Temporal analysis of cooperative behaviour in a blockchain for humanitarian aid during the COVID-19 pandemic

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ABSTRACT

In the last few years, there has been a growing interest in the subject of blockchain technology for good. Among the many endeavours, blockchain technology has lately been exploited to build complementary currencies in the sphere of humanitarian aid: currencies that support national economies to provide humanitarian aid and promote development. While there have been numerous research projects on complementary currencies (CCs) and their success, some critical aspects remain largely unexplored. First, even though cooperation is a key factor in the development of these systems, as local communities organize themselves in times of crisis, there is a lack of studies that investigate the cooperative behaviour in these systems and how it changes over time. Besides, there are only a few works studying these currencies during the recent crisis of the COVID-19 pandemic. In this work, we investigate Sarafu, a digital complementary currency based on blockchain technology. To support cooperation, Sarafu implements a special type of account, the *group account*, thus allowing the study of cooperation groups, that cannot be easily analyzed in other CC systems; furthermore, it was successfully used for humanitarian aid during the COVID-19 pandemic. We find that Sarafu users show strong cooperative behaviour, facilitated by the usage of these group accounts. Furthermore, we observe the increasing importance of cooperation groups over time, as well as differences over time in their spending behaviour. From the analysis, we highlight the presence of cooperation patterns and the importance of group accounts, a takeaway for current and future humanitarian projects.

CCS CONCEPTS

• **Networks** → *Peer-to-peer networks*; **Network economics**; • **Applied computing** → **Digital cash**; **Electronic funds transfer**; **Economics**.

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KEYWORDS

socio-economic network, blockchain, human behavior, transaction network,temporal network

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1 INTRODUCTION

In recent years, there has been a growing interest in the application of blockchain technology for good [1], whether for social or environmental purposes. Over the years, many "Blockchain for Good" projects have emerged, focused on how to exploit the key features of blockchain technology, i.e. cryptocurrencies and smart contracts, for the benefit of humans and the environment [15]. Several applications of Blockchain technology in the field of humanitarian aid are documented, where cryptocurrencies and smart contracts are used to fight corruption and gender inequality, handle property rights and secure digital identities, and support more transparent supply chains [17]. Lately, blockchain technology has been exploited to build complementary currencies in the sphere of humanitarian aid. Complementary currencies (CCs) are currencies that emerge in different geographical contexts, to support the official national currency [5]. There are many examples of CC systems all across the world, with an estimate of around 4,500 CC projects since the 1980s and studies show that they do boost local economies [10].

While there are many studies on complementary currencies, showing their success, there are still some understudied open problems. First, there is limited study on the role of complementary currencies during the COVID-19 pandemic. We find only a few works, some describing successful cases in Brazil [7] and Kenya [16], while a Polish CC [14] was found to be not as effective during the pandemic. Second, while cooperation is a key factor in the creation of these systems, as communities use it to sustain themselves in periods of crisis, there are no studies on cooperative behaviour, and more importantly, how cooperative behaviour changes over time.

To fill these research gaps, we focused on the Sarafu project. Sarafu [12] is a noteworthy example among CCs, mainly because *i)* it is one of the first CC projects that leverage blockchain technology, for fast transactions processing and better tracking of the programs' impact on people's lives; *ii)* it is one of the few projects that was analyzed during the COVID-19 pandemic, as Red cross Kenya relied on Sarafu to successfully deliver humanitarian aid [16]; and *iii)* Sarafu supports the cooperation of 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. This characteristic enables an effective study of cooperation patterns and highlights the behaviour of cooperation groups that cannot be easily analyzed in other CC systems.

In this work, we study cooperative behaviour by focusing on the behaviour of group accounts and their cooperation patterns. Moreover, we analyze a dataset of currency transactions during the COVID-19 pandemic. We analyze monetary flows in the transactions network, to monitor two main aspects: *(i)* the impact of cooperation groups, and *(ii)* cooperation over time, as we consider different pandemic situations and restrictions.

