, housekeeping, shepherds, beauticians, barbers, artists, engineers, managers, programmers, mechanics, security guards, insurance agents, waiters/waitresses, artisans, employees, bricklayers, masons
Food	Sellers of any kind of local food
Farming	Users registered as farmers or working on farms
Shop	Kiosks, boutiques, phones, cafes, pubs, clubs, clothing, furniture, jewelry, detergent, electric tools, perfumery, flower
Fuel/Energy	Sellers of firewood, kerosene, petrol, biogas, charcoal, paraffin, and diesel
Transport	Drivers, bicycle rental, bike, motorbike, and car services
Water	People in charge of managing the water tanks and other water re-sellers
Education	Teachers in schools, coaches, booksellers, tutors, facilitators, Red Cross volunteers, consulting, babysitters
Health	Traditional and official doctors, nurses, pharmacies, laboratories, first aid operators, and veterinarians
Environment	Waste collection, gardening, seeding, tree planting, cleaning, recycling
Savings	A member of a Chama, or a Chama not yet officially recognized by GE staff
Government	Community authorities (e.g. elders), governmental employees, governmental and military officials, soldiers
Faith	Religious chiefs or religious groups
Other	Unknown
System	Accounts run by GE Staff members

- **area type**: the area type determined from user-provided information about the residence place. The provided options are *rural*, *urban*, *periurban* or *other*;
- **area names**: the region or province the user lives in. The possible values span different spots across the whole nation of Kenya. More precisely, we have four urban areas (*Mukuru Nairobi*, *Kisauni Mombasa*, *Misc Nairobi*, *Misc Mombasa*), four rural (*Kinango Kwale*, *Nyanza*, *Turkana*, *Misc Rural Counties*), one classified as periurban (*Kilifi*). Users without a specific location are labeled as *other*.

Transaction information. Each economical transaction specifies its **source** and its **target** as anonymized IDs of the sender and receiver of the cryptocurrency token. Alongside that, we have important additional information for this study: one being the **timestamp**, i.e. the date and time of when a transaction happened, with a granularity of milliseconds *ms*. Another useful feature in the dataset is the **weight** of each transaction, corresponding to the amount of tokens moved from source to target. Finally, we find different types of transactions, described by the **transfer subtype** attribute, whose main values are:

- **standard**:the regular token transfer, the most frequent transaction;
- **disbursement**: the creation of tokens and transfer to an account;
- **reclamation**: the removal of Sarafu from an account;
- **agent out**: exchange of tokens with Kenyan Shillings, (only available for group accounts, that can send tokens to a system account to receive money).

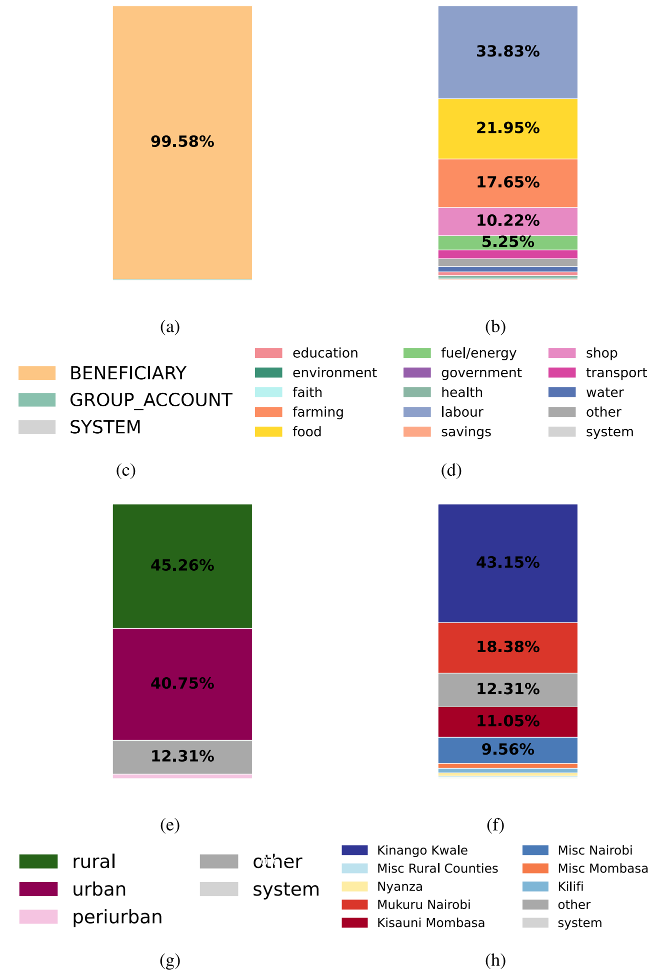


Fig. 1. Distribution for the main user attributes, in order: (a) *held role*, the account type, (b) *business type*, user's economic activity, (c) *area type*, and (d) *area name*, which are derived from the location provided by the user.

Preprocessing. It is worth noting that, since we are interested in transactions involving actual users and group accounts, we opted to exclusively investigate transactions where at least the source or the target are accounts of the *beneficiary* and *group account* categories. We consider all the available transactions, except for the last 5 days of January 2020, since they are characterized by a set of preliminary transactions that served to migrate pre-existing accounts from the prior system [11]. Furthermore, because a few accounts contained inconsistent information, a preprocessing step was necessary. For example, only group accounts should have *business type* set to *savings* according to the information in [12]. However, in our study, we observed certain beneficiary accounts were set to *savings*, which should not have been the case. In the analysis, we do not take this subset of inconsistent accounts into consideration. Moreover, there are some group accounts associated with *business type* values other than *savings*. We opted to set their *business type* to *savings*. Similarly, we made sure that all the accounts used by GE staff (*Token Agent*, *Vendor*, *Admin*) have their *held role* set to *SYSTEM* and all their attributes (*business type*, *area name*, *area type*) to *system* as well. In the end, we consider 54 807 users and 919 930 transactions.

Users' attributes distribution. Fig. 1 depicts the distribution of the user attributes. As shown in Fig. 1a, the majority of users are standard accounts (*beneficiary*, 99.5%). In terms of *business type* (see Fig. 1b), a large fraction of users (88.75%) has one of the following five *business types*: labour (33.8%), food (21.2%), farming

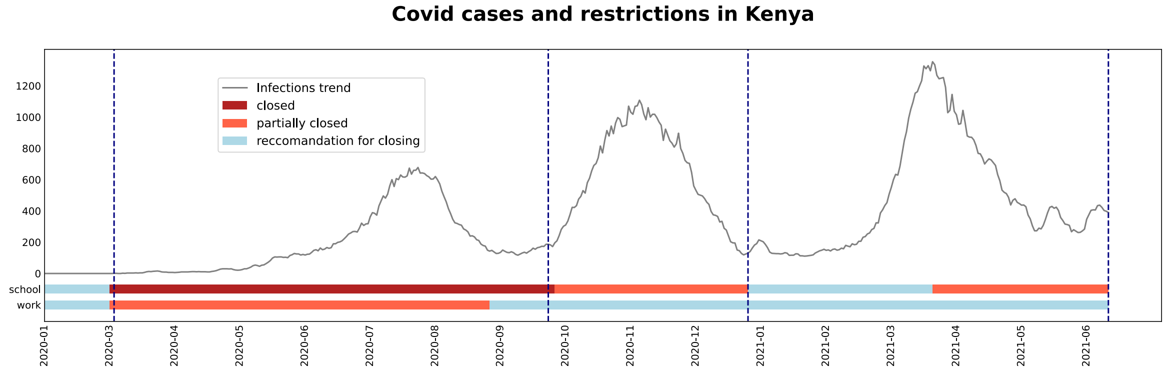


Fig. 2. COVID-19 cases and restrictions in Kenya. As the number of cases (blue line) varies over time, we can observe different restrictions over time (closed, partially closed, recommended closing) for both school and work, during the pandemic period. The figure from [31] is a reworking of data published by Reuters COVID-19 Tracker at [36].

