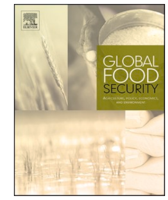
Interactions with the external food environment and dietary quality in Thailand and Laos

Global Food Security 49 (2026) 100916

Contents lists available at ScienceDirect

Global Food Security

journal homepage: www.elsevier.com/locate/gfs



Interactions with the external food environment and dietary quality in Thailand and Laos

Giacomo Zanello [a,*], Marco J. Haenssgen [b], Prasit Leepreecha [b], Eric Deharo [c], Chittur S. Srinivasan [a]

[a] School of Agriculture, Policy and Development, University of Reading, UK
[b] Department of Social Sciences and Development, Chiang Mai University, Thailand
[c] MIVEGEC, University of Montpellier and Centre National de La Recherche Scientifique, Institut de Recherche pour le Développement, Montpellier, France

1. Introduction

The global nutrition transition, characterised by a shift from traditional diets towards those high in energy-dense, processed, and convenience foods, poses a major public health challenge. This transformation has been closely linked to rising rates of obesity, diabetes, cardiovascular disease, and other nutrition-related chronic conditions (NCDs) (Popkin, 2018; Popkin and Ng, 2022). The impact has been especially acute in Low and Middle-Income Countries (LMICs), where rapid socio-economic change has accelerated (Popkin, 2021). Central to understanding and addressing these trends are food environments (FEs), which refer to the diversity, quality, convenience, and affordability of food outlets and products accessible to consumers. FEs are increasingly recognised as key determinants of dietary behaviour and nutritional outcomes (Turner et al., 2018). Over the past two decades, research on FEs has grown in response to concerns that structural features of food environments are contributing to the global rise in unhealthy diets. As a result, identifying how FEs shape dietary choices has become a central priority in food policy research to inform the design of food systems that support healthier consumption patterns.

FEs have been conceptualised as the “interface where people interact with the wider food system to acquire and consume food” (Turner et al., 2019). The wider food system covers the entire food chain from “farm to fork” and includes agricultural production, food storage, transportation and trade, food retail and provisioning (Lartey et al., 2016). These elements of the food system shape the FEs within which consumer dietary choices are made. The FAO envisages a bi-directional relationship between food systems and FEs and consumer choice (Lartey et al., 2016). FEs influence consumer choice through food labelling, food promotion, food prices, physical access, nutrient quality and taste. At the same time food systems are also shaped by food culture and consumer preferences. FEs characterise the availability, accessibility, affordability, convenience and promotional marketing of foods in specific geographic and socio-cultural contexts. “By determining the foods that consumers can access at a given time, at what prices and with what degree of convenience, FEs both constrain and prompt food choices” (Lartey et al., 2016). Another framework developed by Turner et al. (2019) identifies external and personal domains of the FE. The external domain covers dimensions such as food availability, prices, vendor and food product characteristics, marketing and regulations. The personal domain encompasses individual level dimensions covering food accessibility, affordability, convenience and desirability. Food choices emerge from the interaction between the external and personal domain of the FE. Both frameworks allow for a heterogeneity of dietary choices within a given FE, moulded by the endowments and characteristics (personal domain dimensions) of different households. The FE is seen as the context within which individuals or households make decisions about food acquisition, preparation and consumption (CDC, 2023). The spatial dimension is important as the FE is also seen as the sum of spaces in which people make decisions about food and the food and drinks that are made available, accessible and desirable in those spaces (European Public Health Alliance, 2019).

Conceptualisations of the FE in the literature view the FE as the totality of physical, economic, social cultural and political factors that influence where, when and how people engage with the food system. However, empirical assessments of the FE predominantly rely on a narrower view of FEs focusing on the physical and spatial characteristics of FEs and providing indicators of “exposure” to the FE. A distinction is often made between the “community FE” which relates to the distribution of food outlets or sources within a community and the “consumer FE” which relates to foods consumers encounter within specific sources and food outlets. The principal approaches used in the empirical assessments of FEs have been based on (1) Geospatial mapping of food outlets using GIS techniques. A majority of empirical studies have used

* Corresponding author.
E-mail address: g.zanello@reading.ac.uk (G. Zanello).

https://doi.org/10.1016/j.gfs.2026.100916
Received 14 April 2025; Received in revised form 4 December 2025; Accepted 23 March 2026
Available online 2 April 2026
2211-9124/

GIS techniques to map the density and proximity of different types of food outlets in a given "neighbourhood" or geographical area (Cetateanu and Jones, 2016; Wilkins et al., 2017) and the range, quality and affordability of products in these outlets. These indicators have largely focused on market-based outlets, while non-market sources of food have received less attention (2) Store audits, that capture the "consumer" FE and assess the range, prices (affordability) and quality of foods in specific outlets (Glanz et al., 2007; Gustafson et al., 2012; Partington et al., 2015) and (3) Perception surveys, that capture perceived availability, accessibility, affordability and quality of foods or food outlets (Caldwell et al., 2009; Inglis et al., 2008; Moore et al., 2008; Sharkey et al., 2010). While conceptually there is a strong argument to be made that exposure to less healthy FEs will lead to poor diets and nutritional outcomes, the empirical evidence for the association of FEs with dietary patterns or nutritional outcomes is rather weak. A range of studies reports equivocal findings on the association between these FE measures and nutritional/health outcomes or report evidence of weak linkages (Caspi et al., 2012; Feng et al., 2010; Gustafson et al., 2012; Holsten, 2009; Zenk et al., 2011). Indicators of exposure to FE, which conceptualise the FE as a static physical entity, appear to have limited power to explain observed dietary choices in specific locational and social contexts. Somewhat stronger links to dietary outcomes are found in studies that use perception-based measures of the FE. Some of the weak linkages may be attributable to the variations in the methods and techniques used in GIS studies related to data collection, accuracy and classification of outlets (Boruff et al., 2012). GIS-based studies that define the FE in a given "neighbourhood" may ignore the mobility of people traversing several different FEs in the course of their daily activities (Cummins, 2007a; Hillsdon et al., 2015). However, the principal weakness of physical and geospatial "exposure" measures in explaining dietary outcomes appears to arise from the fact that they do not capture the actual use of the FE by households and individuals. Exposure to FEs may not translate into the use of FEs and exposure measures do not reflect the intention, ability or willingness to utilise food outlets and sources (Mattioni et al., 2020). Dietary choices emerge from the utilisation of the FE and it is, therefore, necessary to consider the economic and socio-cultural factors that mediate the influence of the FE on diets (Mattioni et al., 2020). To understand why households adopt certain food purchasing or acquisition practices and choose certain outlets/sources rather than others, an array of factors including affordability (Cummins, 2007b; MacNell et al., 2017), atmosphere and friendliness, physical attributes of outlets (Cannuscio et al., 2014; Chen and Kwan, 2015; Elliston et al., 2017) and transactional elements [e.g., credit] have been considered. The utilisation of the FE by households is one of the most understudied aspects of food access in the FE literature (Downs et al., 2020).