Our analysis based on the transaction networks and on their projections on the types of account and their business types [6] has highlighted some interesting findings. First, we show that cooperative behaviour is extremely important in the Sarafu system: while group accounts represent just 0.48% of the users, they are involved in 37% of the transactions. Second, we observe that the importance of cooperation groups changes over time, in fact, that the amount of money spent by these accounts increases significantly over time, with some small variations over the categories of goods interested, while the food remains the main category of interest. Third, we find evidence of the impact of the mitigation policies and restrictions on how people have used Sarafu, how accounts for supporting cooperation have been strengthened during the pandemic period, and whether the pandemic period has changed how the wealth is redistributed among business categories. We observe that the usage of the Sarafu tools has changed during the pandemic period, for instance when schools and workplaces have been totally or partially closed Sarafu's users have preferred private and direct money transfers, whereas during the following periods the money volume handled by group accounts has considerably increased, strengthening their role. On the other side, the pandemic period has had a marginal impact on how the wealth is distributed among the types of business.

The paper is organized as follows. Section 2 provides a brief introduction of blockchain for humanitarian aid, 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 modelling, extracting and analyzing the transaction networks and their projections is presented in Section 5. Section 6 report the main findings on the role of group accounts in supporting cooperation and the changes in the usage of Sarafu during the pandemic period. Finally, Section 7 concludes the paper, pointing out possible future works.

2 BACKGROUND

Blockchain for humanitarian aid. In recent years, there has been growing interest in the application of blockchain technology for good [1], for either social or environmental improvement. Over the years, many "Blockchain for Good" projects have emerged, focusing on how to rely on blockchain technology's main features i.e. cryptocurrencies and smart contracts, to benefit humans and the environment [15]. Moreover, many works have analyzed the potential and limitations of blockhain for sustainable development [13, 15]. Several applications of Blockchain for humanitarian aid are documented, where cryptocurrencies and smart contracts are used to fight corruption and gender inequality, handle property rights and secure digital identities [17]. Moreover, blockchain technology has been leveraged to provide aid to refugees, provide funding for non-governmental organizations, as well as support local economies [16].

Complementary currencies. Complementary currencies (CCs) are currencies that emerge in different geographical contexts, to support the official national currency [5]. CCs can also be seen as a form of fungible "voucher" or credit obligation redeemable for goods and services [16]. They can also be found in the literature as community currencies or local currencies, interchangeably. There are many examples of CC systems all across the world, with an estimate of 3,500 to 4,500 CC projects since the 1980s in around 50 countries [10]. While many works studied the principles as well as various case studies, there are currently few works focusing on the impact of CCs during the COVID-19 pandemic. Gonzalez *et al.* [7] studied a Brazilian CC called Mumbuca E-Dinheiro, highlighting its success during the pandemic. Whereas Stępnicka *et al.* [14] analyzed the Zielony CC in Poland, claiming that the CC was not as effective during the pandemic as it was during periods of an actual financial crisis. While a recent work by Ussher *et al.* [16] studied Sarafu [12], a Kenyan CC that turned into an improvised COVID-19 response system: Sarafu proved to be quite effective in the support of local communities during the crisis.

Sarafu, complementary currency on blockchain. Sarafu[1] is a digital complementary currency token by Grassroots Economics (GE) foundation[2], a foundation that provides humanitarian aid. With Sarafu users can perform payments using mobile phones, transferring Sarafu digital tokens to other registered users. As described in Ussher *et al.* [16] 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.

An important feature of Sarafu is the adoption of blockchain technology. While the Sarafu project did not run on blockchain since its creation, the project adopted blockchain technology to address some pressing needs [16]. Among the reasons, one key advantage was the increased transparency, as transaction data allows to properly report to donors the impact of their donations. Moreover, the analysis of the data can guide decision-making processes, for example, future investments, and allows GE to detect ways to promote users' welfare and prevent potential misuse. The system first moved to a privately run blockchain, called POA. The name is derived from the consensus protocol, Proof of Authority [2], PoA in short. Then in 2020, the project moved to a public blockchain, called xDai blockchain, to reduce transaction costs [16]. Finally,

[1]Sarafu means currency in Swahili

[2]https://www.grassrootseconomics.org/pages/about-us.html

very recently in May 2022, the project moved to a new blockchain, designed by the GE Foundation to better suit their needs. The new blockchain is called Kitabu ('Ledger or Book' in Swahili) and relies on the proof of authority consensus protocol.

