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Advancing understanding of dietary and movement behaviours in an Asian population through real-time monitoring: Protocol of the Continuous Observations of Behavioural Risk Factors in Asia study (COBRA)

Sarah Martine Edney[1], Su Hyun Park[1], Linda Tan[1], Xin Hui Chua[1], Borame Sue Lee Dickens[1], Salome A Rebello[1], Nick Petrunoff[1], Andre Matthias Müller[1], Cheun Seng Tan[1], Falk Müller-Riemenschneider[1,2,3,*] and Rob M van Dam[1,4,*]

Abstract

Background: Modifiable risk factors for non-communicable diseases, including eating an unhealthy diet and being physically inactive, are influenced by complex and dynamic interactions between people and their social and physical environment. Therefore, understanding patterns and determinants of these risk factors as they occur in real life is essential to enable the design of precision public health interventions.

Objective: This paper describes the protocol for the Continuous Observations of Behavioural Risk Factors in Asia study (COBRA). The study uses real-time data capture methods to gain a comprehensive understanding of eating and movement behaviours, including how these differ by socio-demographic characteristics and are shaped by people's interaction with their social and physical environment.

Methods: COBRA is an observational study in free-living conditions. We will recruit 1500 adults aged 21–69 years from a large prospective cohort study. Real-time data capture methods will be used for nine consecutive days: an ecological momentary assessment app with a global positioning system enabled to collect location data, accelerometers to measure movement, and wearable sensors to monitor blood glucose levels. Participants receive six EMA surveys per day between 8 a.m. and 9.30 p.m. to capture information on behavioural risk factors including eating behaviours and diet composition movement behaviours (physical activity, sedentary behaviour, sleep), and related contextual factors. The second wave of ecological momentary assessment surveys with a global positioning system enabled will be sent 6 months later. Data will be analysed using generalised linear models to examine associations between behavioural risk factors and contextual determinants.

Discussion: Findings from this study will advance our understanding of dietary and movement behaviours as they occur in real-life and inform the development of personalised interventions to prevent chronic diseases.

Keywords

Precision health, personalised health, chronic disease, experience sampling, ambulatory assessment, socio-ecological, ecologically valid

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[1]Saw Swee Hock School of Public Health, National University of Singapore and National University Health System, Singapore, Singapore
[2]Yong Loo Lin School of Medicine, National University of Singapore, Singapore, Singapore
[3]Digital Health Center, Berlin Institute of Health, Charité-Universitätsmedizin Berlin, Berlin, Germany
[4]Departments of Exercise and Nutrition Sciences and Epidemiology, Milken Institute of Public Health, The George Washington University, Washington, DC, USA

[*]Falk Müller-Riemenschneider and Rob M van Dam are co-senior authors.

Corresponding author:
Sarah Martine Edney, Saw Swee Hock School of Public Health, National University of Singapore and National University Health System, 12 Science Drive 2, Singapore, 119260, Singapore.
Email: sarah.edney@nus.edu.sg

Introduction

Non-communicable diseases (NCDs), including cardiovascular disease (CVD) and type 2 diabetes (T2D), are major contributors to ill health and premature death globally.[1] Lifestyle behaviours including being physically inactive, being highly sedentary, getting inadequate sleep ('movement behaviours'[2,3]) or eating an unhealthy diet are risk factors for developing NCDs. As these risk factors are modifiable, interventions promoting healthy behaviours are fundamental to public health efforts to prevent the onset of NCDs.[4–8]

Socio-ecological models[9,10] help us to understand that health behaviours are influenced by complex and dynamic interactions between people and their social and physical environment. Taking this perspective, we need a rigorous understanding of individual, social and environmental determinants of health behaviours to develop effective interventions for the prevention of NCDs. Such understanding could then be used to inform the development of 'precision public health' interventions that are tailored to the unique risk profile of each individual and to the contextual factors that trigger health behaviours for each individual.[11,12]

To date, a large body of evidence from cross-sectional studies has identified multiple factors associated with health behaviours and NCDs.[13–20] Complexity is evident from the sheer number of factors, their interconnected nature, and the tendency to cross different layers of the socio-ecological model.[21] For example, sex has implications for health as both an individual biological factor (e.g. due to different levels of hormones) and socio-culturally when conceptualised as gender (e.g. expectations around seeking help).[22–24] In terms of our physical environment, living near facilities supporting (BMI) physical activity or to fast food restaurants can have positive or negative implications for our body mass index, respectively.[25,26] Yet where we live is driven by individual factors such as our income, which also influences the food and physical activity choices that people can make. Income is also a social determinant as an indicator of socio-economic status, which has well-established health implications.[19,27,28] Similarly, health behaviours themselves are interrelated. Engaging in screen time (often a form of sedentary behaviour) is associated with mindless or distracted eating and consumption of excess calories.[29] Similarly, the light emitted from screens can disrupt natural circadian rhythms and delay the onset of sleep[30,31] and, in turn, short sleep duration is associated with being less physically active and more sedentary.[32] Although existing studies have yielded important insights into determinants of and relationships between health behaviours, there are limitations. Notably, our current understanding has been constrained by conventional data collection methods that often rely on retrospective self-reports of usual behaviours over the past weeks or months.[33] Such an approach does not capture within-person variation in behaviours and dynamic interactions between health behaviours and related contextual determinants in real-life contexts. This is a substantial limitation, given that exposures to triggers of health behaviours may occur multiple times over the course of a day or week.

Understanding temporal patterns of health behaviours and determinants in real-life contexts requires comprehensive and intensive measurements using real-time data capture strategies. These strategies include ecological momentary assessments (EMAs), and wearable and smartphone-based sensors. EMA[34,35] can be delivered via smartphone applications ('apps') that prompt users, at specified or random times throughout the day, to respond to brief sets of questions to ask, for example: what someone is doing, how they are feeling, where they are, or who they are with. EMA surveys are intentionally brief and typically repeated multiple times, capturing the temporality of behaviours and their determinants. Location data can be collected through smartphone-based global positioning system (GPS) technology, allowing for continuous real-time assessment of where people go and how much time they spend there.[36] Real-time variations in glucose concentrations can be captured using small, wearable sensors, reflecting how lifestyle behaviours influence fluctuations in glucose levels.[37,38] Patterns of bodily movement (i.e. physical activity, sedentary behaviour, sleep) can be captured using small wrist-worn accelerometers that are becoming increasingly accurate.[36] Importantly, these data can facilitate combined spatial and temporal analyses of health behaviours and determinants in real-life contexts, as people go about their daily lives.