The FE literature appears to lack a reliable indicator of the utilisation of the FE by households within a given static FE. The aggregate community level geo-spatial indicators provide no information on the variations in food acquisition patterns from the FE across households. We aim to address this gap in the literature by developing an indicator of the household's actual utilisation of the external FE for food acquisition – the index of households' interaction with the FE. We develop a metric to assess the utilisation of the external food environment (EFE) by households within a community. We construct an index of households' interaction with the EFE, based on the range of outlets and sources accessed by a household, the diversity and type of food products acquired from the FE, and the intensity of use of the FE for meeting household food requirements. A household's interaction in the external FE may in turn be shaped by its endowments and characteristics, mobility patterns, access to information, preferences, and socio-political or regulatory constraints. We hypothesise that the empirical link between the FE and dietary choices will be stronger when we consider patterns of utilisation rather than mere exposure. The index provides a means to assess how households within a community navigate a given static FE and the extent and intensity of their engagement with both market and non-market elements of the food environment. Using this indicator, we address the following research questions.

1. What is the association between a household's interaction in the external FE and dietary quality?
2. How does the extent of interaction in the FE influence the consumption of NCD-Protect ("desirable, healthy") foods and NCD-Risk ("non-desirable, unhealthy") foods?
3. Does the influence of the household's interaction in the FE on dietary quality vary across rural-urban communities and countries? Are the pathways of impact on dietary quality different in different settings?

The empirical application of the index is undertaken in rural and peri-urban communities in Thailand and Laos, two Southeast Asian countries undergoing food system and dietary transitions, yet at different developmental stages. These contexts serve as country case studies that offer insight into the broader global health security challenge posed by poor diet quality and nutrition-related chronic disease. Poor diets are now among the leading contributors to global morbidity and mortality, yet the pathways through which food environments shape diets remain insufficiently understood, particularly in LMIC settings where patterns of market engagement are shifting. By examining household interaction with the EFE, this study aims to provide a context-sensitive perspective on how food environment utilisation can be linked to dietary behaviour. Our analysis examines the association between the households' interaction with the EFE and the consumption of "desirable healthy" (NCD-Protect) and "non-desirable unhealthy" (NCD-Risk) foods. The findings show substantial variation in how households interact with the FE and that greater engagement is generally associated with a decline in dietary quality. Importantly, the mechanisms underlying this association appear to differ across countries and between rural and peri-urban areas, underscoring the need for greater attention to context in designing food environment policies.

2. Study area

The study areas comprised a purposive selection of two rural and two peri-urban communities each in Chiang Mai Province, Thailand, and Vientiane Province, Laos (Fig. 1). The criteria guiding the selection included geographic diversity, accessibility, ethnic diversity, and variability of FEs. Data collection was preceded by two focus groups in each community to obtain a deeper qualitative understanding of how the local population navigated the FE and to support the positioning of the quantitative findings. The qualitative data collection also aimed at developing relationships and building trust within the communities prior to engaging in the sampling of survey households.

2.1. Thailand

The Thai communities (rural/urban Thailand community codes: R1TH, U1TH, R2TH, U2TH) showed distinct patterns of market integration influenced by their locations. R1TH village, a highland Hmong village in Mae Rim District, was located 5 km from the nearest market and 15 km from the district market, making it reliant on local food sources with limited commercial access. R2TH village, a highland Karen village in Samoeng District, was 29 km from the district market, further emphasising the challenge of integrating into regional trade networks. The peri-urban villages U1TH village and U2TH village in Saraphi District were located only 2 km and 3 km from their respective district markets, facilitating frequent trade, greater access to processed foods, and stronger integration into urban food supply chains. Both peri-urban communities were in close proximity to Chiang Mai city, allowing for greater engagement in commercial agriculture and local trade networks.

The availability of food shops in these communities varied based on their level of market access. In R1TH and R2TH, food shops tended to be small, family-run businesses, primarily selling locally grown vegetables,

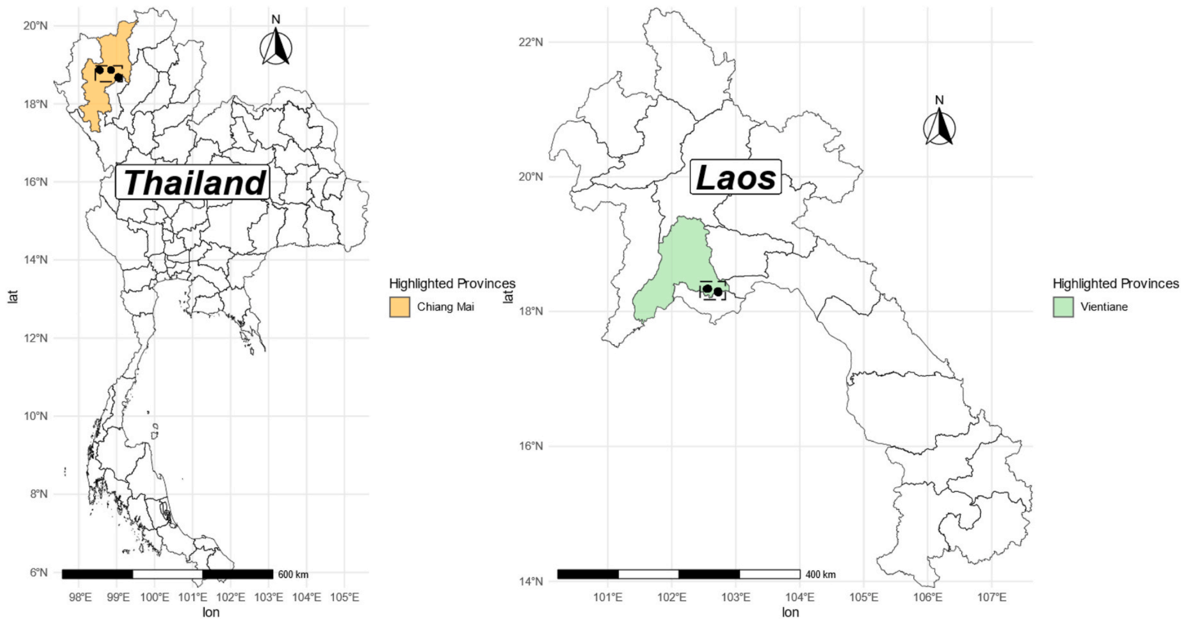


Fig. 1. Study areas.

rice, and handmade products. Many of these shops operated in traditional open-air markets. In U1TH and U2TH, where urban development was expanding, a mix of modern grocery stores and traditional fresh markets offered a wider variety of products, including imported goods and processed foods.