(17.6%), shop (10.2%) and fuel/energy (5.2%). In Table 1 we reported the description provided by [12] for each possible *business type* value. In terms of geographic information, the majority of users are separated into rural (45.3%) and urban areas (40.7%), as shown in Fig. 1c. When we consider the area names (Fig. 1d), the rural region *Kinango Kwale* is at the top, followed by some urban areas *Mukuru Nairobi*, *Kisauni Mombasa*, *Misc Nairobi*. It is to be noted that area types and names are assigned by the GE staff after a standardization process derived from user-provided names [11].

5. Methodology

Modeling. In general, transactions can be modeled as a set of tuples $I = \{(u, v, t, a)\}$ where u and v are users that traded tokens: user u transferred to user v an amount a of Sarafu tokens at time t. Transactions over a time interval $[t_0, t_1]$ can be modeled as a temporal network [34]. Therefore, given the interval $[t_0, t_1]$, the set I can be transformed into a weighted directed graph $\mathcal{G}_{[t_0,t_1]} = (V, E, X, W)$, namely a transaction network, where:

- V is the set of users,
- E is a set of directed weighted links $(u, v) \in E$, two users are linked if they performed at least a trade in the time interval $[t_0, t_1]$,
- X is a $|V| \times f$ matrix of user attributes, where f is the number of available attributes,
- W is a weight matrix representing the flow of money. In fact the weight $w \in W$ of an edge $e = (u, v) \in \mathcal{G}_{[t_0,t_1]}$ is the sum of the amounts sent from u to v during the time interval $[t_0, t_1]$.

Defining a sequence of these *transaction networks*, we may investigate changes in network structure over time [35] as well as total monetary flow in different time intervals.

Analysis. To answer our research questions, in addition to transaction networks, we also rely on Sankey diagrams: Sankey diagrams are an effective visualization tool for many different types of flows such as material, traffic, water, and money [37]. Given a transaction network, we can derive different types of Sankey diagrams that enable the analysis of monetary flows. The construction can be performed by aggregating currency values on incoming and outgoing edges, while we consider user attributes. Therefore, through Sankey representation we can perform various analyses, as nodes can represent different user attributes – i.e. the types of accounts or the *business types*, or the user location – while the directed links indicate the cumulative flows between sources and targets.

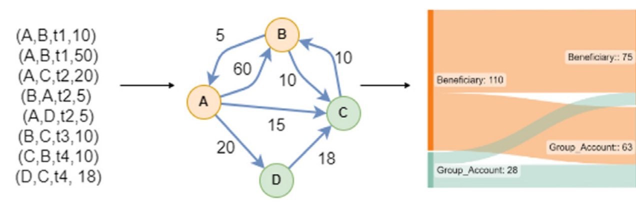


Fig. 3. An example outlining the proposed methodology. Starting from the transactions, in format (sender, receiver, amount, timestamp), we filter them on the timestamps to obtain a subset for the time period of interest. Then, we construct the transaction network. Relying on the weights and attributes of the transaction network, we can aggregate to construct the Sankey diagrams. In the example of the transaction network, nodes are colored according to the type, while the weights on links correspond to the amount of tokens flowing from the source to the destination.

A recap of the proposed methodology is shown in Fig. 3. We first build a transaction network out of the complete dataset. Then, we integrate the dataset with additional contextual information about COVID-19 cases and restriction policies by the Kenyan government, as illustrated in Fig. 2. Using such information, we divided transactions into four time periods, based on the different restriction policies in effect. As a result, we can apply the aforementioned methodology to construct four transaction networks, one for each period. Then, we analyze the transaction networks and understand the differences between different periods.

To answer RQ1 we need to comprehend the importance of group accounts, so we analyze Sankey diagrams with nodes representing the "role" of the account, *beneficiary*, *group account* or *system*. Then, we assess the importance of cooperation in the pandemic scenario using group accounts and we analyze changes over time.

In order to answer RQ2 we need to understand the categories of users that are involved in exchange group accounts: we focus on the group accounts' spending behavior by looking at the categories group accounts are spending on; and we analyze funding, by observing the categories of users who send money to group accounts. We observe the flows both from a static and over-time perspective to obtain a deeper understanding of how COVID-19 cases and restriction policies have influenced users' and cooperation groups' behavior.

For RQ3, we assess the impact of geographic location on user behavior as well as the possible impact on cooperation. Therefore, we first analyze the flows of money across geographic regions using Sankey diagrams that take into account the nodes' geographic information, i.e. their *area name*. Then, we concentrate on cooperation groups, using Sankey diagrams centered on group accounts to study both spending and funding behavior, i.e. which geographic regions get money from group accounts and which give money to group accounts, respectively. We observe both the static and over-time flows, using the geographical information of the *area name* for both users and group accounts. Moreover, we leverage group accounts' geographical area information and users' *business type* to describe the categories of funding and spending in each geographical area. We generate multiple Sankey diagrams, that provide an effective overview of the differences across geographical areas. The same methodology, applied over time, will allow the observation of spending and funding behavior changes in each geographic area.

Finally, we address RQ4. We deal with any potential relationship or interplay between the behavior of a user/cooperation group and their geographic location. In other words, we want to verify if users in a specific category, such as "food", behave differently based on the geographical location, and if such behavior changes over time and vice-versa we would like to see if in a given geographic area, users prioritize different categories and whether their priorities vary over time. A crucial aspect must be kept in mind when studying changes over time: certain changes might simply be due to an increase or reduction in the number of users in a specific category or geographical location. Therefore to highlight changes that are not simply a byproduct of the distribution of users we must account for the changes in the population the so-called *population drift* [38] or *population turnover* [39]. This is an important issue known in data science and computational social science literature: when studying behavioral drift i.e. changes in how people are using a system, we should always monitor population drift as well as system drift i.e. changes in the system itself. We highlight changes over time relying on stacked area plots: these plots dedicate a colored area to describe the variation of different time series, allowing us to visualize changes over time, but at the same time they allow the comparison of different data without overlapping. We study different quantities based on the category or geographical area of users: we focus on spending (the total amount spent by users), funding (the amount received by users), or the number of active users. Therefore, for a given geographical area we can plot the categorical variation, an area plot that separates quantities based on the user category. By comparing the *categorical variation* of each geographical area, we highlight potential differences or characteristics of a given area. Vice-versa, we analyze and compare each category through its *geographical variation*. These plots also are suitable to highlight how cooperation groups are affected: we only need to focus on the category of group accounts (*savings*) to the other user categories. The same methodology is used to compare funding i.e. the money that is sent to the category or area. The methodology allows us to monitor population drift, as we also keep track of the number of active users, allowing us to exclude variations due to population drift. In addition, we make sure to consider system changes based on the time periods observed, accounting for the system drift when we make our observations.

6. Results

In this and the next sections, we have applied the methodology discussed above to the Sarafu dataset, which is modeled as a sequence of transaction networks whose characteristics are displayed in Table 2.

