Mobile Money Adoption in Kenya: The Role of Mobile Money Agents

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Abstract

Mobile money adoption bears great potential for welfare improvements, including consumption smoothing and poverty reduction. The proximity of households to mobile money agents has frequently been shown to be a decisive factor for mobile money adoption. However, the fact that agents can differ from one another on different levels such as their ability to explain potential customers how to use mobile money, convert e-money into cash or offering account opening services, has been largely overlooked up to now. The role of the agent for mobile money is hence not yet well understood. The present study uses georeferenced data from a nationally representative Kenyan household survey and a census of all mobile money agents in Kenya to investigate how mobile money agent characteristics can affect mobile money adoption. We find that agents are in fact quite heterogenous in terms of several relevant characteristics and that some of these traits can be associated with people's decision to adopt mobile money. People are statistically significantly more likely to adopt the technology, if nearby agents offer account opening services, or if nearby agents have received formal training. Other agent characteristics such as liquidity management and business age do not seem to affect mobile money adoption. We further find that the effect of formal agent training on adoption is stronger for people who have no formal education compared to people who have at least some form of formal education. Considering that only 59 percent of agents offer account opening services and only a little more than half of the agents are formally trained, this article points towards a large potential for mobile money lenders and policy makers to foster financial inclusion; especially for people without formal education.

Key Words:

Mobile Money Adoption; Agent Banking; Financial Inclusion

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1. Introduction

Mobile money is an innovation that allows mobile phone users to deposit, transfer, and withdraw money without needing a bank account (Jack and Suri 2014; Suri 2017). The financial service has thereby become an important pillar to enable consumption smoothing (Abiona and Koppensteiner 2020; Aker et al. 2011; Jack and Suri 2014; Suri and Jack 2016; Riley 2018), increase household per capita consumption (Tabetando and Matsumoto 2020) or reduce poverty (Suri and Jack 2016). Consequently, mobile money has been adopted fast and widely across the developing world, with about 1.2 Billion registered accounts in 2021 (Andersson-Manjang and Naghavi 2021).

Given the potential of mobile money for welfare improvements, it is important to understand why people decide to adopt the technology. Previous research has shown that socio-economic characteristics, such as income, education and ownership of mobile phones are important predictors of mobile money adoption (Batista and Vicente 2020; Murendo et al. 2018; Munyegera and Matsumoto 2016). In addition, mobile money adoption is also highly correlated with people's physical proximity to mobile money agents (Jack and Suri 2014; Koomson, Bukari, and Villano 2021). Mobile money users typically need to visit an agent to open a mobile money account and each time they want to convert e-money into cash (or vice versa). Proximity to mobile money agents is therefore strongly related to transaction costs and the success of mobile money in Kenya and elsewhere has been largely attributed to the strong network of mobile money agents (Suri, 2017).

However, mobile money agents are not homogenous and can vary from one to another on many levels. For instance, not all mobile money agents offer account opening services; neither are mobile money agents equally likely to be able to transfer e-money into cash, as they often face stock outs (Jack and Suri 2014). Next to agents´ ability to offer functional services (i.e. account opening and cash transfers), mobile money agents can also differ in other potentially relevant characteristics such as training and perceived trustworthiness. It is an important part of mobile money agents' task to facilitate the mobile money adoption process, for instance, by answering costumers' questions on the technology. Generally, mobile money agents are specifically trained for that (McCarty and Rasugu 2012). However, this does not necessarily apply to all agents. This could to lead to heterogeneous abilities to support costumers and therefore influence mobile money adoption. If and how agent heterogeneity affects mobile money adoption is, however, barely understood up to now. The present study aims to address this research gap.

Our central research question asks, which role mobile money agents' characteristics play in the adoption of mobile money. We use two datasets: i) the nationally representative 2015 Kenya FinAccess household survey (N = 8,865), which entails GIS data on households´ location, a wide range of socio-economic characteristics including mobile money adoption, and ii) the 2015 FinAccess geospatial mapping, which provides a census of all mobile money agents in Kenya, including their GIS data and a small set of mobile money agent-related characteristics (N = 65,835). The GIS data allow an objective and transparent modelling of each households' surrounding network of mobile money agents.

By answering the central research question, this article has two important contributions to the literature on mobile money adoption. First, since the census also entails data on a small number of agent characteristics, such as different services that are offered, liquidity management, or whether the agent received training, this article is the first to investigate if and how agent heterogeneity affects mobile money adoption. Previous related research treats agents as homogenous, which as we show in this article, is not the case. Second, this article is the first to match GIS data of mobile money agents with GIS data from a nationally representative household survey. Opposed to previous related studies, our analysis does not need to rely on households' self-reported distances to the next agent, which can be noisy and biased (Escobal and Laszlo 2008; Munyegera and Matsumoto 2016; Murendo et al. 2018)

Our results show that mobile agents can differ quite substantially in terms of services that are offered. We find that these differences can be relevant for mobile money adoption, since people are statistically significantly more likely to adopt mobile money, if nearby agents offer account opening services, and if nearby agents have received formal training. We further find that the latter association (between formal training of nearby agents and mobile money adoption) is stronger for people who have no formal education, thereby carving out mobile money agents´ important role in financial inclusion for marginalized individuals. Considering that only a little more than half of the agents have received a formal training, this article thus points towards a large potential for mobile money lenders and policy makers to increase financial inclusion.

2. Conceptual background and hypotheses

Mobile money agents are crucial for the distribution of mobile money, primarily because they represent the intersection for the transfer of e-money into cash and vice versa (Suri 2017). From a mobile money adopter's perspective, such transfers imply transaction costs, which involve a small fee from the provider for the transfer itself as well as distance-dependent travel costs of reaching a mobile money agent (including both opportunity and direct cost). Consequently, distance to agents is an important contributor of total transaction costs and therefore predictor of mobile money adoption (Asravor, Boakye, and Essuman 2021; Tabetando and Matsumoto 2020; Jack and Suri 2014). Mobile money agents are also physically visited so that individuals can open a mobile money account at an agent´s outlet. The physical contact is needed so that agents can make sure that the registered account matches the (national) identification document (ID) of the costumer. We therefore hypothesize:

H1: People are more likely to adopt mobile money when nearby agents offer account opening services.

Furthermore, for both agents and mobile money adopters, it is critical that agents effectively manage their liquidity (Jack and Suri 2014; Cull et al. 2018). From an agent´s perspective, liquidity management is important to ensure revenue, as agents earn commissions for transfers. From a costumer´s perspective, agents´ liquidity management is important to be able to spontaneously transfer e-money into cash. Many low-and middle-income countries, including Kenya, are still largely cash-based which often implies that to purchase goods e-money needs to be transferred into cash first. It can hence be expected that if agents are (oftentimes) not able to transfer e-money into cash, the value of having a mobile money account decreases. We hence hypothesize:

H2: People are more likely to adopt mobile money when nearby agents manage their liquidity well.

Next to the aforementioned functional services, non-functional services or characteristics of agents may be important for mobile money adoption as well. One such characteristic is mobile money agent training. Training is advised by GSMA to entail guiding on how the agent interface works, how the agent can make money with the services, information on security matters and, importantly, understanding the costumers´ interface; thereby enabling agents to explain how the service works to (potential) costumers (McCarty and Rasugu 2012). A recent study by Lee et al. (2019) shows that low-cost and easy training of rural households in the Democratic Republic of Congo on how to sign up for and use mobile money increases adoption thereof substantially by more than 48 percentage points. Such explanations could be conducted by well-trained agents directly and thereby increase mobile money adoption. We therefore hypothesize:

H3: People are more likely to adopt mobile money when nearby agents have received training.

Furthermore, it is plausible to assume that explanations by trained agents foremost decrease the share of individuals who do not take up mobile money due to difficulties in understanding the service; which is likely to depend on the education level of people. In Kenya, where a large share of the population does not have any formal education and where mobile money adoption among those without formal education remains relatively low (Central Bank of Kenya, Kenya National Bureau of Statistics, and FSD Kenya 2016), such training may hence be particularly beneficial. We therefore hypothesize:

H4: Low education positively moderates the relationship between agent training and mobile money adoption.