There are few works in the literature describing Sarafu and its impact. Recently, the GE foundation released an anonymized dataset for researchers [12], that covers a year and a half of user transactions. The dataset has been used to study the program's success: Ussher *et al.* [16] provide an accurate description of complementary currencies, the Sarafu project history and an analysis of the dataset, while Mqamelo [9] studied the impact on people's welfare and local economic engagement.

Sarafu group accounts and cooperative behavior. While CCs are usually created through the cooperation of groups facing a crisis, Sarafu emerges as a noteworthy example for an important feature: the support for cooperation groups. In Kenya, people struggling would usually ask for help to informal saving groups called *chama*s [16]. *Chama*s are savings groups formed out of social bonds where members meet at a fixed regularity at a fixed time of the day to pool their savings together and loan the savings total to group members [4]. It can be seen as a saving and lending scheme with no or small interest rate [3]. The Sarafu system implements a special type of account the *group account*, to support these kind of cooperation groups. *Group accounts* were given to *chama*s, allowing them to save and lend Sarafu tokens, like they would for the standard currency. Therefore *group accounts* are the key feature for the analysis: in fact, the higher the amount of currency handled by group accounts in Sarafu, the higher the numbers of group saving and lending, and consequently the greater the cooperation. Therefore *group accounts* allow an effective study of cooperation patterns, as they highlight cooperative behaviour that cannot be easily analyzed in other CC systems.

3 RESEARCH QUESTIONS

In Sarafu, cooperation groups are assigned by the GE foundation group accounts and these officially recognized accounts are used to save money and help the members of the community in need [16]. As we stated in section 2, to understand user cooperative behaviour, we can focus on the impact of *group accounts*.

The key aspect of cooperation behavior that we want to study is the following: how cooperation behaviour is affected by a period of crisis, like the COVID-19 pandemic. In particular, as the pandemic situation changes, how is user behaviour affected? These considerations can be summarized as two main research questions:

Research question 1 (RQ1): To what extent cooperation groups are used as a supporting tool for the Sarafu participants? What is the impact of cooperation groups on the redistribution of resources?

Research question 2 (RQ2): Does the behaviour of cooperation groups change over time? To what extent COVID-19 pandemic and the pandemic mitigation strategies have modified the allocation of resources by cooperation groups?

4 DATASET

The Sarafu dataset includes detailed and anonymized information on token transactions as well as users' features. The data cover the period from January 2020 to June 2021, for a total of 412050 economical transactions and 53277 users. In the following, we describe in detail transactions and users' data, separately.

Transaction information. Each economical transaction specifies its **source** and its **target** as anonymized IDs of sender and receiver of the cryptocurrency token. Essential additional information for this study is the **timestamp**, i.e. the date and time of when a transaction has occurred, with a granularity of *ms*. Another important detail that the dataset offers is the **weight** of each transaction, i.e. the amount of tokens transferred from source to target.

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

- **business type**, standardized category of economic activity derived from the user-provided product classification. Possible values are *labour, food, farming, shop, fuel/energy* and so on;
- **area type**, processed area type derived from user-provided information about the residence place. The available categories are *rural*, *urban*, *periurban* or *other*;
- **held roles**, the role of the user. The most common one is *beneficiary*, which stands for the standard user. An important role is *group accounts*, i.e. accounts representing cooperation groups. The dataset offers other possible roles [12], but in this work we focus only on the cited ones.

Preprocessing. It is to note that, since we focus on the transactions among actual users and group accounts, we decided to consider only transactions involving accounts belonging to the types *beneficiary* and *group account*. Moreover, a preprocessing step was required, since a few accounts had inconsistent information. For instance, according to the metadata in [12], only group accounts should have "business type" set to "savings". However, in our analysis, we found some group accounts associated with values different from "savings". Also, some beneficiary accounts were set to "savings", where this should not be the case. We do not consider these two subsets of accounts in the analysis.

