

Relationship between household attributes and contact patterns in urban and rural South Africa

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Abstract

Households play a crucial role in the propagation of infectious diseases due to the frequent and prolonged interactions that typically occur between their members. Recent studies advocated for the importance of including socioeconomic variables in epidemic models to account for the heterogeneity induced by human behavior. While sub-Saharan Africa suffers the highest burden of infectious disease diffusion, limited efforts have been carried out to investigate the mixing patterns in the countries and their relation with social indicators. This work analyzes household contact matrices measured with wearable proximity sensors in a rural and an urban village in South Africa. Leveraging a rich data collection describing additional individual and household attributes, we investigate how the household contact matrix varies according to the household type (whether it is composed only of a familiar nucleus or by a larger group), the gender of its head (the primary decision-maker), the rural or urban context and the season in which it was measured. We show the household type and the gender of its head induce differences in the interaction patterns between household members, particularly regarding child caregiving. We argue the observed differences directly influence the basic reproductive number of an epidemic and should hence be accounted for the design of effective epidemic mitigation strategies.

1 Introduction

Close-range proximity interactions are the main driver of infectious disease transmission [1, 2]. Quantifying these interactions and understanding their determinants is thus necessary to design optimal epidemic mitigation strategies. Contact matrices describe detailed data on social mixing patterns between groups of individuals and inform epidemic models by accounting for diverse social contexts and age-specific infection risks [3]. Age is commonly adopted to define such groups [4, 5, 6, 7] even if recent works called for a more holistic view, integrating socio-economic variables into epidemic models [8, 9, 10, 11, 12, 13, 14, 15]. Contact matrices are commonly defined within specific contexts where the interactions occurred [16, 17] – *e.g.* household, school, workplace – to account for the diverse importance each context has on the outcome of transmission. Households, in particular, play an important role in spreading the disease, as interactions within these settings are frequent and prolonged [18, 19] and can also act as a bridge between different contexts, such as schools and workplaces.

Although most studies and data collections focus on Western countries, sub-Saharan Africa experiences the highest burden of infectious disease epidemics [20]. The past decade has seen an increase in interest in studying social mixing across sub-Saharan African countries to evaluate the impact of infectious disease

transmission, with diverse approaches ranging from contact diaries [21, 22, 23, 24, 25] to novel technology-driven approaches based on proximity sensors [26, 27, 28, 29]. Findings show a high degree of heterogeneity in the observed contact patterns, with few other recurring features across studies. For instance, primary school children generally display higher contact rates compared to adults [23, 22, 21, 30]. In Kenya [21, 31] and Zambia [32], rural areas record higher contact rates compared to semi-urban regions. On the opposite, in Zimbabwe [22] peri-urban regions display higher contact rates compared to rural ones. In South Africa [25] and Mozambique [33], people living in rural areas experience almost double the contact rates as the ones in urban areas. In these settings, most interactions occur within households [26, 27, 34], and intergenerational contacts are driven by multigenerational households which are more common in rural areas, as reported by studies in Kenya [31], Zimbabwe [22], and Malawi [27]. Community-based social mixing, such as those observed in township settings in South Africa [35], and Zambia [32] are associated with high rates of tuberculosis transmission in the community.

The interaction dynamics within a household are not solely based on age, but also on the roles of its members and the overall organization of the household. In Africa, variations in this organization have been associated with poverty, urbanization, and the loosening of societal norms [36, 37]. The household type (whether it is composed only of a familiar nucleus or by a larger group and its composition (defined by age, gender, marital status, and relationships among the household members) should hence both be considered to describe interactions accurately [38, 39]. Children are regarded as primary introducers of infections like influenza due to high external exposure in schools, while mothers often drive within-household transmission due to frequent caregiving interactions [40, 41]. Multigenerational households have high transmission risks for diseases like influenza and RSV, particularly affecting infants and the elderly [40, 42]. In high-birth-rate settings like Kenya, larger households increase measles transmission [43], while communities composed of extended households may also be more vulnerable to larger, more severe outbreaks of infectious diseases [44]. Similarly, in low-income settings, household composition is more intergenerational and leads to increased intra-household transmission due to more frequent interactions between older adults and younger individuals compared to high-income settings [45]. Studies confirm that household composition, rather than size alone, influences infection risk [46], yet disease models often assume random household mixing despite evidence of structured contact patterns [18]. Most of these studies focused on understanding how household structure and composition influence the transmission dynamics of infectious diseases, but little effort on how structure and composition shape contact patterns relevant to the transmission of infectious diseases.