Lastly, past research suggests that trust can be an important driver for technology adoption (Bahmanziari, Pearson, and Crosby 2003). Agents, who often primarily conduct some other business, such as running a kiosk, can represent well-known and trusted institutions in their communities and thereby overcome potential trust issues in the adoption of mobile money (Cull et al. 2018; Parlasca, Johnen, and Qaim 2022). The trust into mobile money agents is likely to depend on how well they are known in their community, which in turn is expected to be directly related to how long they are running their respective business. In other words, trust into agents is expected to be directly related to the founding year of an agent´s business. We therefore hypothesize:

H5: People are more likely to adopt mobile money if the business age of nearby agents is high.

3. Data and Methods

3.1 Data

The present study is based on the 2015 FinAccess household survey and the 2015 FinAccess geopatial mapping. The 2015 FinAccess household survey represents the fourth in a series of six surveys concerned with the usage of financial services in Kenya. This particular survey was chosen for the present analysis because data collection occurred at the same time as the data collection for the geospatial mapping of mobile money agents. The surveys employ a two-stage stratified cluster sampling design to collect data. The first level encompasses the selection of clusters based on the National Sample Surveys and Evaluation Program, with no substitute households being allowed. In the second level, households are selected in each cluster. From a chosen household an individual aged 16 or above is then randomly selected. We use sampling weights to ensure national representativeness for people aged 16 and above.

The 2015 FinAccess household survey was conducted during the time period of August to October 2015 and resulted in 8,865 respondents. In the present study, we exclude all individuals who are below 18 years of age (N = 457) as this is the legal age for opening a mobile money account; we further drop all individuals with missing data (N = 207), leading to a total sample of 8,001 individuals.

The FinAccess geospatial mapping survey 2015 was undertaken by the FinAccess management team as well; it constitutes the second and latest survey of its kind. The survey includes GIS data of several agricultural and financial institutions, including mobile money agents. A short questionnaire was specifically developed for the enumeration of mobile money agents. The fieldwork was conducted by enumerators through a walk-the-street exercise, where enumerators would physically walk down every street and village in Kenya. Inaccessible areas or areas that were considered unsafe for the enumerators are not included, leading to a total sample of 65,835 agents.

3.2 Methods

The aim of the present study is to investigate the relationship between mobile money agents´ characteristics and mobile money adoption. Mobile money adoption is measured as whether an individual currently has an active mobile money account. The binary nature of the outcome variable, current mobile money account ownership, implies that a logit model can be used to investigate the relationship between agent characteristics and mobile money adoption (Hoetker 2007); we also conduct probit and linear probability models for robustness checks. Based on a thorough literature review, the model includes all clinically and intuitively relevant variables, which are available in the data. This approach is chosen in order to provide the best possible control of confounding within the given data (Hosmer, Lemeshow, and Sturdivant 2013).

In line with previous studies, we assume that individuals, on average, aim to minimize their transaction-cost of adopting and using mobile money (Jack and Suri 2014). As the travel distance to physically visit an agent is the most important transaction-cost driver, individuals are assumed to be, on average, most likely to visit the agent closest to their household to adopt mobile money. Therefore, we investigate the characteristics of the mobile money agent, who is in closest geographical proximity (measured by the Euclidean distance), $AgentCharact_{NearestAgent}$, on mobile money adoption. This selection process yields the following Model 1, which is to be estimated:

$$(1)\quad MM_{adoption_i} = \alpha_i + \beta AgentCharact_{NearestAgent_i} + \gamma Socioeconomics_i + \delta sublocation_i + u_i$$

$MM_{adoption_i}$ is a binary variable that equals unity if an individual is currently registered with a mobile money provider and zero otherwise. $AgentCharact_{NearestAgent_i}$ is a vector of characteristics of the agent who is in closest geographical proximity to the surveyed individual. We match agents and households by minimizing the Euclidean distance (Otterbach et al. 2021). Analyzing the characteristics of the agent who is nearest to a person makes sense from an economic perspective, but has some shortcomings, as agents might tend to cluster in certain areas, for example near to an ATM or at road intersections. The additional transaction cost for reaching other agents once a person has reached an agent cluster might then be marginal. In such a scenario, the characteristics of only the nearest agent may not be decisive for adoption. We therefore also include measures to account for the additional transaction cost of being able to access specific functional services (in case the nearest agent does not offer the functional service). To do that we include measures of the difference in distances between the nearest agent who offers a specific service and the distance to the nearest agent (the difference always equals zero, when the nearest agent offers the specific service).

Agent characteristics include a categorical measure on liquidity management, i.e. how often the agent runs out of cash, meaning the agent is not able to transfer e-money into cash (never; monthly; weekly; daily). We further include a binary measure whether the agent offers account opening services; we also include a measure of the difference in distance (from a household´s perspective) between the nearest agent who offers that functional service and the nearest agent. In addition, we include a categorical measure indicating agents' training: (1) no training, (2) trained by mobile money specialist, (3) trained by sales representative, (4) trained in a classroom, and (5) instructed in outlet. The data do not contain information about what the different forms of training entail; however, based on anecdotal evidence the training forms (2) – (4) can be understood as formal training between agents and mobile money providers; whereas the latter training form (5) can be understood as mere instructions between agents. We also include a measure of the difference in distance between the nearest agent and the nearest agent, who has undergone training. Further, the present study includes a continuous variable which captures the business age of the nearest agent´s business. Following previous studies, we also include the logarithm of the Euclidean distance between the respondent´s household their nearest mobile money agent; as well as agent density, measured as the square root of the number of agents[i] within a radius of one kilometer around the private individual´s place of residence (Jack and Suri 2014; Tabetando and Matsumoto 2020).

$Socioeconomics$ is a vector of socio-demographic and -economic variables of private individuals, including: Gender, which equals unity if the respondent is female and zero otherwise (Batista and Vicente 2020); ID, which equals unity if the respondent owns an identification document – a necessary condition to sign up with a mobile money provider; education, a categorical variable capturing the highest level of the respondent´s education (Batista and Vicente 2020); respondent´s age (Murendo et al. 2018) and age squared to capture non-linear effects; the log of income to capture wealth related effects (Munyegera and

Matsumoto 2016); bank account, a binary variable which equals unity if the respondent owns a bank account (Batista and Vicente 2020); the household size of the respondent (Murendo et al. 2018); the number of financial groups in which the respondent participates to capture social network effects (Munyegera and Matsumoto 2018; Murendo et al. 2018); mobile phone ownership, a binary measure that captures whether the respondent owns a functioning mobile phone (Munyegera and Matsumoto 2016); the number of working people in the respondent´s household (Munyegera and Matsumoto 2016). Lastly, we include 47 sub-location dummies. The random error term u is expected to have a standard logistic distribution; *α, β, γ, and* δ are parameters to be estimated in equation (1).

Model 1 is suitable to test hypotheses 1 ,2, 3 and 5, but not hypothesis 4. In order to test hypothesis 4, i.e. that low education positively moderates the relationship between agent training and mobile money adoption, we estimate interaction effects between people without formal education and agent training (Model 2). Model 2 is otherwise largely similar to Model 1, with the difference that no education is a binary variable which equals unity if the respondent has no formal education. As the models are non-linear in nature, calculating the interaction effects is non-trivial and requires a test of second differences (Mize 2019). Using the binary measure of education is fully sufficient to test hypothesis 4 and facilitates the presentation of the results, as it decreases the number of second differences which need to be calculated.

$$
\begin{aligned}
(2)\ MM_{adoption_i} &\\
&= \alpha_i + \beta AgentCharact_{NearestAgent_i} \\
&+ \varepsilon AgentTraining_{NearestAgent_i} \text{ x } No\ Educ_i + \gamma Socioeconomics_i \\
&+ \delta sublocation_i + u_i
\end{aligned}
$$

Relying on the precise characteristics of specific agents (as we do in Model 1 and Model 2) assumes that individuals know the exact location the agents that are closest as well as their respective characteristics. This assumption may not always hold in reality. We therefore also try an alternative specification in which we express agent characteristics in terms of probabilities that nearby agents offer the desired service.

These probabilities may vary by area, as agent networks may be systematically different. For instance, it could be that agents in some areas systematically do not offer account opening services, while in other areas, most agents offer such services. For a person living in an area described by the latter scenario, unfavorable characteristics of the single nearest agent might not be very decisive as they can be more easily compensated by the immediate agent network. In contrast, in the former scenario, shortcomings of the nearest agents may not be easily compensated by the immediate agent network and therefore more strongly impact mobile money adoption.

