The ENRICH Bot, a smartphone application measuring fruit and vegetable intake and food choice motives

Development and validation for the case of urban Kenyan consumers

Wageningen University & Research · Enrich · Strathmore University · iLab Africa · World Agroforestry · AVRDC The World Vegetable Center · International New Town Institute

Ireen Raaijmakers[1], Jos van den Puttelaar[1], Vincent Linderhof[1], Valerie Janssen[1], Francis Odhiambo[3], Alida Melse-Boonstra[2], Karin Borgonjen[2], Imelda Mueni[3], Stepha McMullin[4], Ralph Roothaert[5], Zahra Kassam[6], Michelle Wanjiru[6], Jeanne H M de Vries[2], Ruerd Ruben[1], 2019. *The ENRICH Bot, a smartphone application measuring fruit and vegetable intake and food choice motives; Development and validation for the case of urban Kenyan consumers.* Wageningen, Wageningen Economic Research, Report 2019-076C. 56 pp.; 15 fig.; 22 tab.; 54 ref.

[1] Wageningen Economic Research, Wageningen University and Research, the Netherlands
[2] Division of Human Nutrition, Wageningen University and Research, the Netherlands
[3] Strathmore University, Kenya
[4] World Agroforestry Centre (ICRAF), Kenya
[5] World Vegetable Centre, Kenya
[6] International New Town Institute, Rotterdam

We thank Charles Ooko Onyango, Lee Birir and Dr. ir. Harriette Snoek for their valuable contributions to the ENRICH project. We thank the field work team for their efforts regarding the data collection.

P.O. Box 29703, 2502 LS The Hague, The Netherlands, T +31 (0)70 335 83 30, E communications.ssg@wur.nl, http://www.wur.eu/economic-research. Wageningen Economic Research is part of Wageningen University & Research.

Confidential Wageningen Economic Research Report 2019-076C | Project code 2282300161

Photos: Wageningen University & Research

Contents

1

Introduction

Introduction

Understanding the complexity of food consumption and choice motivation is vitally important for guiding business and policy efforts towards healthier nutritional intake. We need that insight in order to develop, offer, and design food and nutrition interventions that better fit the diverse range of consumers and eventually lead to a higher intake of healthy foods (e.g. fruit and vegetables). The rise in ownership of smartphones and technical developments provide the opportunity to apply new and innovative metrics. The overall aim of this study was to develop and validate a tool/metrics, the ENRICH Bot, that can provide reliable information on fruit and vegetable intake and food choice motives (FCM) in real time and in situ from urban consumers in low- and middle-income countries (LMICs) with an application to urban consumers living in Nairobi (Kenya).

This section will start by describing the background of the ENRICH study. In the following sections the approach and the outline of the report are described.

1.1 Background of the ENRICH study

1.1.1 Low fruit and vegetable consumption and health benefits

Worldwide, approximately two billion people have micronutrient deficiencies (Sharma et al., 2016; von Grebmer et al., 2014). The intake of fruit and vegetables (F&V) is low despite being rich sources of micronutrients (Afsin et al., 2019; Keding et al., 2017). Low consumption of F&V is considered a risk factor that contributes to the global burden of diseases such as cardiovascular diseases and cancers (Lock et al., 2005). Globally, 2.8 per cent of mortality is due to low intake of F&V with 5.2 million attributable deaths in 2013 (Krishnaswamy and Gayathri, 2018). It is recommended that adults eat at least five servings of 80 g, or a total of 400 g of F&V per day (Hall et al., 2009; Rodriguez-Casado, 2016). However, 78 per cent of men and women from LMICs do not meet this recommendation (Hall et al., 2009; Pengpid and Peltzer, 2018).

To contribute to healthier eating patterns in urban areas in LMICs, it is important to have insights into food consumption behaviour, in this case F&V, and the underlying determinants of food choices. Having an understanding of the complexity of food consumption and food choice motives will help in guiding business and policy efforts towards healthier nutritional intake.

Prospective effects of fruit and vegetable consumption
The protective effects of F&V consumption against chronic diseases are largely attributed to phytochemicals (antioxidants) (Liu, 2013; Rodriguez-Casado, 2016; Stadlmayr et al., 2013). For example, they are good sources of carotenoids, present as red, yellow and orange fat-soluble pigments (Liu, 2013; Pezdirc et al., 2016). Carotenoids are not synthesised in the body and are almost exclusively derived from F&V (Alaluf et al., 2002). The most common dietary carotenoids are β-carotene, β-cryptoxanthin, α-carotene, lycopene, lutein and zeaxanthin. The first three of these can be converted to vitamin A in the human body, which is essential for proper growth, clear vision and development of healthy cells and tissues (Bailey et al., 2015; Biesalski and Nohr, 2003). β-carotene from the diet contributes the most to the provision of vitamin A and is abundant in brightly coloured F&V such as mango, green leafy vegetables and pumpkin (Pezdirc et al., 2016).

Ingested β-carotene that is not converted to vitamin A in the small intestine is transported to various target tissues and stored in the skin (Alaluf et al., 2002), which contributes to yellowness of skin colour (Whitehead et al., 2012). Studies have shown that carotenoid concentrations in the skin reflect those in blood serum (Willet, 2013). Moreover, it has been shown that skin yellowness, which can be measured by spectrophotometry, is associated with serum carotenoid concentrations as well as with intake of F&V (Jahns et al., 2014; Nguyen et al., 2015). Therefore, skin colour spectrophotometry forms a fast and non-invasive biomarker of F&V intake. A study by Coetzee and Perrett (2014) provided evidence that skin yellowness in black Africans is a response to β-carotene supplementation as well. However, to date, skin colour has not been used as a biomarker for F&V intake in an African setting.

1.1.2 Urbanisation and need for a new measurement tool

Globally, more people live in urban than in rural areas and by 2050, 66% of the world's population is projected to be urban. It is expected that more than half of this growth will occur in Africa (UN, 2014; UN, 2015). A country like Kenya is rapidly urbanising, with 50% of the population expected to live in urban areas by 2020 (UN-Habitat, 2011).

Urbanisation, in combination with economic and social development, leads to a change in dietary patterns and nutrient intake. This process is called 'nutrition transition' (Popkin and Adair, 2012).
When income rises the consumption of foods associated with a high-quality diet increases (including fruit, vegetables and milk) (Global Panel, 2016). However, the consumption of products associated with a low-quality diet (e.g. fast food, sugar-sweetened beverages, which are typically more available in urban settings) increases even more strongly. The budget share of vegetables in total food expenditure however declines (Global Panel, 2016). Therefore, economic development does not guarantee a more healthy/high-quality diet (Global Panel, 2016).
Due to the increasing food-related health concerns and the ability to develop, offer and design food and nutrition interventions, it is important to have insights in the actual consumption patterns of consumers and for urban consumers in particular. Moreover, the new application provides opportunities to survey respondents more frequently or even in real time. However, there is a lack of data and insights on what people actually consume (Global Panel, 2016). And if it is available, food intake data is gathered on a national level and does not focus on urban areas or make a distinction between urban and rural areas. In addition, there is an absence of information on the following aspects:

i. Real-time intake data (e.g. seasonal demands of certain fruit and vegetables, snack moments);
ii. Insights into the 'why' of food consumption, the underlying food choice determinants;
iii. Integrated insights of the choice motivations, location, time and intake of foods.

These insights will improve the understanding of why people make particular choices with respect to food and choices, and provide a better picture of food consumption patterns. Information on food consumption and food choice behaviour of consumers in LMICs available in real time and in situ will increase the potential to target effective agriculture-for-nutrition-actions in (peri-) urban areas.

1.1.3 Technical opportunities

Current technological developments and the spread of mobile technologies give the opportunity to collect real-time and situational information on consumption.

Mobile phone ownership

Mobile phone and smartphone ownership is rapidly increasing in LMICs (Datareportal, 2019; GSMA, 2014, 2018; Silver and Johnson, 2018). From 2013–2017 smartphone ownership increased significantly in sub-Saharan Africa (SSA). Silver and Johnson's (2018) report showed that about one-third of adults in SSA own a smartphone and almost half of the adults own a basic mobile phone (Silver and Johnson, 2018). So, the application of a smartphone application/tool is promising, due to the rapid spread of IC technologies and high and increasing rates of smartphone users in LMICs.

Traditional measurement tools

Traditionally, research into food consumption behaviour tends to focus on either (i) dietary intake or (ii) on socio-psychological determinants of food choices, rather than a combination of both research domains. Combined insights in connecting both domains is often lacking, and is one of the rationales behind this study.
Next, the traditional data collection methods in both research domains face a range of drawbacks, which overlap to a large extent (see Figure 1.1).
Traditional dietary assessment tools, such as 24-hour recalls, food frequency questionnaires (FFQ) and food diaries suffer from recall bias, measurement error and have a high burden for the participants (Thompson and Subar, 2008). Moreover, the data collection process and data analysing is laborious and time-consuming, leading to time lags in data information. Next, the source of information is often limited and can be much richer (i.e. including contextual factors such as consumption moment and time) (van den Puttelaar et al., 2016).
Socio-psychological determinants of food choice are traditionally collected with questionnaires or in experimental designs. These methods have a number of

drawbacks, such as they put a significant burden on the participant, there is a risk of them having a social desirability bias, they lack behavioural measures in real time and they provide limited sources of information regarding specific situations, products or contexts (van den Puttelaar et al., 2016).

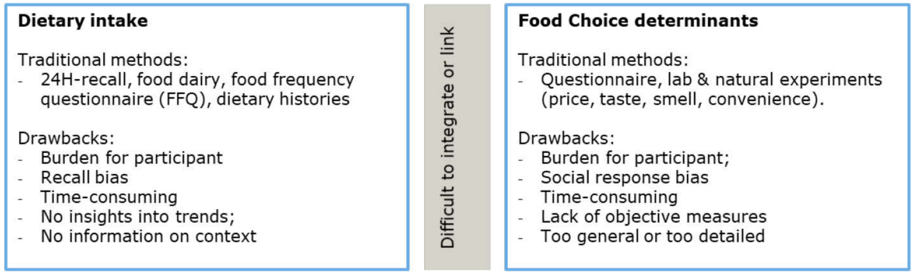


Figure 1.1 Drawbacks of traditional measurement tools

New technologies, such as smartphones and ecological momentary assessment, have created opportunities to collect dietary intake data and socio-psychological determinants in innovative ways. These have the potential to (i) integrate the research domains on dietary intake and socio-psychological determinants aiming to fill a knowledge gap and (ii) to overcome the shortcomings of traditional measurement tools.

1.2 Research aim and research questions

The overall aims of this study were to

1. develop and validate a tool and metrics, the ENRICH Bot, that can provide reliable information on F&V intake and food choice motives in real time and in situ from urban consumers in LMICs with an application to urban consumers living in Nairobi (Kenya);
2. assess the possibility to extrapolate the results of the ENRICH study.

With the ENRICH Bot, we aim to contribute to the overall long-term goal to increase F&V intake in the urban areas of LMICs.

The following research questions were formulated:

- What is the current F&V intake and choice determinants of urban Kenyan consumers?
- Is it possible/feasible to assess both F&V intake and food choice motives accurately and simultaneously by a mobile smartphone application? And what is its validity?
- Would it be feasible to link F&V intake to improved health based on a skin tone test?
- Is it possible to use the Kenya Integrated Household Survey (KIHBS) to extrapolate the results of the ENRICH survey?

1.3 Approach

The main activity was the development of the app, the ENRICH Bot, which is able to collect F&V intake and FCM information. To test the validity of the ENRICH Bot on F&V intake and FCM, a multi-area randomised crossover trial was applied (see Figure 2.1 for the study design). Participants from four different areas in Nairobi participated in the study for ten weeks. The total study consisted of two four-week study periods and a two-week washout period. In one of the study periods participants used the ENRICH Bot to fill in their F&V intake and FCM, and in the other period data on F&V intake and FCM were collected by a 24-hour recall and a self-administered questionnaire. In addition, an objective biomarker (skin tone test) was used to evaluate the reported intake of F&V. Data were collected between June 2018 and December 2018.

1.4 Outline of the report

The structure of the report is as follows. Section 2 explains the study approach and provides a description of the ENRICH Bot and its included measures. Section 3 presents the results of the assessed FCM and F&V intake collected via the ENRICH Bot and the traditional measurement tools. Next, the determinants of F&V intake are presented. A comparison of the study results with the Kenyan Integrated Household Survey is also presented in Section 3. Finally, Section 4 discusses the results, and provides conclusions and recommendations for future research.
As we encountered different challenges in the development of the ENRICH Bot, the data collection and data analysing, Section 4 will mainly focus on these topics.

2 Approach

Approach

This section describes the study design, followed by a description of the developed ENRICH Bot. Next, the applied methods are described, including study location and participants, measurements used and statistics applied. Moreover, the challenges encountered in the implementation of the fieldwork and data analysis are presented.

2.1 Study design

To test the F&V intake and FCM collected with the ENRICH Bot and to compare it with results from traditional survey methods, the study is designed according to a multi-area randomised crossover trial.

As shown in Figure 2.1, participants from each settlement were randomly divided into two groups: A and B. (see Section 2.3 for more information about the study sample and study locations.) Group A started with registering their F&V intake and their FCM in the ENRICH Bot during a four-week period, and underwent two skin colour measurements. After the two-week washout period, a four-week period followed in which group A participants were visited by a trained fieldworker who conducted four 24-hour recalls and two skin measurements (traditional field research). Next, the participants had to fill in the paper-based FCM questionnaire by themselves. Group B followed the same procedures in reverse order.
All participants received an incentive: airtime (800 Ksh weekly) to cover the Internet cost during the study period and for personal use, and a t-shirt with the ENRICH logo after finishing the study.
To validate the developed ENRICH Bot, the results of F&V intake and FCM administered via the ENRICH Bot and the traditional fieldwork are compared.

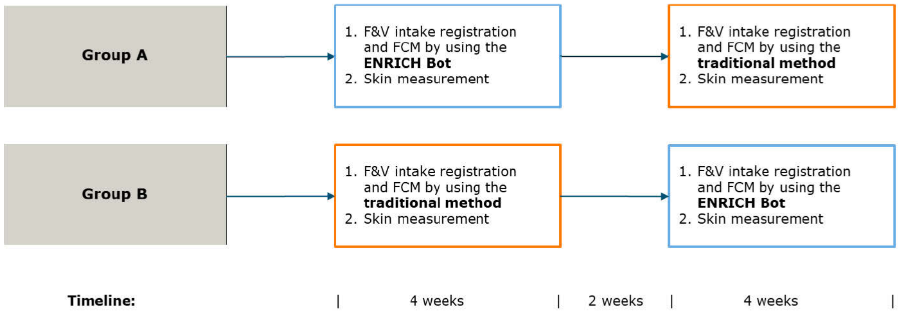


Figure 2.1 Overview of the study design

Due to difficulties encountered during fieldwork (see Section 3.1) it was decided to adjust the timeline, to make sure that the data collection was finished at the beginning of December 2018 (before Christmas). Each period was shortened by one week: so periods 1 and 2 were three weeks instead of four weeks, and the wash-out period was one week instead of two weeks.

2.2 The ENRICH Bot

To measure F&V intake and FCM in an integrated manner, a new metric was developed, the ENRICH Bot. The ENRICH Bot aims to overcome the drawbacks of data collection in traditional measurement tools, such as memory bias and the burden on the participant. Below, a description of the development process is provided. The manual for the ENRICH Bot provides a detailed description of the back end of the ENRICH Bot (please see the deliverable *User Manual* for a detailed description).

2.2.1 Ecological momentary assessment

The ENRICH Bot uses ecological momentary assessment (EMA) to measure F&V intake and FCM. EMA is a method involving repeated measures of participants' current experience, behaviour or mood in real time and in their natural environments (Shiffman, Stone and Hufford, 2008). Implementing EMA in the sampling of F&V intake and FCM provides advantages and might overcome the limitations of the traditional metrics. First, this method is likely to reduce the recall bias and aggregation of information by shortening the recall interval. Second, the participant burden is likely to be reduced as the participant does not have to go through a whole 24-hour recall of what, where and why F&V were consumed. As a result, it is expected that the ecological validity improves as participants will provide information in their natural and real-life environments (Schembre et al., 2018; Schiffman, Stone and Hufford, 2008). As technology has advanced, the usage of EMA using smartphone applications has increased rapidly and provides the opportunity to assess dietary intake over time and across contexts (Schembre et al., 2018; Yang et al. 2018). Therefore, this way of data collection supports the opportunity to include situational and psychological factors to receive more reliable, accurate and enriched information on food consumption behaviour as the measurement tool is more incorporated into a daily life method.

2.2.2 Telegram Bot

As the adoption of smartphones increases rapidly in LMICs (Datareportal, 2019; GSMA, 2018; Silver and Johnson, 2018), the application of a smartphone tool for monitoring/measuring food consumption behaviour is promising. Currently, social and entertainment activities, such as sending text messages and access to social media, are the most popular mobile phone activities (Silver and Johnson, 2018). To stay as close as possible to the real-life environment of the study participants, it was decided to develop a chatbot, a computer program that mimics human conversation by using natural languages (Shawar and Atwell, 2007). The ENRICH Bot is built as a Telegram bot, and can be used on every device that installs Telegram. Telegram looks/feels similar to WhatsApp, which is one of the most popular messing apps in Kenya (Datareportal, 2019). Next, we took into consideration that the ENRICH Bot uses a minimal amount of data and mobile memory storage; we understand that smartphone applications are removed quickly when users need memory space for other apps.

2.2.3 Development process

The ENRICH Bot consists of a front and back end. The front end is the part of the ENRICH Bot that participants see when answering the questions. This part collects the data from participants. The back end is the administration panel for the ENRICH tool for managing the data. Please see deliverable *User Manual* for a detailed description.

The development process of the ENRICH Bot consisted of different parts and steps:

- sampling scheme
- identification numbers
- modification of questionnaires
- flow of questionnaires

Sampling scheme

The ENRICH Bot measures both F&V intake and FCM; both are integrated in one sampling scheme.