In this work, we go beyond age-only contact pattern measurements and focus on additional social attributes, potentially relevant for disease spread. We consider household contact matrices collected during the PHIRST study conducted in South Africa during 2018 [47, 25, 28] that include rich metadata information related to the social role of individuals in the household. Our analysis shows significant differences in the mixing patterns depending on the household type and the gender of the household head, especially regarding the interaction with the children. We show these differences directly influence epidemic spreading by relating the social mixing structure with the basic reproductive number R_0 for a hypothetical infectious disease.

2 Methods

2.1 Data collection

The PHIRST study [47, 25, 28] was conducted in South Africa during 2018. It took place in a rural site – Agincourt, Bushbuckridge Municipality (Mpumalanga Province) – and an urban area – Klerksdorp, Matlosana Municipality (North West Province). The data collection was conducted over three measurement waves with a duration between 10 and 14 days. The first wave was in February (South African summer), the second in April (South African autumn), and the last one in June (South African winter). To measure the contact pattern data, we deployed the proximity sensors developed by the **SocioPatterns** collaboration (sociopatterns.org, [48]). These sensors are non-obtrusive devices worn on the chest of the study participants during the data collection. They emit low-power radio signals exchanging approximately 40 information packets per second when facing one another. They record a proximity interaction if two sensors exchange at least one packet in a 20-second period. In this case, each sensor records the unique identifier of another interacting sensor, the interaction time, and the power attenuation from the sender to the receiver. Proximity interactions within approximately 1.5 meters are identified by filtering the measurements based on their

signal attenuation. These sensors provide high-resolution measurements of human interactions and have been deployed in a variety of contexts, including schools [49, 50], hospitals [51] and conferences [52], among others. We followed the data cleaning procedure described in [28] and excluded households in which data quality issues and did not provide valid measurements. Our cleaned dataset is composed of 307 individuals and 60 households.

2.2 Household classification

To identify households, we follow the study protocol definition that identifies households as groups of three or more people who regularly share at least two meals in the same residence at least two days per week, excluding residential institutions. In Africa, households are diverse and shaped by various factors such as cultural diversity, economic conditions, and historical influences. South Africa is no exception, with its diverse population and the lasting influence of apartheid [37]. To quantify the relation between the household structure and the contact patterns, we group households according to three features.

- **Site (rural or urban).** Socio-demographic characteristics of individuals and households differ across rural and urban settings. Hence, it is important to capture differences and similarities in contact patterns driven by these attributes. The rural site is composed of 28 households, while the urban site by 32.
- **Gender of the household head.** The household head does not have a unique definition, but it generally refers to the person who holds the economic responsibility (for example being the primary breadwinner) or who has the most decision-making power in the household [53]. In our study, the household head is the person identified by the household members as the primary decision-maker. Especially in South Africa, this role is commonly held by the oldest individuals who typically also have the highest income [54]. Regardless of the actual dynamics within the household, men are commonly more likely to be designated as household heads [53], while women-headed households are more susceptible to economic hardships [54]. Our dataset comprises 43 female-headed households (24 in Agincourt, 19 in Klerksdorp) and 17 male-headed households (4 in Agincourt and 13 in Klerksdorp). This agrees with the general trend in South Africa that sees female-headed households more prevalent in rural areas [55].
- **Household type.** For this classification, we follow [36], focusing only on the household types observed in our cohort. These include: (i) *nuclear households* (12 households), formed by a couple (married or cohabiting) and their biological or adopted children; (ii) *single-parent* (13 households) in which the household head lives with his/her children; (iii) *extended households* (33 households), composed by relatives beyond nuclear family such as cousins, aunts, uncles, and grandparents. Our dataset further comprises two households classified as *complex* as they also contain non-relative members. Given that only two households belong to this class, we chose to absorb them into the extended and nuclear households, according to their composition. In our dataset, extended households are larger on average with 5.7 individuals against 3.9 and 4.2 observed in nuclear and single-parent households, respectively. According to the General Household Survey [56], nuclear households are the most common in South Africa, reaching 40.1% of the total. In our dataset, extended households are over-represented in both contexts: 57% in Agincourt versus 45% observed in rural areas; 53% in Klerksdorp versus 30% observed in urban areas. On the opposite, nuclear households are less represented than expected but, in agreement with the national trend, they are more frequent in the urban area (28% in Klerksdorp) than in the rural one (11% in Agincourt).