2.2. Laos

Villages in Laos presented a more remote setting and reflected the relatively weaker economic development compared to Thailand. R1LA and R2LA villages were located 30 km and 25 km, respectively, from the nearest district market, limiting their engagement with larger trade networks and predominantly relying on subsistence farming and localised commerce. In contrast, U1LA village and U2LA were relatively more affluent, situated near a highway connection to Vientiane (a 40-min car drive), and located only 3-4 km from the district market – all of which facilitated frequent trade and commercial exchanges.

Market integration in these communities was evident in the structure of their food retail options. R2LA had a largely subsistence-oriented food economy, complemented by small village markets. R1LA had developed a dual-market system, integrating traditional village commerce with larger regional trade networks, where woven textiles, dried fish, and preserved foods are key commercial products. Meanwhile, U1LA and U2LA had a more developed food market, featuring small grocery stores that stock a mix of imported goods and locally sourced staples.

3. Methodology

3.1. Data

We captured the nature of and people's interactions with FEs through a series individual, household, and food outlet surveys in two waves (spanning rainy and dry seasons) from May to October 2023. The surveys (in the supplemental material) included:

- Household questionnaire: a 10-min questionnaire to collect household characteristics, administered to the household head at the beginning of the study.
- Individual questionnaire: a 15-min questionnaire within the same households to gather individual characteristics and general food-related practices and preferences, administered to the man and woman in the household who are most involved in food provision at the beginning of the study.
- Food sourcing questionnaire: a 15-min questionnaire to identify household food sources for various food categories, administered to the household member who has the most knowledge on food preparation during both survey waves.
- Activity and consumption questionnaire: a 10-min time use survey of daily activities and food choices, administered to the individual questionnaire respondents daily for one week during both survey waves.

First, we collected a pro-poor random sample of 30 households in each community using household registers, including household wealth groups (low/medium/high) and ethnicity produced by each community's village chief. The initial household survey was administered to the head of the households and the main household member responsible for food acquisition (in most cases the head's spouse). The survey captured information about the socio-demographic and occupational characteristics of the household. It also included a section that captured the source (s) of 14 ingredients' groups for cooking (e.g. rice, roots, vegetables, fresh fruits, etc), five prepared ready-to-eat foods (e.g. ready-to-eat snacks, fast food restaurants), nine processed and packed foods (e.g. instant noodles, bakery goods, preserved meat), and five drinks (e.g. tea/coffee, milk, sodas, etc). For each food group, the respondent could list up to four sources, i.e. the name and location, the share of the total household's total consumption coming from that source, and the nature (e.g. own production, purchase, exchange, or communal provision). The list of food outlets reported by the participants in any community, formed the basis for creating the ‘universe’ of outlets that are accessible by the community. We then visited the market sources listed by each individual in the communities and collected information about the nature (e.g. market, convenience, store), food groups available, and other information about the opening times and delivery of food services, as well as a qualitative assessment of the cleanliness, food availability, and affordability. Finally, we administered two individual surveys to the head of the households and the spouse. An initial individual questionnaire collected personal characteristics (e.g. education, language, ethnicity), employment, health, and food perceptions and practices (e.g. cooking habits, diet). Following the individual survey, we followed each individual for two one-week periods and captured their food consumption and time use. In particular, individual food consumption was collected through the administration of a Diet Quality Questionnaire (DQQ) using a locally tailored version to Thailand (Global Diet Quality Project, 2025b) and Laos (Global Diet Quality Project, 2025a). The DQQ is a short, standardised tool designed to measure diet quality across countries using simple yes/no questions on the food groups consumed by an individual in the past 24 h. It captures individual adherence to global dietary recommendations by recording intake of both health-promoting and risk-associated foods. The final full dataset covers 236 households and 408 individuals, 265 food outlets, and 5331 person-days of activity and dietary data with valid observations.

The questionnaires were developed in parallel in English, Thai, and Lao through the multilingual research teams, and subsequently tested in the study communities prior to deployment. The Thai and Lao survey supervisors as part of the research team supervised teams of four enumerators who were recruited directly from each study community and who received 2-day survey training alongside ongoing survey supervision. The data collection used interviewer-administrated questionnaires on tablets operating KoboToolbox. However, in the case of the daily activity and consumption questionnaire, to collect the complex daily diary data in a more natural format, paper questionnaires were administered and subsequently entered into digital format using CSPro. All survey data were subsequently imported into Stata 19 for cleaning and analysis.

3.2. Measures and descriptions

3.2.1. Dietary outcome variables

We use three main indicators to assess diet based on the DQQ (Herforth et al., 2024). The Global Dietary Recommendations (GDR) score, ranging from 0 to 18, indicates adherence to global dietary guidelines that include factors protective against non-communicable diseases. A higher GDR score suggests greater compliance with these recommendations. The GDR is a composite index derived from two components: NCD-Protect and NCD-Risk. The GDR score is then calculated by subtracting the NCD-Risk score from the NCD-Protect score and adding 9.

The NCD-Protect score measures adherence to globally recommended healthy dietary practices, focusing on the consumption of nine health-promoting food groups such as fruits, vegetables, pulses, nuts, seeds, and whole grains. Each food group consumed contributes one point, resulting in an overall score ranging from 0 to 9. A higher NCD-Protect score reflects greater compliance with international dietary guidelines. In contrast, the NCD-Risk score assesses adherence to dietary recommendations concerning foods that should be limited or avoided, including sweet beverages, sweet foods, salty packaged snacks, instant noodles, fast food, deep-fried foods, red meat, and processed meat. This score also ranges from 0 to 9, with higher values indicating greater consumption of these unhealthy food groups. Thus, a higher NCD-Risk score represents lower adherence to global dietary guidelines and can serve as an indirect measure of ultra-processed food intake.

The average GDR score is slightly higher in Vientiane (9.72) compared to Chiang Mai (9.36), indicating a marginally better overall alignment with global dietary guidelines in communities in Vientiane (Table 1). The results are driven by a lower NCD-Risk score (1.16) in Vientiane compared to Chiang Mai (1.61), which offset the higher NCD-Protect score in Chiang Mai (1.97) compared to Vientiane (1.88). Urban-rural dynamics differ between Thailand and Laos. In Thailand, peri-urban communities show higher NCD-Protect scores and lower NCD-Risk scores than rural communities (2.15 and 1.59 compared to 1.77 and 1.63), a reflection of greater intake of healthy foods and fewer ultra-processed products. In contrast, the trend in Laos is reversed; rural communities have higher NCD-Protect scores and lower NCD-Risk scores than peri-urban communities (1.95 and 1.05 compared to 1.26 and 1.27), possibly reflecting greater reliance on locally sourced, unprocessed foods.