Fruit and vegetable intake

A recall period of four hours is applied. Figure 2.2 shows that each day is divided into four-hour blocks. In order to get insight into the F&V consumption behaviour of a person, you do not have to cover a whole day at once, but different snapshots can be collected. A snapshot is a part of the total behaviour that can be assessed, in this case a four-hour time period. Together these snapshots add up to one aggregated full day.

Participants received a prompt – a message – on stratified random moments with the question 'Did you eat F&V in the past four hours?' (see Figure 2.3). Each participant received five prompts per week over the course of four weeks. The collected recordings were combined and represented a four-day recall (see Figure 2.2).

Figure 2.2 Snapshots ENRICH Bot

The figure shows the four-hour blocks, snapshots (green coloured four-hour blocks) and sampling density. All snapshots combined represent an aggregated full day. Subjects received a prompt that preceded the measured snapshot.

Note Subjects did not receive any prompts between 00.00 and 04.00 hours.

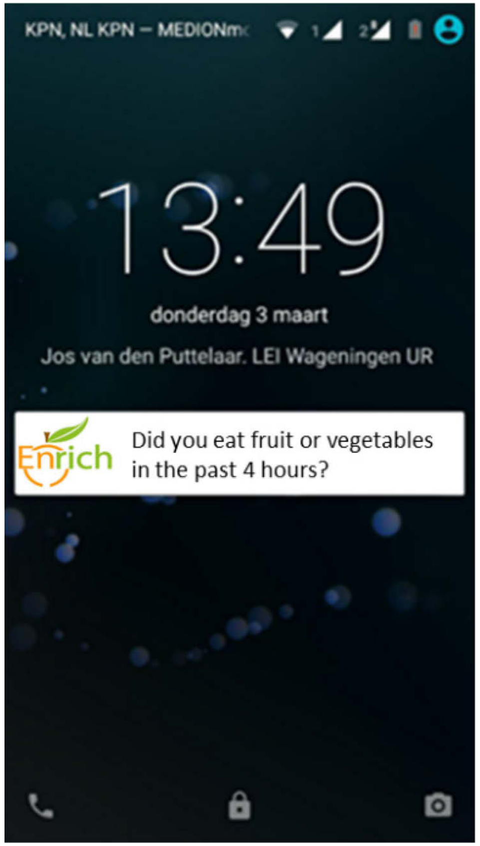


Figure 2.3 Prompt ENRICH Bot

The figure shows the prompt that participants received on their smartphone.

Food choice motives

The measurement of the FCM was combined with the snapshots of the F&V intake. As the FCM consists of multiple motives/constructs (see Section 2), each snapshot included the measurement of one single motive, instead of the whole questionnaire that consists of multiple motives/constructs (see Figure 2.4).

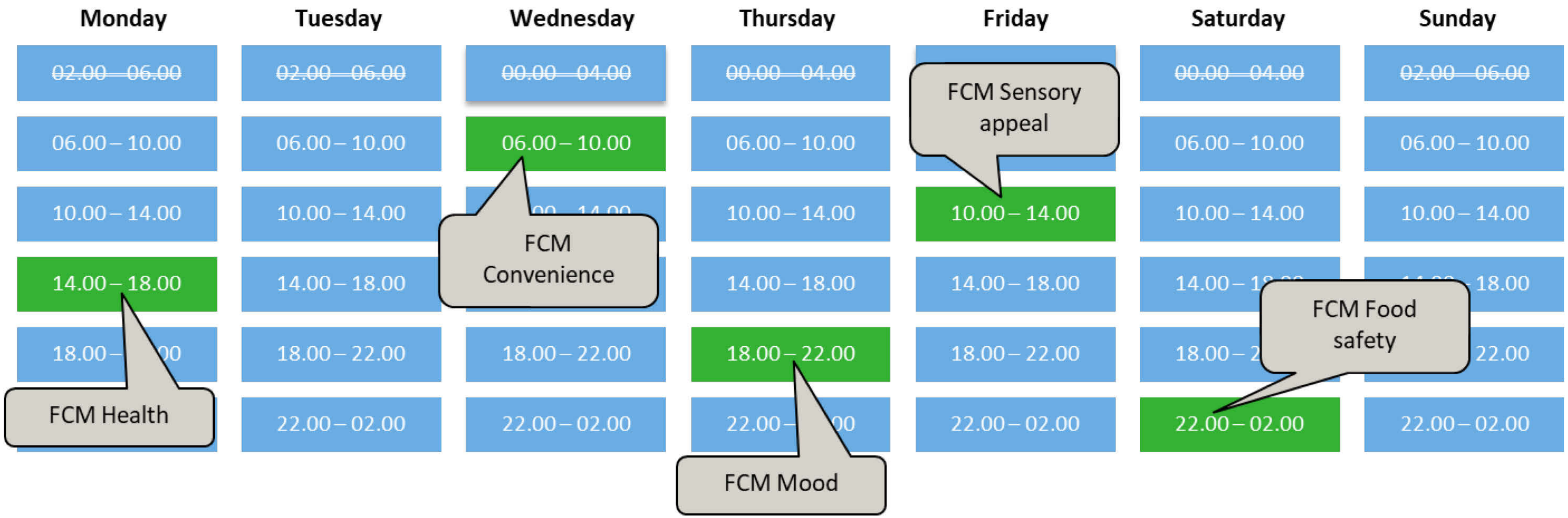


Figure 2.4 Snapshots F&V intake and FCM combined

Identification number
Each participant in the study sample had two unique IDs. One ID was used in the traditional fieldwork and the second was an ID that Telegram created. To make sure we were able to link the participant's answers with the ones measured on the traditional field research, the participant's phone number was used. Linking/matching of the participants in the ENRICH Bot and in the traditional field research is vital for the validation study.

Modification of questionnaires
The 24-hour recall and the questionnaire to measure FCM had to be modified before they could be implemented in the ENRICH Bot. Both questionnaires focused on a longer time period than the four-hour time blocks, could not be administered by the participant themselves and were time-consuming. The modification of both questionnaires was very challenging as the questions had to be restructured, reformulated and made to fit within the technical boundaries of the ENRICH Bot.

The challenges we encountered in the development phase of the ENRICH Bot can be summarised as follows:

- Length of the questionnaire
  - The questionnaire was too long to convert into an app-based questionnaire as a whole. Therefore the length of the questionnaire was shortened by only including the most necessary questions (only repeat variable questions) and the items related to one psychological construct instead of the whole questionnaire, which measures all the different constructs. Longer questions would not be able to provide a good user experience and will increase the level of burden when answering questions during the various prompts.
- Complexity of the questionnaire
  - The format of the F&V intake questionnaire: This was very challenging. In the paper-based questionnaire, multiple level questions were included; the ENRICH Bot only allowed two levels of questions. In the development phase we were not able to overcome this challenge, therefore it was

decided to use Qualtrics for measuring F&V intake. The Qualtrics link was implemented in the ENRICH Bot.

- Estimation of the portion sizes of F&V: Normally, during 24-hour recalls portion sizes are estimated by estimation aids (i.e. by using household measures) and the questions are asked by the trained interviewer. However, in the ENRICH Bot participants had to estimate their consumed F&V portions on their own. As we wanted to use a minimum amount of Internet data, the usage of pictures and/or photos was not possible. Therefore, standard household measures were included (e.g. number of serving spoons or pieces). It is important to make it easier for the participants to estimate their portion size.
- Formulation of the questions: As the screen of a smartphone is quite small, the length of some questions had to be shortened. This to make sure that each question fits the screen and provides a good user experience.

Flow of questionnaires

To be enrolled in the study, participants received an instruction from the fieldwork team (See Appendix 1 for the instruction). First, participants had to download Telegram and register themselves with the ENRICH Bot. Questions in the registration procedure were included to make sure we were able to link each registration to the ID numbers used in the field research. Questions included were related to socio-demographics, place of living (settlement) and phone number. Participants were linked based upon their phone number (see Figure 2.5a for the flow of the registration procedure).

After registration, participants received prompts at random times. The prompt included the following question: 'Did you eat fruit and/or vegetables in the past four hours?' If the answer was yes, the participants received questions on FCM and F&V intake (see the flow chart of the ENRICH Bot in Figure 2.5b).

Figure 2.6 (a,b) presents screen shots of the ENRICH Bot.

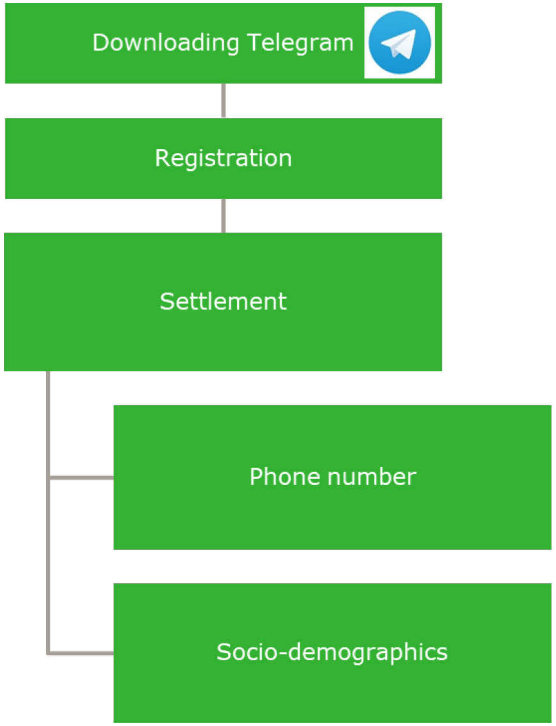


Figure 2.5a Flow of registration procedure

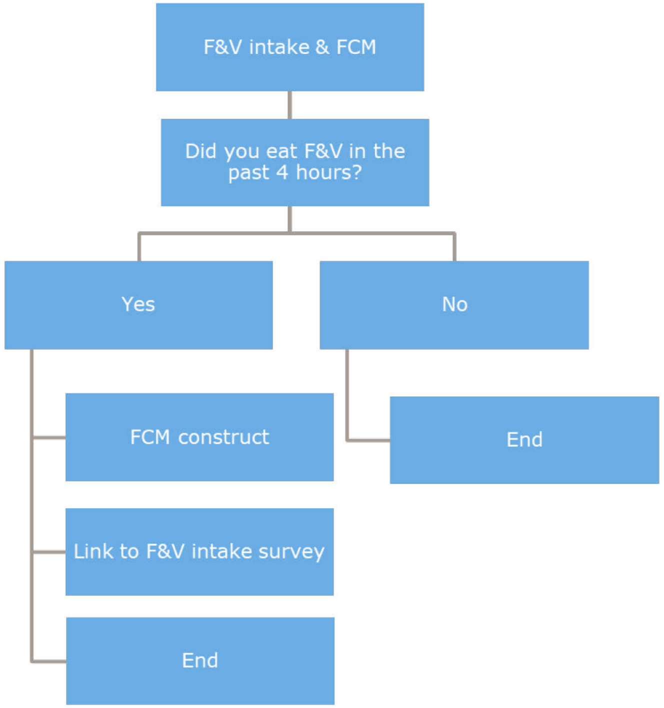


Figure 2.5b Flow of F&V intake and FCM questions

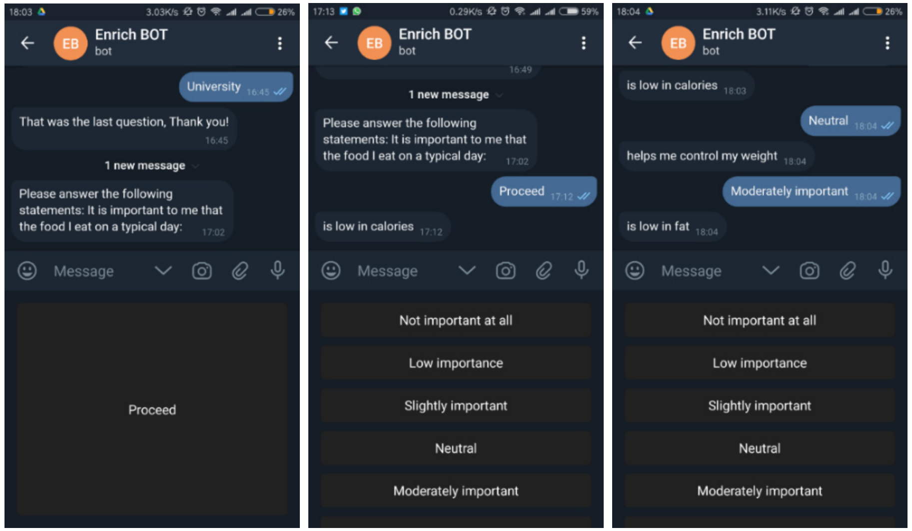


Figure 2.6a Screenshots of the ENRICH Bot – FCM

Includes questions to measure the motive 'Health'.

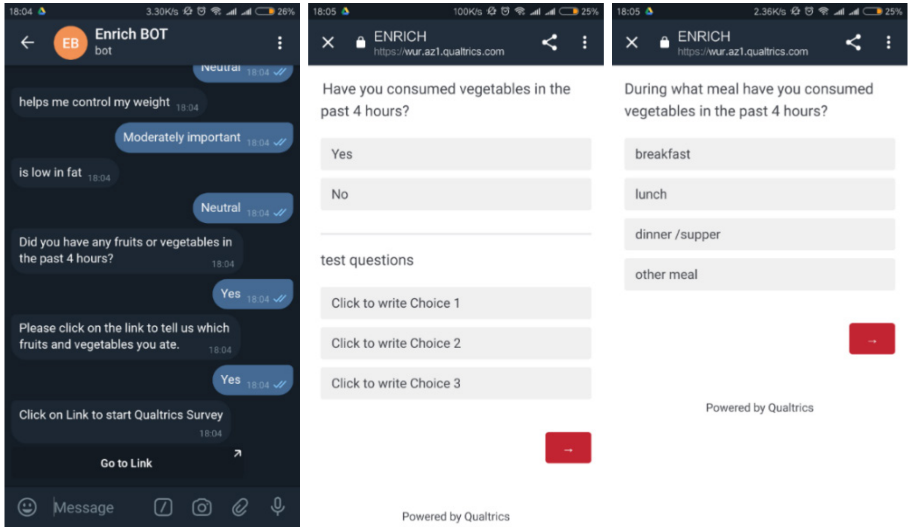


Figure 2.6b Screenshots of the ENRICH Bot – F&V intake

2.3 Study location and participants

2.3.1 Study location

Participants for the validation study were recruited from the settlements of Kibera, Dandora, Buruburu and Kilimani in Nairobi, Kenya. These four settlements were selected as they encompass the settlement requirements and cover the different socio-economic classes. See Table 2.1 and Figure 2.7 for the location of these settlements in Nairobi, Kenya.

Table 2.1 Overview of included settlements

Name of the settlement	Type of settlement
Kibera	Informal settlement
Dandora	Low-income neighbourhood
Buruburu	Low- to middle-income neighbourhood
Kilimani	High-income neighbourhood

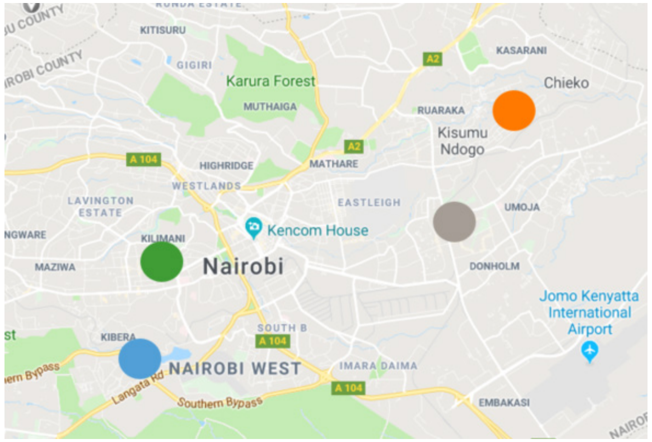


Figure 2.7 Location of the four included settlements in Nairobi, Kenya

Each coloured dot represent a settlement. The colours correspond to the colours in Table 2.1.

2.3.2 Recruitment procedure

Inclusion and exclusion criteria
Inclusion criteria for participation were: 1) adult men and women; 2) aged 18–55 years; 3) own a smartphone with Internet access. Exclusion criteria were: 1) use of vitamin supplements; 2) being apparently unhealthy, i.e. having symptomatic illnesses either physically or mentally; and 3) suffering from a skin disease (e.g. vitiligo). The use of vitamin supplements and a skin disease might influence the results of the skin measurement (reference method).

Recruitment procedure
Participants were recruited by the collaborating community-based organisation (CBO) active in the selected settlements:
- In Dandora, participants were recruited by Dandora Transformation League.
- In Kilimani, participants were recruited by Project Foundation.
- In Buruburu, participants were recruited by volunteers of the CAP- Youth Empowerment Institute, a CBO activate in Buruburu, through door-to-door house calls.

Before deciding to participate, volunteers and local field staff explained the study to participants both verbally and in writing. If participants considered participating, we checked whether they met the inclusion criteria. If so, these participants were informed that taking part in the study was voluntary and that they were allowed to leave the study at any time. Since they were required to use their smart phones, the study provided airtime as an incentive (800 Ksh weekly) to cover the Internet cost during the study period, and a t-shirt after finishing the study.

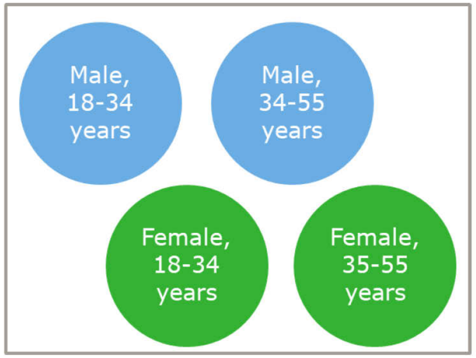
The study was approved by the Kenyatta National Hospital/University of Nairobi Ethics and Research Committee (KNH-UON-ERC P586/10/2017), and a research permit was granted by the National Commission for Science, Technology and Innovation (NACOSTI/P/18/53834/22269). Signed informed consent was obtained from every participant before they were enrolled in the study.