Studies using real-time data capture strategies have yielded important insights but have tended to focus narrowly on selected determinants of single health behaviours. For instance, EMA studies have shown greater fluctuations in perceived energy levels to be negatively associated with physical activity on the same day,[39] and that experiencing negative affect and loneliness are associated with greater intake of unhealthy snacks.[40,41] Links between health behaviours have also been identified using EMA. Shorter sleep duration can result in binge eating the next day[42] and exercising has been linked to consumption of sugar sweetened beverages later on the same day.[41] Wearable glucose sensors have been used to identify fluctuations in glucose levels that are potential indicators of hunger and eating behaviours.[37,38] Data from wearable activity trackers has suggested that exercise[43] is socially contagious on a global scale and that nightly sleep quality can be predicted by the performance of physical activity.[44] Examining the contextual environment in which physical activity occurs is now possible by combining data from accelerometers with location data collected via GPS technology[45] and, in other instances, with repeated self-reported EMA data.[46]

This body of evidence furthers our understanding, yet gaps remain in our understanding of the interplay between socio-ecological factors and health behaviours. A more comprehensive assessment of different socio-ecological factors and lifestyle behaviours together in a single study can provide insights into the relative importance of different determinants and can help to prioritise targets for interventions.

Integration of real-time monitoring from EMA, GPS, wearable glucose sensors and accelerometers in a single large-scale study will enhance our understanding of patterns of healthy and unhealthy behaviours and their determinants. This understanding can be used to enable the identification of the type and timing of intervention strategies that need to be prioritised for personalised lifestyle interventions that can be delivered on a population-wide scale. Traditionally, population-wide lifestyle interventions have taken a ‘one-size-fits-all’ approach where every individual receives the same intervention, regardless of their specific behavioural and contextual profile.[47,48] Using a precision public health approach, interventions could be personalised to the unique risk profile of each person, which would mean the proper intervention is delivered to the right person at the right time.[49–51] Thereby ensuring personal relevance and potentially enhancing the effectiveness of the intervention.[52–54] Further, when delivered via digital platforms (e.g. smartphones) personalised interventions could be programmed to perpetually adapt to the changing needs of each person and delivered to a large number of people simultaneously.[11,12,51,55]

Aims

This protocol describes the design and methods for a prospective cohort study using real-time data collection methods to (1) examine patterns of dietary and movement behaviours in real-time as people go about their daily lives, (2) examine how individuals’ interactions with the social and physical environment influence dietary and movement behaviours, and (3) examine how these patterns differ by socio-demographic characteristics.

Our findings are intended to inform the development of personalised behavioural interventions that will seek to improve health and reduce disparities on population-wide scales.

Methods

Our study is named ‘Continuous Observations of Behavioural Risk Factors in Asia’ (COBRA) and is an observational study in free-living participants. Grounded in a socio-ecological framework,[9,10] the COBRA study will use real-time data capture strategies to monitor health behaviours, interactions between different health behaviours, and how health behaviours vary according to personal characteristics and the social and environmental context in which they occur.

This protocol follows guidelines set out in the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE)[56,57] checklist and the Checklist for Reporting EMA Studies (CREMAS)[58] adaptation. Ethical approval was obtained from the Institutional Review Board of the National University of Singapore (protocol number: NUS-IRB-2020-50) and the study is registered with ClinicalTrials.gov (identification number: NCT05136872). All participants will provide written informed consent before enrolling in the study.

COBRA is nested within a large prospective cohort study of 100,000 Singaporean adults (SG100K), which is currently being established. Because SG100K is part of Singapore’s National Precision Medicine (NPM)[59] strategy, SG100K will provide a comprehensive resource for examining genetic, behavioural, clinical and environmental factors underlying CVD and T2D in Asian populations. SG100K will be established by integrating data from approximately 70,000 participants enrolled in existing cohort studies across three institutions (SingHealth, Nanyang Technological University, and National University of Singapore), and recruiting at least 30,000 additional participants.

Participants for the current study will be recruited from the National University of Singapore site of SG100K. These SG100K participants undergo interviews and physical examinations every three to five years. The interviews include detailed assessments of socio-demographics and information about usual lifestyle and medical history. The physical examination consists of the measurement of anthropometrics (e.g. height, weight, waist and hip circumference), bone density, body fatness and skeletal muscle composition and distribution through dual-energy X-ray absorptiometry (DXA), carotid intima-media thickness through ultrasound, lung function, grip strength, visual acuity and retinal imaging, cardio-metabolic risk factors (i.e. electrocardiograms blood pressure, HbA1c, fasting glucose, blood lipids), and collection of blood and urine samples for future measurements. Additionally, long-term follow-up of chronic disease incidence and mortality is conducted via linkage with national health registries. During the health screening visit, SG100K participants who meet the additional inclusion criteria, detailed below, are invited to join the COBRA study.

Participants and recruitment

SG100K eligibility criteria. To be eligible for the broader SG100K cohort study, participants must be (1) a citizen or permanent resident of Singapore, (2) aged 21 years or above and, (3) not have a mental health condition that impairs their ability to provide informed consent independently.

COBRA eligibility criteria. In addition to being enrolled in SG100K, COBRA participants must be (1) 69 years of age or younger, (2) report as being of Chinese, Malay, or

Indian ethnicity, (3) able to read English, (4) own or have continued access to a smartphone (Apple iOS or Samsung Android) with a data plan, (5) be able to use smartphone apps and finally (6) be able to walk independently. Furthermore, participants are excluded if they have (1) a known sensitivity to medical-grade adhesives, (2) a bleeding disorder, (3) a history of stroke, heart disease, renal failure, thyroid disease, or cancer or (4) have had a vascular bypass surgery or a angioplasty procedure performed.

Following their SG100K health screening, participants who meet the COBRA eligibility criteria and provide informed consent are immediately enrolled in the COBRA study for the following nine days. Participants will be re-contacted six to seven months after their initial enrolment to invite them to participate in a follow-up consisting of nine days of EMA surveys & location monitoring via GPS.

Recruitment commenced in May 2021 and is expected to conclude in 2023.