We therefore also construct a measure of the immediate agent network around a household, $AgentCharact_{AgentNetwork_i}$, by averaging the characteristics of the ten nearest agents around a household. Calculating the average for the two categorical variables agent training and liquidity management is not straightforward. To capture average training within a network we therefore calculate the share of agents who had any form of training, without considering the specific categories. To capture the agent network´s liquidity management, we calculate an approximation of number of days that agents within the network run out of cash[ii]. Using the ten nearest agents reflects the attempt to balance the need for including enough agents so that the average characteristics can reflect systematic differences between networks, and the need to make sure that the immediate agent network is rather dense; so that the distance between, say, the 10th nearest agent and the nearest agent is not so large that an influence of the 10th nearest agent becomes highly unlikely. It is rather obvious that finding an appropriate measure for the number of agents also depends on the region. While the average immediate agent network in the capital city center could be much larger, it might be smaller in remote areas. We therefore also conduct robustness checks in which we vary the agent network size in both directions; by averaging the characteristics of the 5 and 20 nearest agents. The dependent variable, as well as all other confounders are identical as in Model 1. The random error term u is also expected to have a standard logistic distribution; *α, β, γ, and* δ are parameters to be estimated in equation:

$$(3)\ MM_{adoption_i} = \alpha_i + \beta AgentCharact_{AgentNetwork_i} + \gamma Socioeconomics_i + \delta sublocation_i + u_i$$

3.3 Model Specification

We first examine whether the analysis is subject to multicollinearity, a common identification problem with cross-sectional data. We first investigate the correlation matrix and find an extremely high correlation between agent density and agent distance (> 0.71). Due to this high correlation we exclude the former from the regression analysis. We then estimate the variance inflation factor (VIF) between the variables. For Model 1, the VIFs are low and vary between 1.12 (number of household members) and 2.74 (education) with a mean VIF of 1.54. The VIFs in Model 3 are also low and vary between 1.03 (agent network average age) and 2.78 (education), with a mean VIF of 1.48. We further generate a pairwise correlation matrix (Table A1 in the Appendix). With regard to agent characteristics, we find very low correlations, with maximum value of 0.15 in Model 1 (between account opening services and liquidity management) and 0.26 in Model 3 (between the share of agent who offer account opening services and the average liquidity management). In both models we further find very low correlations between agent characteristics and household characteristics, with maximum value of 0.10 and 0.11 respectively. Following previous studies which find considerably higher correlation coefficients (Amoah, Korle, and Asiama 2020), we are confident that the highest correlation coefficient does not severely bias the precision of our estimates. We therefore conclude that multicollinearity does not seem to cause adverse consequences to the model.

The goodness of fit of the models are then tested with the Archer and Lemeshow test. This test is very similar to the more known Hosmer and Lemeshow test, but contrarily, accounts for the complex design of the survey sampling (Archer and Lemeshow 2006). We find high p-values for both main models, Model 1 (p = 0.858) and Model 3 (p = 0.959), and thus strong support that the respective models do not represent a poor fit. To assess whether all the relevant explanatory variables are included in the model, we run a link test. The link test uses the predicted value and its square as the predictors to rebuild the model. The predictor variable should be statistically significant, but not its square. If the latter is statistically significant, this could mean the functional form of the model is inadequate or that relevant variables are omitted (Dudek and Lisicka 2013). For both main models, Model 1 and Model 3, the predictor variable (hat) is statistically significant ($p = 0.000$) but not its square ((1) $p = 0.660$; (2) $p = 0.566$), which shows that the functional forms of the respective models are not inadequate.

4. Descriptive Statistics of Agents and Households

4.1 Agent Descriptive Statistics

To open a mobile money account, people need to physically visit mobile money agents in order to present their proper identification document. This service is therefore crucial for mobile money adoption. However, Table 1 shows that only 59 percent of all mobile money agents state to offer account opening services. This is typically not because agents are not allowed to do so, but rather reflects a voluntary decision. The account opening process involves the requirement that agents or their employees must make sure that the identification document of the costumer matches the registered account. Failures to comply with the aforementioned regulation can lead to hefty penalties, even including contract termination. Therefore, opening accounts may be considered too risky for some agents which explains the relatively low share of agents, who *de facto* offer account opening services.

We further find that most mobile money agents have received some training, i.e. 88 percent. It is recommended that agents undergo training in which they learn how to make money by offering their service, understand their agent interface but also understand and are able to explain the costumer´s interface (McCarty and Rasugu 2012). The data indicate that agent training does not seem to be one standardized process, but in fact four different types of training can be distinguished, potentially leaving the respective agent with different abilities in explaining mobile money. The most common form of training is outlet training 30 percent, which can be understood as instructions between agents. The other three forms of training can be understood as formal training which is directly conducted with mobile money agents (shop-owners); with training conducted by sales representatives being the most common form of training at 29 percent and class room training being the least common form at 13 percent.

Table 1. Agent Characteristics (N=65,835)

Agent Characteristics	Mean
Account Opening Services [%]	59.36
Business age (years)	3.07
	(2.39)
Running out of cash [%]	
Never	47.17
Monthly	23.84
Weekly	21.21
Daily	7.78
Standalone [%]	29.08
Training [%]	
Any Training	87.90
Classroom	13.02
Mobile Money Specialist	16.05
Outlet	29.95
Sales Representative	28.89

Note: N=65,835. Standard Deviations are shown in parentheses. Own calculations based on 2015 FinAccess Geospatial Data Survey.

Another functional service of mobile money agents is to convert e-money into cash and vice versa. It appears that cash management does not seem to be a large obstacle for most mobile money agents, with more than 70 percent of all mobile money agents claiming that they never or only monthly run out of cash; in contrast, 8 percent of agents appear to have large difficulties in liquidity management and run out of cash daily. The data do not indicate how long it takes for an agent to stock up again in cash, i.e. how long the agent is unable to transfer e-money into cash.

Previous studies further indicate that mobile money agents are oftentimes considered rather trustworthy financial service providers (Cull et al. 2018; Parlasca, Johnen, and Qaim 2022). One of the reasons is that most agents primarily conduct some other business, such as running a kiosk, and are therefore assumed to be well-known and trusted in the local societies. The data indeed shows that only 29 percent are standalone agents, meaning that their only source of income comes from mobile money commissions, while more than 70 percent of agents run some other business from their agent shop location as well. In the present study, we proxy trustworthiness with the age of an agents´ businesses, which has an average of 3.1 years.

4.2 Household Descriptive Statistics

Table 2 shows that 69 percent of adult Kenyans have a mobile money account. In order to be able to use mobile money, access to a mobile phone is needed; 76 percent of the adult population own a mobile phone. Furthermore, Know-Your-Costumer regulations require mobile money adopters to own a valid ID (Kipkemboi 2019); ownership of IDs is high with 91 percent of the population owning an ID.

Table 2. Household Sample Description

Dependent Variable	Mean/share	Standard Deviation
Mobile Money adoption [%]	68.51	
Agent Network		
Agent Density [1Km radius]	40.50	98.43
Distance to the next agent [Km]	4.52	11.00
Socio-Demographics		
Age [years]	38.41	16.18
Bank Account Ownership [%]	31.94	
Education [%]		
None	19.64	
Primary	43.37	
Secondary	26.60	
Tertiary	10.39	
Gender [1 = Female]	51.46	
Household Size [Number of People]	4.28	2.43
Income [Kenyan Shilling]	18,415.00	215,367.10
ID Ownership [%]	90.95	
Lives in Rural Area [%]	55.79	
Mobile Phone Ownership [%]	76.38	
Number of Social Groups [Number]	0.74	1.31
Number of Working People [Number]	1.24	0.72
Occupation [%]		
Farmer	32.21	
Employed	12.08	
Casual	17.79	
Self-Employed	19.03	
Money Support	15.69	
Other	3.20	