In the recruitment phase we encountered different challenges, which can be summarised as follows:
- Collaborations and work relationships with local partners
  - As described, we aimed to conduct the validation study in four different settlements in Nairobi, covering the different socio-economic classes. In Dandora a good working relationship already existed, whereas in Kibera, Kilimani and Buruburu we had to start from scratch. Searching for new collaborations and to start building new work relationships from the ground took a lot of time and effort.
  - The contact person from the CBO/collaborating party should be a strong person and a person with influence that supports the project.
- Community engagement and involvement of the local CBO/collaborating party
  - Not all of the local organisations that we collaborated with, were well embedded in the settlements or had direct contact with the participants. The collaborating parties that were well embedded and/or had direct contact with the participants were able to recruit participants more easy, as they participated in the study out of trust.
    In Kilimani and Buruburu the local organisations were less embedded and/or were not in direct contact with the participants so the fieldwork team needed to be more involved in the recruitment phase.
- Changes in the study environment
  - Unfortunately, we decided that we would not start the data collection in Kibera, due to the fact that the research climate in Kibera was unsettled. A new highway was built that cuts across Kibera and many people living there were displaced. As a result, the data for the study was only collected in three settlements (Dandora, Buruburu and Kilimani).
- Length of recruitment period
  - In Buruburu the recruitment period was too short. One of the reasons might be that the collaborating local party had no close relationships with the partners.
- Recruitment and incentives
  - In the study we included different socio-economic classes as we were interested in how data collection via a new metric works. The recruitment procedures and incentives were similar for all the participants and across all the settlements. As the settlements differ, it might have helped to involve the collaborating CBO earlier in the recruitment process. This might have helped to decide on the best recruitment method, and the incentive that is most applicable to the participants living in that specific settlement. For example, in Kilimani we had difficulties including 125 participants (see part below on stratification).

Stratification
It was originally planned to use stratified random sampling for the participants. Participants would be stratified based on:

- The settlement where they were living; per settlement 125 participants would be included (n=500 participants in total)
- Gender (male/female) (50:50)
- Age: 18–34 years and 35–55 years (50:50)

So, it was planned to have four groups of n=31/32 participants per group per settlement (see Figure 2.8).



Per location/settlement 4 groups (N=31/32 per group)

Figure 2.8 Overview of stratification

Power calculation study sample size
Assuming a correlation of carotenoid intake with skin measurement of 0.35, equal to correlations observed with plasma markers (Willett, 2013), and a ratio of within- and between-person variation in carotenoid intake of four (see Willett, 2013) the error term in underestimating correlations would amount to 0.45. Thus an observed correlation of 0.35*0.45 = 0.16 could be expected. Using a power of 80% and a two-tailed test with alpha of 5%, we would need at least 300 participants to observe this (software G*Power 3.0.10). This will be a minimum sample size, as the values 0.35 and 4 are derived from a US population; with 500 participants we will be able to detect a slightly lower correlation between intake and skin measurements (0.26) or alternatively can take higher within-person variability into account (ratio within to between=8) or combination thereof.

2.4 Validation study

To validate the developed ENRICH Bot, the results of F&V intake and FCM assessed via both the ENRICH Bot and the traditional fieldwork needs to be compared; so the two periods of data collection are compared.
The measurement tools, the ENRICH Bot and the questionnaires used in the traditional field research, included items on FCM, F&V intake, socio-demographic and biological factors. A detailed explanation is provided below.

2.4.1 Food choice motives

The FCM were measured with an extended version of the original food choice questionnaire (FCQ) developed by Steptoe et al. (1995). The FCQ is an instrument used to measure the underling motives for food choices and provides insights in the consumers' most prominent reasons for choosing a food/product. In its original form, the FCQ consists of 36 items, representing both health and non-health related food characteristics, classified into nine different motives including health, sensory appeal, natural content, weight control, familiarity, price and ethical concerns (Steptoe et al., 1995). Previous research has shown that the original FCQ did not fit the local context of LMICs (Cunha et al., 2018; Raaijmakers et al., 2018a, 2018b)

Therefore, the original FCQ was extended in three ways:

1. In total seven items were added to the dimensions: the first four were *convenience* ('is easy to clean' and 'is easy to combine with other foods'), *sensory appeal* ('is liked by myself and/or by my family' and 'is easy to swallow'), *price* ('is good quantity for money') *and traditional* ('is commonly eaten by my tribe' and 'fits my traditions' e.g. family traditions, special occasions).
2. Two extra dimensions were added: *functional health* ('gives me energy', 'is good for my blood', 'makes me feel full', 'had medicinal benefits', and 'is good for digestion') and *food safety* ('comes from a clean place', 'is handled in a hygienic way' and 'is free from contaminations (e.g. pesticides, fertilisers or chemicals'). Literature search and previous research indicated that these are also underlying motives for selecting foods (Sosa et al., 2015; Raaijmakers et al., 2018a, 2018b; Rahman et al., 2013; Wang et al., 2015).

3. The dimension *convenience* is split into two factors *convenience of preparation* and *convenience of purchasing foods* as access to and availability of fresh food seemed to be an important barrier in LMICs such as Nigeria (Raaijmakers et al., 2018a; 2018b).

In total, the adapted FCQ consisted of 51 items representing twelve dimensions (see Table 2.2).
Each item was introduced by the affirmative sentence 'It is important to me that the food I eat on a typical day ...' followed by each motive, and evaluated by the respondent on a 7-point Likert scale, going from 1= not important at all to 7= extremely important.

Table 2.2 Overview of the nine identified FCM in the original FCQ (Steptoe et al., 1995)

Motive	Meaning	Included items
		It is important to me that the food I eat on a typical day ...
Health	This factor contains items related to the nutritional aspects that are beneficial to the body in general and the prevention of chronic diseases, and the items are related to general well-being.	Contains a lot of vitamins and minerals, keeps me healthy, is nutritious, is high in protein, is good for my skin/teeth/hair/ nails etc., is high in fibre and roughage
Functional health[a]	Items in this factor are related to the functional health aspects of food.	Gives me energy[a], is good for my blood[a], makes me feel full[a], has medicinal benefits[a], is good for digestion[a]
Mood	Items in this factor are related to a person's emotions and feelings, including relaxation, stress and mood.	helps me cope with stress, helps me to cope with life, helps me relax, keeps me awake/alert, cheers me up, makes me feel good
Convenience of preparation	Convenience items are related to the ease of preparation of the food product.	Is easy to prepare, can be cooked very simply, takes no time to prepare, is easy to clean[a], is easy to combine with other foods[a]
Convenience of accessibility	Convenience items are related to the purchase (ease of accessing) of the food product.	Can be bought on markets, roadside stalls and in shops close to where I live or work, is easily available on markets, road stalls and in shops
Sensory appeal	Sensory appeals includes items related to the appearance, smell, feel, texture and taste of the food product.	Smells nice, looks nice, has a pleasant texture, tastes good, is liked by myself and/or by my family[a], is easy to swallow[a]
Natural content	This dimension reflects the consideration of the consumer with the use of additives and the selection of natural ingredients.	Contains no additives, contains natural ingredients, contains no artificial ingredients
Price	Items are related to economic factors (price).	Is not expensive, is cheap, is good value for money, is good quantity for money[a]
Weight control	This factor consists of items related to the calorie intake of food and dietary restraint.	Is low in calories, helps me control my weight, is low in fat
Familiarity	Items within the familiarity scale concern how important is it for the person to eat their accustomed diet, rather than being adventurous in food choices (trying new things). Items are related to past experiences consumers had dealing with food such as habitual patterns and childhood experiences.	Is what I usually eat, is familiar, is like the food I ate when I was a child, is commonly eaten by my tribe[a], fits my tradition (e.g. family traditions, special occasions) [a]
Ethical concern	Items within this factor are related to political correctness and environmental influences.	Comes from countries I approve of politically, has the country of origin clearly marked, is packaged in an environmentally friendly way
Food Safety[a]	Items within this factor are related to food safety issues.	Comes from a clean place[a], is handled in a hygienic way[a], is free from contamination (e.g. pesticides, fertilisers or chemicals) [a]

[a] These motives and items were added based upon literature search and previous conducted research in Nigeria.

The FCM were assessed in two different ways: via the ENRICH Bot and a self-administered questionnaire (traditional fieldwork).

- *FCM by the ENRICH Bot*
  Participants received a total of 20 prompts randomly divided over the four weeks of data collection, in which they were asked to record the importance of the different FCM. As the FCQ consisted of 51 different items, it took too long to answer all these at once. Participants received the questions per expected dimension (i.e. items of the dimension health or food safety); they were asked to fill in the FCQ dimensions twice. Participants received a prompt. These prompts were sent based upon the four-hour recall (for more information see Section 2.4.2 below on F&V intake in the ENRICH Bot). The prompts were randomly divided over the 28 days of data collection, to cover a each FCM dimension being filled in twice.
- *FCM via a self-administered paper-based questionnaire*
  A trained fieldworker visited the participants and asked the participant to fill in the FCQ by themselves. Participants had to self-administer the questionnaire so the way of filling in the questionnaire was made as similar as possible. Participants answered the questions in the ENRICH Bot by themselves.

2.4.2 Fruit and vegetable intake

The F&V intake is collected by the ENRICH Bot and through the collection of 24-hour recalls.

- *F&V intake by the ENRICH Bot*
  For dietary intake data collection with the ENRICH Bot, participants received a total of 20 prompts randomly divided over the three weeks of data collection. In the prompts, they were asked to report their fruit and vegetable intake over a four-hour period. For this, days were divided into six reporting segments: 6–10 a.m., 10 a.m.–2 p.m., 2–6 p.m., 6–10 p.m. and 10 p.m.–2 a.m. Each participant received an equal number of prompts for each time segment randomly divided over the 28 days of data collection, to cover a total of five full days of dietary intake.
  To decide which F&V should be included in the ENRICH Bot and what portion sizes should be included, a literature study was conducted. See deliverable *Literature review of vegetables consumption patterns and situational factors related to vegetable consumption, Nairobi, Kenya* and *Literature review of fruit consumption patterns and situational factors related to fruit consumption, Nairobi, Kenya* for the results of the literature study.
- *F&V intake via 24-hour recalls*
  The 24-hour recall was conducted by ten trained enumerators, who visited the participants four times in three weeks on non-consecutive days. Participants were unaware when the next visit was so that they would not change their eating habits. They were asked what their consumption was of all foods on the previous day from the time they woke up until the time they again woke up on the day of the interview. More detailed questions on type of product, mode of preparation and quantity of intake were only asked for fruit and vegetables. Amounts of all ingredients were weighed if the food of comparable size was still available in the household. Amounts were estimated using standard sizes, monetary value or volume when the actual food was not available in the household. A market survey was conducted after the data collection to collect prices and other conversion factors.

To estimate the portion size each enumerator was given a portable calibrated weighing scale (Kern and Sohn EMB, Netherlands) for measuring the ingredients at the household. For example, if an onion was used in the dish and the participant had an onion at home of the same size, then its weight was measured. If the actual fruit or vegetable was not available in the household, the size of fruit and vegetable was categorised into small, medium or large. When the size was not indicated, the medium size was used. Amounts per ingredient were collected. To estimate the proportion of the dish that was served to the participant, first the cooked volume of the dish was weighed using water. The bowl of water was measured and estimated as the amount of the dish. Next, the participant’s bowl was filled with water up to the level of the dish and weighed, as well as any leftovers. Finally, the proportion that the participant consumed from the total dish was calculated.

Furthermore, after the completion of the 24-hour recall, the list of the fruit and vegetables that needed a conversion factor and a waste factor was prepared for the market survey. The enumerator visited the marketplaces where the participant mostly purchases fruit and vegetables with the weighing scale to measure the amount of fruit and vegetables needed to convert estimated amounts of fruit and vegetables into grams. The weight of fruit and vegetables in three different markets (open markets, small shops and supermarket) was recorded and the average amount was calculated.

Next to data entry of the 24-hour recall, the conversion factor and edible factor was entered to calculate the amount in grams of fruit and vegetables that the participants consumed. Moreover, all fruit and vegetables were given a food code by using the Kenyan food composition table (KFCT) that was drawn up for the purpose of this study. Nutrient values were derived from various sources in ascending order of priority: Kenya, South African, Mali and USDA food composition tables. The USDA table of nutrient retention factors was used to apply a retention factor for cooking. Finally, the nutrient calculation program Compleat (Version 1.0, Wageningen University, the Netherlands) was used to calculate the amount (µg/day) of the nutrient content, particularly β-carotene.

2.4.3 Objective biomarker

To overcome the concern of the objectivity and accuracy of self-reported dietary intake, an objective nutritional biomarker was used. Serum concentration of β-carotene for example reflects F&V intake and can be used as an objective measurement to evaluate the reported intake of these foods. However, non-invasive methods would have preference since this will pose less burden on participants. Measurement of the yellow colour tone of the skin has recently been developed for this purpose. This is a fast and non-invasive measurement that can serve as a biomarker of F&V intake through the association between carotenoid intake, which is closely related to F&V intake, and yellow skin tone (Coetzee and Perrett, 2014; Jahns et al., 2014; Mayne et al., 2013; Nguyen et al., 2015; Perrone et al., 2016; Pezdirc et al., 2016; Whitehead et al., 2012). Therefore, skin colour spectrophotometry forms a fast and non-invasive biomarker of fruit and vegetable intake. A study by Coetzee and Perrett (2014) provided evidence that skin yellowness in black Africans is responsive to β-carotene supplementation as well.
Skin tone was measured at multiple points in time to see whether or not the skin tone would develop during the period of survey.

Skin tone measurement was used as a non-invasive objective biomarker for further validation with a portable spectrophotometer (Konica Minolta CM-2600d, Japan). Skin tone was measured at a standardised site at the right hand palm, after cleaning the measuring site with a wet tissue. Skin tone measurements were taken twice for each participant in each of the three-week periods of data collection. At each time point, a total of five measurements were taken by the device, and the average was recorded. The device was calibrated against a black and a white calibrator each time before use to assure the quality of the data and to minimise error. Skin tone was measured as CIE Lab units, representing three colour dimensions: L*, dark-light; a*, green-red; and b*, blue-yellow (see Figure 2.9). Yellow skin tone (b* value) was earlier shown to be a reliable biomarker of fruit and vegetable intake, since the yellow-orange pigment β-carotene is stored in the skin (Mayne et al., 2013; Nguyen et al., 2015; Pezdirc et al., 2016; Coetzee & Perrett, 2014; Jahns et al., 2014; Perrone et al., 2016; Whitehead et al., 2012).

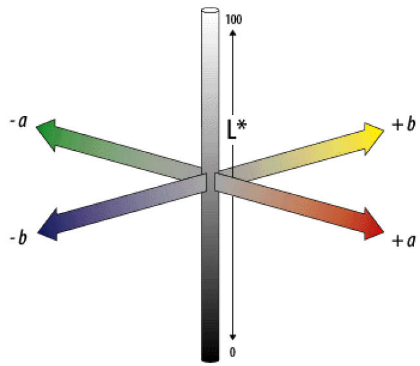


Figure 2.9 The three-dimensional CIE Lab colour space

Source: Baardseth et al., 1976.

2.4.4 Socio-demographic and biological factors

Data on socio-demographic and biological factors such as age, gender, religion, household size and education level were collected by the general questionnaire. Next, smoking behaviour was added, as smoking has an impact on antioxidant status and systematic carotenoid levels may influence the reference method (Alberg and Byers, 2014) (Vassalle et al., 2009).
Body weight (kg) of each participant was measured by using a portable digital scale (Seca GMBH, Hamburg, Germany), and height (cm) was measured by using a stadiometer (Seca GMBH, Hamburg, Germany). Duplicate measurements were taken to assure accuracy of the data, and when the difference between the first and second measurement was too large (>0.5 kg for weight and >1 cm for height), a third measurement was taken. Body mass index (BMI) was calculated with the average weight and height values as kg/m^2.

2.5 Extrapolation of the study results

To extrapolate the study results, the data collected in this study will be compared with the results of the Kenya Integrated Household Budget Survey (KIHBS). KIHBS was designed, to collect key information among others, for the computation of poverty and inequality indicators, labour force indicators, the consumer price index, and to provide data on key socio-economic aspects of the Kenyan population (Kenya National Bureau of Statistics, 2018). For the ENRICH survey we used similar or simplified versions of indicators.

Kenya Integrated Household Budget Survey (KIHBS)
Data collection of the KIHBS took place over a period of 12 months, starting from September 2015. Clusters of households were randomly allocated to four quarters of the year, which were based on the expected seasons in Kenya. This means that any seasonal effects should cancel out upon aggregation of the data. In total, 24,000 households were interviewed, out of which 720 were in Nairobi. From these 720 interviewed households, 554 households could be used in the analysis.

For this analysis we will be using the data from two parts of the KIHBS: 1) questionnaire 1A with information on household members and 2) questionnaire Q1C with information on consumption and expenditure. Questionnaire 1A contains a large range of questions that have been asked at the level of individual household members. Household members are defined as individuals who usually live and eat their meals together in this household. Questionnaire Q1C contains information at the household level. Please see Table 2.3 for an overview of the characteristics and corresponding variables of the KIHBS and the ENRICH study. A more detailed explanation of the variables that were measured differently in the ENRICH study and the KIHBS are described below the table.

Table 2.3 Overview of characteristics of the ENRICH study and KIHBS

	ENRICH study	KIHBS
Period of data collection	June–December 2018	September 2015–September 2016
Sample size	289 participants[1]	In total: 24,000 households, of which 554 were in Nairobi
Study area	Specific settlements: Dandora, Kilimani, Buruburu	Kenya, county level
Corresponding variables	Age, gender, household position, number of household members[2], educational level[2], occupation[2], BMI and F&V intake[2]	

[1] Initially it was aimed to include 500 participants in the study; due to circumstances (as described in Section 3.1) 355 participants were included. Unfortunately, the socio-demographics of only 289 participants was available.