There is a notable variation in the consumption of different NCD-Protect score food groups across sites and areas. In Chiang Mai, we observe a low intake of whole grains and pulses, suggesting these beneficial food groups are underrepresented in the local diet, mainly in rural areas. On the contrary, dark green leafy vegetables and other vegetables are consumed by 44 and 77 per cent of participants, indicating a stronger preference or greater availability of these vegetable types. In Vientiane, consumption of whole grains and pulses are minimal, while a large proportion of the participants, both in rural and rural areas, consume dark green leafy vegetables and other vegetables. Intake of vitamin A-rich fruits and other fruits is higher in Vientiane too,

Table 1
Summary statistics of the outcome indicators, and consumption of food groups, by country.

	Thailand (Chiang Mai)						Laos (Vientiane)					
	Full sample		Peri-urban		Rural		Full sample		Peri-urban		Rural	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
GDR score (0/18)	9.36	1.61	9.57	1.66	9.13	1.53	9.72	1.26	9.54	1.34	9.89	1.14
NCD-Protect score (0/9)	1.97	1.18	2.15	1.23	1.77	1.09	1.88	0.89	1.82	0.97	1.95	0.80
Whole grains	*0.06*	*0.23*	*0.08*	*0.27*	*0.03*	*0.18*	*0.01*	*0.12*	*0.02*	*0.15*	*0.00*	*0.07*
Pulses	*0.12*	*0.33*	*0.15*	*0.35*	*0.10*	*0.30*	*0.01*	*0.09*	*0.01*	*0.11*	*0.00*	*0.06*
Nuts and seeds	*0.05*	*0.21*	*0.05*	*0.22*	*0.04*	*0.20*	*0.02*	*0.14*	*0.03*	*0.16*	*0.01*	*0.12*
Vitamin A-rich orange vegetables	*0.15*	*0.36*	*0.11*	*0.32*	*0.19*	*0.39*	*0.03*	*0.18*	*0.02*	*0.14*	*0.05*	*0.21*
Dark green leafy vegetables	*0.44*	*0.50*	*0.49*	*0.50*	*0.37*	*0.48*	*0.75*	*0.43*	*0.65*	*0.48*	*0.85*	*0.36*
Other vegetables	*0.77*	*0.42*	*0.77*	*0.42*	*0.77*	*0.42*	*0.69*	*0.46*	*0.66*	*0.47*	*0.71*	*0.45*
Vitamin A-rich fruits	*0.10*	*0.29*	*0.11*	*0.31*	*0.08*	*0.28*	*0.17*	*0.37*	*0.18*	*0.38*	*0.15*	*0.36*
Citrus	*0.03*	*0.17*	*0.04*	*0.19*	*0.02*	*0.14*	*0.03*	*0.18*	*0.05*	*0.22*	*0.01*	*0.11*
Other fruits	*0.26*	*0.44*	*0.35*	*0.48*	*0.16*	*0.37*	*0.17*	*0.38*	*0.19*	*0.39*	*0.15*	*0.35*
NCD-Risk score (0/9)	1.61	1.23	1.59	1.18	1.63	1.27	1.16	0.91	1.27	0.97	1.05	0.83
Soft drinks	*0.08*	*0.28*	*0.07*	*0.25*	*0.11*	*0.31*	*0.23*	*0.42*	*0.30*	*0.46*	*0.17*	*0.38*
Baked/grain-based sweets	*0.09*	*0.29*	*0.12*	*0.32*	*0.07*	*0.25*	*0.01*	*0.08*	*0.01*	*0.09*	*0.00*	*0.05*
Other sweets	*0.07*	*0.26*	*0.10*	*0.30*	*0.04*	*0.21*	*0.04*	*0.19*	*0.05*	*0.21*	*0.03*	*0.18*
Processed meat[§]	*0.20*	*0.40*	*0.19*	*0.40*	*0.20*	*0.40*	*0.07*	*0.25*	*0.08*	*0.26*	*0.06*	*0.24*
Unprocessed red meat	*0.77*	*0.42*	*0.79*	*0.41*	*0.75*	*0.43*	*0.65*	*0.48*	*0.66*	*0.48*	*0.65*	*0.48*
Deep fried food	*0.05*	*0.22*	*0.03*	*0.18*	*0.07*	*0.25*	*0.02*	*0.14*	*0.02*	*0.13*	*0.03*	*0.16*
Fast food & instant noodles	*0.09*	*0.29*	*0.06*	*0.24*	*0.13*	*0.33*	*0.04*	*0.19*	*0.03*	*0.18*	*0.04*	*0.19*
Packaged ultra-processed salty snacks	*0.05*	*0.22*	*0.03*	*0.17*	*0.07*	*0.26*	*0.04*	*0.19*	*0.07*	*0.25*	*0.01*	*0.11*
Sample	2423		1272		1151		2908		1474		1434	

Notes: Food groups capture consumption (1) or non-consumption (0). [§]Consumption of processed meat (e.g. sausages) has double weight in the construction of the NCD-Risk score. Figure A.1 and A.2 show the distribution of the NCD-Risk and NCD-Protect scores. The GDR score is calculated by subtracting the NCD-Risk score from the NCD-Protect score and adding 9.

possibly indicating a greater availability or cultural preference. Some relevant urban-rural trends emerge too. In rural Chiang Mai, we observe a higher consumption of Vitamin A-rich orange vegetables compared to peri-urban communities, however peri-urban participants have double consumption of other fruits compared to the rural people.

Dietary patterns of different NCD-Risk score food groups vary between peri-urban and rural areas (Table 1). In Chiang Mai, the intake of processed meat is overall relatively moderate, while the consumption of unprocessed red meat is significantly higher with 77% of participants consuming it, which may indicate cultural or economic preferences for fresh meat over processed alternatives. The consumption of baked or grain-based sweets (9%) and soft drinks (8%) is infrequent. Similarly, the consumption of deep-fried food and fast food is relatively low (5 and 9%). However, consumption of soft drinks, deep-fried food, fast food, instant noodles, and packaged ultra-processed salty snacks is greater in rural areas than in peri-urban areas. In Vientiane, processed meat consumption is lower, averaging 7%, and unprocessed red meat is consumed less frequently than in Chiang Mai. Finally, 23% of participants consume soft drinks, with a greater proportion in peri-urban areas. Like in Chiang Mai, the consumption of fast food and deep-fried foods is relatively low, yet consistent between peri-urban and rural settings.