Users' attributes distribution. Figure 1 shows the distribution of the user attributes. The users are mainly standard accounts (*beneficiary*, 99.5%). As regards the business type of the users, a large fraction of them (88.75%) are classified in five business types: labour (27.6%), food (24.2%), farming (19.3%) , shop (11.4%) and fuel/energy (6.2%). In Table 1 we reported the description provided by [12] for each possible business type value. In terms of geographical information, the majority of users are divided into rural (51.16%) and urban areas (43.49%). Note that the area types are assigned by the GE staff, after a standardization process derived from user-provided names.

5 METHODOLOGY

Modeling. In general, transactions can be modelled as a set of tuples $I = \{(u, v, t, a)\}$ where u and v are users, who are trading tokens: user u sent 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 [8]. Here, the transaction data over time are represented as a weighted directed graph $\mathcal{G}_{[t_0,t_1]} = (V, E, X, W)$, where:

- V is the set of users,

[3] https://www.lowimpact.org/how-chamas-mutual-credit-changing-africa/

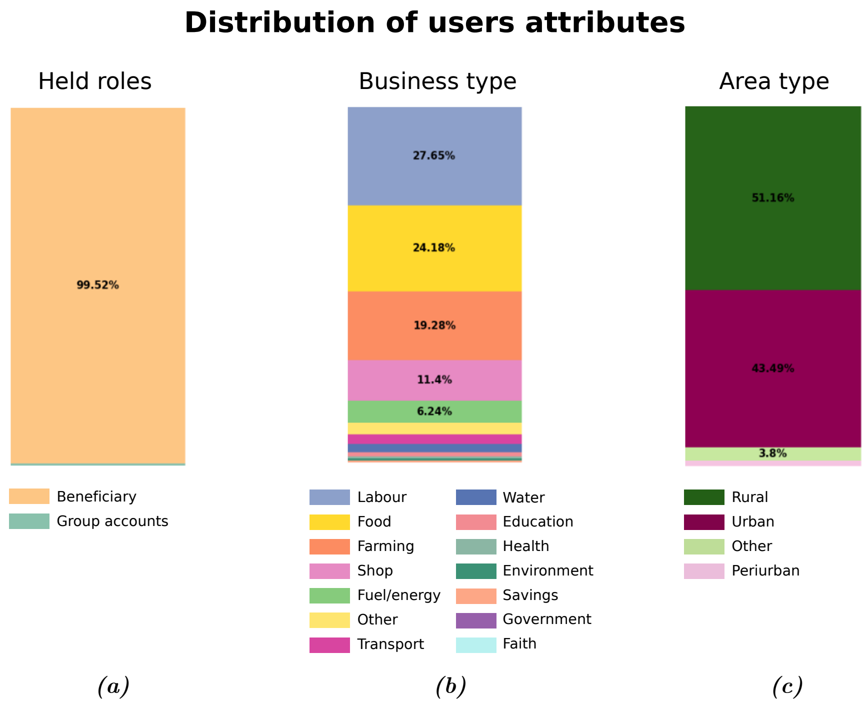


Figure 1: Distribution for the main user attributes, in order: a) *held role*, the account type, b) *business type*, user's economic activity, and c) *area type*, which is derived from the location provided by the user.

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, waiter/waitress, artisans, employees, bricklayers, masons;
Food	Sellers of any kind of local food
Farming	Users registered as farmers or working on farms;
Shop	Kiosks, boutiques, phone, cafes, pubs, clubs, clothing, furniture, jewellery, 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

- 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, needed to study flow of money through the weights $w \in W$: the weight 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 $[t_0, t_1]$.

Relying on transaction networks, we can study the changes over time in the network structure [3] as well as the overall monetary flow in different time intervals.

Analysis. To answer our research questions, we rely not only on transaction networks but also on Sankey diagrams: Sankey diagrams are an effective visualization tool for many different types of flows such as material, traffic, water, and money [11]. Given a transaction network, we can analyze the monetary flows, aggregating currency values on incoming and outgoing edges, considering user attributes. In this representation, nodes represent the types of accounts or the business types - according to the analysis, and the directed links indicate the cumulative flows between sources and targets. So, to answer RQ1 we construct a transaction network using the entire dataset. Then, we analyze Sankey diagrams where nodes are types of account *beneficiary* or *group account*, to understand the importance of group accounts. After that, we focus on the categories involved, to understand the categories of users involved in group accounts: we focus on the spending behaviour, by looking at the categories that group accounts are spending on; and we analyze the funding, by observing the categories of users that send money to group accounts. In order to answer RQ2 by looking for differences over time, we rely on the additional contextual information about COVID-19 cases and restriction measures by the Kenyan government, as shown in Figure 2. Using such information, we group transactions into 4 periods of time, based on the different restriction measures that were in place. Therefore, we can apply the above methodology to construct 4 transaction networks, one for each period. We can then describe the transaction networks and understand the differences between different periods. In the pandemic scenario, we monitor the importance of cooperation through group accounts, and we analyze changes over time.