[2]* These variables were measured different in the ENRICH study and the KIHBS.

Number of household members
Unlike the ENRICH survey, where the number of household members is directly asked of the respondent, we generated the number of household members for the KIHBS by counting the number of rows per household ID. There is a separate row in the KIHBS dataset for each member of the household.

Comparison of indicators
The corresponding variables are defined in a similar way as in the KIHBS questionnaire. In some cases, like education and occupation, we applied simplified versions of the indicators because the KIHBS definitions were too detailed. However, the information of ENRICH indicators are defined in such a way that the associated indicators need to be aggregated for comparison.

Educational level
The ENRICH and KIHBS questionnaires differed from each other with regards to education (Table 2.4):

Table 2.4 Overview of classification of educational level in ENRICH study and KIHBS

ENRICH Study	KIHBS
None, preschool	No school, pre-primary
Primary school (eight grades)	Primary
Secondary school (six grades)	Secondary
Post-secondary (college/polytech/ vocational education: four grades)	College (middle level), post-primary/vocational
University (five grades for bachelor's degree, one category for MSc, one category for PhD)	University undergraduate, University postgraduate

Note: The category 'Other' included in both studies was left out, so that it was possible to turn education into an ordinal variable.

Occupation

Both surveys also differ with regards to occupation. Whereas in the ENRICH study the occupation variable is measured with one single question 'What is your occupation?', the KIHBS has an extensive list of questions which follow on from the previous one. They ask in detail about all household members' occupations. To create comparable categories over both surveys, the following categories were used (Table 2.5):

Table 2.5 Overview of classification of occupation in ENRICH study and KIHBS

ENRICH Study	KIHBS
Farmer	Self small-scale agriculture, self-pastoralist activities
Self-employed	Self-employed (modern), self-employed (informal), individual/private household
Paid labour (season)	National government (civil service ministries, judiciary parliament, commissions, state-owned enterprise/institution, teachers service commission), county government, international organisations/NGO, local NGO/CBO, faith-based organisation, informal sector 'Jua Kali' (employed), small-scale agriculture (employed), pastoralist activities (employed), individual boards (BOM) employees
Paid labour (permanent), civil servant/government employee	National government (civil service ministries, judiciary parliament, commissions, state-owned enterprise/institution, teachers service commission), county government, international organisations/NGO, local NGO/CBO, faith-based organisation, informal sector 'Jua Kali' (employed), small-scale agriculture (employed), pastoralist activities (employed), individual boards (BOM) employees
Unemployed including being at home	Unemployed
Other	Other

Note: In the KIHBS a distinction in the working patterns of the primary/main activity was made: full time, part time, seasonal, casual worker and other. To create comparable categories, everybody that was engaged in paid labour, only if 'full time' or 'part time' were selected, they were counted as permanent paid labour. To create 'seasonal paid labour', individuals with paid labour were counted, if they selected 'seasonal'.

Fruit and vegetable intake
The questionnaire in the KIHBS contains a list of 27 categories of vegetables, and 23 categories of fruit (see Appendix 2). For each of these categories, participants were asked how much was purchased and how much was consumed by the household in the last seven days before the interview. The questions on consumption was split up into four different sub-questions, asking how much was consumed respectively from purchases, own stock, own production, and from gifts and other sources. These questions were phrased as follows:

- How much [ITEM] was consumed from purchases?
- How much [ITEM] was consumed from own stock?
- How much [ITEM] was consumed from own production?
- How much [ITEM] was consumed from gifts and other sources?
- How much [ITEM] in total did your household consume in the past week (seven days)?

The answers required a quantity as well as a unit code. There were 19 options of unit codes, e.g. grams, kilograms, litres, teaspoons and bowls. Recalculations to kilograms were already done, such that we could directly use this data instead of having to convert each unit code to kilograms.

The KIHBS and ENRICH surveys differ with regards to the recall time. Whereas the KIHBS asks about consumption in the last seven days, the ENRICH survey asks about the last 24 hours. Therefore, the results of the ENRICH survey could be more accurate. Moreover, the surveys also differ as the ENRICH survey specifically asks how many people have shared a certain meal, whereas for the KIHBS, we divided total household consumption by the number of people in the household. However, this does not take into account that not every meal might have been shared with the same number of people as the number of people that normally live and eat their meals in the household.

2.6 Statistics

Descriptive summary statistics were calculated for participant characteristics, FCM, F&V intake and skin colour tone measurements. Data distributions of variables were inspected for normality, based on which either parametric tests for normally distributed data and non-parametric tests for non-normally distributed data were used. Correlations between FCM, F&V intake, skin colour tone measurements and socio-demographics were calculated. Linear regression was used to further investigate associations between intake and skin tone, thereby adjusting for sex, age and BMI.

Validation of the ENRICH Bot
A paired t-test was used to assess the level of agreement between the importance of the FCM by the ENRICH Bot and self-administered, paper-based FCM questionnaire. To assess the level of agreement between intake assessed by the dietary recalls and the ENRICH Bot we plotted the average intake measured by each method against the difference between the two methods in a Bland-Altman plot, but due to the small data sample obtained with the ENRICH Bot this was no longer useful[1].

Extrapolation of the ENRICH study results
T-tests and Pearson's chi-square tests were used to compare whether the means from the ENRICH study and the KIHBS differ significantly. The Mann–Whitney U test was applied to determine whether both samples (ENRICH study and KIHBS) had the same distribution.

[1] Only the data of Buruburu was included in F&V intake; as a result, the sample size was too small.

3

Data and results

Data and results

This section presents the study results and the structure is as follows. We will start with the description of the data collection of the FCM, followed by F&V intake then a combination of the data of the F&V intake and FCM. Finally, the results of the extrapolation are presented.

3.1 Study sample

Due to challenges encountered in the implementation of the data collection, fieldwork and data analysis, we were unable to collect data for the planned number of participants (N=500) (see Section 2 for the challenges encountered in the recruitment process). In total, we collected data from 355 participants, although they did not participate in all the surveys conducted i.e. the ENRICH Bot and traditional fieldwork (24-hour recall, general questionnaire and self-administered FCM questionnaire). Table 3.1 shows the number of participants from whom data is available.
In Section 3.1.1 below the challenges encountered in the data collection, fieldwork and data analysis are described. These challenges affected the number of included participants from whom the data was available for the analysis.

Table 3.1 Overview of the sample size per survey

Type of survey	Number of participants that were planned to be in the study	Number of actual participants	Number of participants from whom data is available	Number of participants from whom data is missing
ENRICH Bot[1]	500	355	117	238
General questionnaire	500	355	282	73
FCM (self-administered, paper-based questionnaire)	500	355	289	66
F&V intake (24 hour recalls)[2]	500	355	141[2]	214
Skin measurement	500	355	271	84

[1] 117 unique IDs were found in the ENRICH back end. These were the data from the participants in Buruburu. From 16–32 participants, data on FCM were applicable for further analysis. Only the participants that filled out at least one FCM construct as a whole were included. Participants that did not answer all the items per construct were not included in the data analysis. Regarding F&V intake, from 10 participants data on F&V intake was applicable for further analysis.

[2] In the description of the results, only the F&V intake data are presented of participants in Buruburu.

3.1.1 Challenges encountered in data collection

In both ways of data collection using the ENRICH Bot and the traditional way we encountered different barriers and challenges, which can be summarised as follows:

Data collection – ENRICH Bot

- Use of mobile phone and lack of awareness of possibilities for apps
  - At the start we knew that the use of mobile phones was high, and that smartphones were mainly used for social and entertainment purpose, and

for sending and receiving payments (knowledge within project team; GSMA, 2014, 2018; *Silver and Johnson*, 2018). Many *participants* were not aware that apps could also be used for other purposes as well.
  - WhatsApp is more widely known and used than Telegram. However, Telegram looks quite similar to WhatsApp. The fieldwork team received questions related to downloading and enrolment in the ENRICH study.
- ID Matching
  - The phone number of the participant was used as the key identifier to link the collected data of the ENRICH Bot and the more traditional data collection from each participant. As not all participants provided their phone number at the start, we asked for this multiple times.
    In this research setup, each participant had two identical ID numbers: one for the ENRICH Bot and one for the traditional fieldwork. To identify and match the participants, their phone number was used. Unfortunately, not all participants answered these questions or provided phone numbers. As a result there was missing data and we had difficulties in matching the data.
- Low response rate on prompts
  - In the first weeks of the data collection we noticed that the response rate on the prompts was very low. To identify the reasons for this low response rate, a number of short interviews were conducted in Dandora.
    In total, 20 participants in the first group that used the ENRICH Bot were interviewed. The main insights were related to the poor communication and instructions for downloading the ENRICH Bot:
    - None of the interviewed participants received the sign-up instructions from the CBO (see Appendix 1). These instructions described the steps that needed to be taken before the participants were enrolled in the ENRICH study. (Step 1: download Telegram messenger; step 2: sign up to the ENRICH Bot; step 3: respond to the received prompts).
    - Eight out of the twenty interviewed participants managed to conduct step 1 (download the Telegram messenger). Only half of these participants managed to sign up for the ENRICH Bot and were able to answer the sign-up questions (steps 2 and 3).
    - The participants who successfully implemented the three steps indicated that the questions were simple to understand, precise and well formulated, and they were easy to answer.

    Based on these results, we decided to focus on a clear communication and instruction by the fieldwork team. We wanted to make sure the participants in group B, the ones that would start the ENRICH Bot in period 2, were successfully enrolled in the study (see Figure 2.1 for an overview of the study design). Two fieldworkers were in charge of this clear communication and guiding the participants in the steps to enrol in the study.
  - After improving the communication, the responses on the sent prompts increased. Unfortunately, the response rate was still low after all the efforts made. This might be due to a number of reasons:
    - difficulties in ID matching
    - participants had multiple phone numbers
    - participants lost their phone
    - participants used all the data they received (incentive)
    - lack of motivation and awareness of participants
- Pilot testing
  - The ENRICH Bot was tested; during the survey in the first settlement, errors were discovered.
- Airtime incentive
  - Originally it was planned to send each participant some airtime when they responded to a prompt. As it was stated in the informed consent that each participant would receive 100 Ksh of airtime each week, we had to align with this condition.

Data collection – traditional fieldwork

- Size of the study area
  - The settlements in the study differed in size. Kilimani was a large settlement and the travel distance between the participants was long. This had an impact on time and expenses.
- Urban areas and repeated measures
  - In urban areas, participants were more often away from home, especially in the high-income settlement Kilimani. Participants living in Kilimani were unavailable for interviews during the day as they were at work so not at home. As a result, appointments with the participants were rescheduled or participants were not at home for the appointment.

Data collection – overall

- Lack of awareness
  - There was a lack of awareness of the health benefits of fruits and vegetables, particularly among the lower social classes.

- Educational level of the participants
  - Participants with different educational levels participated in this research. This might have an impact on the reading and interpretation of the self-administered questionnaire.
- Community engagement and involvement of the local CBO/collaborating party
  - The power and involvement of the local CBO/collaborating party is very important as they know the area and could facilitate the logistics on the ground.
  - It is necessary to really engage with the projects so that logistics on the ground, for example, are better secured.
  - A suggestion might be to work more closely with the head of the CBO to overcome the difficulties in engagement and incentives.
  - Communication to participants: what was the message to the participants in this project? What are the direct benefits for the participants to be involved in this study? Perhaps next time, an event could be organised to create awareness.
- Use of incentives
  - At the start of the study it was decided to use both airtime and a t-shirt as an incentive. However, these incentives were not relevant for all the participants. For example, the use of a t-shirt as an incentive was good in Dandora, but was not a success in Kilimani.

3.2 Food choice motives

This section presents the results of the analysis of the FCM. It will start with a description of the study sample, as the one used here differs from those used in the other sections due to missing data (see Section 3.1 for more information). After the description of the study sample, the results of the self-administered, paper-based FCM questionnaire are presented and followed with a case in which the results of the paper-based questionnaire and the ENRICH Bot are validated.

3.2.1 Study sample

The initial sample consisted of 355 participants, and for 289 participants there were data available on the FCM. Complete data on the FCM and the socio-demographics were available from 230 participants. The data of the 289 participants are used in the analysis described in Section 3.2.2.

Table 3.2 presents the summary statistics of the socio-demographics characteristics of the 230 participants where all FCM data were available. As shown, more than half (62.2%) were female. The age ranged from 18 to 51 years, with a mean of 29.36 years, and half those in the sample (53%) were the head of the household.
More than one-third of the sample graduated from post-secondary school or university. The mean BMI was 26.17.

Table 3.2 Socio-demographic characteristics of the study sample (FCM)

		Total[1]	Dandora[1]	Buruburu[1]	Kilimani[1]
		N= 289	N= 113	N= 137	N=39
		100%	39.1%	47.4%	13.5%
Age	Range (average age in years)	18–51 (29.36)	18–50 (29.48)	19–51 (29.06)	20–45 (30.21)
Gender (%)	Male	37.8	34.5	37.8	57.9
	Female	62.2	65.5	62.2	42.1
Position in the household (%)	Head of household	53	47.8	56.1	68.4
	Partner of household head	31.7	40.7	24.5	15.8
	Child of household head	13.9	10.6	17.3	15.8
	Other	1.3	0.9	2	0
People living in the household (%)	One	16.1	14.2	17.3	21.1
	Two	13.9	13.3	15.3	10.5
	Three	24.8	27.4	21.4	26.3
	Four	21.3	24.8	18.4	15.8
	Five	15.2	13.3	19.4	5.3
	Six	6.1	4.4	6.1	15.8
	Seven or more	2.6	2.7	2	5.3
Children living in the household (%)	Yes	56.7	74.3	48.2	35.9
	No	43.3	25.7	51.8	64.1
Educational level (%)	No education/ Preschool	0.4	0	0.7	0
	Primary school	14.9	23	7.3	5.3
	Secondary school	38.6	46	35.4	10.5
	Post-seconday school	33.8	27.4	38.5	47.4
	University	12.3	3.5	17.7	36.8

		Total[1]	Dandora[1]	Buruburu[1]	Kilimani[1]
Religion (%)	Christian	94.8	92	96.9	100
	Muslim	4.8	8	2	0
	Other/None	0.4	0	1	0
Occupation (%)	Self-employed	48.3	59.3	39.8	26.3
	Paid labour (permanent) civil servant/government employee	20	4.4	33.7	42.1
	Paid labour (seasonal)	10.9	9.7	10.2	21.1
	Not employed/ Caretaker at home	17	23	11.2	10.5
	Other/student	3.9	3.5	5.1	0
Smoker (%)	Yes	9.1	15.9	3.1	0
	No	90	84.1	96.9	100
BMI[2] (%)	Underweight	2.6	3.6	2.1	0
	Normal weight	41.9	35.1	47.4	52.6
	Overweight	33	40.5	25.8	26.3
	Obese	22.5	20.7	24.7	21.1

[1] Total sample: From N=289 participants FCM data was available, from N=59 participants (20.4%) data on socio-demographics was missing, so the table includes information for N=130. Dandora: From N=113 FCM and socio-demographic data was available. Buruburu: From N=137 FCM data was available, from N=39 (28.5%) data on socio-demographics was missing, so the table includes information for N=98. Kilimani: From N=39 FCM data was available, from N=20 participants (51.3%) data on socio-demographics was missing, so the table includes information for N=19.

[2] BMI: Underweight: BMI ≤18.5 kg/m^2, Normal weight: 18.5–25.0 kg/m^2, Overweight: 25.0–30.0 kg/m^2, Obese: ≥30 kg/m^2.

3.2.2 Description of the food choice motives

Results from statistical analysis

Exploratory and confirmatory factor analyses (EFA and CFA) were performed to determine the underlying factor structure of the FCQ. First, EFA was performed on the 51 items in SPSS using oblimin rotation, because the factors were expected to correlate. Eigenvalues (above 1.0) and scree plots were used to define the number of factors. EFA revealed a factor structure of 15 items with a total explained variance of 68.6%. Eight items loaded more than 0.35 on more than one factor were deleted before conducting a new EFA. These items were: 'fits my traditions', 'makes me feel good', 'is good for my blood', 'smells nice', 'tastes good', 'is commonly eaten by my tribe', 'is what I usually eat' and 'helps me cope with life'. As the rest of the factor loadings made sense, a new EFA was conducted without the items that loaded more than one factor. The new EFA revealed a twelve-factor structure, and items loaded on the factors as expected. In general, the dimensions revealed in the EFA were similar to the original factor structure with most items loading on the intended factors. Also, all new items on function 'health' loaded on one separate factor, and 'safety' loaded on a separate factor combined with one item expected to load on 'ethical concern', namely 'is packaged in an environmentally friendly way'.

To test whether convenience was better fitted in one or in two factors, confirmatory factor analysis was done in AMOS. A model was drawn with the nine original FCQ dimensions and the two new dimensions 'functional health' and 'tradition', and a similar alternative model with 'convenience' split in two dimensions. Next, we tested which model best fitted the data. The fit of the model with two convenience dimensions fitted the data better than the one with a single convenience dimension (χ^2 = 2541.9 and 2647.0 with degrees of freedom = 1158 and 1169 respectively; delta χ^2=105.076 with delta DF=11, p<0.001).

Cronbach's alpha was calculated for the twelve factors, the item loadings. These scores are shown in Table 3.3.

The final model was calculated in AMOS without the items that did not contribute to the Cronbach's alpha. Based on the modification indices, several error terms within the same dimension were allowed to correlate (22 correlations in total): χ^2 = 1568.8 with degrees of freedom = 905, p<0.001. Fit indices were satisfactory: CFI=0.87, GFI=0.82, RMSEA=0.05.