Transaction volume had grown substantially over time, with a notable increase in active users in the second period when the pandemic reached Kenya and the Red Cross made an effort to promote Sarafu to respond to the crisis [4]. We see an interesting difference when we consider only the *standard* transactions between beneficiary and group accounts as we did in our previous work [31] and as shown in Table 3. We observe that the quantity of unique active users of beneficiary and group accounts diminishes in subsequent time periods, but still with a large number of active users in the last time period. However, as we consider all the transactions in the dataset, we can observe that a bigger portion of users can be considered active, as they were involved in at least one system-related action in subsequent time periods.

Table 2
Transactions and transaction network statistics over the entire dataset and in different periods. The periods are selected based on changes in the mitigation policies and restrictions adopted during the pandemic period (see Fig. 2).

Start	End	Active users	Edges	Transactions
2020-02-01	2020-03-15	4 218	10 449	14 486
2020-03-15	2020-10-01	39 410	162 226	411 191
2020-10-01	2021-01-01	41 472	91 155	182 013
2021-01-01	2021-06-16	47 928	131 000	306 855

Table 3
Transactions and transaction network statistics in different periods, but considering only *standard* transactions between beneficiary and group accounts, in the same periods as in the previous Table 2.

Start	End	Active users	Edges	Transactions
2020-02-01	2020-03-15	3 802	7 325	10 744
2020-03-15	2020-10-01	28 070	96 266	251 594
2020-10-01	2021-01-01	7 030	22 872	63 262
2021-01-01	2021-06-16	13 960	35 225	85 026

6.1. Impact of cooperation

As indicated in Section 3, our first research topic focuses on the role of group accounts in money flows. Fig. 4 portrays the Sankey diagram of money transfers constructed using the entire dataset.

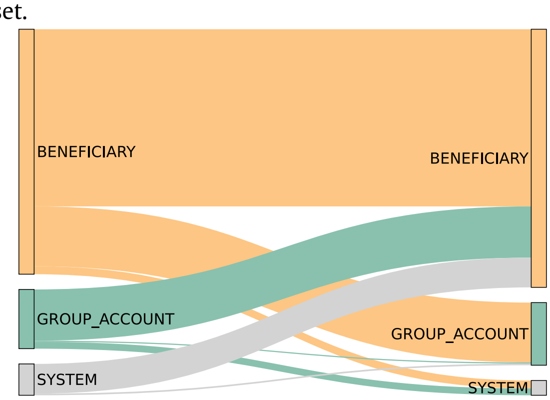
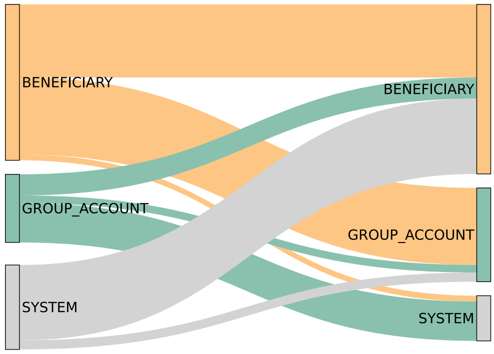


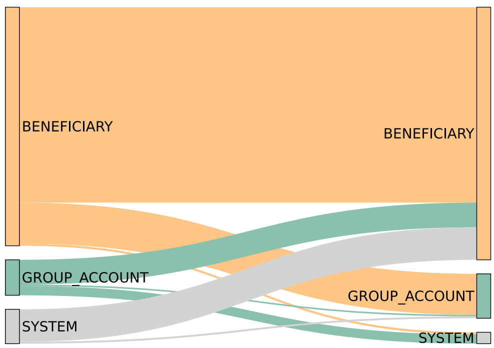
Fig. 4. Study of the importance of group accounts: Sankey diagram of monetary flows from group accounts to beneficiary accounts and vice-versa.

Due to the distinct nature of group accounts (which account for 0.42% of all users only), the percentage of money flows involving them is significant (36%). This result clearly emphasizes the importance of group accounts, which are few and yet handle over one-third of all currency transactions.

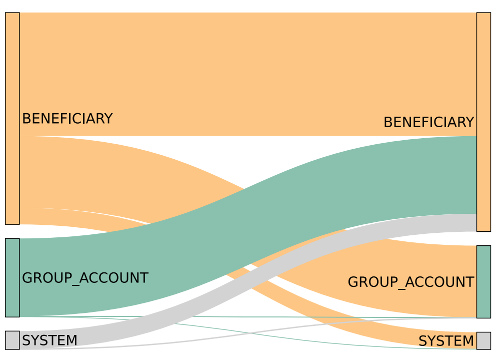
We proceed with the study of the role of group accounts and their spending behaviors, by identifying potential changes during different pandemic phases. Fig. 5 shows the money flows grouped by the held roles we consider: beneficiary and group accounts. It is clear from the Sankey diagrams that the impact of group accounts changes over time. The first observation concerns the rise of flows from group accounts beginning in the third period: although the percentage of flows from group accounts



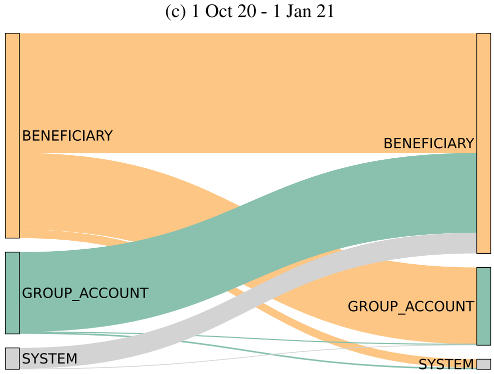
(a) 1 Feb 20 - 15 Mar 20



(b) 15 Mar 20 - 1 Oct 20



(c) 1 Oct 20 - 1 Jan 21



(d) 1 Jan 21 - 16 Jun 21

Fig. 5. The impact of group accounts over time, as measured by monetary flows. We display the monetary flows from group accounts to beneficiary accounts, and vice-versa, for each period.

to *beneficiary* users, in the first two periods, is on average 7%, it rises to 25% in the last two periods. As noted in [11], group accounts are able to exchange tokens for Kenyan Shillings, the importance of the functionality is observable through the flow from *group accounts* to *system* accounts. A second interesting observation can be made by observing the period characterized by the most stringent mitigation policies. In fact, the second period corresponds to the first wave of COVID-19 cases, and it is also the most different period, because of its outlier percentage of transactions among beneficiary accounts. In this situation, the complete closure of schools and the partial closure of workplaces – both of which impose significant restrictions on mobility and sociality – may have encouraged private and direct transfers of money, bypassing the use of group accounts. On the same note, if we observe the number of group accounts in Table 4, we can see how more group accounts are established. In the remaining periods, the flows within beneficiary accounts remain almost stable (from 40% to 39% of transactions), whereas the percentage of operations from group accounts to *beneficiary* users grows (from 8% to 25%). Finally, the pre-pandemic period is the only one where beneficiary accounts exchange money with other beneficiary accounts and group accounts in balanced percentages. In fact, they only differ by 0.36% while in the other periods, the difference is consistently greater than 13%.

Therefore, we can conclude that (a) group accounts are few and yet handle a significant volume of currency; and (b) their importance increases over time.

Table 4
Number of group accounts over time, at the end of each period. The periods are selected based on changes in the mitigation policies and restrictions adopted during the pandemic period.