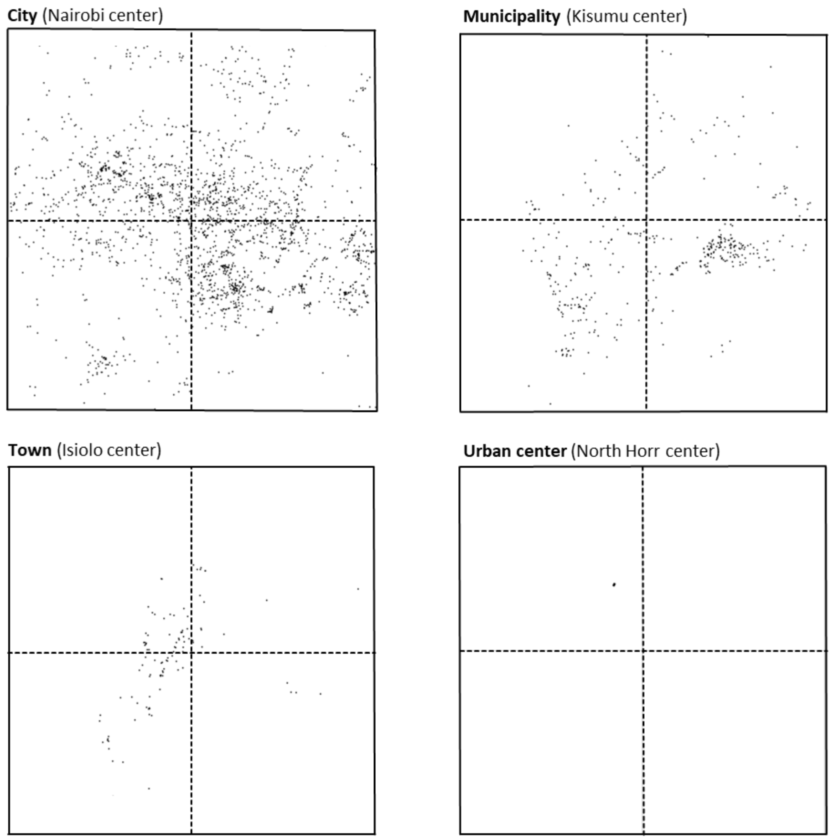
Note(s): N = 8,001. All means are calculated using sampling weights. Authors´ own calculations based on FinAccess household survey 2015

The average age of respondents is 38 years, of whom most live in rural areas (56 percent). Women represent 51 percent, which fits to the latest census conducted in Kenya, where women also represent 51 percent (KNBS 2019). The share of respondents who own a bank account is rather low at 32 percent. Education is also low on average, with 63 percent of respondents who have left school with primary education or even before, while only 10 percent have tertiary education. As in many developing countries, farming is the most common occupation and only 12 percent of the respondents are employed.

Table 2 further shows that the average distance between households and agents is 4.5 kilometers, with a standard deviation of more than 10 kilometers. The reason for this large standard deviation lays in the nature of the commission-based agent business, which causes agents to cluster in areas with high economic activity, mostly urban centers. That implies that for people living in remote areas, distances to mobile money agents can be extremely far. The maximum distance in our sample is 95 kilometers, which is still a lower bound due to the use of Euclidian distances. Similarly, the average number of agents within a 1-kilometer radius around a household is 40.5, with a standard deviation of almost 100 agents.

Figure 1 and Figure 2 visualize the clustering of agents that cause the standard deviations. Figure 1 highlights the extreme differences in agent quantity between urban area types on a 2 by 2 Kilometer grid. These agent densities vary greatly by area, with thousands of agents in the center of the largest city in Kenya (Nairobi) and sharply decreasing agent quantities with decreasing sizes of urban areas, to only two agents in a randomly chosen urban center North Horr.

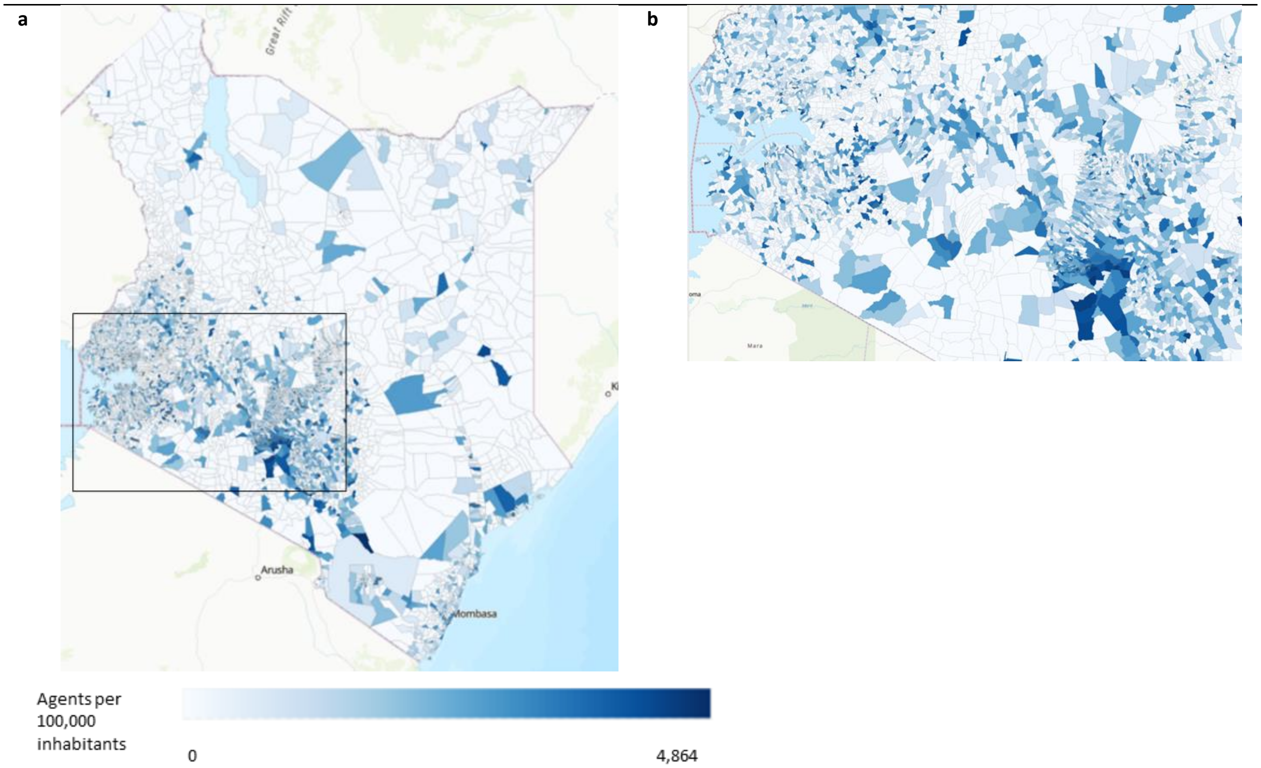
Figure 1. Examples of agent density for four types of urban areas



Note: Examples of mobile money agent quantities on a 2 x 2 kilometer grid are shown for four different types of urban centers, where every black dot represents the location of a mobile money agent. The grids were randomly selected within each urban area type, but do not necessarily have to be representative. Definition of urban center type by population size: city >= 500,000; Municipality >= 250,000 & < 500,000; town >= 10,000 & < 250,000; urban center >= 2,000 & < 10,000. Source: Own elaboration based on the 2015 FinAccess Geospatial Mapping.

The visual inspection of Figure 1 further indicates that the decrease in the number of agents per square kilometer appears to be larger than the decrease in population size of the respective urban areas. This would imply that access to mobile money is relatively better in areas with larger population sizes. However, as mentioned before, Figure 1 is not meant to be representative for the urban area types and conclusions should be drawn with care; we therefore include Figure 2. Figure 2 depicts the agent density measured as number of agents per 100,000 individuals, for each sub-location in Kenya. The figure thereby highlights that not only the number of agents, but the number of agents per inhabitants varies greatly by area in Kenya. Especially, in the economically more active areas in south-east Kenya and south-west Kenya (around Mombasa), agent density relative to population size is much higher compared to economically less developed areas in northern and western Kenya.

Figure 2. Agents density relative to population size by sub-location



Note: a) agent density relative to population size for each sub-location (N=6,800) in Kenya; b) close-up of the framed area in a, to enhance visualization of the large number of very small sub-locations in that area. The highest agent density is in the sub-location Biashara at 4,864 agents per 100,000 inhabitants (Number of Agents = 296; Populationsize = 6,085). Population sizes are retrieved from the 2019 KNBS population census. The number of agents per sub-location is caluclated in ArcGIS Pro, based on the 2015 FinAccess Geospatial Mapping.

5. Empirical Results and Discussion

5.1 Agent Characteristics and Mobile Money Adoption

Estimation results from logistic regressions of mobile agent characteristics on the likelihood of mobile money adoption are presented in Table 3 (all estimations are calculated using STATA 16). Model 1, 2, and 3 are discussed together in this section.