Sample size estimation

We will recruit 1500 participants and expect approximately 20% of them will drop out or experience a device failure for the accelerometer or glucose sensor by the end of the study, leaving 1200 participants with valid data. At a 5% level of significance, our study design and sample size ($N = 1200$) are adequately powered ($\geq 80\%$) to detect the effect of a time-varying, continuous (or binary) factor on a repeated, continuous measurement during the nine days of EMA surveys that explains at least 0.5% of the coefficient of determination (R^2). For example, if the R^2 of the full model is 30%, the R^2 of the reduced model without EMA is 29.5%. This calculation is based on the multiple linear regression model with (i) the difference in the time-varying factor from two time points as one of the independent variables and the corresponding difference in repeated measurement as the dependent variable, and (ii) the R^2 of the full model is at least 25% with adjustment for 10 confounders. Similarly, we are adequately powered at a 5% level of significance to detect time as an effect modifier on a relationship between a static, continuous (or binary) factor at baseline (or initiation) and a repeated, continuous measurement that explains at least 0.5% of R^2. This calculation is also based on the multiple linear regression model with (i) the difference in measurement from two time points as the dependent variable, and the interaction between the static factor and difference in time included as one of the independent variables, and (ii) the R^2 of the full model and number of confounders as mentioned previously.

Recruitment will be stratified by sex, age and ethnicity to ensure an equal proportion of men and women and of participants in five-year bands between the ages of 21 and 69 years. We will over-sample ethnic Malay and Indian participants (50% Chinese, 25% Malay, 25% Indian) as compared to the distribution in the Singapore population (74.3% Chinese, 13.5% Malays, 9.0% Indians, 3.2% other[60]) to ensure sufficient number of participants in each ethnic subgroup for data analyses.[61]

Study procedures

Participation in COBRA requires two visits to the health screening site approximately 11 days apart that are combined with visits for the SG100K physical examination. During the first visit, COBRA study procedures will take up to 1 h. Participants provide informed consent and complete a web-based, self-administered baseline questionnaire. In addition, participants are guided through downloading the EMA app (Ethica Data, ethicadata.com/, Canada), onto their phone and granting the app permission to passively collect location (GPS) data and are provided with brief instructions on how to use the app. Finally, they are fitted with the accelerometer(s)(Axivity AX3 accelerometer, Newcastle upon Tyne, United Kingdom (UK)) and Freestyle Libre Pro iQ glucose sensor, Abbott Diabetes Care, Witney, Oxon, UK), given an opportunity to ask any questions, and scheduled for their second visit. Participants are instructed to go about their usual daily activities for the following nine days.

The second visit occurs on day 11 (or after day 11 but no later than day 18) and takes up to 30 min, during which participants return the study devices (accelerometer(s), glucose sensor, (described in 2.4 Data Collection)) and data are inspected for completeness.

Six to seven months after the second visit, participants will be contacted and invited to participate in the second wave of EMA surveys with GPS monitoring for nine days.

Figure 1 gives an overview of the timing of the COBRA study procedures.

Data collection

Self-administered baseline questionnaire. The COBRA baseline questionnaire is self-administered during study visit one. It includes assessments of personality,[62] habit strength concerning physical activity,[63] usual physical activity participation,[64] perceptions of the neighbourhood physical activity[65] and food environments,[66] habitual eating behaviours[67] and usual diet[68] and typical use of screen devices.[69] Questions on physical activity cognitions (e.g. self-efficacy, perceived importance),[70–72] social and physical environments of both physical activity and eating, usual involvement in the planning and preparation of meals at home, and participation in population-wide health behaviour programmes are also included. Details of the specific surveys and items used in the baseline questionnaire are presented in Supplemental Tables 1 and 2. REDCap electronic data tools hosted at the National University of Singapore are used to capture and manage study questionnaire data.

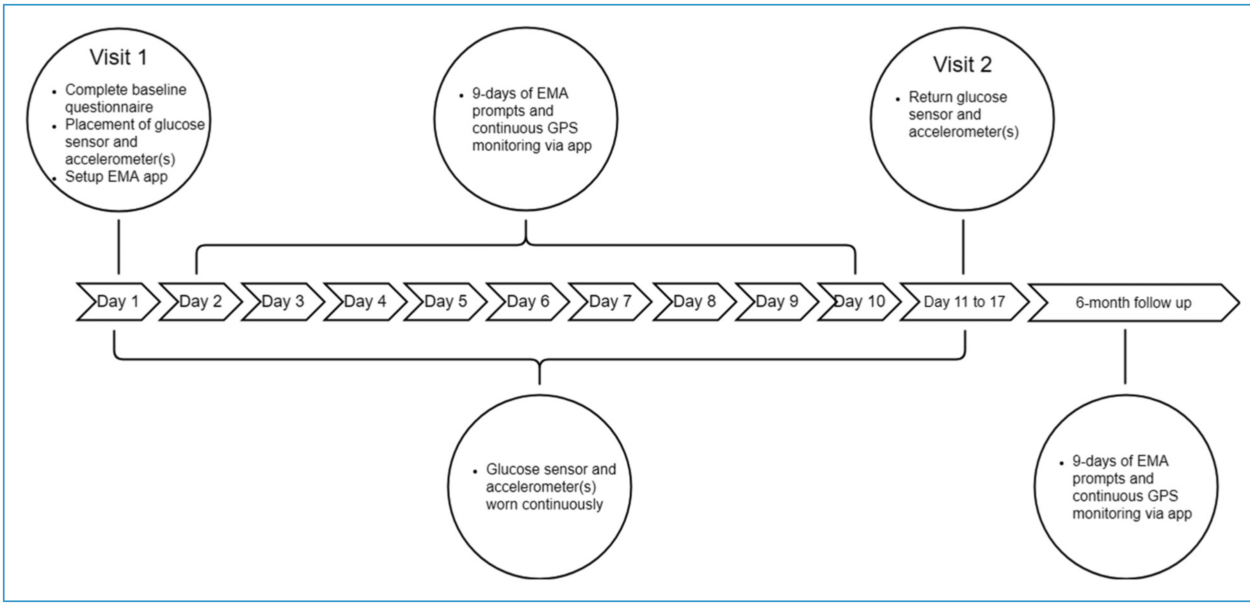

Figure 1. Timing of the Continuous Observations of Behavioural Risk Factors in Asia (COBRA) study procedures.

Real-time monitoring of health behaviours and contextual determinants. Health behaviours and contextual determinants are monitored in real-time over nine consecutive days using an EMA app with GPS enabled, wearable flash glucose monitoring sensors, and accelerometers. For participants who agree, there is a nine-day follow-up six months later consisting of EMA and GPS monitoring only.