2.3 Contact matrices

We categorize the participants according to their age and gender. All participants disclosed a binary gender attribute. Age categories are defined as *children* for the age range 0 – 10 years, *adolescents* for the age range 11 – 18, and *adults* for individuals older than 18 years old. Out of the 307 participants, children represent 39.1% of the population, while adolescents and adults account for 18.6%, and 42.3% respectively. Each household is classified according to the definitions described in Section 2.2. The entries of a household

contact matrix indicate the daily average interaction duration in minutes between age-pair groups. The attribute-related contact matrix is then obtained by averaging over all households with a particular attribute (*e.g.* female-headed). More formally, we let a, b be two gender-age indices (for instance, female-adults). $R_{ab}^{(h)}$ denotes the average daily contact interaction between a and b . For the attribute α (*e.g.* $\alpha = \text{female-headed}$), we let χ_α be the set of households with that attribute. We write the attribute-related contact matrix as

$$\tilde{R}_{ab}(\alpha) = \frac{1}{|\chi_\alpha|} \sum_{h \in \chi_\alpha} \frac{R_{ab}^{(h)}}{n_a^{(h)} \cdot n_b^{(h)}}, \quad (1)$$

where $n_a^{(h)}$ indicates the number of individuals in class a and household h and is used to properly account for the population sizes. As an additional attribute α we also investigate the role of seasonality by averaging the contact matrices depending on the measurement waves.

2.4 Basic reproductive number

Multi-class compartmental models, such as the SIR (Susceptible-Infected-Recovered) model, are widely used in epidemiology [57]. In this model, susceptible individuals (S) become infected (I) when entering into contact with already infected individuals. After some time, infected individuals recover (R). By including contact matrices in this model, one can account for across-group heterogeneities in the social mixing behavior. In this model, two parameters – β and μ – quantify the probability per unit time of infection and recovery, respectively. These parameters are disease-dependent and determine the basic reproductive number R_0 , which is the average number of secondary infections caused by a single infected person in a fully susceptible population. Its value crucially determines the epidemic outcome since if $R_0 < 1$, the epidemic likely dies quickly, while if $R_0 > 1$, it is expected to spread rapidly through the population. For the SIR model, the R_0 has a known expression depending on the disease parameters β, μ and on the contact matrix R [58]:

$$R_0 = \frac{\beta \rho(RN^{-1})}{\mu}, \quad (2)$$

where ρ denotes the largest eigenvalue of a matrix, and N is the diagonal matrix containing the number of people in each group, specifically $N_{aa} = n_a$. For a given infectious disease, the parameters β, μ are fixed, and variations to $\rho(RN^{-1})$ across household groups imply differences in the epidemic outcome.

3 Results

We here report our results of comparison of the contact matrices aggregated according to the attributes described in Section 2.2.