Table 3.3 Factor loading and Cronbach's α for the extended food choice questionnaire (FCQ)

Factor	Item	Factor loading	Cronbach's α
Health	Contains a lot of vitamins and minerals	0.819	0.850
	Keeps me healthy	0.813	
	Is nutritious	0.815	
	Is high in protein	0.831	
	Is good for my skin/teeth/hair/nails etc.	0.819	
	Is high in fibre and roughage	0.847	
Functional health	Gives me energy	0.657	0.716
	Is good for my blood	0.656	
	Makes me feel full	0.711	
	Has medicinal benefits	0.630	
	Is good for digestion	0.679	
Mood	Helps me cope with stress	0.795	0.814
	Helps me cope with life	0.778	
	Helps me relax	0.769	
	Keeps me awake/alert	0.766	
	Cheers me up	0.768	
	Makes me feel good[1]	0.812	
Convenience of preparation	Is easy to prepare	0.689	0.775
	Can be cooked very simply	0.655	
	Takes no time to prepare	0.727	
	Is easy to clean	0.729	
	Is easy to combine with other foods[1]	0.774	
Convenience of accessibility	Can be bought on markets, road stalls and in shops close to where I live or work	N.A.[2]	0.766
	Is easily available on markets, road stalls and in shops	N.A.[2]	
Sensory appeal	Smells nice	0.701	0.735
	Looks nice	0.651	
	Has a pleasant texture	0.670	
	Tastes good	0.691	
	Is liked by myself and/or by my family	0.724	
	Is easy to swallow	0.725	
Natural content	Contains no additives	0.684	0.706
	Contains natural ingredients	0.544	
	Contains no artifical ingredients	0.612	
Price	Is not expensive[1]	0.781	0.783
	Is cheap	0.673	
	Is good value for money	0.617	
	Is good quantity for money	0.666	
Weight control	Is low in calories	0.660	0.707
	Helps me control my weight	0.516	
	Is low in fat	0.657	
Familiarity	Is what I usually eat	0.791	0.793
	Is familiar	0.752	
	Is like the food I ate when I was a child	0.742	
	Is commonly eaten by my tribe	0.716	
	Fits my traditions (e.g. family traditions, special occasions)	0.744	
Ethical approval	Comes from countries I approve politically	0.192	0.776
	Has the country of origin clearly marked	-0,059	
	Is packaged in an environmentally friendly way[1]	0.772	
Food safety	Comes from a clean place	0.693	0.773
	Is handled in a hygienic way	0.639	
	Is free from contaminations (e.g. pesticides, fertilisers or chemicals)	0.747	

1 Item discarded due to poor loading.

2 As the factor consists of two items it was not possible to calculate the Cronbach's alpha.

Description of food choice motives – traditional way of data collection
Regarding the FCM, overall the motive *food safety* was considered the most important (M=5.95). The motives *health, functional health, convenience of* accessibility, *natural content, weight control* and *sensory appeal* all scored high, between 4.67 and 5.04. *Ethical concerns* and *familiarity* were considered the least important motives (see Figure 3.1).

Significant differences regarding the importance of the different FCM were found between the settlements (p<0.05). As shown in Table 3.4, significant differences were found regarding the motives *food safety, health, functional health, natural content, price, convenience of preparation, mood, familiarity and ethical approval.*

The participants living in Kilimani attached a greater importance to the motives related to convenience (*convenience preparation* significantly higher, and *convenience of accessibility* a trend). Participants living in Dandora attached the least importance to the motives *food safety* and *health* compared to the participants living in Kilimani and Buruburu.

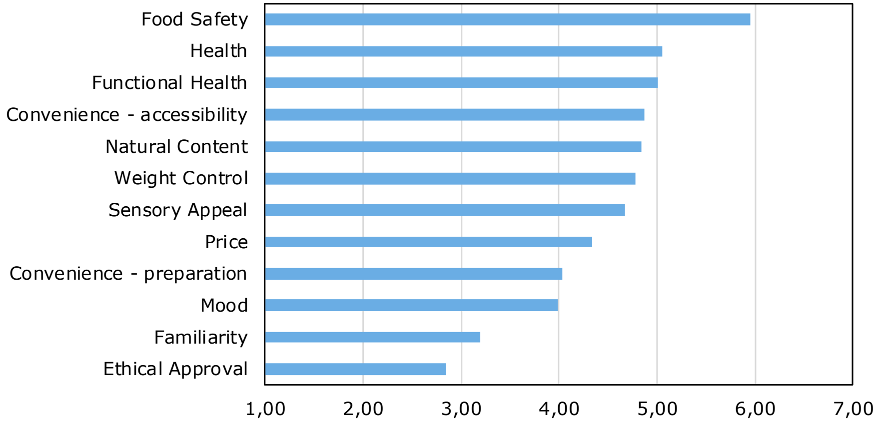


Figure 3.1 Mean values of the food choice motives (Total sample, N=289)

Note: A 7-point Likert scale is applied ranging from 1 = not important at all to 7= extremely important.

Table 3.4 Food choice motives per settlement

		Dandora (N=113)	Kilimani (N=39)	Buruburu (N=137)	Statistics F(2,286)
Food safety	Mean	5.27b	6.15a	6.46a	33,123***
	SD	*1.50*	*1.17*	*0.77*	
Health	Mean	4.70b	5.02ab	5.34a	7.132**
	SD	*1.41*	*0.86*	*1.39*	
Functional health	Mean	4.74b	5.13ab	5.20a	4.953**
	SD	*1.20*	*1.11*	*1.20*	
Convenience of accessibility	Mean	4.84	5.38	4.76	2.501
	SD	*1.46*	*1.46*	*1.64*	
Natural content	Mean	4.55b	4.57b	5.16a	5.822**
	SD	*1.50*	*1.63*	*1.47*	
Weight control	Mean	4.75	4.68	4.82	0.190
	SD	*1.38*	*1.56*	*1.42*	
Sensory appeal	Mean	4.53	4.74a	4.78	1.445
	SD	*1.24*	*1.22*	*1.17*	
Price	Mean	3.99b	4.54ab	4.55a	4.436*
	SD	*1.50*	*1.65*	*1.59*	
Convenience of preparation	Mean	3.91b	4.58a	3.98b	3.418*
	SD	*1.32*	*1.23*	*1.57*	
Mood	Mean	3.99a	3.23b	4.19a	7.401**
	SD	*1.35*	*1.47*	*1.38*	
Familiarity	Mean	3.51a	2.72b	3.09ab	4.740**
	SD	*1.48*	*1.43*	*1.55*	
Ethical approval	Mean	3.34a	2.00c	2.66b	9.873***
	SD	*1.77*	*1.46*	*1.80*	

Note: A 7-point Likert scale is applied ranging from 1 = not important at all to 7 = extremely important.

*p<0.05, **p<0.005, ***p<0.001.

[ab] Different letters indicate a significant difference between the settlements.

3.2.3 Validation of FCM – ENRICH Bot

As described in Section 3.1, the response rate in the ENRICH Bot was very low. In detail, it was found that 85% of the participants living in Buruburu signed up to the ENRICH Bot. From these, only 23% completed the responses so that data was available for analysing. Despite the low response rate, we assessed the level of agreement between the importance of the FCM between the ENRICH Bot and the self-administered, paper-based questionnaire. The

results below should be considered as illustrative results because of the low response rate and the lack of power.
A total of 117 participants replied to the issued prompts, although not all data from these participants could be used in the analysis because 1) we were not able to match the ENRICH Bot data to the data from the paper-based questionnaire; 2) each FCM construct (motive) consists of multiple items, which were not all responded to. When not all the items in a construct were answered, that construct was not included in the analysis. So from 16 to 32 participants the importance of the different FCM was not available (number differed due to the way of asking each FCM construct separately in the ENRICH Bot).
As shown in Table 3.4 the importance of the FCMs *food safety, natural content, functional health, health, sensory appeal, convenience of accessibility, price, convenience of preparation* and *mood* did not significantly differ (p>0.05). However, the two least important FCMs *familiarity* and *ethical approval* significantly differed (see Figure 3.2).

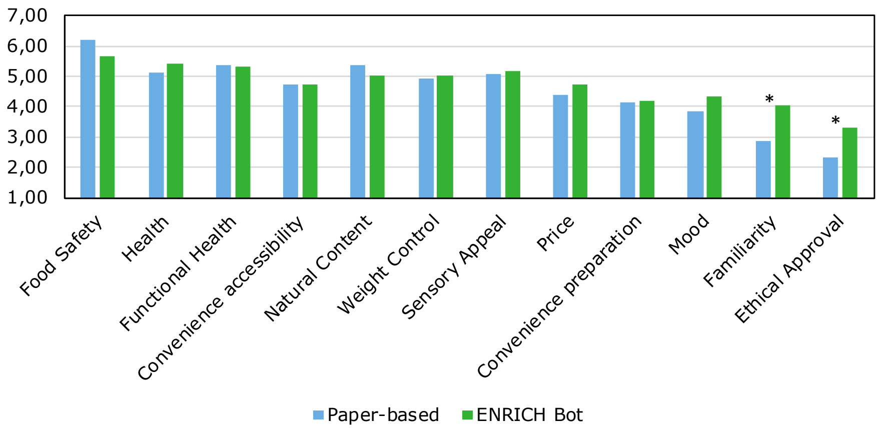


Figure 3.2 Mean values of the importance of the FCM answered in the self-administered, paper-based questionnaire and in the ENRICH bot

Note: Only participants that filled in all the items of one factor (e.g. all the six items of the motive Health) in the ENRICH Bot and who we were able to link match with the paper-based questionnaire. As a result, the number of participants that were included in the paired t-test per motive differs. Food safety: N=16, Health: N=22, Functional health: N=22, Convenience of accessibility: N=20, Natural content: N=28, Weight control: N=28, Sensory appeal: N=20, Price: N=22, Convenience of preparation: N=21, Mood: N=31, Familiarity: N=26, and Ethical approval: N=25.

Note: A 7-point Likert scale is applied ranging from 1 = not important at all to 7 = extremely important.

3.3 Description of fruit and vegetable intake

This section presents the results of the analysis of the F&V intake. In this section we will start with the description of the study sample of the participants in Buruburu. We decided to describe the results of the F&V intake of the participants in Buruburu as data is more available (e.g. 24-hour recalls and data collection ENRICH Bot). We assessed the level of agreement between intake assessed by the dietary recalls and the ENRICH Bot by plotting the average intake measured by each method against the difference between the two methods in a Bland-Altman plot. However, due to the small data sample obtained with the ENRICH Bot this was no longer useful. Next, a description of the objective biomarker is presented.

3.3.1 Study sample

In total, 157 participants were enrolled in the study. Complete data (participant characteristics, dietary recalls and skin tone) were available for a total of 94 participants. Dietary intake data collected through the ENRICH Bot were available for 21 participants, of whom only 10 also produced complete data from the dietary recalls and skin tone measurement. We therefore report detailed data from the set of 94 participants and only briefly describe the results from the ENRICH Bot. The study population consisted of 61% women, and 76% were younger than 34 years; 26% were obese, 26% overweight and 3.2% underweight.

3.3.2 Fruit and vegetable intake

Description of fruit and vegetable intake – traditional way of data collection
Median intake of fruit, vegetables and fruit plus vegetables in Buruburu was 99 g, 226 g and 339 g, respectively (Table 3.5). Out of the 94 participants, 25% met the recommendation of consuming two portions (160 g) of fruit per day, whereas 47% met the recommendation of consuming three portions (240 g) of vegetable per day and 12% met both recommendations. Vegetable intake tended to be higher for men than for women (P=0.078), but fruit or fruit plus vegetable intake did not differ. There were also no significant differences in intake among age and BMI groups.

Table 3.5 Median fruit and/or vegetable intake (g/day) in Buruburu, Nairobi

	N	Fruit	Vegetables	F&V
All	94	99 (57,160)	226 (165,338)	339 (254,432)
Men	37	98 (59,169)	273 (196,363)	351 (269,520)
Women	57	100 (54,162)	201 (150,314)	338 (251,417)
Age groups:				
<34 years	71	102 (57,172)	231 (170,351)	355 (254,473)
≥34 years	23	87 (60,147)	204 (146,317)	338 (275,393)
BMI groups:				
< 25	46	100 (54,169)	226 (160,350)	349 (248,485)
≥ 25	48	95 (57,148)	226 (168,331)	339 (268,425)

Note: Values are medians (25th, 75th percentiles).

Of the total vegetable intake, 35% was derived from green leafy vegetables (i.e. collard greens (20%), amaranth (5.5%), chard (4.5%), cowpea leaves (3%), and other (2%)). The share of intake by top five ranking vegetable types were tomatoes (27%), collard greens (20%), red onion (19%), cabbage (12%) and amaranth (5.5%). For fruit, these were watermelon (28%), banana (26%), avocado (13%), oranges (8.7%), and pineapple (8%). Median (25th; 75th percentile) total intake of fruit and vegetables registered by the 21 participants through the ENRICH Bot was 5,445 (2,455; 8,059) g/day.

3.3.3 Validation of fruit and vegetable intake – ENRICH Bot

In view of the small sample size with complete data (N=10) and the extent to which fruit and vegetable intake collected through the ENRICH Bot deviated from realistic intake as assessed by recall (>16 times), we decided not to analyse these data any further.

3.3.4 Fruit and vegetable intake and correlation biomarker

Values of L*(dark-light), a* (green-red) and b* (blue-yellow) for skin colour are displayed in Table 3.6. Men had a lower L* value for their skin colour than women (52.9 ± 3.7 vs. 55.6 ± 3.2, P<0.001), whereas they had a higher a* value (13.1 ± 1.2 vs. 12.5 ± 1.3, P=0.012). Older participants tended to have a lower L* value (53.4 ± 3.8) than the younger group (54.9 ± 3.5, P=0.086). They also tended to have a slightly higher b* value (19.4 ± 1.4 vs. 18.8 ± 1.3, P=0.052). Participants with BMI <25 kg/m2 tended to have a lower L* value (53.8 ± 3.7) compared to those with BMI ≥25 kg/m2 (55.2 ± 3.5, P=0.054).

L* correlated negatively with a* (r=−0.52, P<0.001) and positively with b* (0.33, P=0.001). Values for a* and b* were not correlated (r=−0.05, P=0.607). Age was negatively associated with b* (r=−0.21, P=0.044) and positively with BMI (r=0.31, P=0.003). Intake of fruit and vegetables correlated positively with intake of β-carotene (r=0.66, P<0.001). β-carotene intake was more strongly correlated to vegetable intake (r=0.65, P<0.001) than to fruit intake (r=0.25, P=0.017). Overall, L* values correlated negatively with vegetable intake (r=−0.22, P=0.034), and this was most pronounced in the younger age group (r=−0.27, P=0.024). β-carotene intake tended towards a negative correlation with L* values (r=−0.20, P=0.055) and a positive correlation with a* values (r=0.18, P=0.089); however, this was not true for men. In men, fruit intake was positively correlated with L* values (r=0.41, P=0.013) and negatively with a* values (r=−0.34, P=0.041). Intake of fruit, vegetables or β-carotene was not correlated with b* values (Table 3.7).

In linear regression, L* values could be significantly predicted by portion (80 g) of vegetable intake (β=−0.62, 95% CI: −1.24, 0.01) after adjustment for gender, age and BMI. Neither a* nor b* could be predicted by fruit, vegetable, F&V or total β-carotene intake. Intake of lycopene-rich products (tomato, guava, mango and watermelon) explained 3% (P=0.217) of the variation in a* after adjustment for gender. Intake of green leafy vegetables (per portion of 80g) was negatively associated with L* (β=−1.29, 95%CI: −2.19, −0.39) and tended to be negatively associated with b* as well (β = −0.32, 95% CI: −0.70, 0.07) after adjustment for gender, age and BMI.

Table 3.6 Measures of skin colour in Buruburu, Nairobi

	N	L*	a*	b*
All	94	54.5 ± 3.6	12.7 ± 1.3	19.3 ± 1.4
Men	37	52.9 ± 3.7	13.1 ± 1.2	19.2 ± 1.5
Women	57	55.6 ± 3.2[*]	12.5 ± 1.3[†]	19.4 ± 1.3
Age groups:				
<34 years	71	54.9 ± 3.5	12.7 ± 1.3	19.4 ± 1.4
≥34 years	23	53.4 ± 3.8	12.8 ± 1.2	18.8 ± 1.3
BMI groups:				
< 25	46	53.8 ± 3.7	12.7 ± 1.2	19.2 ± 1.5
≥ 25	48	55.2 ± 3.5	12.7 ± 1.3	19.4 ± 1.3

Note: Values are mean ± SD. [*]Statistically significant difference, P<0.001; [†]P<0.05.

Note: L*= dark-light, a*= green-red, and b*= blue-yellow.

Table 3.7 Spearman correlation coefficients of fruit and vegetable intake with skin colour measurements

	N		L*	P-value	a*	P-value	b*	P-value
All	94	Fruit intake	0.14	0.173	−0.03	0.763	0.05	0.655
		Vegetable intake	−0.22	0.034	0.14	0.176	−0.03	0.809
		Total intake	−0.08	0.460	0.10	0.331	0.04	0.736
		β-carotene	−0.20	0.055	0.18	0.089	−0.02	0.867
Men	37	Fruit intake	0.41	0.013	−0.34	0.041	0.08	0.657
		Vegetable intake	−0.19	0.269	0.12	0.478	−0.01	0.977
		F + V intake	0.01	0.974	0.00	0.994	0.10	0.577
		Β-carotene	0.24	0.149	−0.01	0.953	0.10	0.560
Women	57	Fruit intake	0.02	0.898	0.12	0.357	0.03	0.807
		Vegetable intake	−0.16	0.232	0.07	0.613	−0.02	0.910
		F + V intake	−0.07	0.630	0.11	0.415	0.03	0.833
		β-carotene	−0.18	0.189	0.27	0.044	−0.08	0.555
Age <34 years	71	Fruit intake	0.09	0.450	0.02	0.889	−0.02	0.896
		Vegetable intake	−0.27	0.024	0.18	0.140	−0.01	0.931
		F + V intake	−0.14	0.252	0.15	0.211	0.02	0.865
		β-carotene	0.17	0.161	0.12	0.308	0.02	0.873
Age ≥34 years	23	Fruit intake	0.31	0.152	−0.16	0.468	0.27	0.208
		Vegetable intake	−0.17	0.446	0.04	0.844	−0.20	0.354
		F + V intake	0.16	0.455	-0.13	0.550	−0.03	0.897
		β-carotene	−0.31	0.155	0.37	0.079	−0.20	0.373
BMI <25	46	Fruit intake	0.13	0.377	0.04	0.777	0.05	0.725
		Vegetable intake	−0.28	0.057	0.13	0.398	−0.16	0.275
		F + V intake	−0.11	0.453	0.11	0.455	−0.07	0.636
		β-carotene	−0.21	0.168	0.09	0.575	0.04	0.776
BMI ≥25	48	Fruit intake	0.16	0.266	−0.11	0.476	0.04	0.778
		Vegetable intake	−0.18	0.221	0.17	0.249	0.13	0.367
		F + V intake	−0.07	0.618	0.12	0.405	0.17	0.249
		β-carotene	−0.25	0.091	0.29	0.043	−0.10	0.501

Note: L*= dark-light, a*= green-red, and b*= blue-yellow.