6 RESULTS

In this section, we show how we apply the methodology outlined above to the Sarafu dataset, modelled as transaction networks whose properties are listed in Table 2. We can see that transaction volume has increased significantly over time, with a considerable increase in active users in the second period when the pandemic spread to Kenya. While the number of unique active users has decreased in subsequent periods, there is still a significant number of users, which is more than before the pandemic (first period).

6.1 Impact of cooperation

Our first research question, as described in Section 5, focuses on the importance of group accounts in the money flows. Figure 3a shows the Sankey diagram of money transfers in the whole dataset. Given the particular nature of group accounts (they account for only 0.48% of all users), the percentage of transfers involving them is considerable (37.25%). This result highlights the important role of group accounts, since they are few but handle more than one-third of the overall volume of money transfers. To get a deeper understanding of the money flows from and to group accounts, we also plot a double Sankey diagram (Figure 3b) grouped by *business type* of the *beneficiary node*. By observing Figure 3b, it is evident that the most common categories remain stable: the first four (food, farming, shop, and labor) represent 79.25% of the incoming operations to group accounts and 79.27% of the outgoing ones. However, the ranking of these first categories is different from the general ranking over the whole dataset, depicted in Figure 1b.

The *food* and *shop* categories gain importance (first and second place, respectively) in both directions when the business types are ranked not by frequency but by the magnitude of flows (money involved in the transactions grouped by categories). On the other hand, *labour* is less relevant (fourth position instead of first).

6.2 Cooperation over time

Proceeding with the next research question, our study aims to discover whether the role of group accounts and their spending behaviours changes during different pandemic periods. Figure 4 depicts the money flows divided by the held roles we focused on: beneficiary and group accounts. Observing the Sankey diagrams, it is evident that the impact of group accounts changes over time.

The first observation concerns the increase of flows from group accounts from the third period: while in the first two periods the percentage of flows from group accounts to beneficiary is on average 10%, in the last two periods it reaches 29%. This observation may account for the first transformation of Sarafu users due to the pandemic and mitigation policies. A second interesting trait regards the strongest period in terms of the severity of the mitigation policies. In fact, the first wave of COVID-19 cases is the most divergent period, due to its outlier percentage of transactions within beneficiary accounts. In this case, the full closure of schools and the partial closure of workplaces - strong limitations for mobility and sociality - may have promoted private and direct transfers of money, bypassing the usage of group accounts. As regards the other 3 periods, the flows within beneficiary accounts remain almost stable (from 43% to 47% of the transactions), while the number of operations from group accounts to beneficiary increases (from 11% to 29%). Lastly, 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 differ just by 0.41% while in the other periods, the difference is always over 20%.

To deepen the spending behaviours of beneficiary and group accounts during the different pandemic periods, we can analyze the Sankey diagrams depicted in Figure 5. At first sight, it is evident that the incoming and outgoing amounts change during the time. Initially, there is a tendency to accumulate money on group accounts, that in turn spend just a fraction of the income (the outgoing total is 30.94% of the incoming total). As time goes by, the percentage of outgoing over incoming amount grows so much that in the third period is higher than the incoming. Figure 6 shows the total money of all transactions directed to and coming from group accounts in the different periods. In addition to the ratio of incoming to outgoing amounts, the magnitude of money spent has

[3]https://graphics.reuters.com/world-coronavirus-tracker-and-maps/countries-and-territories/kenya/