Congruent to previous studies, we find that the distance to the nearest agent is statistically significantly negatively associated with mobile money adoption (Asravor, Boakye, and Essuman 2021; Jack and Suri

2014; Munyegera and Matsumoto 2016; Murendo et al. 2018). We further find a considerable and positive correlation (0.22) between agent density and mobile money adoption (s. Table A1 in the Appendix). This finding generally supports previous findings of Jack and Suri (2014), who hypothesize that agent density is a proxy for the access to functional services, which may be important for mobile money adoption. However, as mentioned above, due to the extremely high correlation between agent density and agent distance, the former is not considered in the regression analyses.

With regard to specific agent characteristics, we find strong support for hypothesis 1. More precisely Table 3 shows a highly statistically significant positive association between the functional account opening service of the nearest agent and mobile money adoption. This finding is in line with hypotheses on the importance of functional services of agents in mobile money adoption (Jack and Suri 2014). As mentioned before, under the assumption that individuals aim to minimize their transaction cost, we assume that on average individuals are most likely to visit their nearest agent; the statistically significant association with characteristics of the nearest agent indicates that this assumption is reasonable.

We do not find a statistically significant association between mobile money adoption and the additional distance from the nearest agent to the nearest agent, who offers account opening services. This finding could indicate that the assumption that individuals know the location of the nearest agent with this specific characteristic might be too strict. As described in section 3.2, it may therefore be more appropriate to capture network effects by calculating the average probability that agents offer a specific service in the immediate network. Indeed, Table 3 shows that an increase in the probability that nearby agents offer account opening services is also highly statistically significantly and positively associated with mobile money adoption; indicating that not only the nearest agent but also the immediate agent network´s average characteristics affect mobile money adoption.

Table 3. Estimates of logit models of the determinants of mobile money adoption

Variables	(1) Nearest Agent	(2) Agent Network
Account opening services		
Agent Network *(Share of Agents offering account opening services)*		0.338**
		(0.145)
Nearest Agent (yes = 1)	0.250***	
	(0.090)	
Additional distance to nearest agent offering account opening services	0.002	
	(0.005)	
Business Age		
Agent Network *(Average business age in network in years)*		-0.002
		(0.063)
Nearest Agent *(years)*	-0.018	
	(0.024)	
Distance to Nearest Agent (log-kilometers)	-0.116***	-0.109***
	(0.033)	(0.032)
Liquidity Management		
Agent Network *(Average number of days that agents within a network run out of cash)*		0.001
		(0.001)
Nearest Agent *(Base = Never runs out of cash)*		
Runs out monthly	-0.032	
	(0.113)	
Runs out weekly	0.067	
	(0.110)	
Runs out daily	-0.074	
	(0.175)	
Training		
Agent Network *(Share of agents within network who received any form of training)*		0.934***
		(0.225)
Nearest Agent *(Base = No Training)*		
Mobile Money Specialist	0.247*	
	(0.148)	
Sales Representative	0.378***	
	(0.146)	
Classroom	0.445**	
	(0.179)	
Outlet	0.175	
	(0.135)	
Additional distance until trained agent	0.024	
	(0.017)	
Socioeconomic Control Variables	YES	YES
Constant	-10.106***	-10.718***
	(0.805)	(0.829)
Observations	8,001	8,001
Goodness of Fit		
Archer-Lemeshow (p-value)	0.858	0.959
Link Test		
Hat	0.000	0.000
Hat (squared)	0.660	0.566

Note: ***p < 0.01, **p < 0.05, *p < 0.1; Mobile money agent characteristics in column one refer to the nearest agent. Agent characteristics in column 2 refer to the average over the ten nearest agents. Robust standard errors are shown in parentheses (hc1); Full table with all control variables is shown in Table A2 in the appendix; Authors´ own calculations based on 2015 FinAccess Household Survey

We do not find support for hypothesis 2, i.e. we do not find a statistically significant association between the liquidity management of mobile money agents and mobile money adoption, where coefficient sizes are also small. This null-finding has two possible explanations. First, it is plausible that agents' liquidity management does not influence adoption decisions because people are not aware of agents' liquidity management before they decide to use mobile money. This does not mean that liquidity management of agents is not important for consumers, as it may very well affect satisfaction and frequency of mobile money use. Second, the insignificant relationship between liquidity management and mobile money adoption could, however, also be caused by reverse causality. Mobile money agents may run out of cash more often precisely when they have a lot of customer contact. Mobile money adoption could therefore also be a reason for liquidity management problems. However, we do not find any further evidence to support the latter explanation since the relationship between agents´ liquidity management and mobile money demand per agent, proxied by the number of withdrawals per agent, is weak; with a small correlation value of 0.022 between liquidity management of an agent and the number of daily withdrawals taking place at that agent´s shop (s. Table A1).

We further hypothesize that agent training is positively associated with mobile money adoption (hypothesis 3). Indeed, Table 3 shows that if nearby agents receive formal training, i.e. training from sales representatives, mobile money specialists, or classroom-trainings, mobile money adoption is statistically significantly higher (Model 1). Table 3 further shows that the share of trained agents in the immediate agent network is positively and highly statistically significantly associated with mobile money adoption.

Congruent to previous studies, we argue that this positive association is likely to occur as agent training ideally entails training on how to explain mobile money usage to costumers and thereby the share of individuals refraining from adopting mobile money who do not (fully) understand how to adopt or use the service (Lee et al. 2021; McCarty and Rasugu 2012). We therefore further hypothesize that the association between agent training and mobile money adoption is stronger for individuals with lower levels of education (hypothesis 4).

To test this assumption, we first interact agent training (measured as binary variable) with a binary variable which takes value one if the respondent has no formal education (Table 4). Congruent to our expectation, we find that the interaction effect is statistically significant, supporting hypothesis 4. First differences (or average marginal effects) show that agent training is associated with an 8 percentage points increased probability of mobile money adoption among non-educated individuals; whereas the association is much weaker (1 percentage point increase) and not statistically significant for individuals who have at least some form of formal education. We interpret the finding as further indication that agent training increases the ability to explain mobile money to interested customers and therefore mobile money adoption.

Table 4. Interaction Effect of Education and Agent Training on Mobile Money Adoption

		Training[1]	Mobile Money Specialist[2]	Sales Representative[2]	Classroom[2]	Outlet[2]
First Difference	$AME_{\text{No Education}}$	8.1*** (2.9)	14.1***(3.5)	9.8*** (3.5)	12.9** (6.3)	3.5 (3.4)
	$AME_{\text{Some Education}}$	1.1 (1.4)	-0.2 (1.7)	1.9 (1.6)	2.5 (1.8)	0.7 (1.5))
Second Difference		7.0** (3.0)	14.3*** (3.7)	7.9** (3.6)	10.3 (6.4)	2.8 (3.6)

Note: N= 8,001. Dependent Variable = Mobile Money Adoption. AME = Average Marginal Effect (commonly referred to as first difference); Second difference tests whether two first differences are equal using a Wald test. [1] Estimation of Model 2) with Training defined as binary variable; [2] Estimation of Model 2 with training defined as categorical variable; ***p < 0.01, **p < 0.05, *p < 0.1; Robust standard errors are shown in parentheses; Authors´ own calculations based on 2015 FinAccess Household Survey and 2015 FinAccess geospatial mapping

We further investigate the different training types. First differences in Table 4 show that all three forms of formal training are statistically significantly associated with mobile money adoption among individuals without formal education; while none of these three training forms are statistically significantly associated with mobile money adoption among individuals with some formal education. The second differences indicate whether the difference between individuals with no formal education and those with at least some formal education are statistically significant. This is the case for mobile money specialist training and sales representative training; in case of classroom training average differences in the effect sizes are also large (> 10 percentage points) but not statistically different from zero. This does not necessarily mean that classroom training is less effective among non-educated, since the null-finding may be driven by the large standard errors of individuals who are non-educated and live near an agent who was trained in a classroom, due to the small number of individuals in that group (N=87).

Lastly, we find that outlet training is not statistically significantly related with mobile money adoption for both people without any formal education and those with at least some (despite constituting the largest share of training type in both groups). This finding is somewhat congruent with the notion that this form of training can be interpreted as inherently different from all other types of training, i.e. mere instructions between agents. While the results should be interpreted with care, formal training seems to be suitable to increase mobile money adoption among individuals without any form of formal education, whereas instructions between agents do not appear to be effective in that regard.