3.3.5 Conclusion and discussion – fruit and vegetable intake

Median intake of fruit and vegetables registered through the ENRICH Bot exceeded intake assessed through dietary recall >16 times, resulting in unrealistic intake estimates. Moreover, we found no significant association between fruit and vegetable intake and skin yellowness (b*).

The lack of association between fruit and vegetable intake and skin yellowness was unexpected. Previous studies consistently found a positive association (Pezdirc et al., 2016) or a positive change in skin yellowness after a period of increased intake of fruit and vegetables (Stephen et al., 2011; Pezdirc et al., 2015; Whitehead et al., 2012). Although these studies were primarily conducted with Caucasian subjects, a study by Coetzee et al., (2014) showed that black African skin is also responsive to β-carotene supplementation. In agreement with our observations, Whitehead et al. (2012) and Tan et al. (2015) found that increased fruit and vegetable intake for six weeks decreased skin lightness. However, Pezdirc et al. (2016) did not find any differences in skin lightness after intervention with a high vs. low carotenoid diet for four weeks. In addition, we found that β-carotene intake was positively associated with skin redness (a*) in women and in subjects with a BMI >25. Some other studies found an increase in skin redness (a*) values after a period of increased fruit and vegetable consumption (Tan et al., 2015; Whitehead et al., 2012), whereas others did not (Pezdirc et al., 2016). Skin redness is, among others, obtained due to red pigments such as lycopene. Lycopene is found in red-coloured fruit and vegetables such as tomatoes, watermelon, guava, and red peppers (Liu, 2013; Pezdirc et al., 2016; Whitehead et al., 2012). Like β-carotene, lycopene is stored in the skin and contributes to skin redness (Whitehead et al., 2012). However, variation in skin redness could not be explained by intake of lycopene-rich fruit and vegetables in our study.

The lack of association between fruit and vegetable intake and skin yellowness (b*) may be explained by a number of factors. First, intake of β-carotene was relatively low, which may have prevented it from being stored sufficiently in the skin. Second, the dietary recalls may not have captured habitual intake for a long enough time period to reflect skin carotenoid stores, despite the repeated recalls over a period of three weeks. Third, the type of fruit and vegetables consumed in this population may differ from earlier studies; as seen, more than a third of vegetable consumption consisted of green leafy vegetables which may contain phytochemicals that contribute to skin tone other than yellow. Last, higher expression of melanin in the skin of black people may have prevented measurement of subtle changes in yellow skin tone.

This has been the first observational study investigating the association between fruit and vegetable intake and skin colour in an African setting. We developed the ENRICH Bot to simultaneously assess food choice motives and F&V intake in an urban setting. We faced challenges in the development of the ENRICH Bot, the data collection and the testing of the validity. The development of the ENRICH Bot took more time than anticipated. Although the tool was supposed to record F&V intake, the questionnaire in the ENRICH Bot on F&V intake was less detailed than in the case of a personal survey through paper or mobile devices.

The data collection turned out to be challenging as well. Not all four settlements could be used for the survey as circumstances within one settlement (Kibera) changed during the project. Also, the costs of surveying were much higher than anticipated, therefore the number of participants was reduced as well.

To test the validity of the new approach of surveying FCM and F&V intake in an urban setting, we used repeated 24-hour recalls for the measurement of fruit and vegetable intake with detailed questions on preparation and cooking methods. In addition, we took two skin colour measurement in each participant to account for intra-individual variation. The biggest limitation was the small number of participants who registered their fruit and vegetable intake through the ENRICH Bot, which hampered us in validating it. The large discrepancy in quantity of intake through the bot in comparison to the dietary recalls suggests that it does not provide reliable data. Overall, our sample size was less than one-third of the targeted sample (300 participants equally divided over the four settlements), as only participants from Buruburu were included in this analysis Therefore, data cannot be generalised to the Nairobi county level as we cannot differentiate across settlements.

There was some discussion on whether or not the advantages of the tool have been demonstrated.

In conclusion, we have not been able to meet our original aim to assess the validity of the ENRICH Bot for collecting reliable information on fruit and vegetable intake. The limited data available suggest that it is not suitable to capture quantitative information on fruit and vegetable intake. Moreover, skin yellowness did not appear to be a good biomarker for fruit and vegetable intake, whereas skin lightness and redness served the purpose better in this particular population. In order to explore this further, larger studies with more diverse intake patterns of fruit and vegetables would be required.

3.4 Determinants of fruit and vegetable intake

Enriching the data: To fill the knowledge gap and the added value of an integration of the research domains dietary intake and socio-psychological determinants, the collected data on F&V intake, FCM and socio-demographics are combined. The results below only include the participants from whom data on socio-demographics, FVI and FCM (on paper) were available. As a result the data from 94 participants is available on fruit and from 91 participants on vegetables.

To determine the determinants of fruit and vegetable consumption, the data on socio-demographics, food choice motives and fruit and vegetable intake of the participants living in the settlement Buruburu were used. Regression analysis revealed that being a female who valued the motive *functional health* as more important reported a lower vegetable consumption. A higher BMI indicates a higher vegetable intake. A trend was found for the motive *sensory appeal*, so a person who valued the motive *sensory appeal* as more important seemed to have a higher vegetable intake. Other determinants for fruit intake were found. Regarding fruit consumption, being a household head and attaching a greater importance to the motive *ethical concern* and *convenience of accessibility* negatively influenced the fruit intake. However, participants who valued the motive *mood* indicated a higher fruit intake. A trend was found for the motive *familiarity.* Although significant differences were found, the associations were weak and in total only 12.9% of the variance of vegetable intake and only 9.7% of the variance of fruit intake was explained by these variables.

Table 3.8 Results stepwise regression analysis on the drivers of vegetable intake

	Standardised beta coefficients	t-value	p-value	R^2 change
First step				
(Constant)		2.020	0.047	0.148, F(8, 82)= 1.79, *p*>0.05
Gender (female)	−0.443	−3.202	0.002*	
Household head[1]	−0.208	−1.519	0.133	
Household size	0.046	0.382	0.703	
Educational level preschool	0.006	0.059	0.953	
Educational level Primary school	0.032	0.272	0.786	
Educational level Secondary school	0.017	0.114	0.910	
Educational level University	0.080	0.544	0.588	
BMI	0.335	2.751	0.007*	
Second step[2]				
Functional health	−0.318	−2.036	0.046*	0.174, F(20,70)= 1.665, *p*>0.05
Mood	−0.205	−1.806	0.075	
Health	0.171	1.123	0.265	
Convenience of preparation	−0.022	−0.146	0.884	
Sensory appeal	0.239	1.736	0.087	
Natural content	0.167	1.322	0.190	
Price	0.185	1.526	0.131	
Weight control	0.025	0.199	0.843	
Familiarity	0.123	0.723	0.472	
Ethical approval	−0.113	−0.773	0.442	
Food safety	−0.143	−1.200	0.234	
Convenience of accessibility	0.049	0.357	0.722	

1 Houseold head as a dummy variable with not being a household head as the reference.

2 The beta is reported for the step when the variable was introduced.

Table 3.9 Results stepwise regression analysis on the drivers of fruit intake

	Standardised beta coefficients	t-value	p-value	R^2 change
First step				
(Constant)		2.392	0.019	0.094, F(8, 82)= 1.067, p>0.05
Gender (female)	−0.233	−1.629	0.107	
Household head[1]	−0.289	−2.047	0.044*	
Household size	−0.095	−0.772	0.443	
Educational level preschool	0.096	0.870	0.387	
Educational level Primary school	−0.087	−0.706	0.482	
Educational level Secondary school	0.100	0.669	0.505	
Educational level post-secondary school	0.187	1.237	0.220	
BMI	0.105	0.835	0.406	
Second step[2]				
Functional health	−0.305	−1.920	0.059	0.204, F(20,70)= 1.485, p>0.05
Mood	0.235	2.030	0.046*	
Health	0.059	0.382	0.704	
Convenience of preparation	0.233	1.507	0.136	
Sensory appeal	0.029	0.208	0.836	
Natural content	0.002	0.013	0.990	
Price	−0.168	−1.362	0.178	
Weight control	0.153	1.176	0.244	
Familiarity	0.324	1.871	0.066	
Ethical approval	−0.298	−2.003	0.049*	
Food safety	0.210	1.730	0.088	
Convenience of accessibility	−0.343	−2.478	0.016*	

[1] Houseold head as a dummy variable with not being a household head as the reference.

[2] The beta is reported for the step when the variable was introduced.

3.5 Extrapolation of the study results

In this section the results of the exploration of the results of the ENRICH study with the Kenyan Integrated Household Budget Survey (KIHBS) is made. As the KIHBS is a representative study over the population of Kenya, such a comparison will allow us to check whether the ENRICH sample is representative of the overall population of Nairobi. If this is the case, it shows that with a smaller sample it is possible to say something about a larger sample, which could decrease the high costs associated with conventional ways of collecting data.

At the same time, the comparison also serves as an upscaling of the data. Whereas the general questionnaire of ENRICH can be disaggregated by settlement (Buruburu, Dandora and Kilimani), the KIHBS does not contain any public information on any administrative divisions lower than the county level, which would be Nairobi in this case. Therefore, the three settlements of the general questionnaire will be combined in this comparison with the KIHBS. None of these three settlements, however, is generally considered to be low-income. This means it is possible that differences between both surveys are a result of the settlements included in the ENRICH survey. The results of the KIHBS therefore also give an overview of what we might expect upon upscaling to the city level. Similarly, the ENRICH data was collected at one specific point in time, while the interviews by the KIHBS have been spread out equally over the different months of the year, to limit the effect of seasonality. The KIHBS data, in this regard, thus provides an overview of what can be expected if the ENRICH survey had also been conducted in all months of the year.

This section will first focus on the comparison between household and respondent characteristics of the general questionnaire and the KIHBS, and then on comparing indicators related to fruit and vegetable consumption.

3.5.1 Comparison of household characteristics

For both surveys, we can identify a couple of similar characteristics at the household level. It is possible to compare the surveys on five household characteristics: (1) the number of household members, (2) the age of the household head, (3) the gender of the household head, (4) the level of education of the household head, and (5) the occupation of the household head. Differences between the surveys can be a result of differences in the sampling strategy, as the sampling of the ENRICH survey might not be entirely representative over the full population of the three settlements of interest. On the other hand, differences can also be a result of differences between these three settlements and Nairobi as a whole, as the KIHBS does not focus on specific settlements within the city boundaries.

Table 3.10 below shows the descriptive statistics of both surveys on the numeric household characteristics. On average, participants of the ENRICH survey have significantly larger households than participants of the KIHBS. ENRICH participants have 3.4 people in their household, whereas the average household size of households included in the KIHBS is 3.0 people.

Table 3.10 Descriptive statistics on age and gender of household head, and the number of household members

	ENRICH			KIHBS			T-test
	Mean	St dev	N	Mean	St dev	N	
Number of household members	3.38	1.66	296	2.98	1.78	554	3.29***
Age of household head	31.20	7.79	158	36.18	11.79	554	−6.25***
Gender household head (1= Female)	0.32	0.47	158	0.23	0.42	554	2.35**

For a smaller sample of the ENRICH survey, namely participants who are heads of the household, it is also possible to make a comparison on age and gender of the household head. On average, ENRICH household heads are significantly younger and more often female compared to household heads in the KIHBS survey.
With regards to education, the surveys differed slightly in education categories (see Section 2, Paragraph 2.5). After a small restructuring of the education categories in both surveys for comparability purposes, the household heads in the ENRICH survey, on average, seem to have a significantly higher level of education compared to the KIHBS heads of the household. There is a large difference especially between both surveys in the percentage of household heads that have only received primary education (see Table 3.11).

Table 3.11 Descriptive statistics on education level and occupation of household head

		ENRICH		KIHBS		Test result[1]
		N	Percentage	N	Percentage	
Education level of household head	No education/ pre-primary	1	0%	9	2%	W = 101110***
	Primary	22	8%	158	29%	
	Secondary	109	38%	186	34%	
	Post-secondary	101	35%	125	23%	
	University	56	19%	75	14%	
Occupation of household head	Paid labour (permanent)	102	34%	275	50%	Chi^2 = 101.7***
	Paid labour (seasonal)	48	16%	11	2%	
	Self-employed	137	46%	179	32%	
	Unemployed	6	2%	34	6%	
	Other	5	2%	55	10%	

[1] As education is an ordinal variable, a Wilcoxon–Mann–Whitney test is used to determine the difference between both surveys. For occupation (categorical), a chi-squared test is used.

There are also significant differences between both surveys with regards to the occupation of the household head. For both surveys, three categories are distinguished: permanent paid labour, seasonal paid labour, self-employment, unemployment and other. Household heads of participants interviewed in the ENRICH project are more often self-employed or employed in seasonal paid labour, and less often permanently employed in paid labour compared to KIHBS heads of the household.

3.5.2 Comparison of individual characteristics

To compare the two surveys on individual characteristics we use the data from the KIHBS that was collected per household member. ENRICH focuses on participants in the age category of 18–55 years old, so all individuals from the KIHBS outside this age range have been left out of the comparison. It is possible to compare the surveys on six characteristics: (1) position in the household, (2) age, (3) gender, (4) level of education, (5) occupational status, and (6) BMI.

Table 3.12 below shows that, at an individual level, ENRICH participants differ from KIHBS participants with regards to age, gender and BMI, but not concerning household position. In both surveys about half of the participants between the ages of 18 and 55 are heads of the household. On average, ENRICH participants, with an average age of 29.5, are significantly younger than participants in the KIHBS, and they are more often female – 61 per cent of KIHBS participants are female, whereas 48 per cent of KIHBS participants are female.

Table 3.12 Descriptive statistics on household position, age, gender and BMI

	ENRICH			KIHBS			T-test
	Mean	St dev	N	Mean	St dev	N	
Head of household	0.53	0.5	298	0.51	0.5	1006	0.58
Age	29.55	7.6	298	31	9.16	1006	−2.75***
Gender (1= female)	0.60	0.49	298	0.48	0.5	1006	3.48***
BMI	26.08	5.16	294	24.08	4.49	588	5.66***

On the level of individual household members, the KIHBS also contains information on body height and weight, which enables us to make a comparison with the ENRICH survey on BMI. On average, ENRICH participants have a BMI of 26, which is significantly higher than the mean BMI for the KIHBS, at 24.

With regards to education and occupation, there are also significant differences between both surveys on the individual level. The levels of education of individuals appear to be slightly more similar between surveys compared to the education levels of the household heads. However, ENRICH participants have, on average, still received a higher level of education than individual household members in the KIHBS (see Table 3.13). The ENRICH survey especially includes fewer individuals who have only had primary education, and more individuals who have had a post-secondary education (e.g. college or vocational education).

We already saw that heads of the household of ENRICH participants were most often self-employed, while heads of the household of the households included in the KIHBS were most often permanently employed in paid labour. Upon comparing the ENRICH participants with all household members aged 18–55 from the KIHBS, we see that there is still a significant difference. Similarly to the results for heads of the household, individuals of the ENRICH survey are more often self-employed or employed in seasonal paid labour, and less often in paid permanent labour. For both surveys the share of unemployed individuals is much higher than the share of unemployed heads of households. However, the share of unemployed individuals is higher for the KIHBS than for the ENRICH survey.

Table 3.13 Descriptive statistics on education level and occupation

		ENRICH		KIHBS		Test result[1]
		N	Percentage	N	Percentage	
Education level	No education / pre-primary	1	0%	10	1%	W = 174400***
	Primary	40	14%	242	24%	
	Secondary	105	35%	388	39%	
	Post-secondary	100	34%	229	23%	
	University	50	17%	137	14%	
Occupation	Paid labour (permanent)	61	20%	387	38%	Chi^2 = 130.48***
	Paid labour (seasonal)	37	12%	13	1%	
	Self-employed	139	47%	285	28%	
	Unemployed	42	14%	239	24%	
	Other	19	6%	82	8%	

[1] These 1,650 individuals are equal to 1,286.6 adult male equivalent.

3.5.3 Fruit and vegetable intake

Based upon the data on fruit and vegetable consumption as described in Section 2, we were able to construct a top five of fruit and vegetables in total quantity consumed, as well as the share of people consuming each type. For each of the top five fruit and vegetables in quantity consumed, Table 3.14 shows the total quantity consumed in kilograms, the price per kilogram in Kenyan shillings (Ksh), and the average consumption per adult male equivalent (AME). The total kilograms are aggregated over 1,650 individuals living in 554 households in Nairobi. To make these individuals more comparable, we corrected for the differences in energy requirements between age categories and gender. The average consumption per AME therefore shows the average consumption of a male aged 18–30 (see Appendix 3 for conversion rates) (Coates et al., 2017). Overall, ripe bananas, avocado, oranges, mangoes and melons were the most consumed fruits in terms of quantity. Tomatoes, onion bulbs, kale, chard and cabbages were the most consumed vegetables in terms of quantity. Based on the KIHBS survey, we find that an average male aged 18–29.9 consumes 0.42 kilograms of ripe bananas a week, and 0.46 kilograms of tomatoes.