3.2.2. Interaction in the external food environment (EFE) index

As explained previously, the universe of outlets that constituted the relevant FE for each community was derived from the complete list of outlets reported as being utilised by any of the surveyed households within that community. The resulting EFE therefore represents the full set of outlets collectively selected and used by community members. The EFE available in a community may depend on the overall food demand in the community, which may in turn be determined by the socio-demographic characteristics of the community. However, this EFE remains exogenous to the individual household, i.e., the individual household is unlikely to influence the nature of the EFE available in the community. We then developed an indicator to capture the extent to which a household interacts with this given EFE, i.e. the degree to which its food is acquired through purchase or other market-based transactions. The multi-dimensional indicator (ranging from 0 to 1) is based on three components:

- **The number of outlets accessed by the household:** This component captures the breadth of food outlets accessed by the household (as identified from the food sourcing module of the household survey). Any household will be accessing only a fraction of all outlets available in the community. The household's score for the range of outlets accessed is converted to a 0-1 index using the Min-Max procedure.
- **The diversity of food products acquired from the EFE:** This component captures the breadth of the food groups acquired by the household from the EFE. The score for this component is the sum of the count of food groups acquired from the EFE, weighted by the Food Composition Score of each food group developed by the World Food Programme (WFP). The score is converted into a 0-1 index using the Min-Max procedure.
- **The intensity of use of the EFE for meeting household food requirements:** This component captures the proportion of each food group acquired from the EFE. The household score for this component is the weighted average of the proportion of requirements for each food group acquired from the EFE, with the weights for each food group being the Food Composition Score for that group (e.g., the acquisition of cereals and pulses from the EFE have a larger weight than the acquisition of sugar from the EFE). The scores for the intensity of use of the EFE are also converted into a 0-1 index using the Min-Max procedure.

The overall households' interaction index is then computed as a simple average of these three component indices, assuming equal weighting:

$$\text{Household EFE Interaction Index} = \frac{(\text{Outlets index}) + (\text{Diversity index}) + (\text{Intensity index})}{3}$$

Low index values, denoting low interaction of the household with the EFE, reflect access to only a limited range of food outlets, low intensity of use, and low diversity of products acquired from the EFE. It should be noted that the household EFE interaction index is computed with respect to the universe of outlets relevant to the entire community. Households may decide to interact with a limited number of outlets based on factors such as convenience, accessibility and affordability. The breadth of interaction with the available outlets, the diversity of food products obtained from these outlets and the intensity of use of the EFE are postulated to be a key determinant of a household's dietary quality.

Fig. 2 shows the distribution of the EFE interaction index and its components (Range, Diversity, and Intensity) across peri-urban and rural areas, by country. At the median, households in Chiang Mai experience higher integration into the EFE (0.61 versus 0.56 in Laos). This difference is primarily driven by greater intensity of use and a wider range of outlets accessed in Chiang Mai compared to Laos. In Chiang Mai, rural households have a higher median EFE interaction index (0.63) with a more compact distribution. In contrast, peri-urban households show a slightly lower mean (0.57) but with a broader spread, suggesting greater variability in their interaction with the FE. The difference between rural and peri-urban households is mainly attributed to the greater intensity of use among rural households (0.81 versus 0.79 in peri-urban communities). In Vientiane, differences between peri-urban and rural households are less pronounced. Household interactions with the EFE are similar at both the aggregate level and across individual components.

3.2.3. Individual and household-level variables

The summary statistics show notable differences in household and individual characteristics across the surveyed communities in Thailand and Laos (Table 2). In Chiang Mai, the average household size is 3.6 members, with rural households tending to be larger than peri-urban ones. Approximately 73% of households engage in agricultural activities, with a higher prevalence in rural areas. The wealth index indicates a relatively higher economic status among peri-urban households. In Vientiane, the average household size is slightly larger at 4.21 members, with a more even distribution between urban and rural areas. While agricultural engagement is similarly high in the full sample (79%), it is markedly lower in peri-urban communities and almost universal in rural areas. The wealth index suggests that peri-urban households in Vientiane have marginally higher economic resources than their rural counterparts, though the gap appears smaller than in Chiang Mai.

At the individual level, gender distribution is balanced across both countries, with a slight majority of female participants (while the surveys allowed participants to disclose diverse gender identities, none did). The age composition varies across locations, with Chiang Mai having a higher proportion of older adults, particularly in rural areas

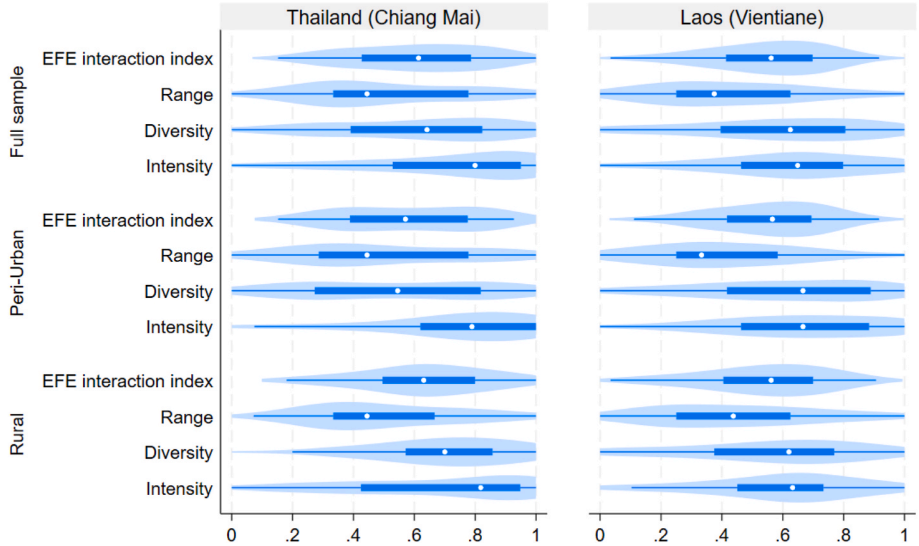


Fig. 2. Violin plots of the EFE interaction index and its components, by site and country.
Notes: The width of each violin represents the density of observations, with white dots indicating the median, thick blue bars representing the interquartile range (IQR), and **thin blue lines (whiskers) extending to the minimum and maximum values.** The distributions of the variables are in light blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Household and *Individual characteristics*

	Thailand (Chiang Mai)						Laos (Vientiane)					
	Full sample		Peri-urban		Rural		Full sample		Peri-urban		Rural	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Household characteristics												
Household size	3.60	2.19	2.95	1.81	4.33	2.37	4.21	1.87	4.22	1.91	4.20	1.84
Agricultural household (0 = no, 1 = yes)	0.73	0.44	0.69	0.47	0.78	0.42	0.79	0.41	0.62	0.49	0.97	0.18
Wealth index	0.79	0.18	0.80	0.18	0.77	0.18	0.73	0.15	0.74	0.10	0.72	0.19
Observations (household-level)	116		61		55		120		60		60	
Individual characteristics (proportions)												
Sex												
Male	0.45	0.50	0.40	0.49	0.50	0.50	0.39	0.49	0.35	0.48	0.43	0.50
Female	0.55	0.50	0.60	0.49	0.50	0.50	0.61	0.49	0.65	0.48	0.57	0.50
Age (years)	54.57	16.01	61.78	15.40	47.04	12.91	50.38	12.66	52.29	12.61	48.36	12.45
Observations (individual-level)	188		96		92		220		113		107	
Observations (day-level)	2423		1272		1151		2908		1474		1434	

Note: The EFE interaction index takes values between 0 and 1. The wealth index is based on a score that captures the ownership of seven assets (TV, rice cooker, mobile phone, computer, motorbike, car, refrigerator) and normalised [0,1] (Haenssgen et al., 2019).