We further hypothesize that the business age of agents is positively related to mobile money adoption (hypothesis 5). However, we do not find a statistically significant correlation between business age of nearest agent (Model 1) or the immediate agent network (Model 3) and mobile money adoption in addition to very small coefficient sizes and therefore no support for hypothesis 5 (Table 3). This could indicate that trust in the nearest agent (or at least whether the nearest agent is well-known) does not affect mobile money adoption. However, even though previous research have used a similar proxy for trustworthiness (Cull et al. 2018), the variable has some shortcomings. It is plausible that a large share of people who are well-known and trusted entrepreneurs, at some point in their life, had to close their business and open a new business; in such a case the founding year of the current business does not reflect the track record in the community and hence trustworthiness of the agent. This is supported by the fact that the average business age is only 3.1 years, which is unlikely to fully reflect the track record of the agent in the community.

The association between the socio-demographic and -economic control variables and mobile money adoption are by and large in line with previous findings (s. Table A2 in the Appendix). Congruently to previous studies, we do not find a statistically significant association between gender on mobile money adoption (Munyegera and Matsumoto 2016; Murendo et al. 2018; Batista and Vicente 2020). In contrast to previous studies we do find that people in larger households are less likely mobile money adoption. While previous studies investigating mobile money adoption have not found a significant effect of age (Murendo et al. 2018), the present study, congruently to other technology adoption literature (Loges and Jung 2001), finds a positive and statistically significant association between age and mobile money adoption; at a decreasing rate, as indicated by the negative and statistically significant effect of age-squared. Bank account ownership, similar to the findings by Batista and Vincente, 2020, is positively and statistically significantly related to mobile money adoption. Previous studies have further shown that wealth is positively related to mobile money adoption (Munyegera and Matsumoto 2016). Similarly, we find that income is positively and statistically significantly associated with mobile money adoption. Further, the number of financial groups in which the respondent participates, a proxy for the size of the respondent´s social network, is in line with previous studies (Murendo et al. 2018) positively and statistically significantly associated with mobile money adoption. In addition, similar to previous studies, the number of working people within the respondent´s household is statistically significantly associated with mobile money adoption (Munyegera and Matsumoto 2016).

5.2 Robustness and Model Specification

We run multiple robustness checks in order to determine whether the coefficients of the main effects are stable. More precisely, we re-estimate Model 1 and Model 3 by (1) estimating a linear probability model (LPM), (2) a probit model, and (3) by excluding all household variables to check for potential adjustment effects (s. Tables A3 and A4 in the appendix).

Regarding Model 1, we do not find considerable changes in sign, magnitude, or statistical significance throughout the robustness checks, concluding that the associations between agent characteristics of the nearest agent and mobile money adoption are stable (Table A3). The coefficients in Model 3 are also largely stable in regard to sign, magnitude and, significance (Table A4); except for robustness check (3). Here we find a statistically significant relationship between the average business age of agents within the immediate network and mobile money adoption in accordance with hypothesis 5. However, given that this relationship is non-significant throughout all other robustness checks and the main models, we do not view this as solid support for hypothesis 5.

Given the strong similarities regarding the main findings of Model 3 using logistic regression and LPMs, we estimate the possible influence of omitted variable bias on the main findings in Model 1 (using LPMs). For Model 1, we estimate robustness values (RVs) for the estimates of agent training (3.78 per cent), and account opening services (3.84 per cent). The RVs indicate a threshold of how much of the residual variance both of the treatment and the outcome an unobserved confounder would need to explain to bring the lower bound of the confidence interval of the estimated effect to zero (significance level 5 per cent) (Cinelli and Hazlett 2020). To facilitate the interpretation of what that means, we use education as a benchmark for the RVs, as education is correlated with all confounders and a strong predictor of mobile money adoption. We find in each case that unobserved confounders as strong as education would not be sufficient to explain away the observed estimate; with the higher bound estimates for education at 1.83

percent being below the respective RVs of agent training (3.78 percent) and account opening services (3.84 percent). This gives further confidence that the association between both investigated agent characteristics of the nearest agent (training and account opening services) and mobile money adoption are robust. Similarly, we find that the RVs in Model 3 for agent network account opening (3.23) and agent network training (7.08) are larger than the higher bound estimates of education (1.71); indicating that even unobserved confounders as strong as education are not sufficient to explain away the main findings in Model 3.

Lastly, we conduct several robustness checks regarding the plausibility of our assumptions. We assume that, on average, individuals are most likely to visit the agent closest to them in order to minimize transaction costs of mobile money adoption/usage. This assumption is based on both previous studies and economic theory. Our results support this assumption as agent characteristics of the immediate agent network are statistically significantly associated with mobile money adoption. Based on this assumption, we expect that if we include the characteristics of, say, the second nearest agent, the relationship between the characteristics of the nearest agent and mobile money adoption to be more pronounced compared to the characteristics of the second nearest agent and mobile money adoption, on average. Indeed, when including the characteristics of the second nearest agent in the Model 1 (s. Table A3), we do not find any statistically significant relationship for any of the agent characteristics of the second nearest agent and mobile money adoption; while the relationship between the characteristics of the nearest agent and mobile money adoption remain very similar to Model 1 in sign, magnitude and significance. We view this finding as further indication that the closest agent takes a special role in mobile money adoption of households.

Regarding Model 3, we argued that the agent network might matter in mobile money adoption, as people can counterbalance shortcomings of the nearest agent in the immediate network. The average characteristics of the network somewhat indicate how easily an individual can counterbalance potential shortcomings of a single agent. Arguably, the network could be expected to be particularly beneficial when it is dense, i.e. when distances between agents in the immediate network are short, as additional transaction costs to use other agents are low. This assumption also implies that when the distance between agents in the immediate network increases, network effects are expected to decrease. Indeed, we find that when the difference in distance between the nearest agent and the farthest agent within the immediate network (from a private individual´s perspective) exceeds one kilometer, the relationship between the network characteristics and mobile money adoption becomes insignificant. In contrast, when the network is dense (i.e. the difference in distance between the nearest agent and the farthest agent within the immediate network from a private individual´s perspective is smaller than or equal to one kilometer), the association between agent network characteristics remain statistically significant and coefficient sizes increase compared to Model 3. The authors view this result as some further indication that network characteristics are important for mobile money adoption. However, this result does not represent a potential effect of network density and mobile money adoption, as network density might be endogenous, e.g. systematically different in wealthy and poor areas. We further mention in section 2 that the immediate network size has emerged from a consideration of not defining the immediate network as so small that averages become meaningless and so large that for a large number of individuals many agents are so far away that their influence on the decision to adopt mobile money becomes unlikely. As mentioned earlier, we choose ten agents as a reasonable number, but tested the sensitivity to results of defining the network by a smaller or larger number of agents. We therefore re-estimated Model 3 considering 5 and 20 agents as network size, with differences in distances from a private individual's perspective between the nearest to the farthest agent of 1.4 and 5.1 kilometers respectively. We find that results are similar results compared to the definition of 10 agents and, again, we also find that if the spread of the agent network from a household's perspective increases the network effects vanish.

6. Conclusion

Mobile money is largely recognized to enhance welfare of adopters. The network of mobile money agents is a critical factor for the success of mobile money, but their role in the adoption of mobile money adoption is not yet well understood. In the present study we therefore identify specific agent characteristics which are relevant in mobile money adoption. Our results show that for both the nearest agent and the immediate agent network, account opening services are statistically significantly and positively associated with mobile money adoption. The present study thereby shows that increasing the share of mobile money agents who offer account opening (59 percent) could bear some potential to increase mobile money adoption and therefore provide an important risk management instrument for people in many developing countries. This could be achieved, for instance, through higher commissions for opening a new account, which reflect the risk of this undertaking – especially when not agents themselves but their employees open an account.

The present study further shows that agent training is important for mobile money adoption, especially for people lacking formal education. This finding follows the reasoning that agent training enables agents to explain comprehensibly how to use mobile money to potential customers. We further show that not every training seems to be equally suitable to increase mobile money adoption and that only 58 percent of agents have received a form of training which is statistically significantly associated with mobile money adoption among individuals without formal education. This finding, therefore, uncovers further potential for mobile money lenders to increase their customer base. However, training might be expensive and the cost to train more agents might not be economically worthwhile if it largely leads to new customers with very low education, who might be expected poorer and therefore less profitable for the mobile money providers. In that case, policy makers could consider incentives for agent training as a way to foster financial inclusion, especially in regions with low education levels.