Table 3.14 Total consumption of top five fruit and vegetables

Item	Total kg	Price per kg (in Ksh)	Average consumption per AME
		Fruit	
Ripe bananas	541	50.7	0.42
Avocado	384	48.3	0.30
Oranges	308	57.1	0.24
Mango	204	53.0	0.16
Melon	155	75.8	0.12
		Vegetables	
Tomatoes	588	80.4	0.46
Onions – bulbs	215	101.3	0.17
Collard greens	695	32.4	0.54
Chard	476	34.8	0.37
Cabbage	458	27.7	0.36

The top five fruit and vegetables remains largely the same when looking at the percentage of households consuming each type of fruit or vegetable on a weekly basis. Figure 3.3 shows that, according to the KIHBS, tomatoes are consumed on a weekly basis by the vast majority – 94% of all households. Ripe bananas are consumed by 80% of households. At the lower end of the top five we find that for vegetables, cabbages are consumed by 58% of households and mangoes by 29% of households.

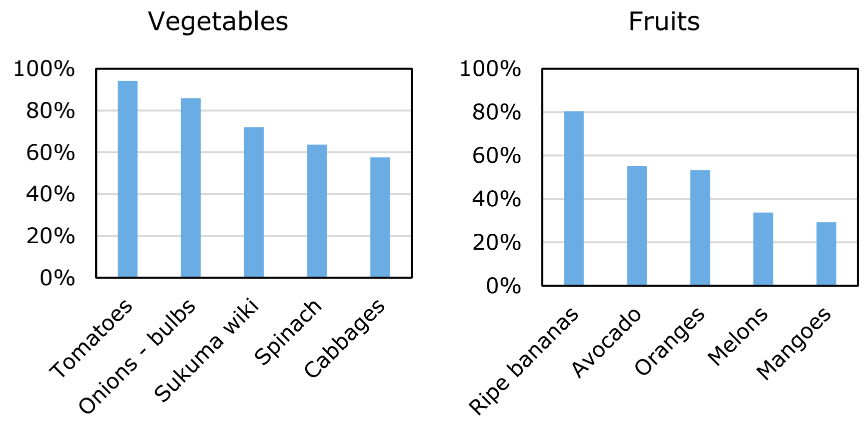


Figure 3.3 Share of households consuming top five types of vegetables and fruit

Upon aggregating all the different types of fruit and vegetables, instead of just looking at the top five, households included in the KIHBS on average consume 0.25 kilograms of fruit per AME per day. Moreover, they consume 0.37 kilograms of vegetables per AME per day, and an equivalent of 0.01 kilograms of fruit juice per day. The low quantity of fruit juice is a result of only 9% of households consuming fruit juice at all. This results in an average of 0.72 kilograms of fruits and vegetables per AME per day. In terms of costs, households spend an average of Ksh 41.7 on fruit and vegetables, of which 59% is spent on vegetables (Ksh 24.6), and the remaining 41% (Ksh 16.6) on fruit and fruit juice (Ksh 1.3).

Similar data on fruit and vegetable consumption is also available for ENRICH participants living in Buruburu. We find that these participants, on average, consume significantly fewer fruit and vegetables compared to households in the KIHBS. Per AME, they consume on average 0.32 kilograms of vegetables per day, and 0.12 kilograms of fruit per day. Only regarding fruit juice do they consume the same as KIHBS households, but fruit juice is only consumed by a small share of individuals.

Table 3.15 Consumption of fruit and vegetables per AME by survey

	ENRICH (Buruburu)			KIHBS			T-test
	Mean	St dev	N	Mean	St dev	N	
Vegetables	0.32	0.14	100	0.46	0.37	548	−6.48***
Fruit	0.12	0.08	100	0.25	0.25	548	−9.75***
Fruit juice	0.01	0.03	100	0.01	0.04	548	−0.23

The data on the source of consumed fruits and vegetables from the KIHBS shows that 96% of consumption of both vegetables and fruit was consumed from purchases. The remaining 4% of consumption is spread over the three other categories: consumption from the household’s stock, from own production, or from other sources (e.g. gifts). Only for fruit juice, the purchased share is lower (82%); 11% was consumed from stock and 7% was consumed from own production.

3.5.4 Socio-demographics and fruit and vegetable intake

The regressions based upon the data from the KIHBS survey was done on characteristics of the household head, as the questions on consumption were also done at the level of the household. The results show that with regards to vegetables, female household heads have higher vegetable intake per AME of the household, and the same is true for older heads of the household (see Table 3.16). Moreover, larger households consume fewer vegetables per AME.

Table 3.16 Regression results vegetable intake per AME

	Coefficients	t-value	p-value	R2 change
(Constant)	.355	2.417	0.016	0.071, F(9,300)= 3.63, p<0.001
BMI of household head	.000	0.089	0.929	
Female household head	.196	3.625	0.000	
Education of household head	.028	1.293	0.197	
Age of household head	.004	2.153	0.032	
Number of household members	−.054	−3.882	0.000	
Occupation status household head (reference group = permanent paid employment):				
Self-employed	−.037	−0.722	0.471	
Seasonal paid employment	−.181	−0.922	0.357	
Unemployed	−.068	−0.678	0.498	
Other	.003	0.043	0.966	

With regards to fruit intake, the same relation concerning household size exists: larger households consume less fruit per AME of the household. The relation with gender is no longer significant, which means there is no significant difference in fruit intake per AME between male and female heads of the household (see Table 3.17). Households with older heads do consume more fruit per AME though, and so do households with higher educated household heads.

Table 3.17 Regression results fruit intake per AME

	Coefficients	t-value	p-value	R2 change
(Constant)	.034	0.341	0.734	0.096, F(9,300)= 3.55, p<0.001
BMI of household head	.004	1.009	0.314	
Female household head	.059	1.592	0.112	
Education of household head	.035	2.334	0.020	
Age of household head	.003	2.571	0.011	
Number of household members	−.039	−4.092	0.000	
Occupation status household head (reference group = permanent paid employment):				
Self-employed	.015	0.413	0.680	
Seasonal paid employment	−.193	−1.441	0.151	
Unemployed	.048	0.702	0.483	
Other	−.003	−0.058	0.954	

3.5.5 Extrapolation of the study results

Overall, there appear to be significant differences between both surveys on most points of interest. It is likely that one of the main reasons for these differences is caused by the fact that the ENRICH data has been collected in three settlements: Dandora, Buruburu and Kilimani. These settlements are classified as middle to high income. The ENRICH data shows, on average, higher levels of education compared to the KIHBS for both participants as well as heads of the households. Under the assumption that there is a relationship between education and income, this difference between the surveys can thus be explained as a result of the regions.

However, there are probably also other factors at play concerning bias or measurement errors. It is likely that there is some degree of bias in the sampling of the ENRICH data, as, for example, the percentage of female participants and female heads of the household is significantly higher compared to the KIHBS survey.

Measurement error, on the other hand, is likely to be present in the KIHBS data concerning fruit and vegetable intake. The KIHBS data provides a more representative sample as it covers the entire city of Nairobi and all twelve months of the year. However, the questions on food consumption have been asked with a seven-day recall period, and of the entire household. Moreover, waste was not accounted for in the analysis of the KIHBS. This might be reason why we find higher intake of fruit and vegetables among households in the KIHBS.
We also ran separate tests comparing the results of the ENRICH survey with a sub-sample of the KIHBS with interviews from November and December, as the results for Buruburu have been collected in these two months. However, we found no significant differences between this sub-sample and the full sample, and the results of the comparison with the ENRICH survey remained the same. Therefore, we can conclude that the differences between the surveys are not due to seasonality, and if the ENRICH survey had been collected throughout the year, results are likely to have been similar to the current results.

In conclusion, the surveys are comparable in the sense that it is possible to compare participants after some restructuring of the data. The data, however, is not comparable between surveys. There are large differences in socio-economic characteristics as well as F&V intake. It is possible to extrapolate the ENRICH survey in order to obtain F&V intake on a more representative sample, namely that of the KIHBS. There are no large differences in F&V consumption after such an extrapolation, which shows that the differences in F&V consumption between both surveys are most likely due to measurement error (e.g. recollection period of the KIHBS). An additional step that could be taken to reduce this measurement error is to correct the KIHBS for waste. Additionally, a subset of the KIHBS data of middle incomes could be taken to create a sample more comparable to the inhabitants of Buruburu. The differences in household characteristics are probably a result of sampling bias (e.g. settlements and mobile phone users).

4 Conclusions and discussion

Conclusions and discussion

4.1 Conclusions

This study aimed to develop and validate a tool, the ENRICH Bot, that can provide reliable information on F&V intake and FCM in real time and in situ from Kenyan consumers. The ENRICH Bot, and the associated tool/metrics that were developed, is a working smartphone application that is able to collect data on F&V intake and FCM of urban Kenyan consumers. However, the results should be carefully interpreted as we were not able to validate the ENRICH Bot due to different challenges encountered in both the development phase and data collection phase.
In addition, another aim was to check whether it would be possible to see if the collected data of a smaller study sample could be extrapolated for a larger urban area. The results of the extrapolation show that the results of the traditional collected ENRICH data are comparable in the sense that it is possible to re-compare the participants after restructuring the data from KIHBS and ENRICH. However, the data from both surveys are not fully comparable, as there is a large difference between the socio-economic characteristics and intake of F&V consumption. The large differences in intake were most likely due to measurement errors and slight differences in definition of household characteristics, and due to sampling bias in the ENRICH survey.

4.2 Discussion and recommendations

The development, collection and analysis of the data collected with the ENRICH Bot was challenging. Based upon the experiences of our study, we present a number of recommendations for the following topics:

1. technical quality
2. recruitment
3. responses

4.2.1 Technical quality

Current format of traditional questionnaires
Traditional questionnaires, such as the 24-hour recall and the food choice questionnaire, are too long and too complex to convert into an app-based questionnaire. In the current format, the burden on the participant would be very high and answering all the questions would be very time-consuming. Next, some of the questions have to be reformulated as they do not fit within the design (e.g. consumption, a specific behaviour or emotion in a certain time period) or does not properly fit on the screen of a smartphone, as the screen is quite small. To provide a good user experience, the best options to convert traditional questionnaires into an app-based questionnaire should be considered.

Recommendations for future research: There are different options available to make it easier to be able to convert a questionnaire into an app-based questionnaire:

- Shortening the questionnaire:
  - Use single-item instead of multiple-item questions for measuring a construct. Simplifying the questions will avoid long matrixes.
  - Stratify the multiple-item questions or matrixes over time. More specifically, when measuring FCM all the different motives can be measured at once, or be stratified over time by measuring one motive at a time.
- Change wording:
  - Use the correct words to simply describe the level of interest: more on a general or a detailed level. For example: consumption in general or consumption in the last four hours.
- Length of sentences:
  - Make sure that each question or answer fits the screen of the smartphone. This will provide a good user experience.

Complexity of the questionnaire and technical boundaries
The format of the questionnaire to measure F&V intake was too complex to convert into the Telegram bot. The traditional paper-based questionnaire included multiple level questions, while the ENRICH Bot only allowed two-level questions (parent and child questions).

Recommendations for future research:
- Use simple structures of questionnaires.
- Make sure that the structure of the questionnaire fits within the technical possibilities of the smartphone application.
- Make sure that all the questions are formatted in a manner that allows for easier granularity and also a tree structure that will allow easier navigation of the level of questions (so-called parent and child questions).

Pilot testing
The ENRICH Bot was tested. However, after the start of surveying in Dandora and Kilimani, there were errors discovered in the app. The errors were fixed in the first four-week period of the study, but it took time so the study design as indicated in Section 2 was not maintained and modified. These errors discovered in the ENRICH Bot did not affect the data collection in Buruburu.

Recommendations for future research:
- Include participants that meet the inclusion criteria in the pilot testing.
- Take time to conduct multiple tests.

ID matching
ID matching is a key element when conducting surveys in separate parts. In the ENRICH study the telephone number of the participant was used as the unique ID. A key document was used to link the collected data via the ENRICH Bot and the traditional fieldwork. We were not able to identify all the participants, because we did not collect all the phone numbers via the ENRICH Bot or participants used multiple phone numbers. As a result, we observed missing data in our sample and difficulties in matching the collected data with the ENRICH Bot and via the traditional way from some participants.

Recommendations for future research:
- It would be better to use one unique ID, instead of a unique ID for each method applied.
- If participants are visit by a fieldworker, next time the fieldworker should download the ENRICH Bot together with the participant and enter the research ID in the ENRICH Bot. This number should then also be entered in the key file.
- Use another variable that could be used for matching the collected data and identification, such as:
  - Location: region, location, village
  - Group members, group names
  - A random ID that will be used in both cases
  - A solution when a participant downloads the app twice

4.2.2 Recruitment

Collaborations and work relationships with local partner/CBO
It is important to work closely with local organisations as they have a lot of local knowledge. In some of the settlements that we included in our study we had to search for new partners and had to start building new work relationships form the ground. This took a long time. Next, in some of the settlements it might have been better to include the local partners at an earlier stage in the project, so that for example the recruitment could be easier.

Recommendations for future research
- Start building a network with local partners as soon as possible and include them at a very early stage.

Community involvement of the local partner/CBO
Not all of the local organisations that we collaborated with where well embedded in the settlements or had direct contact with the participants. The collaborating parties that were well embedded and/or had direct contact with the participants were able to recruit participants more easily, as they participated in the study out of trust.

Recommendations for future research:
- The contact person of the CBO/collaborating party should be a strong person with influence, who supports the project.
- Most political initiatives support initiatives that tackle malnutrition, so liaising with local leaders and politicians might be useful.

- A suggestion might be to work more closely with the head of the CBO to overcome the difficulties in engagement and incentives.

Length of recruitment period
In some settlements the recruitment period was too short. Therefore it was very challenging to meet the target number of participants.

Recommendations for future research:
- Take more time for the recruitment of interviewers.

Recruitment and incentives
In the study we included different socio-economic classes as we were interested in how data collection via a new metric works. The recruitment procedures and incentives were similar for all the participants and across all the settlements. We discovered that the airtime incentive for the participants in Kilimani was not sufficient, while this was acceptable for the participants in Buruburu and Dandora.

Recommendations for future research:
- Involve the collaborating CBO/local partner earlier in the recruitment process to decide on the best recruitment method and incentives that are most applicable to the participants.

Community engagement and involvement of the local CBO/collaborating party
- The power and involvement of the local CBO/collaborating party is very important as they know the area and could facilitate the logistics on the ground.
- Really engage with the projects so that logistics on the ground, for example, are more secured.
- A suggestion might be to work more closely with the head of the CBO to overcome the difficulties in engagement and incentives.
- Communication to participants: what was the message to the participants in this project? What are the direct benefits to the participants to be involved in this study? Perhaps next time, an event could be organised to create awareness.

4.2.3 Responses

Use of smartphone and lack of awareness of usage possibilities
At the start we knew that the use of mobile phones was high, and that smartphones were mainly used for social and entertainment purpose, and also for sending and receiving payments (knowledge within project team; GSMA, 2014, 2018; Silver and Johnson, 2018). Many participants were not aware that apps could be used for other purposes as well. WhatsApp is more common and used more than Telegram. However, Telegram looks quite similar to WhatsApp.

Recommendations for future research:
- Put more attention on the awareness of using a tool/smartphone application.
- Check what is the best method/tool for your data collection: it might also help to improve the sensitisation of users through the use of social media.

Lack of awareness
There was observed a lack of awareness of the health benefits of fruit and vegetables, particularly among the lower social classes.

Recommendations for future research:
- Awareness campaigns about the importance of consuming vegetables can be intensified at various levels: national, local government or community level. Ongoing nutritional campaigns with the Ministry of Health, Ministry of Agriculture or non-governmental networks can be leveraged. Examples of effective promotion and training approaches to increase the consumption of vegetables have been assessed by Schreinemachers (2016) and Ochieng et al. (2018).
- Hold inception workshops about the project's objectives with the targeted communities. Promise and conduct a feedback meeting about the research findings to the community to keep them interested. Involve local leaders and other influential people in the meetings.

Educational level of the participants
Participants with different educational levels participated in this research. This might have an impact on the reading and interpretation of the self-administered questionnaire.

Recommendations for future research:
- Check what is the best method/tool for the data collection: it might also help to improve the sensitisation of users through the use of social media.
- Questions should be more simple and straightforward.
- Use of the smartphone application/tool should be simple and straightforward.

Low response rate on prompts
Difficulties in ID matching
- participants had multiple phone numbers
- participants lost their phone
- participants used all the data that they received (incentive)
- participants lacked motivation and awareness

Airtime incentive
The applied incentive – airtime and a t-shirt – were not relevant for all the participants. For example, the usage of t-shirts as an incentive in Dandora was good, while the incentive was not a success in Kilimani (high-income settlement). A more appropriate incentive might have been providing participants with different kinds of F&V to start changing their patterns, or an F&V workshop as the start of the recruitment phase.

Recommendations for future research:
- Rethink the type of incentive: is it appropriate for the different participants? Look very closely at the setting and what people need and want. It might be a good idea to include someone from the local community in this decision.
- Use a broad incentive; do not give money.

References and websites

Afshin, A., Sur, P. J., Fay, K. A., Cornaby, L., Ferrara, G., Salama, J. S., … Afarideh, M. (2019). 'Health Effects of Dietary Risks in 195 Countries, 1990–2017: A Systematic Analysis for the Global Burden of Disease Study 2017'. *The Lancet* 393 (10184), 1958-1972.

Alaluf, S., Heinrich, U., Stahl, W., Tronnier, H., and Wiseman, S. (2002). 'Dietary Carotenoids Contribute to Normal Human Skin Color and UV Photosensitivity'. *The Journal of Nutrition* 132 (3), 399-403.

Alberg, A. J., and Byers, P. (2014). 'Cigarette smoking and endogenous antioxidants'. *Systems Biology of Free Radicals and Antioxidants*, 1633-1642.