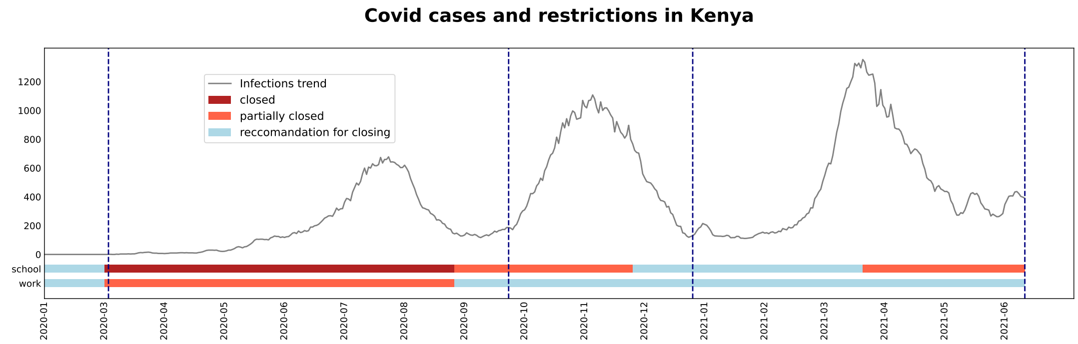
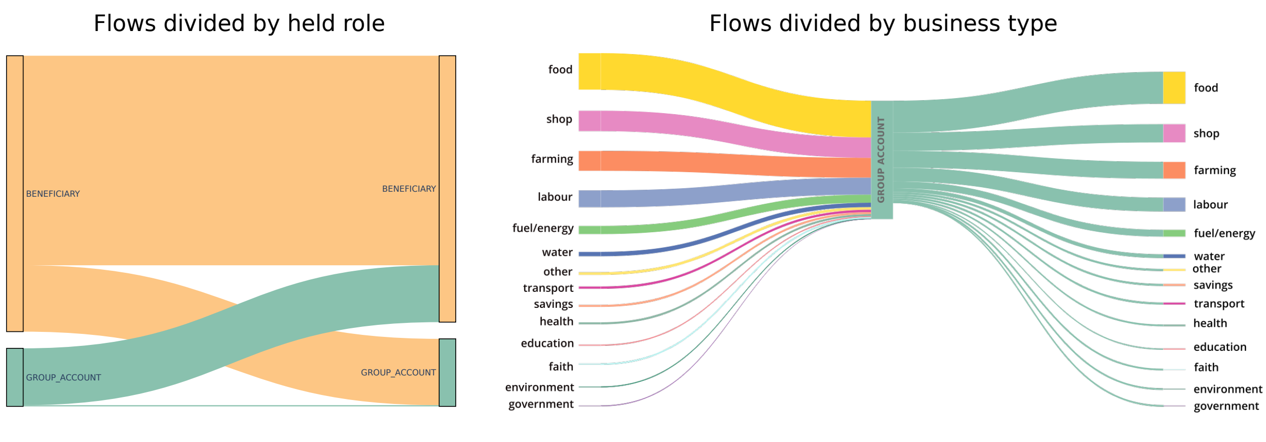


Figure 2: COVID-19 cases and restrictions in Kenya. As the number of cases (blue line) varies over time, we can observe different restrictions over time (closed, partially closed, recommended closing) for both school and work, during the pandemic period. The figure is a reworking of data published by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

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.

Start	End	Active users	Edges	Transactions
2020-01-26	2020-03-15	4217	8281	12168
2020-03-15	2020-10-01	28070	96266	251594
2020-10-01	2021-01-01	7030	22872	63262
2021-01-01	2021-06-16	13960	35225	85026
Entire period		40343	143239	412050



(a) *(b)*

Figure 3: Study of the importance and behaviour of group accounts: in a) monetary flows from group accounts to beneficiary accounts and vice-versa, b) group account funding and spending behaviour, through a double Sankey diagram. For funding, we show the categories of users that send money to group accounts, while for the spending behaviour, we look at the categories of receiving users.

increased over time. Indeed, the central periods have a significantly higher total than the others.