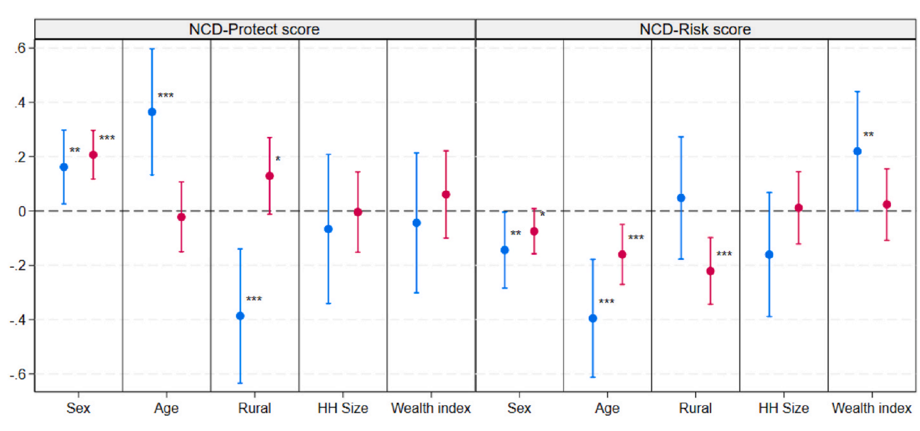


Fig. 3. Differences between socio-demographic characteristics and dietary outcomes (NCD-Protect and NCD-Risk scores) in Thailand and Laos.

where nearly 40% of respondents are over 60 years old. By contrast, Vientiane's population is slightly younger, with a greater concentration of individuals in the middle-age range.

3.2.4. Dietary patterns across individual and household characteristics

Fig. 3 reports differences in dietary outcomes across socio-demographic characteristics in Thailand and Laos. In Thailand, women have overall better diets than men, with significantly higher NCD-Protect scores (0.162, $p < 0.05$) and lower NCD-Risk scores (−0.144, $p < 0.05$). Dietary quality improves with age, with older adults reporting significantly higher NCD-Protect scores (0.364, $p < 0.01$) and lower NCD-Risk scores (−0.395, $p < 0.01$). Rural households show lower NCD-Protect scores compared with urban households (−0.387, $p < 0.01$), reflecting more limited access to or consumption of healthier foods. Wealthier households report greater consumption of unhealthy foods (0.220, $p < 0.01$). By contrast, differences by household size are not statistically significant.

In Laos, the associations are more nuanced. Women have significantly higher NCD-Protect scores (0.206, $p < 0.01$) and lower NCD-Risk scores (−0.075, $p < 0.10$), confirming gender as a consistent factor across both countries. Rural households consume fewer unhealthy foods than their urban counterparts (−0.221, $p < 0.01$), while at the same time having higher NCD-Protect scores (0.129, $p < 0.10$), indicating an overall better diet profile. Age does not affect the consumption of protective foods, but older adults consume fewer unhealthy foods (−0.160, $p < 0.01$). Household size and wealth do not show any consistent relationship with dietary outcomes.

Note: Estimates are from separate OLS regressions of NCD-Protect and NCD-Risk scores on household and individual characteristics (sex, rural/urban location, household size, asset ownership, and age), run separately for Thailand and Laos. Household size, asset ownership, and age were split at the median. Reference categories are: male (sex), urban (location), small household (≤median), low assets (≤median), and younger age (≤median). By construction, the coefficients represent the mean differences in dietary scores between groups, while the estimations provide the statistical significance of these differences. Standard errors are clustered at the household level. Points show mean differences relative to the reference group, with 95% confidence intervals. Full results in Table A.1. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

3.3. Multi-level analysis

Due to the differences in FEs between the field sites that emerged from the focus groups, we stratified the analysis into sub-samples for Chiang Mai and Vientiane villages. We employed multi-level regression models for dietary intakes to account for the hierarchical structure of our data (i.e. individual dietary choices nested within households, which are nested within villages) (Rabe-Hesketh and Skrondal, 2022). The 3-level (individual > household > village) random intercept models were estimated using Stata (version 19) with the MIXED commands. The plots were generated using the user-written command COEFPLOT (Jann, 2014).

We estimated two sets of multi-level models sharing the same specifications:

- Diet quality: Multi-level linear regression models were estimated for dietary quality, using the NCD-Protect and NCD-Risk scores as separate dependent variables. The NCD-Protect score captures the intake of protective food groups (e.g. fruits, vegetables, whole grains), while the NCD-Risk score captures the intake of risk-associated food groups (e.g. sugary drinks, processed foods).
- Specific food group consumption: A series of multi-level probability linear regression models was estimated to examine the determinants of whether each individual food group was consumed (yes/no). These models were run separately for all food groups that compose the NCD-Protect and NCD-Risk scores.

Each model included individual-level variables (sex, age, and age squared to capture potential non-linear relationships) and household-level variables (household size, farming status, a wealth index based on asset ownership, and interaction with the EFE interaction index, which is our variable of interest). The models accounted for three levels of data: individual, household, and village. The wealth index was constructed as a score that captures the ownership of seven assets (TV, rice cooker, mobile phone, computer, motorbike, car, refrigerator) and normalised [0,1] (Haenssgen et al., 2019). The EFE interaction index, our primary explanatory variable, was a composite score derived from the density of local food outlets, market accessibility, and food availability. Finally, we estimated each model using the full sample for each country and separately for the rural and peri-urban sub-samples.

4. Regression results

4.1. Interaction with the external food environment and diets

Fig. 4 presents the coefficients for the EFE interaction index in the multi-level models with NCD-Protect and NCD-Risk scores as dependent variables (coefficients of socio-economic control variables omitted for simplicity). The full estimations are in Tables A.2-A.5 in the Appendix and the coefficients reflect individual-level variation within households and villages. The results indicate a distinct divergence in the association between EFE interaction and diet quality across locations and countries.