Ecological momentary assessment (EMA). Formative work was undertaken to develop and refine a set of EMA questions to capture the required breadth and depth of health behaviours and socio-ecological factors. The final question set was developed iteratively by reviewing relevant literature, drawing on our experience using EMA in the local population,[73,74] and through group discussions, until the research team was satisfied that the questions comprehensively covered the constructs of interest. Systematic reviews of EMA studies[35,58,75,76] guided the design of the schedule.

Two rounds of pilot testing were conducted by the study team members to refine the EMA question set and EMA schedule. Questions were removed, where possible, to balance the burden on participants against capturing the full breadth and depth of health behaviours and related socio-ecological factors. For example, questions about sleep and wake times that would already be captured by the accelerometer[77] were removed. Refinements to the schedule, question content, and branching logic were also made. A further round of pilot testing was conducted by the study operations team, to check the relevance of the questions for the target population and the local context. The study operations team is responsible for all data collection for a series of large-scale ongoing cohort studies,[78] including those from which participants to the current study will be recruited. Feedback on this round included minor amendments to question response options.

Overview of the EMA questions and schedule. EMA surveys are sent via an app (Ethica Data, ethicadata.com/, Canada) downloaded on the participants' smartphones. Participants will be sent six EMA surveys per day for nine days on a time-stratified sampling schedule[79] commencing the day after their enrollment in the study. To ensure sampling coverage across the day, surveys are sent at random times within the following fixed time windows: 8 a.m. to 9:30 a.m., 10:30 a.m. to noon, 1 p.m. to 2:30 p.m., 3:30 p.m. to 5 p.m., 6 p.m. to 7:30 p.m., and 8:30 p.m. to 9:30 p.m. The time windows have a buffer in between to allow multiple reminders to be sent. Four reminders are sent for the first five surveys of the day (via app push notification) 10 min apart. For the final survey of the day, two reminders are sent spaced 10 min apart.

These EMA surveys include 33 unique questions related to sleep, general activities, diet, physical activity, screen time, stress, hunger, fatigue, affect, self-efficacy and behavioural intentions, physical environment, and social interactions. Each survey takes between 1 and 5 min to complete and presents participants with a minimum of five and a maximum of 40 questions. The first survey of the day commences with the question 'Did you eat or drink anything after the last prompt and before going to sleep yesterday?' and then related follow-up questions (via branching logic). Participants are then asked, 'What have you been doing since the last prompt?' and then related follow-up questions. The remaining five surveys each day start by asking, 'What have you been doing since the last prompt?' and the actual number of questions presented is determined by what the participant indicates they have been doing and the relevant branching logic. For example, respondents who indicate they have been doing physical activity or exercise are then asked a series of questions to determine the type, location, and social and physical environment of the activity. Each of the six EMA surveys ends by presenting respondents with questions assessing their perceived stress, hunger, fatigue, and positive affect (see Supplemental Figures 1 and 2 showing the branching logic and app screenshots). Supplemental Table 3 contains details of all the EMA questions, including each construct being assessed, the question wording and response options, timing and frequency, source and details of modifications made (if any), and related data that will be captured by other sources within the COBRA study.

The validity of the EMA questions will be assessed using data from the accelerometers, GPS, blood glucose levels, and the baseline questionnaires. For example, the type of physical activity performed (reported via EMA) will validate against accelerometer data. Information on types of food consumed throughout the day will be validated against the usual diet as assessed by the Food Frequency Questionnaire (FFQ).[68]

Location. The EMA app (Ethica Data, ethicadata.com/, Canada) automatically captures location data, comprising latitude and longitude coordinates, every five minutes for one minute using GPS satellite technology. For participants with Android devices, location data is additionally captured via cell towers and Wi-Fi access points.

These data will be used to identify where people spend time (e.g. home, work), and will be linked to geographical information system (GIS) layers to assess characteristics of the built environment that may influence health behaviours (e.g. green space,[80] exercise facilities,[81] fast food outlets,[82] neighbourhood walkability[83,84]).

Glucose monitoring. Participants will be fitted with a flash glucose monitoring sensor ('glucose sensor'; Freestyle Libre Pro iQ; Abbott Diabetes Care) on the upper part of their non-dominant arm to wear continuously for the following nine days. The glucose sensor has a thin filament inserted just below the skin to measure glucose in the interstitial fluid every 15 min to estimate plasma glucose concentrations. Glucose monitoring will capture variations in glucose concentrations as a biomarker of food ingestion and a potential determinant of hunger and eating behaviour.[37] These sensors have excellent validity for estimating glucose levels in people with diabetes ($r = 0.98$, compared to venous blood samples[85]) and for estimating plasma glucose concentrations in a non-diabetic population (mean absolute difference 10.5%, compared to plasma glucose samples[86]). For the current study, derived variables will include mean glucose, coefficient of variation (CV%) and time-in-range for desirable glucose levels.[87]

Accelerometers. Participants will be fitted with an accelerometer (AX3; Axivity Ltd). These are small tamper-proof electronic devices that will be placed on the wrist of the non-dominant hand using a watch-like strap. Participants will be asked if they are willing to wear a second thigh-worn accelerometer (AX3; Axivity Ltd). For those who agree, the accelerometer will be taped to the thigh, on the same side of the body as the non-dominant arm, using medical-grade adhesive. Participants will be instructed to wear the accelerometers continuously for the following nine days. Device-measured acceleration data will be collected at a sampling frequency of 100 Hz to augment the physical activity information collected via EMA. They will be used to derive information on light, moderate, and vigorous physical activity, inactivity and sedentary behaviour, and sleep, continuously throughout the entire day. Wrist-worn Axivity devices have been shown to accurately measure movement in laboratory settings (balanced accuracy of 90–96% when compared to direct observation[88]) and there is evidence of their accuracy when affixed to the wrist or the thigh in free-living conditions ($r = 0.64$–0.68 compared to doubly labelled water for estimating physical activity energy expenditure[89]). In addition to patterns of movement behaviours, the thigh-worn accelerometer will provide information on time spent in different postures (i.e. lying, sitting, standing).