Group accounts for each area	15 Mar. 2020	1 Oct. 2020	1 Jan. 2021	16 Jun. 2021
Kilifi	1	1	3	5
Kinango Kwale	56	73	73	78
Misc Mombasa	2	2	2	3
Misc Nairobi	8	9	9	9
Mukuru Nairobi	4	45	45	48
Nyanza	0	3	3	5
Kisauni Mombasa	0	0	0	61
Turkana	0	0	0	1
Other	0	0	0	1
Total group accounts	71	133	136	211

6.2. Cooperation groups funding and spending

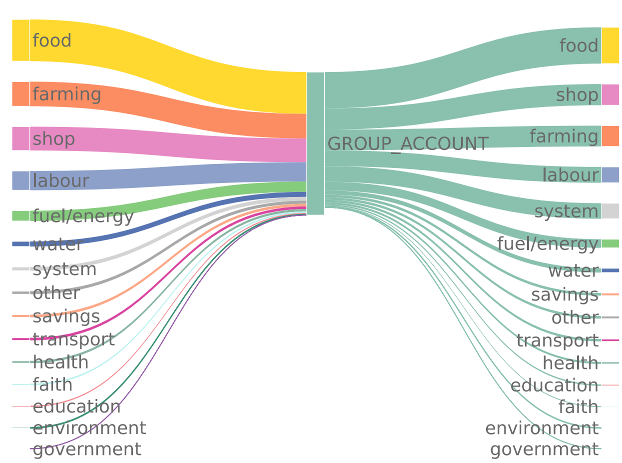


Fig. 6. The importance and behavior of group accounts. Through a double Sankey diagram, we highlight group account funding and spending behavior. For funding, we show the categories of users that send money to group accounts, while for the spending behavior, we look at the categories of receiving users.

Moving on to the next research question, we proceed with the study of group accounts and their spending behaviors. To get

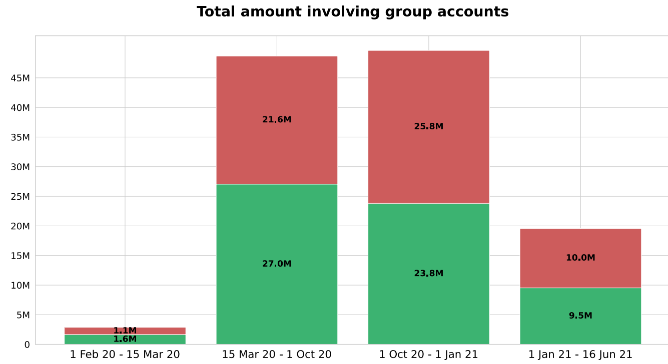


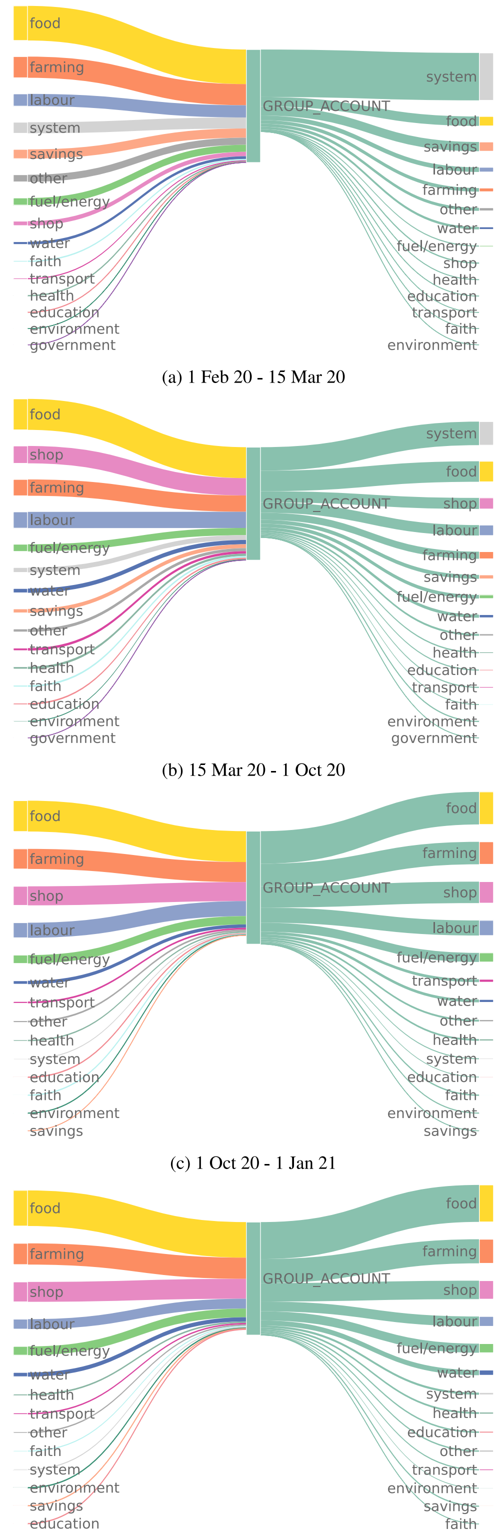
Fig. 7. The total amount of money handled by group accounts for each period. For each period, the stacked barplot shows both incoming and outgoing money for group accounts. The amounts consider the transactions involving users, group accounts and system accounts.

a deeper understanding of the money flows from and to group accounts, we rely on a double Sankey diagram (see Fig. 6, where flows are grouped by *business type* of the *beneficiary node*. Fig. 6 shows that the most prevalent categories remain stable: the first four (food, farming, shop, and labour) account for 70% of the incoming operations to group accounts and 75% of the outgoing ones. Note that the ranking of the top categories is different from the general ranking over the whole dataset, depicted in Fig. 1b, allowing us to exclude that the ranking is just a byproduct of the distribution of users in the dataset. Indeed, when the *business types* are ranked not by frequency but by the percentage of flows (the relative amount of money involved in the transactions grouped by categories) we can observe that: *food* and *shop* categories gain importance (first and second place, respectively) in both directions while the, *labour* is less important (fourth position instead of first).

Fig. 7 shows the total amount of money of all transactions transferred to and from group accounts throughout each period. In addition to the ratio of incoming to outgoing amounts, the magnitude of money spent has risen over time. In fact, the central periods have a substantially higher total than the other ones.

We can further investigate the spending behavior of beneficiary and group accounts throughout specific pandemic periods through the Sankey diagrams shown in Fig. 8. At first sight, it is noticeable that the incoming and outgoing relative amounts vary over time. Initially, there is a propensity to store money on group accounts, which spend only a small percentage of the income (the outgoing total is only 49% of the incoming total). Over time, the percentage of outgoing over incoming amount grows so much that in the third period, the outgoing amount is actually higher than the incoming. Another interesting observation from Fig. 8 concerns the order of the categories. First, the *saving* category presents an anomalous behavior: we observe a great flow in the first period (even if in the general distribution shown in Fig. 1b this category is just the third last), in the successive periods it loses some positions and then becomes even less frequent. On the contrary, the *shop* category begins at a very low ranking position (after the first six) but moves up in the top three from the second period. With the exception of the *savings* and *system* categories, the top six slots of the ranking are always taken by the first eight categories in the overall distribution. Furthermore, the *food* category is always on the top, with a large lead from the second one. It is also worth noting that the categories generally keep the same position with incoming and outgoing transactions.

So, we can conclude that: (a) spending behavior is not just a byproduct of the distribution of users; and (b) the allocation of resources by cooperation groups changes over time, as users adjust to the Covid-19 pandemic, mitigation policies, and changes in the Sarafu system.