In Thailand, greater interaction with the EFE is significantly associated with lower consumption of healthy foods, whereas in Laos the association is not statistically significant (Table A.2 and Table A.4). Households that engage more with the EFE tend to eat fewer health-promoting foods, as shown by the negative association with the NCD-Protect score (−0.593, $p < 0.1$). The association is particularly strong in rural areas (−1.003, $p < 0.05$), where greater reliance on the EFE is linked to noticeably lower healthy diet. In peri-urban Thailand, the relationship is weaker and not statistically significant, suggesting that better market access does not necessarily lead to healthier diets. Besides exposure to EFE, sex is the main driver of consumption choices. Within households and villages, in Thailand women are correlated with higher consumption of healthy food (0.094, $p < 0.05$). In Laos, women are associated with 0.192 ($p < 0.01$) higher NCD-Protect scores than men, with a larger gain in urban than rural areas (0.228, $p < 0.01$ and 0.152, $p < 0.01$, respectively). The variance components and intraclass correlation coefficients (ICC) show that most of the variation in dietary outcomes is at the household and individual levels, with limited variance at the village level. Values are higher in Thailand than in Laos, indicating stronger within-community differences across households. In Thailand, this pattern is more pronounced in peri-urban areas than in rural areas. In Laos, household- and individual-level correlations are about half those observed in Thailand, with little difference between peri-urban and rural communities. In both countries, village-level variance is low, and EFE factors, while relevant, do not fully explain variations in diet quality.

The NCD-Risk models (Table A.3 and Table A.5) show no significant association between EFE interaction and NCD-Risk scores in Thailand. In contrast, Laos presents a different trend, where greater EFE interaction is consistently associated with higher NCD-Risk scores across the full sample (0.511, $p < 0.01$) and peri-urban and rural samples (0.420, $p < 0.1$ and 0.492, $p < 0.05$, respectively), providing evidence that in these settings access to markets and commercial food outlets may drive higher consumption of ultra-processed and unhealthy foods. Besides interaction with the external food environment, gender and age are the main factors associated with unhealthy food consumption within households and villages in both countries. In Thailand, females are associated with a decrease in the NCD-Risk scores (−0.159, $p < 0.05$) in peri-urban areas. In Laos, females are associated with lower NCD-Risk scores in the full sample (−0.120, $p < 0.01$) and in peri-urban areas (−0.187, $p < 0.01$). In rural Thailand, a unit increase in age is associated

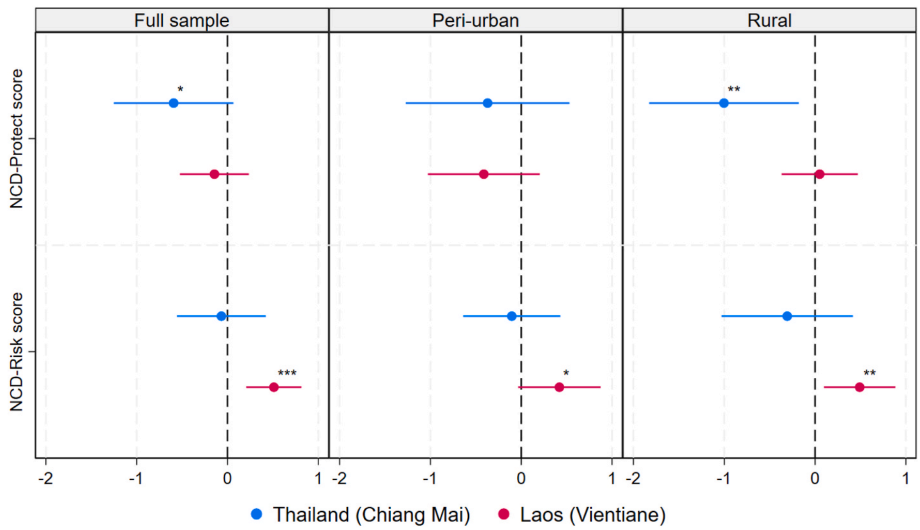


Fig. 4. Coefficients of the EFE independent variable from a set of multi-level models with NCD-Risks score and NCD-Protect score as dependent variables, by location and country (Thailand and Laos).
Note: The unit of analysis is at the individual/day level. Models include three levels (village > household > individual) and are controlled for sex, age, household size, whether it is an agricultural household, and wealth index. Significance levels are denoted as follows: *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$. Full estimations in Tables A.2 – A.5 in the Appendix.

with a 0.025 ($p < 0.1$) decrease in the NCD-Risk score, with the significant relationship driven by rural areas (−0.066, $p < 0.01$). In Laos, by contrast, age is positively associated with higher consumption of healthy foods (0.031, $p < 0.01$), with this pattern driven primarily by households in rural areas (0.044, $p < 0.01$). In both cases, the quadratic term is significant but close to zero, indicating a diminishing marginal effect as individuals grow older. The variance components and intraclass correlation coefficients (ICC) indicate a reduced role of household and individual level in consumption of unhealthy food, compared to NCD-Protect models, with the biggest reduction in Thailand where values are halved. However, the variation in unhealthy diets is attributable to differences at the individual levels, which hints at the role of preference, convenience, and taste.

4.2. *Interaction with the external food environment and consumption of food groups*

Figs. 5 and 6 present the coefficients of the EFE interaction index from the multi-level models estimating its correlation with the consumption of NCD-Protect and NCD-Risk food groups, by country and location. The full estimations are reported in the Supplementary Material. In Thailand, greater interaction with the EFE is negatively associated with the consumption of NCD-Protect foods, primarily due to a reduction in the likelihood of consumption of whole grains and other fruits (−0.116, $p < 0.1$ and −0.225, $p < 0.05$). However, the dynamics differ between peri-urban and rural communities. In peri-urban communities, greater interaction with the EFE is associated with a higher likelihood of consuming nuts and seeds (0.075, $p < 0.05$) and other