Baardseth, P., Skrede, G., Naes, T., Thomassen, M. S., Iversen, A., & Kaaber, L. (1988). 'A comparison of CIE (1976) L* a* b* values obtained from two different instruments on several food commodities'. Journal of Food Science, 53(6), 1737-1742.

Bailey, R. L., West Jr, K. P., and Black, R. E. (2015). 'The Epidemiology of Global Micronutrient Deficiencies'. *Annals of Nutrition and Metabolism* 66 (Suppl. 2), 22-33.

Biesalski, H., and Nohr, D. (2003). 'Importance of Vitamin-A for Lung Function and Development'. *Molecular Aspects of Medicine* 24 (6), 431-440.

Coates, J., Rogers, B. L., Blau, A., Lauer, J., and Roba, A. (2017). 'Filling a dietary data gap? Validation of the adult male equivalent method of estimating individual nutrient intakes from household-level data in Ethiopia and Bangladesh'. *Food policy* (72), 27-42.

Coetzee, V., and Perrett, D. I. (2014). 'Effect of Beta-carotene Supplementation on African Skin'. *Journal of Biomedical Optics* 19 (2), 025004.

Cunha, L. M., Cabral, D., Moura, A. P., and de Almeida, M. D. V. (2018). 'Application of the Food Choice Questionnaire Across Cultures: Systematic Review of Cross-cultural and Single Country Studies'. *Food Quality and Preference* 64, 21-36.

Datareportal. (2019). Digital 2019: Kenya. https://datareportal.com/reports/digital-2019-kenya

Global Panel on Agriculture and Food Systems for Nutrition. (2016). *Food Systems and Diets: Facing the Challenges of the 21st Century*. London, UK.

GSMA. (2014). 'The Mobile Economy: Sub-Saharan Africa 2014'. https://www.gsma.com/mobileeconomy/archive/GSMA_ME_SubSaharanAfrica_2014

GSMA. (2018). 'The Mobile Economy: Sub-Saharan Africa 2018'. https://www.gsmaintelligence.com/research/?file=809c442550e5487f3b1d025fdc70e23b&download

Hall, J. N., Moore, S., Harper, S. B., and Lynch, J. W. (2009). 'Global Variability in Fruit and Vegetable Consumption'. *American Journal of Preventive Medicine* 36 (5), 402-409. e5.

Jahns, L., Johnson, L. K., Mayne, S. T., Cartmel, B., Picklo Sr, M. J., Ermakov, I. V., Gellermann, W., and Whigham, L. D. (2014). 'Skin and Plasma Carotenoid Response to a Provided Intervention Diet High in Vegetables and Fruit: Uptake and Depletion Kinetics'. *The American Journal of Clinical Nutrition* 100 (3), 930-937.

Keding, G. B., Kehlenbeck, K., Kennedy, G., and McMullin, S. (2017). 'Fruit Production and Consumption: Practices, Preferences and Attitudes of Women in Rural Western Kenya'. *Food Security* 9 (3), 453-469.

Kenya National Bureau of Statistics. (2018). *Basic Report on Well-being in Kenya: Based on Kenya Integrated Household Budget Survey, 2015/2016*. Kenya National Bureau of Statistics.

Krishnaswamy, K., and Gayathri, R. (2018). 'Nature's Bountiful Gift to Humankind: Vegetables & fruits & Their Role in Cardiovascular Disease & Diabetes'. *Indian Journal of Medical Research* 148 (5), 569-595.

Liu, R. H. (2013). 'Health-promoting Components of Fruits and Vegetables in the Diet'. *Advances in Nutrition* 4 (3), 384S-392S.

Lock, K., Pomerleau, J., Causer, L., Altmann, D. R., and McKee, M. (2005). 'The Global Burden of Disease Attributable to Low Consumption of Fruit and Vegetables: Implications for the Global Strategy on Diet'. *Bulletin of the World Health Organization* 83 (2), 100-108.

Mayne, S. T., Cartmel, B., Scarmo, S., Jahns, L., Ermakov, I. V., and Gellermann, W. (2013). 'Resonance Raman Spectroscopic Evaluation of Skin Carotenoids as a Biomarker of Carotenoid Status for Human Studies'. *Archives of Biochemistry and Biophysics* 539 (2), 163-170.

Nguyen, L. M., Scherr, R. E., Linnell, J. D., Ermakov, I. V., Gellermann, W., Jahns, L., ... Zidenberg-Cherr, S. (2015). 'Evaluating the Relationship Between Plasma and Skin Carotenoids and Reported Dietary Intake in Elementary School Children to Assess Fruit and Vegetable Intake'. *Archives of Biochemistry and Biophysics*, 572, 73-80.

Ochieng, J., Afari-Sefa, V., Rajendran, S., Karanja, D., Kessy, R., and Silvest, S. (2018). 'Rating Consumption of Traditional Vegetables in Tanzania Using the Awareness, Interest, Desire and Action (AIDA) Model'. *Acta Horticulturae* 1225, 377-384.

Pengpid, S., and Peltzer, K. (2018). 'The Prevalence and Social Determinants of Fruit and Vegetable Consumption Among Adults in Kenya: A Cross-sectional National Population-based Survey, 2015'. *Pan African Medical Journal* 31, 137.

Perrone, A., Pintaudi, A., Traina, A., Carruba, G., Attanzio, A., Gentile, C., ... Livrea, M. (2016). Raman Spectroscopic Measurements of Dermal Carotenoids in Breast Cancer Operated Patients Provide Evidence for the Positive Impact of a Dietary Regimen Rich in Fruit and Vegetables on Body Oxidative Stress and BC Prognostic Anthropometric Parameters: A Five-Year Study. *Oxidative medicine and cellular longevity*, 2016; 2016: 2727403.

Pezdirc, K., Hutchesson, M. J., Whitehead, R., Ozakinci, G., Perrett, D., and Collins, C. E. (2015). 'Fruit, Vegetable and Dietary Carotenoid Intakes Explain Variation in Skin-color in Young Caucasian Women: A Cross-sectional Study'. *Nutrients* 7 (7), 5800-5815.

Pezdirc, K., Hutchesson, M. J., Williams, R. L., Rollo, M. E., Burrows, T. L., Wood, L. G., … Collins, C. E. (2016). 'Consuming High-carotenoid Fruit and Vegetables Influences Skin Yellowness and Plasma Carotenoids in Young Women: A Single-blind Randomized Crossover Trial'. *Journal of the Academy of Nutrition and Dietetics* 116 (8), 1257-1265.

Popkin, B. M., Adair, L. S., and Ng, S. W. (2012). 'Global Nutrition Transition and the Pandemic of Obesity in Developing Countries'. *Nutrition Reviews* 70 (1), 3-21.

Raaijmakers, I., Snoek, H., Maziya-Dixon, B., and Achterbosch, T. (2018a). 'Drivers of Vegetable Consumption in Urban Nigeria: Food Choice Motives, Knowledge, and Self-efficacy'. *Sustainability* 10 (12), 4771.

Raaijmakers, I., Ojide, M., Akinola, A., and Snoek, H. (2018b). 'Drivers of Food Choices: A First Step in the Development of a Food Choice Questionnaire for Urban Nigeria'. Poster sessions presented at the 3rd Agriculture, Nutrition & Health Academy Week, 25–29 June 2018 Accra, Ghana.

Rahman, S. A., Khattak, M. M. A. K., and Mansor, N. R. (2013). 'Determinants of food choice among adults in an urban community: A highlight on risk perception'. *Nutrition & Food Science*, 43(5), 413–421.

Rodriguez-Casado, A. (2016). 'The Health Potential of Fruits and Vegetables Phytochemicals: Notable Examples'. *Critical Reviews in Food Science and Nutrition* 56 (7), 1097-1107.

Schembre, S. M., Liao, Y., O'Connor, S. G., Hingle, M. D., Shen, S. E., Hamoy, K. G., … Boushey, C. J. (2018). 'Mobile Ecological Momentary Diet Assessment Methods for Behavioral Research: Systematic Review'. *JMIR mHealth and uHealth* 6 (11), e11170.

Schreinemachers, P., Patalagsa, M. A. and Uddin, N. (2016). 'Impact and Cost-effectiveness of Women's Training in Home Gardening and Nutrition in Bangladesh'. *Journal of Development Effectiveness* 8 (4), 473–488.

Sharma, P., Dwivedi, S., and Singh, D. (2016). 'Global Poverty, Hunger, and Malnutrition: A Situational Analysis'. In U. Singh, C. S. Praharaj, S. S. Singh, N. P. Singh (Eds.), *Biofortification of Food Crops* (pp. 19-30). New Delhi: Springer.

Shawar, B. A., and Atwell, E. (2007). 'Chatbots: Are They Really Useful?' *LDV Forum* 22 (1), 29-49.

Shiffman, S., Stone, A. A., and Hufford, M. R. (2008). 'Ecological Momentary Assessment'. *Annual Review of Clinical Psychology* 4, 1-32.

Silver, L., and Johnson, C. (2018). 'Internet Connectivity Seen as Having Positive Impact on Life in Sub-Saharan Africa'. Pew Research Center. https://www.pewresearch.org/global/2018/10/09/internet-connectivity-seen-as-having-positive-impact-on-life-in-sub-saharan-africa/

Sosa, M., Cardinal, P., Contarini, A., and Hough, G. (2015). 'Food Choice and Emotions: Comparison Between Low and Middle Income Populations'. *Food Research International* 76, 253-260.

Stadlmayr, B., Charrondière, U. R., Eisenwagen, S., Jamnadass, R., and Kehlenbeck, K. (2013). 'Nutrient Composition of Selected Indigenous Fruits from sub-Saharan Africa'. *Journal of the Science of Food and Agriculture* 93 (11), 2627-2636.

Stephen, I. D., Coetzee, V., and Perrett, D. I. (2011). 'Carotenoid and Melanin Pigment Coloration Affect Perceived Human Health'. *Evolution and Human Behavior* 32 (3), 216-227.

Steptoe, A., Pollard, T. M., and Wardle, J. (1995). 'Development of a Measure of the Motives Underlying the Selection of Food: The Food Choice Questionnaire'. *Appetite* 25 (3), 267-284.

Tan, K. W., Graf, B. A., Mitra, S. R., and Stephen, I. D. (2015). 'Daily Consumption of a Fruit and Vegetable Smoothie Alters Facial Skin Color'. *PloS One* 10 (7), e0133445.

Thompson, F. E., and Subar, A. F. (2008). 'Dietary Assessment Methodology'. In A. M. Coulston, and C. J. Boushey (Eds.), *Nutrition in the Prevention and Treatment of Disease* (2nd ed.) (pp. 3–39). New York, NY: Academic Press.

UN-Habitat (United Nations Human Settlements Programme), 2011. 2008, 'The State of African Cities – A Framework for Addressing Urban Challenges in Africa'. UN-HABITAT, Nairobi. http://www.zaragoza.es/contenidos/medioambiente/onu/535-eng-ed2008.pdf

United Nations, Department of Economic and Social Affairs, Population Division. (2014). 'World Urbanization Prospects: The 2014 Revision, Highlights (ST/ESA/SER.A/352)'. San Francisco, CA: United Nations.

United Nations, Department of Economic and Social Affairs, Population Division. (2015). 'World Population Prospects: The 2015 Revision, Key Findings and Advance Tables; Working Paper No. ESA/P/WP.241'. San Francisco, CA: United Nations.

van den Puttelaar, J., Verain, M. C., and Onwezen, M. C. (2016). 'The Potential of Enriching Food Consumption Data by use of Consumer Generated Data: A Case from RICHFIELDS'. In Proceedings of Measuring Behavior 2016 A. J. Spink (Ed.). 25-27 May 2016. Dublin, Ireland,

Vassalle, C., Maffei, S., Ndreu, R., and Mercuri, A. (2009). 'Age-related oxidative stress modulation by smoking habit and obesity'. *Clinical biochemistry*, 42(7-8), 739-741.

von Grebmer, K., Saltzman, A., Birol, E., Wiesman, D., Prasai, N., Yin, S ... Sonntag, A. (2014). *2014 Global Hunger Index: The Challenge of Hidden Hunger*. Washington, DC: International Food Policy Research Institute; Dublin: Concern Worldwide; Bonn: Welthungerhilfe.

Wang, O., De Steur, H., Gellynck, X., and Verbeke, W. (2015). 'Motives for Consumer Choice of Traditional Food and European Food in Mainland China'. *Appetite* 87, 143-151.

Whitehead, R. D., Re, D., Xiao, D., Ozakinci, G., and Perrett, D. I. (2012). 'You Are What You Eat: Within-subject Increases in Fruit and Vegetable Consumption Confer Beneficial Skin-color Changes'. *PLoS One*, 7 (3), e32988.

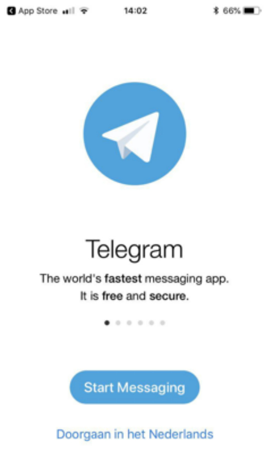
Willett, W. (2013). *Nutritional Epidemiology*, 3rd ed. Oxford: Oxford University Press.

Yang, Y. S., Ryu, G. W., Han, I., Oh, S., and Choi, M. (2018). 'Ecological Momentary Assessment Using Smartphone-Based Mobile Application for Affect and Stress Assessment'. *Healthcare Informatics Research* 24 (4), 381-386.

Appendix 1 Instruction ENRICH Bot

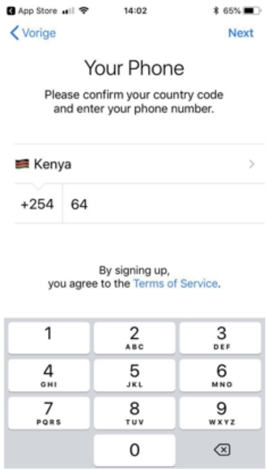
1. Search for Telegram Messenger in the [Appstore] or the [Playstore]
2. Download Telegram Messenger

Step 1

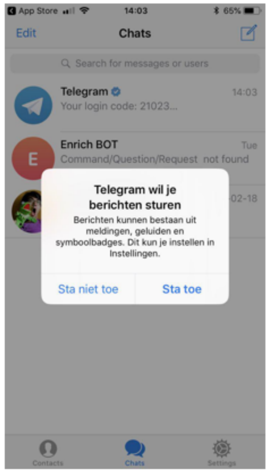


Step 2

3. Start the app and register your phone
4. Accept notifications

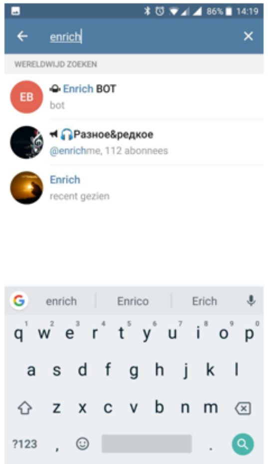


Step 3

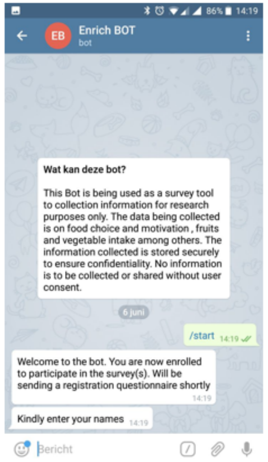


Step 4

5. Search for **ENRICH BOT in the contact list.**
6. Now you can use the ENRICH Bot and will regularly receive questions

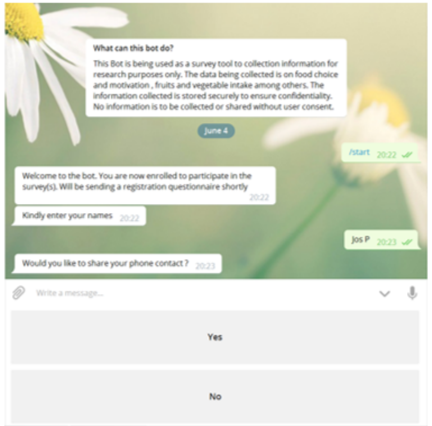


Step 5



Step 6

You will regularly receive questions. After answering you will periodically receive airtime



Example of questions asked in the ENRICH bot

Appendix 2 Fruit and vegetable categories KIHBS

Total list of fruit and vegetable types consumed by households in KIHBS survey

Vegetables	Fruit
Tomatoes	Avocados
Onions – bulbs	Oranges
Kale – Sukuma wiki	Melons
Cabbages	Apples
Coriander leaves (dania)	Lemons
Carrots	Paw Paws
Cooking bananas	Coconuts
Onions – leeks	Pears
Pumpkins/butternut squash	Tree tomatoes
Peas (garden, snap, snow)	Plums
Lettuce, celery	Loquats
Baby and sweet corn	Peaches
Mushrooms and Asian vegetables	
Runner/broad beans	
Turnips	

Appendix 3 Conversion rates

Adult male equivalent (AME) conversion factors based on caloric intake:

	Male	Female
Infants (6–23 months)	0.29	0.27
Children (24–59 months)	0.41	0.38
Youth (5–17 yrs)	0.78	0.68
Adults (18–65 yrs)	0.97	0.82
Elderly (>65 yrs)	0.8	0.69

Wageningen Economic Research
P.O. Box 29703
2502 LS The Hague
The Netherlands
T +31 (0)70 335 83 30
E communications.ssg@wur.nl
www.wur.eu/economic-research

Wageningen Economic Research
REPORT
2019-076C

The mission of Wageningen University and Research is 'To explore the potential of nature to improve the quality of life'. Under the banner Wageningen University & Research, Wageningen University and the specialised research institutes of the Wageningen Research Foundation have joined forces in contributing to finding solutions to important questions in the domain of healthy food and living environment. With its roughly 30 branches, 5,000 employees and 10,000 students, Wageningen University & Research is one of the leading organisations in its domain. The unique Wageningen approach lies in its integrated approach to issues and the collaboration between different disciplines.