(a) 1 Feb 20 - 15 Mar 20

(b) 15 Mar 20 - 1 Oct 20

(c) 1 Oct 20 - 1 Jan 21

(d) 1 Jan 21 - 16 Jun 21

Fig. 8. Group account funding and spending behavior, over time. For each time period, we have a double Sankey diagram, showing both funding and spending monetary flows. For funding, we show the categories of users that send money to group accounts, while for the spending behavior, we look at the categories of receiving users. Below each figure, we report the time interval.

6.3. Geographical location and cooperation groups

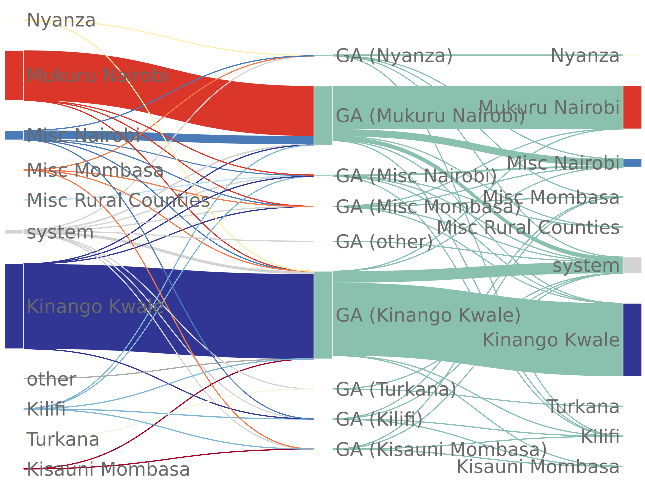


Fig. 9. Monetary flows across different geographic regions. Through a double Sankey diagram, we highlight group account funding and spending in different geographic regions. For funding, we show the area type of users that send money to group accounts, while for the spending behavior, we look at the area type of receiving users.

We also focused on the role of geographic information in cooperative behavior. As a tool, we rely on double Sankey diagrams where we observe the flows to and from group accounts, grouped by the geographic area of the *beneficiary* users. Moreover, we also consider the geographical area of the group accounts for a more expressive representation of the flows.

We obtain the Sankey diagram in Fig. 9 when we consider the flows based on the *area name* of the *beneficiary node*. We can observe a money flow to group accounts from all areas. While there are flows among different geographical areas, most of the circulation is local, in line with the observation in Mattson et al. [30]. We can observe that the biggest flows involve the top 2 areas in terms of overall users, i.e. *Kinango Kwale* and *Mukuru Nairobi* (as we noticed in the overall distribution in Fig. 1). However, the ingoing and outgoing flows of *Kisauni Mombasa* are less than those from *Misc Nairobi*, even though the former has fewer users.

We also analyzed how flows change over time as displayed in Fig. 10. We can see in the first time period, for *Mukuru Nairobi*, one of the main urban areas, there is almost no flow towards and no money received from group accounts; instead, in other areas, there is a reliance on group accounts right from the starting period. However, this trait changes during the second period, when cooperation groups increase their spending: the area of *Mukuru Nairobi* receives a comparable amount of money to the top one *Kinango Kwale*. However, in the last two periods, the gap between these areas increases again: while the flow to *Mukuru Nairobi* is similar, we observe an increase in the flow to the *Kinago Kwale* area. These changes in behavior for *Mukuru Nairobi* may be a direct consequence of the important growth coinciding with the effort by *Red Cross Kenya* to provide aid during the pandemic: while it shows the importance of Sarafu, it is not simply a change of behavior or use caused by the pandemic. Similarly, the flows seem to highlight the effects of the policy changes in the third and fourth periods, when users were incentivized to spend more by the GE Foundation [4].

Then, we leverage geographical area information associated with the group account and users' *business type* to describe funding and spending in each geographical area. The different Sankey diagrams, reported in Fig. 11, provide an effective overview of the differences across geographical areas. Overall, we can see how geographical areas tend to have different priorities. Except

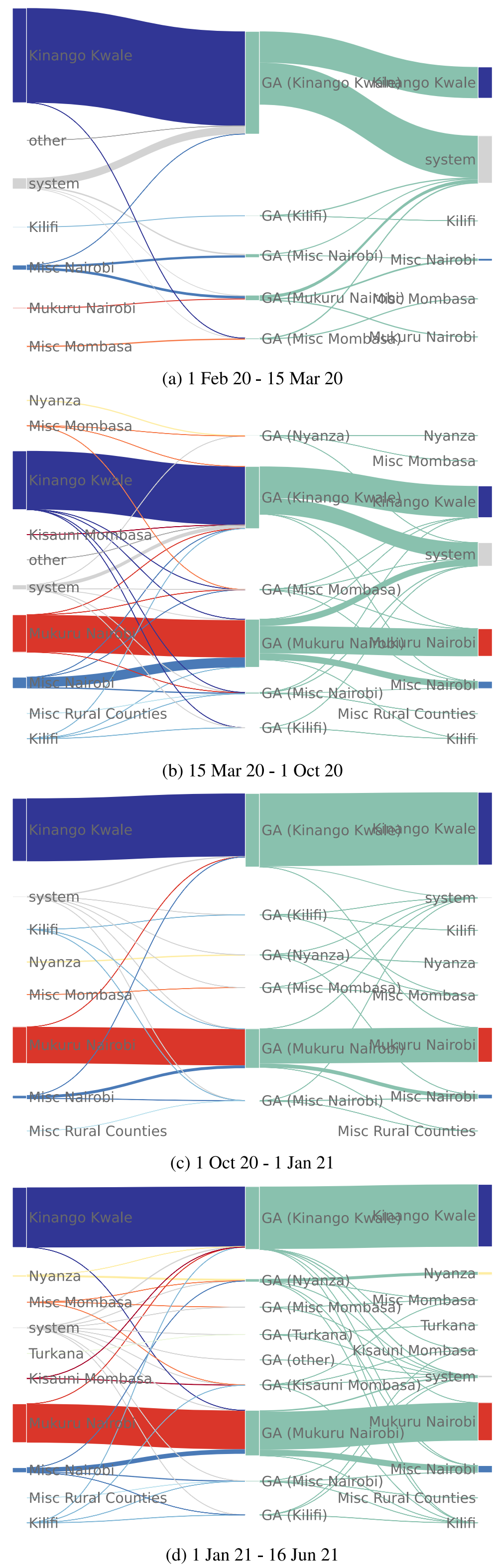
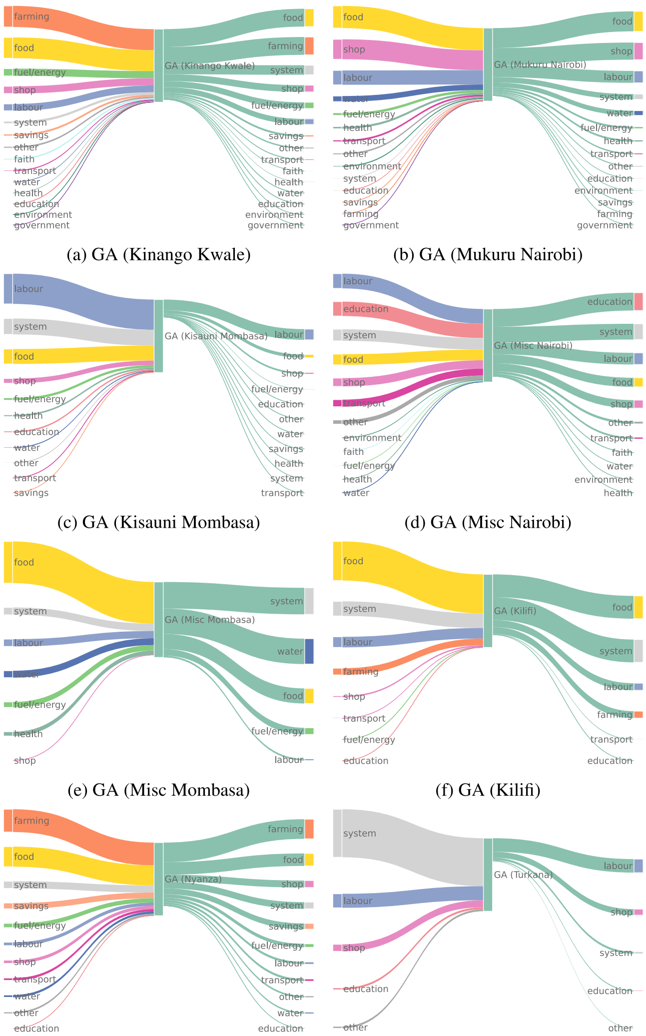