3.1 Season

The contact matrices show a similar structure across the three waves, as reported in Figure 1. Children, and in particular male children, are responsible for the highest contact rates. A remarkable difference appears also between male adults and female adults, in particular in their interactions with children. We assessed the robustness of the contact matrix structure by computing the Spearman correlation coefficient between the entries of the matrices referred to different waves. The Spearman test is non-parametric, hence it allows us to effectively deal with the great heterogeneity of the activity parameters across classes. The test provides highly significant ($p < 0.02$) correlations between all pairs with $r = 0.60$ between the first and the second waves, $r = 0.50$ between the first and the third waves, and $r = 0.81$ between the second and the third waves meaning that the contact patterns are robust across seasons. The total interaction time, however, varies substantially from summer (223 minutes of total interactions per day per household) to autumn and winter (548 and 612 minutes of total interactions per day per household, respectively).

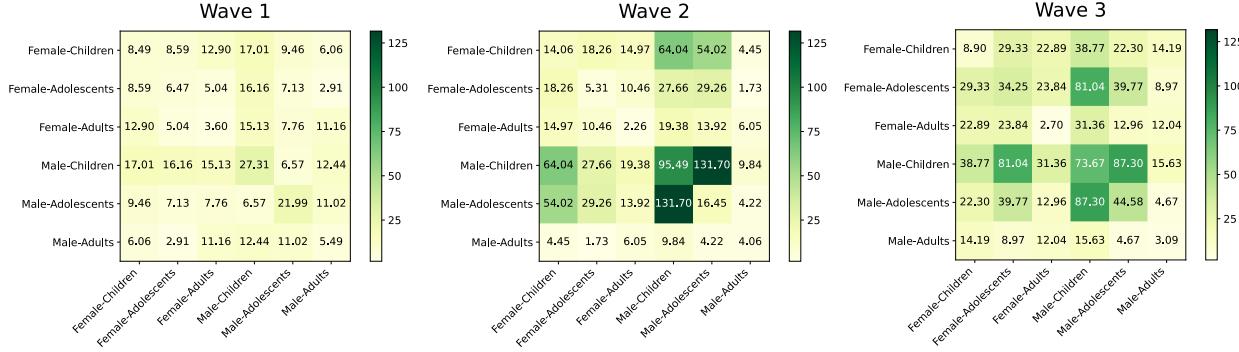


Figure 1: **Seasonal contact matrices.** Each plot refers to a measurement wave and shows the household contact matrix \tilde{R} defined in Equation (1) using the measurement waves as the parameter α to aggregate the data. The matrix entries denote the daily average contact duration per household by gender-age group, expressed in minutes and normalized by the population sizes. Wave 1 is during Summer, wave 2 during autumn, and wave 3 during winter.

3.2 Site

Figure 2 reports the contact matrices aggregated by site. Some global trends characterize both matrices, such as the high activity rates of male children, or the higher engagement of female adults with children with respect to men adults. Globally, however, the interaction patterns differ in the two sites ($r = 0.30$, $p = 0.21$) and higher contact rates in the urban setting (349 minutes of interactions per day per household) than rural setting (286 minutes of interactions per day per household). The stark difference in the contact patterns is mostly related to the role played by adolescents. In the rural setting, female adolescents have higher interaction times with male children than male adolescents as opposed to the urban setting, where we find an opposite scenario.

3.3 Household type

Figure 3 shows the contact matrices aggregated according to the household type. This aggregation leads to substantially different patterns, showing that this feature is a relevant determinant of in-household interactions. In particular, extended households record the highest contact rates with 367 minutes of interactions per day per household, against 191 in nuclear households and 140 in single-parent households. This observation agrees with extended households being larger on average as already discussed. The role of adolescents is prominent only in extended households, in which most adolescents live. Extended households are also the ones in which children – and particularly male children – have the highest interaction rates, likely due to the presence of cousins of comparable age. In nuclear households, we observe similar interaction times between