Data analysis

For Aim 1, to examine the patterns of dietary and movement behaviours from the EMA surveys over the nine days, we will perform exploratory analysis by applying clustering approaches[90] to the variables on dietary and movement behaviour, respectively, to identify distinct subgroups within each day. From the subgroups identified, we will rank them according to their frequency and characterise them with the variables used to perform the clustering. We will explore whether specific subgroups of dietary behaviour are associated with subgroups from movement behaviours. We will also perform a follow-up analysis to identify potential individual, social and environmental determinants for the subgroups identified for dietary and movement behaviours. This agnostic data analysis strategy will facilitate the generation of hypotheses on potential factors that co-occur in time and space with dietary and/or movement behaviours. Hence, providing a shortlist of potential social and physical environment determinants on dietary and movement behaviours for Aim 2. To control for multiple testing in this exploratory analysis, we will use the false discovery rate (FDR)[91] which is widely used in the genomics literature. In Aim 2, to examine the interplay of participants' characteristics with the social and physical environment in influencing dietary and movement behaviours, we will utilise the temporal patterns of health behaviours and determinants. We will use generalised linear models with generalised estimating equations (GEEs) or generalised linear mixed models to examine the association of time-varying daily determinants with behavioural risk factors, accounting for correlations between repeated daily behaviour measurements and for potential confounders.[92] As Aim 3 is examining how these patterns differ by socio-demographic characteristics, besides including them as predictors in the longitudinal regression models, the interactions between socio-demographic factors with social or physical environment factors will also be investigated. Analyses will be undertaken using statistical software programs including Stata and R.

Discussion

Continuous Observations of Behavioural Risk Factors in Asia (COBRA) is the first study to rigorously capture the dynamic variation and interplay of multiple socio-ecological determinants that shape health behaviours under real-life conditions. The six-month follow-up will enable further assessment of changes in health behaviours over time. With these data integrated, we will be able to examine health behaviours and determinants at a level of granularity that has not previously been possible in large population-based studies. We will generate detailed insights into patterns of health behaviours and their determinates which can be targeted for NCD prevention efforts.

Ultimately, these data will be used to inform the design of personalised interventions delivered on population-wide scales, a goal being actualised in the next step of the SG100K project.[59] Although there are concerns that personalisation of interventions may widen, rather than reduce, health disparities[51,93–95] our approach seeks to mitigate this by leveraging technology that people already own and use (smartphones) to deliver interventions. Smartphone penetration is high (over 90%[96]) in Singapore and in lower-income countries. For example, there are over 750 million smartphone users in India,[97] and the number of users is rapidly increasing, suggesting that smartphone-based personalised interventions could be accessible even in lower-income countries. Our findings are also intended to inform other types of population-wide interventions that are complementary to efforts to prevent NCDs in the population, such as those targeting the built and food environment.

The first study of its kind in Asia and globally, COBRA will generate detailed information on social, environmental and lifestyle factors that are associated with NCDs in the multi-ethnic population of Singapore. The study will recruit a large sample (1500 participants) with representation of the major ethnic groups in Singapore (Chinese, Malay, Indian) to ensure the results are relevant for each group. A further strength of COBRA is the rigorous, pre-specified and piloted[73] study protocol. Embedded within a prospective cohort study, COBRA contributes to a comprehensive resource for examining genetic, behavioural, clinical and environmental factors underlying CVD and T2D in Asian populations. Beyond COBRA, a wealth of additional data on these participants will be available from past, present and future SG100K health screenings undertaken by COBRA participants. This longitudinal approach will enable us to assess the role of behavioural risk factors in changes to body weight and cardio-metabolic risk factors and in the development of NCDs.

Conclusion

Dietary and movement behaviours play a key role in the development of NCDs such as type 2 diabetes, cardiovascular diseases and various types of cancer. It is crucial to develop more effective interventions to improve dietary and movement behaviours to stem the rise of NCDs, but this requires a better understanding of the determinants of these behaviours. We will conduct a detailed examination of patterns of lifestyle behaviours and their psychological and environmental determinants using real-time data capture strategies. Findings from our study will provide insight into the way personal characteristics and the social and physical environment interact to shape lifestyle behaviours. These insights will be used to inform health promotion strategies, including the design of precision public health interventions, personalised to the socio-demographic, psychological and environmental characteristics of individuals.

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Guarantor: SE.

ORCID iDs: Sarah Martine Edney https://orcid.org/0000-0002-3925-517X
Linda Tan https://orcid.org/0000-0001-5317-0458