Fig. 10. Monetary flows across different geographic regions. Through a double Sankey diagram, we highlight group account funding and spending in different geographic regions. For funding, we show the area type of users that send money to group accounts, while for the spending behavior, we look at the area type of receiving users. Below each figure, we report the time interval.

for the food category, which can be usually found among the top categories, the categories of interest vary between areas.



(a) GA (Kinango Kwale) (b) GA (Mukuru Nairobi)

(c) GA (Kisauni Mombasa) (d) GA (Misc Nairobi)

(e) GA (Misc Mombasa) (f) GA (Kilifi)

(g) GA (Nyanza) (h) GA (Turkana)

Fig. 11. Monetary flows from group accounts to beneficiary accounts, and vice-versa, for each period, leveraging geographical information (area name) of group accounts.

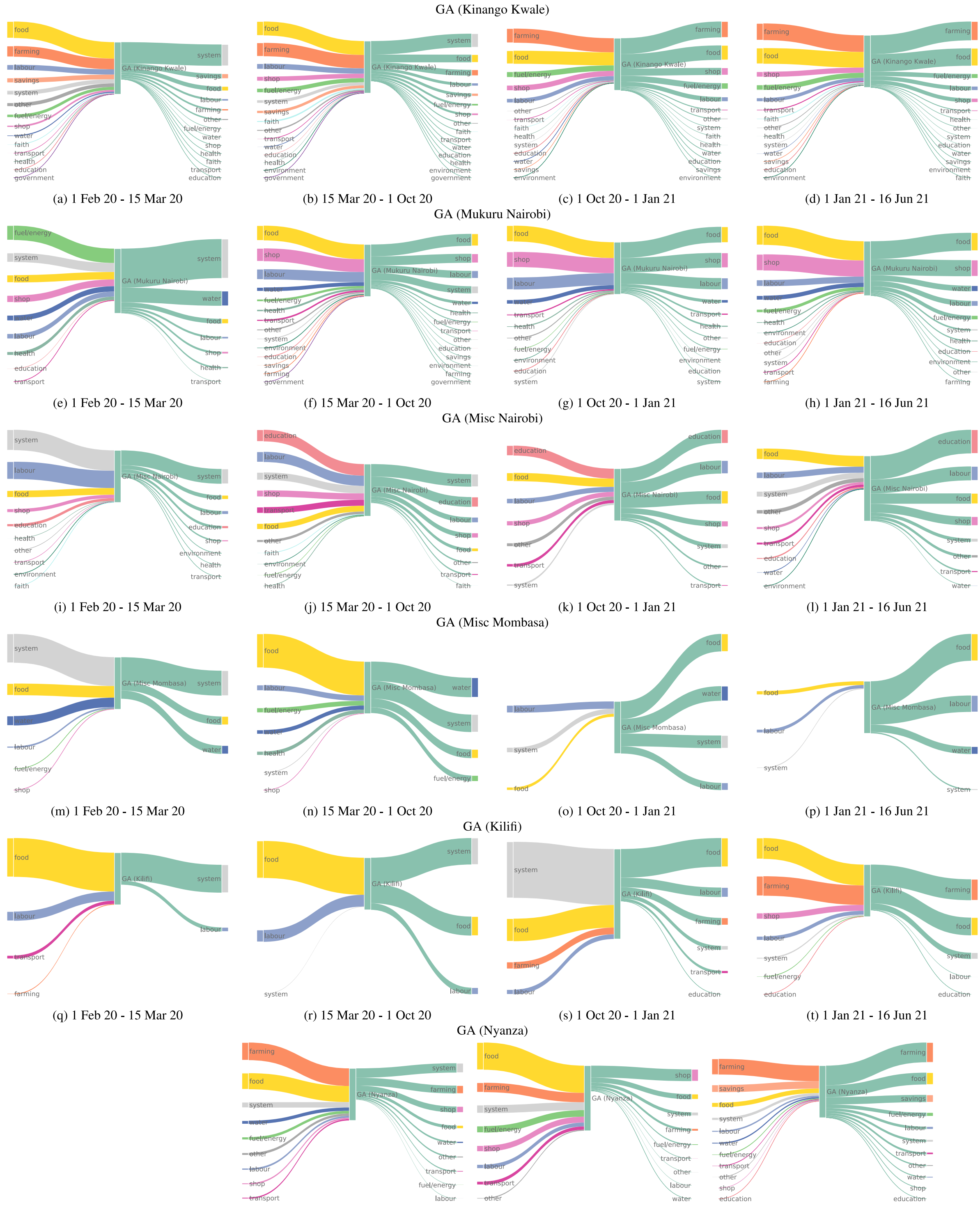
In terms of overall flow, we can see how group accounts in more established areas such as *Kinango Kwale*, *Mukuru Nairobi* have spent most of their tokens, while in smaller or growing areas, there was a tendency to accumulate tokens. An example is the *Turkana* area, established only in the last period, where we can see significant funding flows from *system* accounts, as new users join the platform. Another interesting insight is how the same categories are much more important in certain areas. For instance, in the area of *Misc Nairobi*, users, whose occupation is in *education*, are quite important in both funding and spending. Similarly, in the area *Misc Mombasa*, there are fewer categories and most of the tokens are spent on *water* users.

Finally, the same methodology can be applied over time, to provide additional insights. Fig. 12 supports an analysis of how spending and funding behavior changes over time in each geographic area. The subdivision over time highlights the differences in this area in the earlier period, where there is a bigger influx of money from the system, as users registered and obtain various bonuses for being active [11]. Similarly in funding, we can see a flow from *group accounts* to *system* accounts, as groups were relying on the exchange functionality. Similarly, we can observe how most of the areas tend to save money in the first period and increase their spending attitude as time progresses.

In conclusion, we notice that: (a) both urban and rural areas rely on cooperation groups, and (b) geographical areas are characterized by their own different behavior, with their priorities changing over time.