While the present study finds important and robust associations between agents´ characteristics and mobile money adoption on a national level, some limitations need to be acknowledged. First, the survey of more than 60,000 agents does not allow for in-depths questions, such as questions which indicate the quality of agent trainings, their content, and therefore differences of the training types. Given the considerable and robust association between agent training and mobile money adoption, we recommend future studies to further investigate which mechanisms, mostly which training content, makes some forms of training more successful than others. Second, even though the present study uses some econometric approaches and several robustness checks, it cannot make causal claims on the effects of agent characteristics on mobile money adoption. We therefore encourage future research to use experimental or quasi-experimental approaches to corroborate the findings about the associations between mobile money agents´ characteristics and mobile money adoption. Third, even though Kenya is a vanguard for mobile money usage, socio-cultural, political and other relevant differences should be considered when results are transferred to other contexts. We therefore strongly encourage future research to investigate the role of agents in other countries.

Data Availability

The data of the 2015 FinAccess survey are available on 'Harvard Dataverse' with the digital object identifier https://doi.org/10.7910/DVN/QUTLO2. The 2015 FinAccess geospatial mapping is also available on 'Harvard Dataverse' with the digital object identifiers https://doi.org/10.7910/DVN/SG589T . Due to data privacy, GIS data of households are not publicly available.

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Table A1. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
(1) Account Open (Closest Agent)	1.00																									
(2) Account Open (Network)	0.59	1.00																								
(3) Additional Distance (Account Open)	-0.21	-0.31	1.00																							
(4) Distance (Closest Agent)	0.03	0.05	0.00	1.00																						
(5) Liquidity Management (Closest Agent)	0.15	0.12	-0.05	0.02	1.00																					
(6) Liquidity Management (Network)	0.15	0.26	-0.12	0.04	0.51	1.00																				
(7) Training (Network)	0.15	0.23	-0.01	-0.13	0.12	0.17	1.00																			
(8) Training (Closest Agent)	0.12	0.15	-0.06	-0.08	0.09	0.11	0.57	1.00																		
(9) Additional Distance (Account Open)	-0.09	-0.10	0.21	0.11	-0.08	-0.05	-0.21	-0.32	1.00																	
(10) Business Age (Closest Agent)	0.11	0.05	0.03	-0.03	0.02	-0.00	0.06	0.07	-0.04	1.00																
(11) Business Age (Network)	0.09	0.09	0.10	-0.05	0.00	-0.02	-0.01	-0.01	-0.03	0.35	1.00															
(12) Age (Respondent)	0.03	0.04	-0.01	0.16	0.00	-0.01	0.02	0.00	0.01	0.01	0.01	1.00														
(13) Bank Account Ownership	0.01	-0.00	-0.04	-0.26	-0.02	-0.00	0.08	0.04	-0.02	0.03	0.03	-0.01	1.00													
(14) Education	0.04	0.02	-0.08	-0.39	-0.00	0.00	0.16	0.08	-0.08	0.05	0.05	-0.29	0.43	1.00												
(15) Gender	0.03	0.03	-0.01	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.01	-0.05	-0.16	-0.14	1.00											
(16) Household Size	-0.03	-0.01	0.06	0.29	0.00	0.02	-0.13	-0.05	0.06	-0.04	-0.04	-0.10	-0.15	-0.19	0.09	1.00										
(17) ID	-0.01	-0.01	-0.00	-0.03	-0.00	-0.01	-0.02	-0.02	0.02	0.00	0.02	0.26	0.19	0.01	-0.03	-0.04	1.00									
(18) Mobile Phone Ownership	-0.01	-0.00	-0.03	-0.25	0.00	-0.01	0.06	0.03	-0.05	0.03	0.04	-0.14	0.28	0.35	-0.08	-0.06	0.15	1.00								
(19) Income	-0.04	-0.06	0.01	-0.22	-0.00	-0.01	0.01	-0.00	0.00	0.02	0.02	-0.11	0.40	0.35	-0.21	-0.09	0.17	0.30	1.00							
(20) Nr. of Groups	0.05	0.03	-0.04	-0.04	0.03	0.02	0.09	0.04	-0.04	0.01	0.02	0.00	0.12	0.12	0.15	-0.01	0.08	0.15	0.11	1.00						
(21) Nr. of Working People	0.03	0.02	-0.02	-0.11	-0.00	0.03	0.11	0.06	-0.06	0.01	0.01	-0.11	0.12	0.20	-0.05	0.18	0.00	0.10	0.14	0.10	1.00					
(22) Occupation	-0.01	-0.01	0.00	-0.23	-0.00	0.00	0.02	0.02	-0.00	-0.01	-0.00	-0.10	0.00	0.05	0.13	-0.04	-0.11	0.01	-0.07	-0.02	-0.07	1.00				
(23) Sub-Location	0.09	0.11	-0.09	0.24	0.05	0.12	-0.02	0.00	-0.01	-0.03	-0.06	-0.01	-0.09	-0.06	0.00	0.16	-0.06	-0.10	-0.16	-0.05	-0.00	-0.07	1.00			
(24) Rural	0.08	0.10	0.05	0.59	-0.00	-0.01	-0.03	-0.05	0.06	-0.02	-0.03	0.16	-0.24	-0.28	0.01	0.21	-0.01	-0.18	-0.20	-0.00	-0.04	-0.21	0.18	1.00		
(25) Number of Withdrawals (Closest Agent)	0.14	-0.01	0.06	-0.08	0.02	0.01	0.08	0.11	-0.01	0.18	0.09	-0.00	0.02	0.06	-0.00	-0.01	-0.03	0.03	0.01	0.00	0.04	0.02	-0.00	-0.04	1.00	
(26) Agent Density	-0.08	-0.11	-0.05	-0.71	-0.00	-0.02	0.03	0.02	-0.07	0.00	0.01	-0.20	0.24	0.30	-0.02	-0.25	0.00	0.18	0.22	0.01	0.04	0.19	-0.32	-0.58	0.01	1.00

Note: N = 8,001. Authors´ own calculations based on 2015 FinAccess Household Survey and 2015 FinAccess geospatial mapping

Table A2. Estimates of logit models of the determinants of mobile money adoption (incl. results of socio-demographic variables)

Variables	(1) Nearest Agent	(2) Agent Network
Account opening services		
Agent Network *(Share of Agents offering account opening services)*		0.338**
		(0.145)
Nearest Agent (yes = 1)	0.250***	
	(0.090)	
Additional distance to nearest agent offering account opening services	0.002	
	(0.005)	
Business Age		
Agent Network *(Average business age in network in years)*		-0.002
		(0.063)
Nearest Agent *(years)*	-0.018	
	(0.024)	
Distance to Nearest Agent/ Nearest Network (log-kilometers)	-0.116***	-0.109***
	(0.033)	(0.032)
Liquidity Management		
Agent Network *(Average number of days that agents within a network run out of cash)*		0.001
		(0.001)
Nearest Agent *(Base = Never runs out of cash)*		
Runs out monthly	-0.032	
	(0.113)	
Runs out weekly	0.067	
	(0.110)	
Runs out daily	-0.074	
	(0.175)	
Training		
Agent Network *(Share of agents within network who received any form of training)*		0.934***
		(0.225)
Nearest Agent *(Base = No Training)*		
Mobile Money Specialist	0.247*	
	(0.148)	
Sales Representative	0.378***	
	(0.146)	
Classroom	0.445**	
	(0.179)	
Outlet	0.175	
	(0.135)	
Additional distance until trained agent	0.024	
	(0.017)	
Socioeconomic Control Variables		
Age	0.067***	0.068***
	(0.013)	(0.013)
Age (squared)	-0.001***	-0.001***
	(0.000)	(0.000)
Bank Account Ownership (1 =yes)	1.094***	1.077***
	(0.121)	(0.120)
Education (Base = None)		
Primary	1.118***	1.016***
	(0.113)	(0.113)
Secondary	1.556***	1.456***
	(0.139)	(0.141)
Tertiary	1.748***	1.657***
	(0.251)	(0.252)
Gender (1 = Female)	0.015	-0.006
	(0.085)	(0.085)
Household Size (Nr. of Individuals)	-0.066***	-0.057***
	(0.019)	(0.019)
ID Ownership (1 = yes)	1.120***	1.139***
	(0.143)	(0.143)
Mobile Phone Ownership (1= yes)	6.194***	6.181***
	(0.753)	(0.751)
Total Income (log of Ksh)	0.479***	0.483***
	(0.079)	(0.079)
Interaction Income*Mobile Phone Ownership	-0.334***	-0.331***
	(0.087)	(0.086)
Number of Groups	0.174***	0.165***
	(0.045)	(0.045)
Number of Working Individuals in Household	0.342***	0.318***
	(0.057)	(0.057)
Occupation (Base = Farmer)		
Employed	0.378*	0.376*
	(0.200)	(0.199)
Casual Worker	0.170	0.157
	(0.115)	(0.116)
Self-Employed	0.321***	0.306**
	(0.121)	(0.121)
Money Support	0.252**	0.263**
	(0.114)	(0.114)
Other	-0.778***	-0.797***
	(0.259)	(0.259)
Sub-Region	-0.000	-0.000
	(0.000)	(0.000)
Rural (1= Rural)	0.220**	0.195*
	(0.111)	(0.108)
Constant	-10.106***	-10.718***
	(0.805)	(0.829)