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References

1. World Health Organization (WHO). *Global status report on noncommunicable diseases 2010: description of the global burden of NCDs, their risk factors and determinants*. Geneva: WHO, 2011. https://apps.who.int/iris/handle/10665/44579
2. Canadian 24-Hour Movement Guidelines for Adults aged 18-64 years: An Integration of Physical Activity, Sedentary Behaviour, and Sleep. Canadian Society for Exercise Physiology (CSEP); 2020. doi: 10.1139/apnm-2020-0467
3. Tremblay MS, Carson V, Chaput J-P, et al. Canadian 24-Hour Movement Guidelines for children and youth: an integration of physical activity, sedentary behaviour, and sleep. *Appl Physiol Nutr Metab* 2016; 41: S311–S327. doi: 10.1139/apnm-2016-0151
4. Ding D, Lawson KD, Kolbe-Alexander TL, et al. The economic burden of physical inactivity: a global analysis of major non-communicable diseases. *Lancet* 2016; 388: 1311–1324. https://doi.org/10.1016/S0140-6736(16)30383-X
5. Lee IM, Bauman AE, Blair SN, et al. Annual deaths attributable to physical inactivity: whither the missing 2 million? *Lancet* 2013; 381: 992–993. https://doi.org/10.1016/S0140-6736(13)60705-9
6. Lee IM, Shiroma EJ, Lobelo F, et al. Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy. *Lancet* 2012; 380: 219–229. doi: 10.1016/S0140-6736(12)61031-9
7. Global burden of 87 risk factors in 204 countries and territories, 1990-2019: a systematic analysis for the Global Burden of Disease Study 2019. *Lancet* 2020; 396: 1223–1249. https://doi.org/10.1016/S0140-6736(20)30752-2
8. Neuhouser ML. The importance of healthy dietary patterns in chronic disease prevention. *Nutr Res* 2019; 70: 3–6. doi: 10.1016/j.nutres.2018.06.002
9. Cohen DA, Scribner RA and Farley TA. A structural model of health behavior: a pragmatic approach to explain and influence health behaviors at the population level. *Prev Med* 2000; 30: 146–154. doi: 10.1006/pmed.1999.0609
10. Sallis JO, Owen N and Edwin B. Ecological models of health behavior. In: Glanz K, Rimer BK and Viswanath K (eds) *Health behavior and health education: theory, research, and practice*. 5th ed. San Francisco: Jossey-Bass, 2015, pp. 465–485.
11. Hekler E, Tiro JA, Hunter CM, et al. Precision health: the role of the social and behavioral sciences in advancing the vision. *Ann Behav Med* 2020; 54: 805–826. doi: 10.1093/abm/kaaa018
12. Kee F and Taylor-Robinson D. Scientific challenges for precision public health. *J Epidemiol Community Health* 2020; 74: 311–314. doi: 10.1136/jech-2019-213311
13. Bauman AE, Reis RS, Sallis JF, et al. Correlates of physical activity: why are some people physically active and others not? *Lancet* 2012; 380: 258–271. doi: 10.1016/S0140-6736(12)60735-1
14. Müller AM, Chen B, Wang NX, et al. Correlates of sedentary behaviour in Asian adults: a systematic review. *Obes Rev* 2020; 21: e12976. https://doi.org/10.1111/obr.12976
15. Boutayeb A and Boutayeb S. The burden of non-communicable diseases in developing countries. *Int J Equity Health* 2005; 4: 2. https://doi.org/10.1186/1475-9276-4-2
16. Flegal KM, Graubard BI, Williamson DF, et al. Cause-specific excess deaths associated with underweight, overweight, and obesity. *JAMA* 2007; 298: 2028–2037. doi: 10.1001/jama.298.17.2028
17. Williams EP, Mesidor M, Winters K, et al. Overweight and obesity: prevalence, consequences, and causes of a growing public health problem. *Curr Obes Rep* 2015; 4: 363–370. doi: 10.1007/s13679-015-0169-4
18. Prüss-Ustün A, van Deventer E, Mudu P, et al. Environmental risks and non-communicable diseases. *Br Med J* 2019; 364: l265. https://doi.org/10.1136/bmj.l265
19. Marmot M and Bell R. Social determinants and non-communicable diseases: time for integrated action. *Br Med J* 2019; 364: l251. https://doi.org/10.1136/bmj.l251
20. Bauer UE, Briss PA, Goodman RA, et al. Prevention of chronic disease in the 21st century: elimination of the leading preventable causes of premature death and disability in the USA. *Lancet* 2014; 384: 45–52. doi: 10.1016/S0140-6736(14)60648-6
21. Rutter H, Savona N, Glonti K, et al. The need for a complex systems model of evidence for public health. *Lancet* 2017; 390: 2602–2604. doi: 10.1016/S0140-6736
22. Day S, Mason R, Lagosky S, et al. Integrating and evaluating sex and gender in health research. *Health Res Policy Syst* 2016; 14: 75. https://doi.org/10.1186/s12961-016-0147-7
23. Oertelt-Prigione S. Sex and gender in medical literature. In: *Sex and gender aspects in clinical medicine [Internet]*. London: Springer, 2012, pp. 9–15.
24. Phillips SP. Defining and measuring gender: a social determinant of health whose time has come. *Int J Equity Health* 2005; 4: 11. https://doi.org/10.1186/1475-9276-4-11
25. Wu Y, Wang L, Zhu J, et al. Growing fast food consumption and obesity in Asia: challenges and implications. *Soc Sci Med* 2021; 269: 113601. doi: 10.1016/j.socscimed.2020.113601
26. Mason KE, Pearce N and Cummins S. Associations between fast food and physical activity environments and adiposity in mid-life: cross-sectional, observational evidence from UK Biobank. *Lancet Public Health* 2018; 3: e24–e33. doi: 10.1016/S2468-2667(17)30212-8
27. Präg P, Mills M and Wittek R. Income and income inequality as social determinants of health: do social comparisons play a