Another interesting point regarding Figure 5 concerns the categories rank: first, the saving category has an anomalous behaviour. It presents a high percentage in the first period (even if in the general distribution shown in Figure 1b is the third last), in the second it loses some positions and then its the less frequent. On the contrary, the shop category starts in a very low ranking position (after the

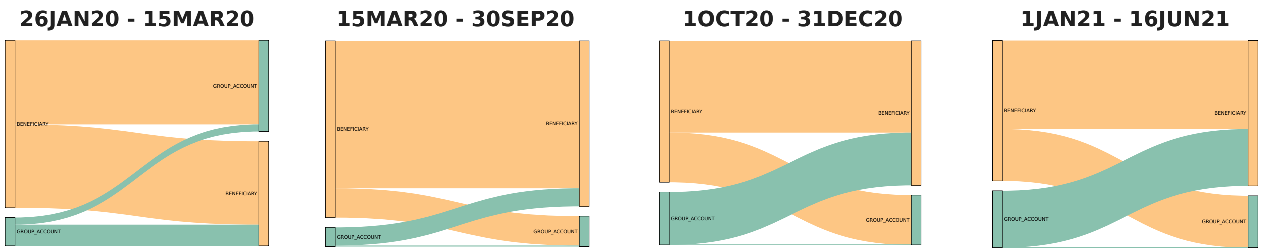


Figure 4: Impact of group accounts over time, observed through monetary flows. For each period, we observe the monetary flows from group accounts to beneficiary accounts, and vice-versa.