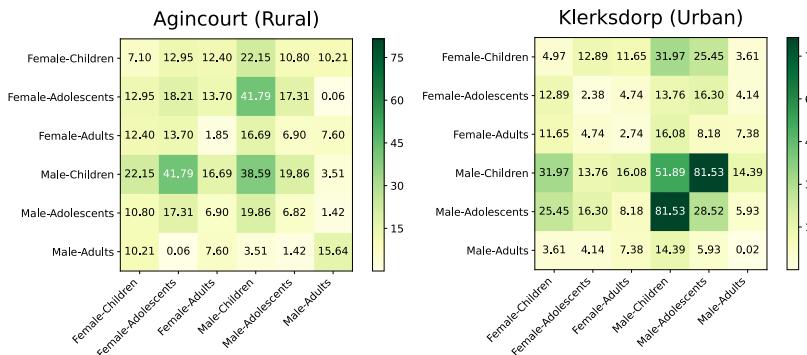


Figure 2: **Site contact matrices.** The plots show the contact matrix \tilde{R} of Equation (1) for α being all households in the rural site, Agincourt, and α being all households in the urban site, Klerksdorp. The contact matrices show the daily average contact duration per household by gender-age group, expressed in minutes and averaged by the population sizes.

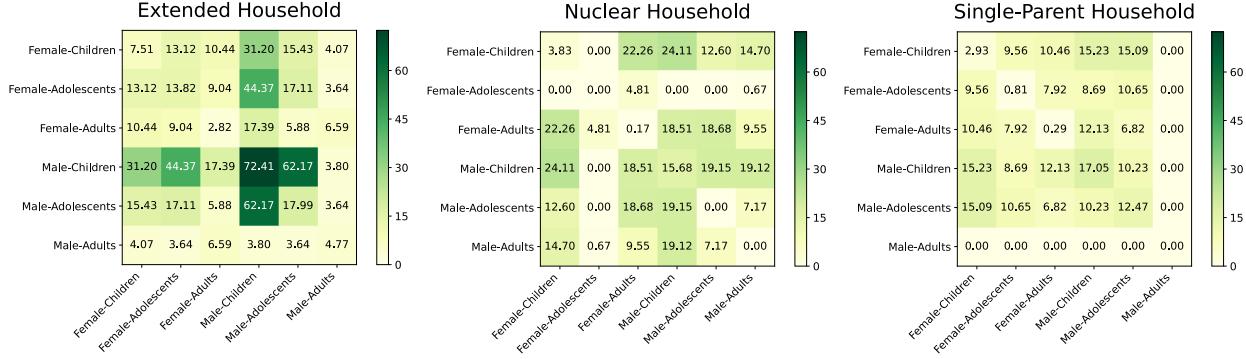


Figure 3: **Contact matrices aggregated by household type.** The plots show the contact matrix \tilde{R} of Equation (1) for α being the set of extended households (left plot), the set of nuclear households (central plot) and the set of single-parent household (right plot). The contact matrices show the daily average contact duration per household by gender-age group, expressed in minutes and averaged by the population sizes.

male adults and female adults and children, suggesting that fathers and mothers have similar roles. On the opposite, the interactions of female adults with children are much greater than the ones of male adults in extended and single-parent households. In the latter case, we observe that, in our dataset, all single-parent households are female-headed.

3.4 Gender of the household head

The stark difference in the role played by adolescents in rural and urban sites is well explained by the gender of the household head, as observed comparing Figure 4 with Figure 2. In female-headed households, adult and adolescent women have a similar burden in child care, which surpasses that of males. On the opposite, extremely high contact activity of male adolescents is observed in male-headed households. This suggests radically different patterns of interaction between family members depending on their gender and the gender of the household head, making this attribute a relevant determinant of in-household interactions.

3.5 Epidemiological impact of age and gender stratification according to the household classification

As recently shown in [14], when combining multiple levels of stratification to define groups (for example, age-gender instead of only age), Equation (2) still holds, but the spectral radius ρ – *i.e.* the largest eigenvalue – of the normalized contact matrix RN^{-1} (and, consequently, R_0) cannot decrease. Therefore, single-attribute stratifications may be insufficient for capturing relevant heterogeneity patterns. The matrices introduced