role? *Euro Sociol Rev* 2014; 30: 218–229. https://www.jstor.org/stable/24479877
28. Marmot M. The health gap: the challenge of an unequal world. *Lancet* 2015; 386: 2442–2444. doi: 10.1093/ije/dyx163
29. Chaput JP, Klingenberg L, Astrup A, et al. Modern sedentary activities promote overconsumption of food in our current obesogenic environment. *Obes Rev* 2011; 12: e12–e20. doi: 10.1111/j.1467-789X.2010.00772.x
30. Nelson RJ and Chbeir S. Dark matters: effects of light at night on metabolism. *Proc Nutr Soc* 2018; 77: 223–229. doi: 10.1017/S0029665118000198
31. Fonken LK and Nelson RJ. The effects of light at night on circadian clocks and metabolism. *Endocrine Rev* 2014; 35: 648–670. doi: 10.1210/er.2013-1051
32. Lin Y, Tremblay MS, Katzmarzyk PT, et al. Temporal and bi-directional associations between sleep duration and physical activity/sedentary time in children: an international comparison. *Prev Med* 2018; 111: 436–441. doi: 10.1016/j.ypmed.2017.12.006
33. Dunton GF. Ecological momentary assessment in physical activity research. *Exerc Sport Sci Rev* 2017; 45: 48–54. doi: 10.1249/JES.0000000000000092
34. Reichert M, Giurgiu M, Koch ED, et al. Ambulatory assessment for physical activity research: state of the science, best practices and future directions. *Psychol Sport Exerc* 2020; 50: 101742. doi: 10.1016/j.psychsport.2020.101742
35. Maugeri A and Barchitta M. A systematic review of ecological momentary assessment of diet: implications and perspectives for nutritional epidemiology. *Nutrients* 2019; 11: 2696. doi: 10.3390/nu11112696
36. Hurvitz P, Moudon A, Kang B, et al. Emerging technologies for assessing physical activity behaviors in space and time. *Frontiers Public Health* 2014; 2: 2. https://doi.org/10.3389/fpubh.2014.00002
37. Chaput JP and Tremblay A. The glucostatic theory of appetite control and the risk of obesity and diabetes. *Int J Obes (2005)* 2009; 33: 46–53. doi: 10.1038/ijo.2008.221
38. Liao Y and Schembre S. Acceptability of continuous glucose monitoring in free-living healthy individuals: implications for the use of wearable biosensors in diet and physical activity research. *JMIR Mhealth Uhealth* 2018; 6: e11181. doi: 10.2196/11181
39. Maher JP, Dzubur E, Nordgren R, et al. Do fluctuations in positive affective and physical feeling states predict physical activity and sedentary time? *Psychol Sport Exerc* 2019; 41: 153–161. doi: 10.1016/j.psychsport.2018.01.011
40. Jeffers AJ, Mason TB and Benotsch EG. Psychological eating factors, affect, and ecological momentary assessed diet quality. *Eat Weight Disord* 2020; 25: 1151–1159. https://doi.org/10.1007/s40519-019-00743-3
41. Grenard JL, Stacy AW, Shiffman S, et al. Sweetened drink and snacking cues in adolescents. A study using ecological momentary assessment. *Appetite* 2013; 67: 61–73. doi: 10.1016/j.appet.2013.03.016
42. Parker MN, LeMay-Russell S, Schvey NA, et al. Associations of sleep with food cravings and loss-of-control eating in youth: an ecological momentary assessment study. *Pediatric Obes* 2021; n/a: e12851. doi: 10.1111/ijpo.12851
43. Aral S and Nicolaides C. Exercise contagion in a global social network. *Nature Comm* 2017; 8: 14753. https://doi.org/10.1038/ncomms14753
44. Sathyanarayana A, Joty S, Fernandez-Luque L, et al. Sleep quality prediction from wearable data using deep learning. *JMIR Mhealth Uhealth* 2016; 4: e125. doi: 10.2196/mhealth.6562
45. Delclòs-Alió X, Vich G and Miralles-Guasch C. The relationship between Mediterranean built environment and outdoor physical activity: evidence from GPS and accelerometer data among young adults in Barcelona. *Landsc Res* 2020; 45: 520–533. https://doi.org/10.1080/01426397.2019.1702937
46. Liao Y, Intille SS and Dunton GF. Using ecological momentary assessment to understand where and with whom adults' physical and sedentary activity occur. *Int J Behav Med* 2015; 22: 51–61. doi: 10.1007/s12529-014-9400-z
47. Kreuter MW, Strecher VJ and Glassman B. One size does not fit all: the case for tailoring print materials. *Ann Behav Med* 1999; 21: 276–283. doi: 10.1007/BF02895958
48. Phillips CM. Metabolically healthy obesity: personalised and public health implications. *Trends Endocrinol Met* 2016; 27: 189–191. doi: 10.1016/j.tem.2016.02.001
49. Olstad DL and McIntyre L. Reconceptualising precision public health. *BMJ Open* 2019; 9: e030279. doi: 10.1136/bmjopen-2019-030279
50. Dolley S. Big data's role in precision public health. *Front Public Health* 2018; 6. https://doi.org/10.3389/fpubh.2018.00068
51. Khoury MJ, Lademarco MF and Riley WT. Precision public health for the era of precision medicine. *Am J Prev Med* 2016; 50: 398–401. doi: 10.1016/j.amepre.2015.08.031
52. Schoeppe S, Alley S, Van Lippevelde W, et al. Efficacy of interventions that use apps to improve diet, physical activity and sedentary behaviour: a systematic review. *Int J Behav Nutr Phys Act* 2016; 13: 127. https://doi.org/10.1186/s12966-016-0454-y
53. Tong HL, Quiroz JC, Kocaballi AB, et al. Personalized mobile technologies for lifestyle behavior change: a systematic review, meta-analysis, and meta-regression. *Prev Med* 2021; 148: 106532. doi: 10.1016/j.ypmed.2021.106532
54. Weeramanthri TS, Dawkins HJS, Baynam G, et al. Editorial: precision public health. *Front Public Health* 2018; 6. https://doi.org/10.3389/fpubh.2018.00121
55. Payne PRO and Detmer DE. Language matters: precision health as a cross-cutting care, research and policy agenda. *J Am Med Inform* 2020; 27: 658–661. doi: 10.1093/jamia/ocaa009
56. von Elm E, Altman DG, Egger M, et al. The strengthening the reporting of observational studies in epidemiology (STROBE) statement: guidelines for reporting observational studies. *Lancet* 2007; 370: 1453–1457. https://doi.org/10.1136/bmj.39335.541782.AD
57. Mahajan R, Burza S, Bouter LM, et al. Standardized protocol items recommendations for observational studies (SPIROS) for observational study Protocol reporting guidelines: protocol for a Delphi study. *JMIR Res Protocols* 2020; 9: e17864. doi: 10.2196/17864
58. Liao Y, Skelton K, Dunton G, et al. A systematic review of methods and procedures used in ecological momentary assessments of diet and physical activity research in youth:

an adapted STROBE checklist for reporting EMA studies (CREMAS). *J Med Internet Res* 2016; 18: e151. doi: 10.2196/jmir.4954
59. PRECISE: Precision Health Research Singapore: Consortium for Clinical Research and Innovation Singapore (CRIS); 2021. Available from: https://www.npm.sg/.
60. Statistics Singapore. Population Trends, 2020. Singapore Department of Statistics.
61. Bilheimer LT and Klein RJ. Data and measurement issues in the analysis of health disparities. *Health Serv Res* 2010; 45: 1489–1507. doi: 10.1111/j.1475-6773.2010.01143.x
62. Gosling SD, Rentfrow PJ and Swann WB. A very brief measure of the big-five personality domains. *J Res Personality* 2003; 37: 504–528. https://doi.org/10.1016/S0092-6566(03)00046-1
63. Gardner B, Abraham C, Lally P, et al. Towards parsimony in habit measurement: testing the convergent and predictive validity of an automaticity subscale of the Self-Report Habit Index. *Int J Behav Nutr Phys Act* 2012; 9: 102. https://doi.org/10.1186/1479-5868-9-102
64. Nang EE, Gitau Ngunjiri SA, Wu Y, et al. Validity of the international physical activity questionnaire and the Singapore prospective study program physical activity questionnaire in a multi-ethnic urban Asian population. *BMC Med Res Methodol* 2011; 11: 141. doi: 10.1186/1471-2288-11-141
65. James FS, Jacqueline K, Jordan AC, et al. Evaluating a brief self-report measure of neighborhood environments for physical activity research and surveillance: physical activity neighborhood environment scale (PANES). *J Phys Act Health* 2010; 7: 533–540. doi: 10.1123/jpah.7.4.533
66. Green SH and Glanz K. Development of the perceived nutrition environment measures survey. *Am J Prev Med* 2015; 49: 50–61. doi: 10.1016/j.amepre.2015.02.004
67. Karlsson J, Persson LO, Sjöström L, et al. Psychometric properties and factor structure of the Three-Factor Eating Questionnaire (TFEQ) in obese men and women. Results from the Swedish obese subjects (SOS) study. *Int J Obes: J Int Assoc Study Obes* 2000; 24: 1715–1725. https://doi.org/10.1038/sj.ijo.0801442
68. Whitton C, Ho JCY, Tay Z, et al. Relative validity and reproducibility of a food frequency questionnaire for assessing dietary intakes in a multi-ethnic Asian population using 24-h dietary recalls and biomarkers. *Nutrients* 2017; 9: 1059. doi: 10.3390/nu9101059
69. Vizcaino M, Buman M, DesRoches CT, et al. Reliability of a new measure to assess modern screen time in adults. *BMC Public Health* 2019; 19: 1386. https://doi.org/10.1186/s12889-019-7745-6
70. Godino JG, Watkinson C, Corder K, et al. Awareness of physical activity in healthy middle-aged adults: a cross-sectional study of associations with sociodemographic, biological, behavioural, and psychological factors. *BMC Public Health* 2014; 14: 421. doi: 10.1186/1471-2458-14-421
71. Prapavessis H, Gaston A and DeJesus S. The theory of planned behavior as a model for understanding sedentary behavior. *Psychol Sport Exerc* 2015; 19: 23–32. https://doi.org/10.1016/j.psychsport.2015.02.001
72. Sniehotta FF, Schwarzer R, Scholz U, et al. Action planning and coping planning for long-term lifestyle change: theory and assessment. *Euro J Social Psychol* 2005; 35: 565–576. https://doi.org/10.1002/ejsp.258
73. Park SH, Yao J, Chua XH, et al. Diet and physical activity as determinants of continuously measured glucose levels in persons at high risk of type 2 diabetes. *Nutrients* 2022; 14. doi: 10.3390/nu14020366
74. Park SH, Petrunoff NA, Wang NX, et al. Daily park use, physical activity, and psychological stress: a study using smartphone-based ecological momentary assessment amongst a multi-ethnic Asian cohort. *Ment Health Phys Act* 2022; 22: 366. https://doi.org/10.1016/j.mhpa.2022.100440
75. Degroote L, DeSmet A, De Bourdeaudhuij I, et al. Content validity and methodological considerations in ecological momentary assessment studies on physical activity and sedentary behaviour: a systematic review. *Int J Behav Nutr Phys Act* 2020; 17: 35. https://doi.org/10.1186/s12966-020-00932-9
76. Heron KE, Everhart RS, McHale SM, et al. Using mobile-technology-based ecological momentary assessment (EMA) methods with youth: a systematic review and recommendations. *J Pediat Psychol* 2017; 42: 1087–1107. doi: 10.1093/jpepsy/jsx078
77. Plekhanova T, Rowlands AV, Yates T, et al. Equivalency of sleep estimates: comparison of three research-grade accelerometers. *J Measurement Physical Behaviour* 2020; 3: 294–303. https://doi.org/10.1123/jmpb.2019-0047
78. Singapore Population Health Studies (SPHS) 2019 [17 May 20121]. Available from: https://blog.nus.edu.sg/sphs/.
79. Shiffman S. Designing protocols for ecological momentary assessment. In: Stone A, Shiffman S, Atienza A and Nebeling L (eds) *The science of real-time data capture: self-reports in health research*. New York: Oxford University Press, 2007, pp. 27–53.
80. de Keijzer C, Bauwelinck M and Dadvand P. Long-term exposure to residential greenspace and healthy ageing: a systematic review. *Current Environ Health Rep* 2020; 7: 65–88. doi: 10.1007/s40572-020-00264-7
81. Jansson AK, Lubans DR, Smith JJ, et al. A systematic review of outdoor gym use: current evidence and future directions. *J Science Med Sport* 2019; 22: 1335–1343. https://doi.org/10.1016/j.jsams.2019.08.003
82. Ahern M, Brown C and Dukas S. A national study of the association between food environments and county-level health outcomes. *J Rural Health* 2011; 27: 367–379. doi: 10.1111/j.1748-0361.2011.00378.x
83. Sarkar C, Webster C and Gallacher J. Neighbourhood walkability and incidence of hypertension: findings from the study of 429,334 UK Biobank participants. *Int J Hyg Environ Health* 2018; 221: 458–468. doi: 10.1016/j.ijheh.2018.01.009
84. Hajna S, Ross NA, Brazeau A-S, et al. Associations between neighbourhood walkability and daily steps in adults: a systematic review and meta-analysis. *BMC Public Health* 2015; 15: 768. https://doi.org/10.1186/s12889-015-2082-x
85. *Performance data freestyle libre pro iQ*. Oxon, UK: Abbott Diabetes Care Ltd, 2020.
86. Fechner E, Op 't Eyndt C, Mulder T, et al. Diet-induced differences in estimated plasma glucose concentrations in healthy, non-diabetic adults are detected by continuous glucose monitoring—a randomized crossover trial. *Nutr Res* 2020; 80: 36–43. doi: 10.1016/j.nutres.2020.06.001

87. Battelino T, Danne T, Bergenstal RM, et al. Clinical targets for continuous glucose monitoring data interpretation: recommendations from the international consensus on time in range. *Diab Care* 2019; 42: 1593–1603. doi: 10.2337/dci19-0028
88. Hedayatrad L, Stewart T and Duncan S. Concurrent validity of ActiGraph GT3X+ and Axivity AX3 accelerometers for estimating physical activity and sedentary behavior. *J Measurement Physical Behaviour* 2021; 4: 1–8. https://doi.org/10.1123/jmpb.2019-0075
89. White T, Westgate K, Hollidge S, et al. Estimating energy expenditure from wrist and thigh accelerometry in free-living adults: a doubly labelled water study. *Int J Obes* 2019; 43: 2333–2342. https://doi.org/10.1038/s41366-019-0352-x
90. Xu R and Wunsch II DC. *Clustering*. Hoboken, New Jersey: John Wiley & Sons, Inc., 2009.
91. Storey JD and Tibshirani R. Statistical significance for genomewide studies. *Proc Natl Acad Sci U S A* 2003; 100: 9440–9445. https://doi.org/10.1073/pnas.1530509100
92. Fitzmaurice G, Laird NM and Ware JH. *Applied longitudinal analysis*. 2nd ed. New Jersey: Wiley, 2012.
93. Chowkwanyun M, Bayer R and Galea S. "Precision" public health – between novelty and hype. *N Engl J Med* 2018; 379: 1398–1400. doi: 10.1056/NEJMp1806634
94. Menon U, Ashing K, Chang MW, et al. Application of the ConNECT framework to precision health and health disparities. *Nurs Res* 2019; 68: 99–109. doi: 10.1097/NNR.0000000000000329
95. Obermeyer Z, Powers B, Vogeli C, et al. Dissecting racial bias in an algorithm used to manage the health of populations. *Science* 2019; 366: 447–453. doi: 10.1126/science.aax2342
96. *Statistica*. Number of smartphone users in Singapore from 2010 to 2020 and a forecast up to 2025 (in millions). 2021.
97. Deloitte. India to have 1 billion smartphone users by 2026: Deloitte report. Business Standard. 2022 February 22 2022.