6.4. Interplay of funding and spending behavior with geographical locations

In this section, for answering RQ4, we analyze the interplay between categories and geographic areas and whether there is an impact on cooperation groups. We start our analysis from the plot for each area of its *categorical variation*, i.e. an area plot that separates quantities based on the user category. We monitor different important quantities: (i) the number of active users, (ii) spending (the total amount spent by users), and (iii) funding (the amount received by users). Through the use of stacked area plots, we can visualize the variation over time for each area separated by category, as well as compare the overall volume changes, as also described in Section 5. While keeping track of the distribution of active users, we are able to account for the problem of population drift [38] or population turnover [39] i.e. the changes in the population using Sarafu, as the system grows: we are able to identify whether we are observing an actual change in behavior or if it is more likely a byproduct of the user population changing. We represent the actives users distribution in Fig. 13(b) (active users count normalized per time period, so we obtain a percentage/distribution), the users' spending behavior in Fig. 13(c) and users' funding behavior in Fig. 13(d). We can observe that every area type has a very different profile. Focusing on the distribution of user categories in Fig. 13(b), we can notice that the frequency of categories is not the same for all areas. As expected, in the rural area *Kinango Kwale*, the most frequent are *farming*, *food*, *shop*, *fuel/energy*. We can see that the *Nyanza* province is similar, with food more present; whereas the *Misc Rural Countries* has an important presence of education and more *labour* nodes. The *Turkana* Area has no variation values since the project started only in the last period. The urban areas have different distributions. Starting from the most populous one, *Mukuru Nairobi*, we can see that food and shop are still largely present. But, we have almost no *farming* and less *fuel/energy*, as well as higher *labour*. The area of *Misc Nairobi* is similar, while the two *Mombasa* areas show a few differences: *Misc Mombasa* shows the presence of more *labour* nodes, while *Kisauni Mombasa* has a bigger *shop* component, more *labour*, *government* and *other*. The peri-urban area (*Kilifi*) is also quite similar to the urban ones. So, even though every area shows some characteristic traits, we also find some similarities and common characteristics. Furthermore, when we observe the variation in spending (Fig. 13(c)) and funding behavior (Fig. 13(d)), we can see that the area plots tend to be quite different for each geographic area. Here, we only discuss the outcomes in the spending plots, since spending and funding plots are pretty similar, except for small variations in the sizes of the areas. Most of the geographic areas experience a peak of spending/funding in the second period - the policies are stricter and most of them relied more on Sarafu during this period - and we observe a decline for some areas in the third period - policies have become less strict. Finally, areas tend to differ in the fourth period, with a few still decreasing, while most are showing growth. Some of those variations coincide with the variation of overall users, while others seem actual changes in behavior that happen independently from the number of users. For example, in the rural area of *Kinango Kwale*, most of the spending occurs by users of the categories *farming food* and *savings*, and their spending rises significantly in the second period. While the rise in *food* category is in line with the rise in the number of *food* users. For *farming*, and especially *savings* (the



(a) 1 Feb 20 - 15 Mar 20 (b) 15 Mar 20 - 1 Oct 20 (c) 1 Oct 20 - 1 Jan 21 (d) 1 Jan 21 - 16 Jun 21

(e) 1 Feb 20 - 15 Mar 20 (f) 15 Mar 20 - 1 Oct 20 (g) 1 Oct 20 - 1 Jan 21 (h) 1 Jan 21 - 16 Jun 21

(i) 1 Feb 20 - 15 Mar 20 (j) 15 Mar 20 - 1 Oct 20 (k) 1 Oct 20 - 1 Jan 21 (l) 1 Jan 21 - 16 Jun 21

(m) 1 Feb 20 - 15 Mar 20 (n) 15 Mar 20 - 1 Oct 20 (o) 1 Oct 20 - 1 Jan 21 (p) 1 Jan 21 - 16 Jun 21

(q) 1 Feb 20 - 15 Mar 20 (r) 15 Mar 20 - 1 Oct 20 (s) 1 Oct 20 - 1 Jan 21 (t) 1 Jan 21 - 16 Jun 21

(u) No group accounts here in this period (v) 15 Mar 20 - 1 Oct 20 (w) 1 Oct 20 - 1 Jan 21 (x) 1 Jan 21 - 16 Jun 21

Fig. 12. Monetary flows from group accounts to beneficiary ones, and vice-versa, for each period, using geographical information (area name) of group accounts.

category of group accounts), this is not the case: the number of *savings* accounts remains just a small fraction, and *farming* users are actually dropping even though their spending volume rises. Similarly in the successive periods, we observe drops in spending and funding but they do not correspond to significant swings in the distribution. Similarly, when we look at the main urban area of *Mukuru Nairobi*, we can observe the growth of *food*, *labour* and *shop* categories, but it does not coincide with a change in the distribution of users for those categories: there are different variations based on the geographic area that the distribution of user categories in that area cannot only explain. When it comes to cooperation groups, the split by geographic area shows that in some areas the spending/funding of group accounts is very significant compared to other categories: for example in the rural *Kinango Kwale*, *Nyanza*, and in the urban *Misc Mombasa*, the area of spending for *savings* covers a huge portion of the overall area

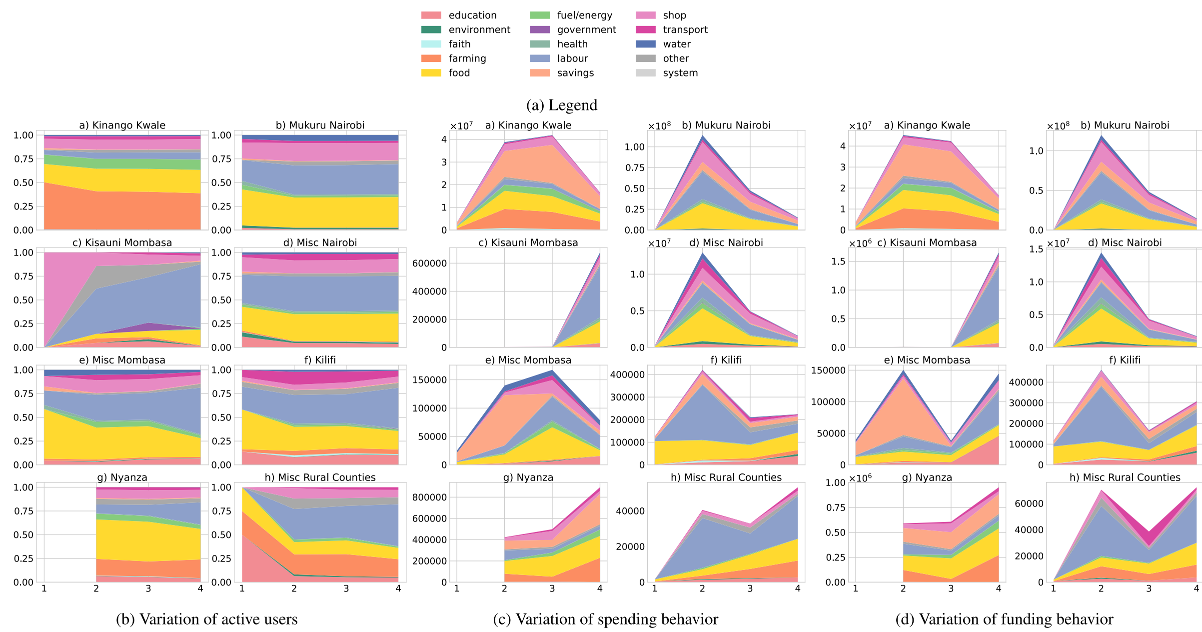


Fig. 13. Variation of (a) active users and (b) spending behavior (c) funding behavior in each of the areas, separated through category information. Colored areas represent categories. Please note that the *Turkana* area was omitted, as the project started only in the last time period.

plots, while in other areas it is not as huge, at least in comparison to the rest of the categories. Indeed, cooperation, while always present, is also dependent on the geographic area.