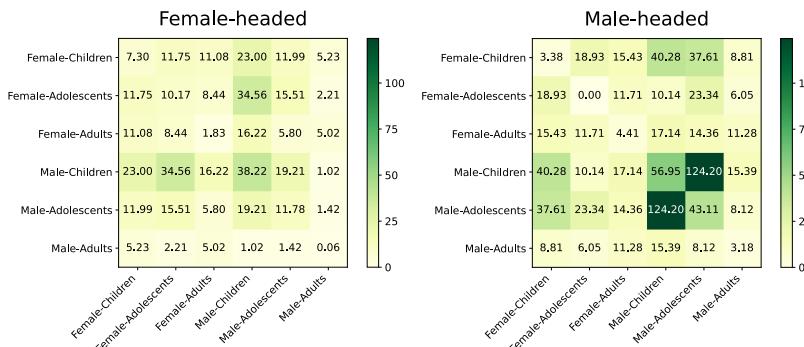


Figure 4: **Site contact matrices.** The plots show the contact matrix \tilde{R} of Equation (1) for α being all female-headed households (left plot) and all male-headed households (right plot). The contact matrices show the daily average contact duration per household by gender-age group, expressed in minutes and averaged by the population sizes.

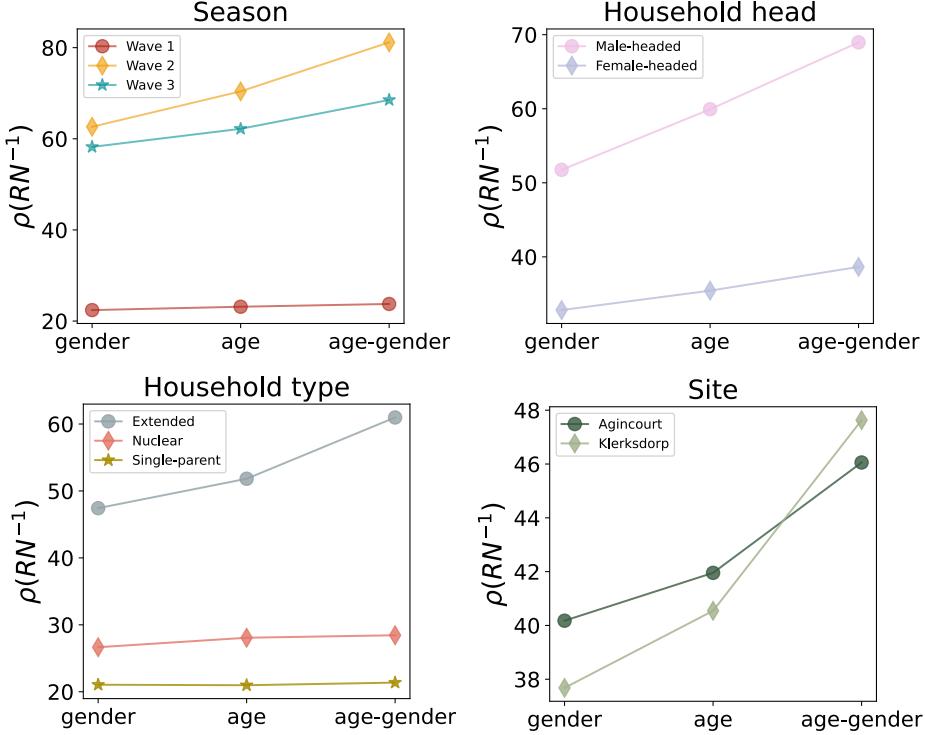


Figure 5: **Largest eigenvalue of the contact matrix for different aggregation and indexing strategies.** Each panel shows an aggregation based on a specific attribute indicated by the title. We consider three indexing strategies (shown on the x-axis) for each matrix: age, gender, and age-gender. The y-axis shows $\rho(RN^{-1})$, the largest eigenvalue of contact matrices the normalized contact matrix, which is proportional to R_0 .

in Section 3 utilize a two-level stratification that combines age and gender. To evaluate the significance of this stratification, Figure 5 compares the spectral radius of three contact matrices for each of the household classifications discussed in Section 3: one using only gender for indexing groups, another using only age, and a third combining both age and gender. As expected, age accounts for a higher level of heterogeneity than gender, but less than the combination of both attributes, which results in a considerably larger R_0 in several cases, such as for male-headed households, extended households, and urban sites.