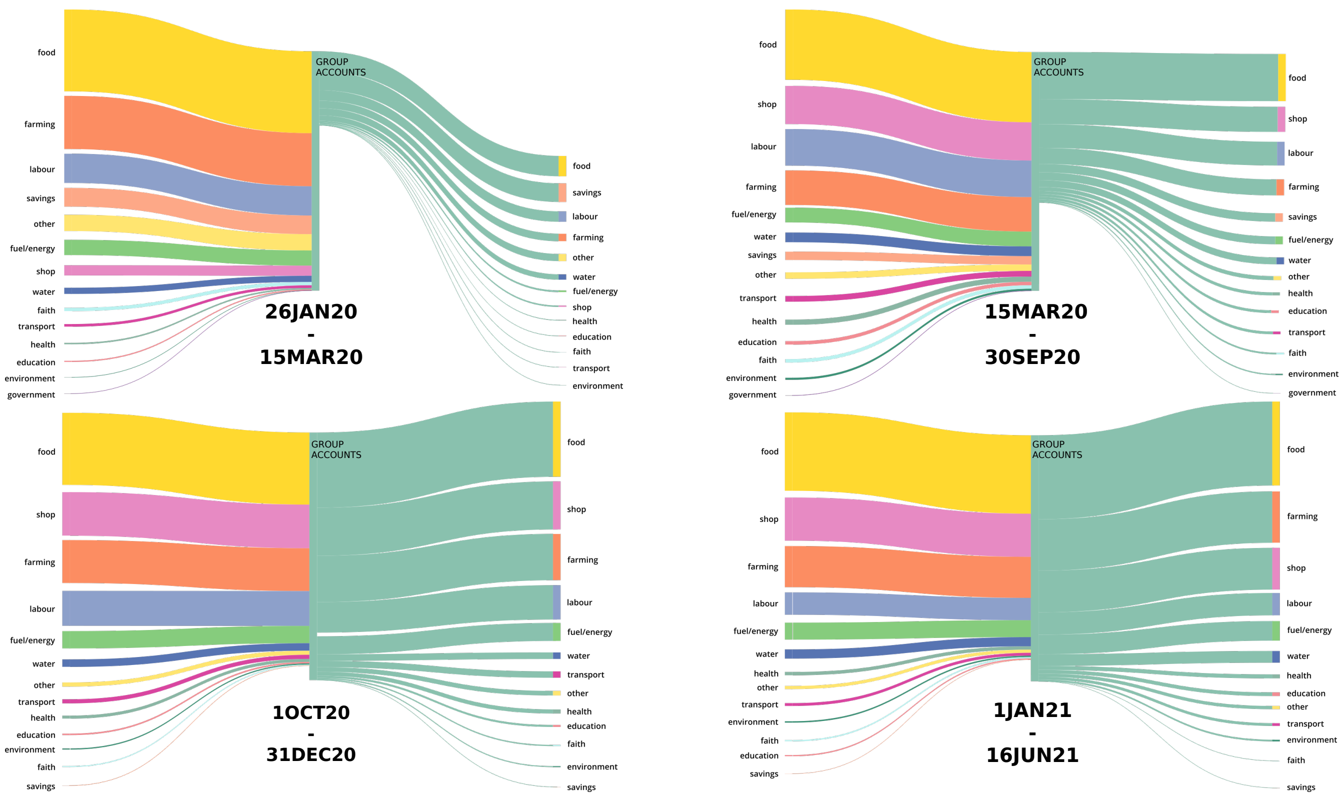


Figure 5: Group account funding and spending behaviour, over time. For each time period, we have a double Sankey diagram, showing both funding and spending monetary flows. For funding, we show the categories of users that send money to group accounts,while for the spending behaviour, we look at the categories of receiving users.

first six), but from the second period is in the top 3. Savings category aside, the first six positions of the ranking are always occupied by the first eight categories in the general distribution. Moreover, the food category is always in the first place with a significant gap from the second one. It is also worth noting that in general, the categories maintain the same position both with incoming and outgoing transactions.

7 CONCLUSION

In this work, we analyze cooperation behaviour in a complementary currency system on blockchain for humanitarian aid. We relied on the data from Sarafu, an interesting use case relying on blockchain technology, to analyze cooperation behaviour during a period of crisis like the COVID-19 and how cooperation behaviour changes over time. While previous works highlighted the importance of complementary currency systems like Sarafu, to the best of our knowledge, there are currently no works focused on cooperation behaviour and its characteristics over time. By focusing on group

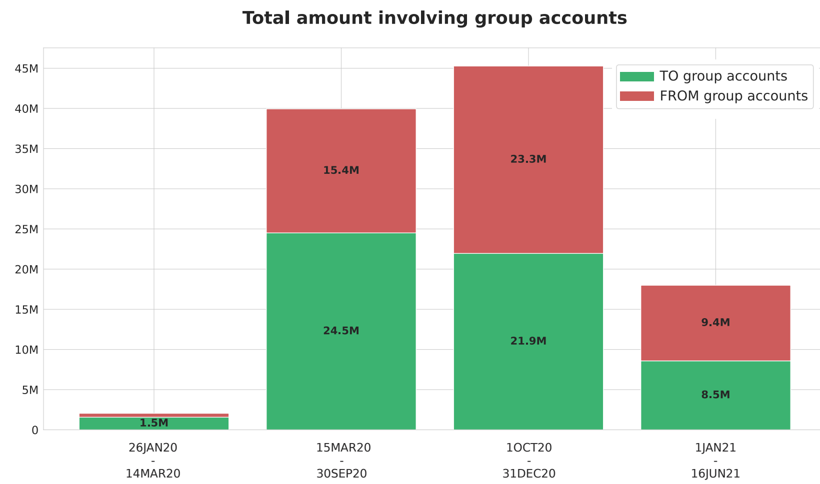


Figure 6: The total amount of money handled by group accounts for each period. For each period, the stacked barplot shows both incoming and outgoing money for group accounts.

accounts i.e. accounts handled by multiple users cooperating, we show that cooperation behaviour exists in Sarafu. We found that cooperation behaviour is important, as group accounts are involved in a significant amount of transactions, even though they account for a small fraction of users. We also showed that cooperation behaviour changes over time: group accounts become more important over time, with monetary flows reaching group accounts increasing over time. Moreover, the amount of money spent by these accounts increases significantly over time, with some variations in the categories of goods interested.

The results show the importance of complementary currencies, as well as the success of Sarafu in the field of humanitarian aid. The analysis highlights the importance of cooperation behaviour, with group accounts emerging as an important factor in encouraging user cooperation - an important takeaway for current and future humanitarian projects. Further steps include the use of the proposed methodology as the basis of further studies. The methodology can be applied to other CC systems to study group accounts if available. Moreover, the same methodology is flexible and can be used to study the impact of any subset of accounts: e.g. studying the impact of certain user categories like minorities. These allows organizations to redirect resources and focus towards specific subsets. In addition, the analysis could be extended to include other available attributes, such as the geographical information and the use of additional contextual information, related to the pandemic or the national economic situation.

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