Note: N = 8,001. ***p < 0.01, **p < 0.05, *p < 0.1; Mobile money agent characteristics in column one refer to the nearest agent. Agent characteristics in column 2 refer to the average over the ten nearest agents. Robust standard errors are shown in parentheses (hc1); Authors´ own calculations based on 2015 FinAccess Household Survey and 2015 FinAccess geospatial mapping

Table A3. Robustness checks of the effects of the nearest and second nearest agent´s characteristics on mobile money adoption

Variables	(1) OLS	(2) Probit	(3) No Sociodemographics (logit)	(4) Incl. 2nd nearest agent (logit)
Account opening services				
Nearest Agent (yes = 1)	0.027***	0.132***	0.136*	0.260***
	(0.009)	(0.049)	(0.074)	(0.092)
Second Nearest Agent (yes = 1)				-0.041
				(0.093)
Additional distance to nearest agent offering account opening services	0.000	0.001	-0.006**	
	(0.001)	(0.003)	(0.003)	
Business Age				
Nearest Agent *(years)*	-0.002	-0.012	0.020	-0.020
	(0.002)	(0.013)	(0.019)	(0.024)
Second Nearest Agent (years)				-0.003
				(0.024)
Distance to Nearest Agent/ Nearest Network (log-kilometers)	-0.012***	-0.063***	-0.370***	-0.113***
	(0.003)	(0.017)	(0.022)	(0.033)
Difference in Distance between Nearest and Second Nearest Agent				0.016
				(0.014)
Liquidity Management				
Nearest Agent *(Base = Never runs out of cash)*				
Runs out monthly	-0.003	-0.012	-0.034	-0.046
	(0.011)	(0.061)	(0.091)	(0.117)
Runs out weekly	0.005	0.030	0.106	-0.022
	(0.010)	(0.060)	(0.090)	(0.113)
Runs out daily	-0.010	-0.045	-0.129	-0.141
	(0.018)	(0.094)	(0.138)	(0.169)
Second Nearest Agent *(Base = Never runs out of cash)*				
Runs out monthly				-0.004
				(0.106)
Runs out weekly				0.285
				(0.124)
Runs out daily				0.172
				(0.158)
Training				
Nearest Agent *(Base = No Training)*				
Mobile Money Specialist	0.032**	0.137*	0.208	0.160
	(0.016)	(0.081)	(0.128)	(0.151)
Sales Representative	0.044***	0.212***	0.366***	0.294**
	(0.016)	(0.080)	(0.122)	(0.145)
Classroom	0.048***	0.242**	0.581***	0.435**
	(0.017)	(0.096)	(0.142)	(0.188)
Outlet	0.021	0.109	0.184	0.107
	(0.015)	(0.074)	(0.113)	(0.138)
Second Nearest Agent *(Base = No Training)*				
Mobile Money Specialist				0.243
				(0.160)
Sales Representative				0.165
				(0.133)
Classroom				-0.010
				(0.162)
Outlet				0.020
				(0.136)
Additional distance until trained agent	0.002	0.013	0.006	
	(0.002)	(0.010)	(0.017)	
Socioeconomic Control Variables	YES	YES	NO	YES
Constant	-0.650***	-5.538***	0.425***	-10.066***
	(0.061)	(0.416)	(0.117)	(0.801)

Note: N = 8,001. ***p < 0.01, **p < 0.05, *p < 0.1; Re-estimation of Model 1 using (1) an OLS model, (2) a probit model, (3) excluding all socio-demographic variables to check for adjustment effects, & (4) including the characteristics of the second nearest agent in the logit model. Robust standard errors are shown in parentheses (hc1); Authors´ own calculations based on 2015 FinAccess Household Survey and 2015 FinAccess geospatial mapping

Table A4. Robustness checks of the effects of the agent network characteristics on mobile money adoption (OLS, Probit, &Adjustment Effects)

Variables	(1) OLS	(2) Probit	(3) No Sociodemographics
Account opening services			
Agent Network *(Share of Agents offering account opening services)*	0.041***	0.175**	0.210*
	(0.015)	(0.080)	(0.121)
Business Age			
Agent Network *(Average business age in network in years)*	-0.002	-0.012	0.107**
	(0.006)	(0.035)	(0.046)
Distance to Nearest Agent/ Nearest Network (log-kilometers)	-0.011***	-0.059***	-0.353***
	(0.003)	(0.017)	(0.021)
Liquidity Management			
Agent Network *(Average number of days that agents within a network run out of cash)*	0.000	0.000	-0.001
	(0.000)	(0.001)	(0.001)
Training			
Agent Network *(Share of agents within network who received any form of training)*	0.122***	0.538***	1.194***
	(0.027)	(0.127)	(0.189)
Socioeconomic Control Variables	YES	YES	NO
Constant	-0.737***	-5.876***	-0.613***
	(0.066)	(0.431)	(0.232)

Note: N = 8,001. ***p < 0.01, **p < 0.05, *p < 0.1; Re-estimation of Model 3 using (1) an OLS model, (2) a probit model, & (3) excluding all socio-demographic variables to check for adjustment effects. Robust standard errors are shown in parentheses (hc1); Authors´ own calculations based on 2015 FinAccess Household Survey and 2015 FinAccess geospatial mapping

Table A5. Robustness checks of agent network effects on mobile money adoption by varying network density and network size

Variables	(1) Dense Network	(2) Spread Network	(3) Network = 5 Agents	(4) Network = 20 Agents
Account opening services				
Agent Network *(Share of Agents offering account opening services)*	0.420**	0.156	0.073***	0.019**
	(0.173)	(0.260)	(0.027)	(0.008)
Business Age				
Agent Network *(Average business age in network in years)*	-0.014	-0.001	-0.004	-0.001
	(0.081)	(0.096)	(0.010)	(0.004)
Distance to Nearest Agent/ Nearest Network (log-kilometers)	-0.102**	-0.150***	-0.111***	-0.109***
	(0.042)	(0.054)	(0.032)	(0.032)
Liquidity Management				
Agent Network *(Average number of days that agents within a network run out of cash)*	0.001	0.001	0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.001)
Training				
Agent Network *(Share of agents within network who received any form of training)*	1.192***	0.363	0.118***	0.057***
	(0.263)	(0.396)	(0.040)	(0.012)
Socioeconomic Control Variables	YES	YES	YES	YES
Constant	-11.015***	-10.167***	-10.387***	-10.814***
	(1.180)	(1.192)	(0.821)	(0.827)
Observations	4,956	3,045	8,001	8,001

Note: ***p < 0.01, **p < 0.05, *p < 0.1; Dense network in column 1 refers to a difference in distance between the farthest agent in the network and the closest agent in the network (from a household´s perspective) of <= 1 kilometer; Spread network in column 2 refers to a difference in distance between the farthest agent in the network and the closest agent in the network from a household´s perspective of > 1 kilometer. Agent characteristics in column 3 and 4 refer to the average over the 5 and 20 nearest agents respectively. Robust standard errors are shown in parentheses (hc1); Authors´ own calculations based on 2015 FinAccess Household Survey and 2015 FinAccess geospatial mapping

Endnotes

[i] The square root is chosen to reduce the influence of large values and bunching at zero, as agent density has a long right tail as well as a relatively large number of zeros

[ii] To approximate the average liquidity management within an immediate network we first approximate for each agent in the network the number of days per year the agent runs out of cash. Since the categories in the variable liquidity management are mutually exclusive, we approximate zero days when the agent never runs out of cash; 12 days when the agent runs out of cash monthly; 52 days when the agent runs out of cash weekly; and 365 when the agent runs out of cash daily. We then calculate the sum of the number of days agents run out of cash for all agents within an immediate network and divide by the number of agents (N=10).