Finally, we analyze for each category its *geographical variation*: i.e. an area plot that separates quantities based on the users' geographic location. In this case, the stacked area plots visualize the variation over time for each category, with the measurements separated by category. Each area plot is focused on changes in either (i) the number of active users (ii) spending (the total amount spent by users), (iii) funding (the amount received by users), separated by the users' geographical information i.e. the attributes *area type* or area name. We present the users' distribution in Fig. 14(b) (number of users normalized per time period to obtain a percentage/distribution), the spending behavior in Fig. 14(c) and funding behavior in Fig. 14(d). From Fig. 14(b) we can see that every category has different user distributions. Most noticeable is that farming and fuel/energy are mostly present only in one area. The others tend to be more distributed across regions. When we consider the spending variations in Fig. 14(c), we can observe that in most categories, spending volume is dominated by the urban area *Mukuru Nairobi* and the periurban *Kilifi*. However, in some categories *faith*, *farming*, *fuel/energy*, and *savings*, *Kinango Kwale* is predominant: the total amount of flow surpasses the dedicated flow in the other areas by a large margin. But while for *farming* and *fuel/energy* is sort of in line with the changes in the overall distribution, for *faith* and *savings* it is not. In fact, it is interesting how faith nodes play such a huge role in one area only. Finally, in terms of cooperation groups (*savings*), we can see that spending and funding grow in all areas, in line with the previous observations.

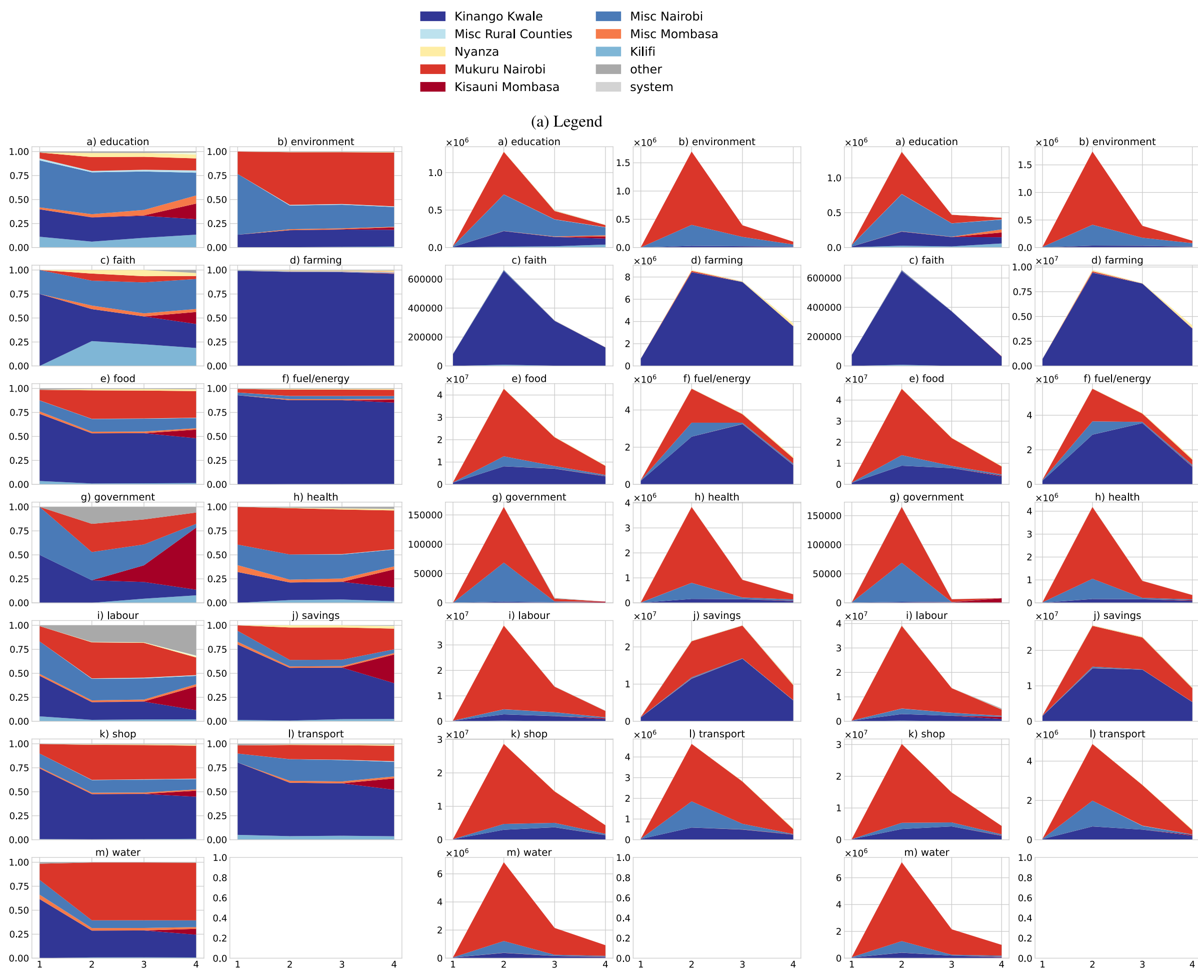
According to these observations, we can conclude that (a) geographical areas are each characterized by their own profile, with urban and periurban areas showing more similarities, (b) in some areas the spending/funding of group accounts is much more significant compared to other categories, (c) categories also have different profiles, and certain categories are only important in a subset of geographical areas, and (d) cooperation groups maintain their importance in every area.

7. Conclusion

Our findings on group accounts suggest that this sort of account or similar mechanisms that promote cooperation could be useful for other humanitarian or community development projects: with this methodology, we could analyze currency flows to detect cooperation and coordination, and when absent, consider how to promote it. Moreover, similar cooperation enhancers could have an important role in other social development projects, and in general, in any setting where there is a strong need to foster cooperation for reaching social good. Finally, it would be interesting to understand if group accounts could be a catalyst of cooperation in other systems or scenarios: if so, the introduction of similar "institutional" cooperation accounts could be an effective solution for systems where there is a strong need to foster cooperation, a key factor in reaching social good and other sustainable development goals.

In addition, the proposed methodology could be used for the analysis of other currency systems, to analyze changes over time as well as to detect potential issues or anomalies. We have shown how our methodology effectively highlights the impact of external events as well as the effects of policies and organizational intervention. A similar study applied to other CC systems could provide invaluable information to administrators, policymakers, or even the government to leverage CCs, especially in times of crisis. In general, it can help to detect the strengths and weaknesses of a CC system, and how they should intervene. For example, the methodology proposed for the analysis of user behavior in terms of funding and spending categories could help define which users should be engaged for discussing issues, implementing changes, or evaluating the system's performance. Moreover, we have shown how leveraging geographical information can distinguish the need and priorities of a community: understanding the needs of people would allow better delivery of humanitarian aid. In fact, recognizing inequalities across should be important for effective management and decisions - making locality-based policies and incentives.

Overall, the resulting information from data-driven quantitative studies with this methodology could be especially beneficial in decision-making processes for current and new humanitarian aid initiatives, as well as currency systems in general.



(a) Legend

(b) Variation of active users (c) Variation of spending behavior (d) Variation of funding behavior

Fig. 14. Variation of (a) active users, (b) spending behavior, and (c) funding behavior in each category group by geographical area. Colored areas represent the geographical areas.

CRediT authorship contribution statement

Cheick Tidiane Ba: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Matteo Zignani:** Conceptualization, Methodology, Resources, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Sabrina Gaito:** Conceptualization, Methodology, Resources, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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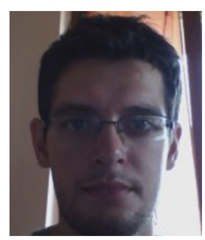

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