Discussion

Our findings show household contact matrices to be relatively robust across seasons, even if the frequency of interactions increases during winter. This observation agrees with other studies in Western countries that observed people spending more time outside the household during summer [59, 60]. Male children are responsible for the highest contact rates, supporting the known fact that children are the primary introducers of influenza-like illnesses in households [40, 41]. However, accounting for the household composition is necessary to interpret the observed contact patterns better.

Extended households are generally larger than nuclear and single-parent households and have higher interaction rates on average. Most of the activity involving male children is recorded in these households, possibly due to the presence of siblings and cousins of similar age. In these households, women (including adolescents) have higher interaction rates with children than adult men. This observation agrees with the fact that in many African cultures, including South Africa, women are identified as the primary caregivers for children, even when they are not the biological mothers [61]. In extended households, women are often in charge of caregiving also for the elderly [62]. From an epidemiological perspective, these observations provide an interpretation of why these large and multigenerational households experience higher risks of transmission of diseases such as influenza, RSV, and measles [40, 42, 43, 44]. In nuclear households, adult

males and females interact with children more evenly than in extended households. Fathers and mothers seem to undertake similar roles in child-rearing in this type of household. All single-parent households in our dataset are female-headed. This agrees with a global picture with 84% of single-parent households run by women [63]. The most common reasons explaining the gender gap are widowhood, divorce, the presence of children outside marriage, and migrant workers [64].

Female-headed households are more prevalent in rural settings and display a generally higher involvement of women. Nonetheless, we observed that male-headed have higher activity rates than female-headed households. This is a non-obvious result because female-headed households tend to be larger than male-headed households as they mostly fall under the extended category.

The differences between the rural and urban settings are mainly ascribed to a greater diffusion in rural settings of extended and female-headed households. The higher contact rates we observed in rural areas are consistent with previous results in Zimbabwe [22], but in contrast to other studies in similar contexts from low-resource settings in the sub-Saharan region [21, 31, 32, 25, 33], suggesting that the rural-urban context might not be as influential as the household composition or gender head. The higher involvement of women in rural contexts agrees with a societal norm that heavily influences household roles. The relatively better balance between gender roles in the urban setting can be attributed to relaxed societal gender norms [65]. Evidence from Zambia [66] also suggests that in urban areas, caregiving responsibilities are becoming more balanced as men and male adolescents are increasingly involved in care duties, explaining the high involvement of males in interactions in the urban area.

We evaluated the epidemiological implications of observed differences in contact patterns by computing a proxy of the basic reproductive number associated with contact matrices collected in various social contexts and different seasons. The R_0 is mainly driven by age-based heterogeneities, even though the full degree of heterogeneity becomes apparent when accounting for both age and gender. Notably, the most significant variations are observed with changes in seasonality, consistent with the findings presented in Section 3. Smaller, yet still relevant differences appear when comparing male-headed households to female-headed ones, as well as in extended households compared to nuclear and single-parent ones. Conversely, much smaller differences are observed across different sites.

Let us now comment on the main limitations of our work. Due to the limited number of households considered, we were unable to quantify contact patterns separately for each site across all attributes (season, household type, and gender of the household head). As such our study does not investigate the interdependencies of the different household attributes. For the same reason, our observations are not statistically supported and are hence hypothesis-generating and not conclusive. Moreover, the dataset used for this study contains only in-household interactions and our conclusions do not apply to the across-household interactions that are fundamental in epidemic modeling. Despite these limitations, our results show the important role played by the household structure and compositions in shaping face-to-face interactions. These results contribute to addressing the limited data gap on face-to-face interactions in sub-Saharan Africa where the prevalence and re-emergence of infectious diseases pose a significant public health challenge. Our analysis emphasizes the importance of considering context and setting specific intervention and mitigation strategies, which best fit the sociodemographic characteristics of the population during outbreaks. Our results also encourage future data collection on face-to-face interactions to include rich metadata information related to the social role of individuals in the household.

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Competing interests

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