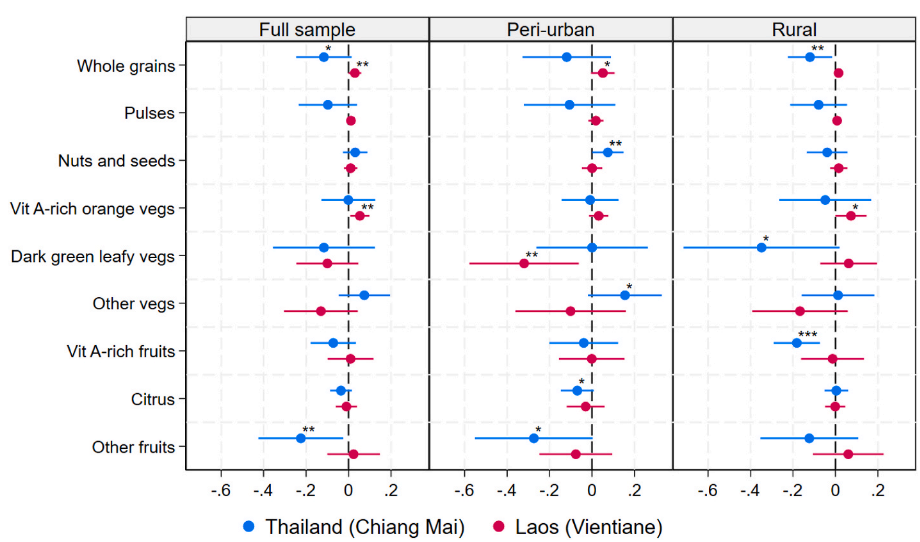


Fig. 5. Coefficients of the EFE independent variable from a set of multi-level models with consumption of individual NCD-Protect food groups as dependent variables, by location and country (Thailand and Laos).
Note: Models include three levels (village > household > individual) and are controlled for sex, age, household size, whether it is an agricultural household, and wealth index. The unit of analysis is at the individual/day level. Significance levels are denoted as follows: *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$. Full estimations are reported in Supplementary Tables S1–S3 (Thailand) and S7-S9 (Laos).

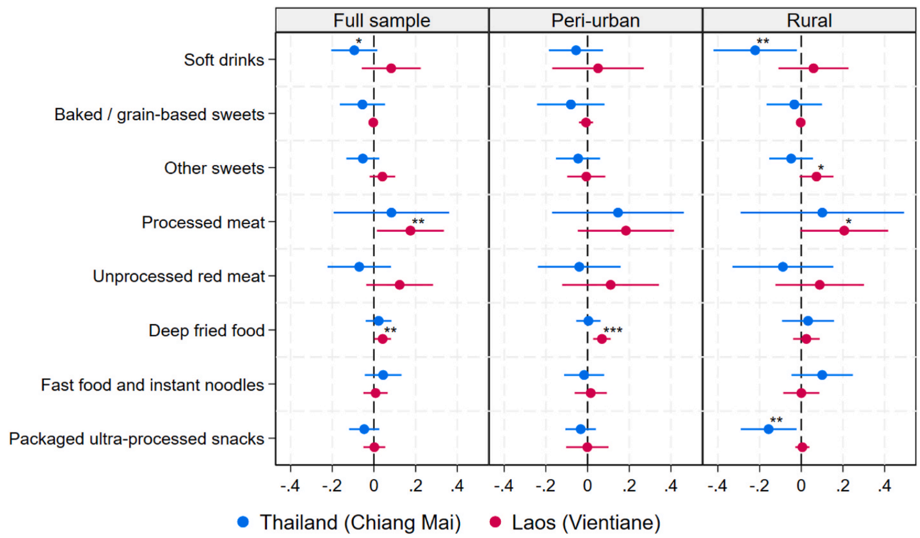


Fig. 6. Coefficients of the EFE independent variable from a set of multi-level models with consumption of individual NCD-Risk food groups as dependent variables, by location and country (Thailand and Laos).
Note: Models include three levels (village > household > individual) and are controlled for sex, age, household size, whether it is an agricultural household, and wealth index. The unit of analysis is at the individual/day level. Significance levels are denoted as follows: *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$. Full estimations are reported in Supplementary Tables S4–S6 (Thailand) and S10-S12 (Laos).

vegetables (0.155, $p < 0.1$), while simultaneously being linked to a reduction in the consumption of citrus fruits and other fruits (−0.069, $p < 0.1$ and −0.274, $p < 0.05$). In rural areas, the association between greater interaction with the EFE and a lower likelihood of consuming healthy foods extends to whole grains (−0.120, $p < 0.05$), dark green leafy vegetables (−0.348, $p < 0.1$), and vitamin A-rich fruits (−0.182, $p < 0.01$).

In Laos, while the effect of EFE interaction is not significant for the overall NCD-Protect score, it has a significant relationship to specific food groups. Greater interaction with the EFE is significantly associated with an increased likelihood of consumption of whole grains (0.030, $p < 0.05$) and vitamin A-rich orange veg (0.054, $p < 0.05$) in the full sample, primarily associated with an increase likelihood in the consumption of vitamin A-rich vegs among rural individuals (0.073, $p < 0.01$). In peri-urban communities, there is evidence that greater interaction with the EFE is associated with a decreased likelihood of consuming dark green leafy vegetables (−0.320, $p < 0.05$).

Fig. 6 reports the effect of EFE interaction on the consumption of food groups within the NCD-Risk score. The results show a stronger and more consistent association between EFE participation and the intake of unhealthy food items, with significant correlation predominantly in Laos. Greater participation in the EFE is significantly associated with an increase in the likelihood of consuming processed meat (0.175, $p < 0.05$) and deep-fried food in the full sample (0.042, $p < 0.05$) as well as in peri-urban settings (0.069, $p < 0.01$). In Thailand, greater interaction with the EFE is associated with a lower likelihood of consuming soft drinks in the full sample (−0.094, $p < 0.01$) and in rural communities (−0.221, $p < 0.05$), as well as ultra-processed snacks (−0.157, $p < 0.05$) in rural communities.

5. Discussion

Our analysis of granular food-related behaviour data from rural and peri-urban households in Thailand and Laos has demonstrated that greater interaction with the EFE (EFE) is linked to lower dietary quality. However, the pathways through which EFE interaction influences diet quality differ across the two study sites.

In Thailand, greater interaction with the EFE is not necessarily associated with an increased consumption of unhealthy foods. Instead, it is linked to a decline in the intake of healthy foods, a pattern that has historically been observed in the study of 'food deserts' (Cummins, 2007b). In this case, market-based sources seem to offer less variety than non-market-based sources, thus shifting and constraining the dietary choices. Households with higher EFE interaction scores have lower consumption of protective dietary components, such as whole grains and pulses, which suggests that an expanded reliance on market-based food sources does not ensure greater dietary diversity in healthier options due to desirability or affordability constraints. This finding underscores that EFEs in Thailand may lack adequate healthy food options or that market-based acquisition is displacing traditional sources of nutrient-rich foods. The transition towards greater EFE reliance could inadvertently weaken traditional dietary habits that are more aligned with global dietary recommendations, raising concerns about long-term nutritional implications. Similar observations have been made in studies that examine food retail environments in low-, middle-, and high-income countries (Christian, 2012; Gustafson et al., 2012).

In contrast, in Laos, greater interaction with the EFE is associated with higher consumption of unhealthy foods, characteristic of 'food swamps' (Rose et al., 2010). Households that are more integrated into the external food market tend to consume more processed and ultra-processed foods, including sweetened beverages and packaged snacks. This suggests that the commercial FE in Laos is dominated by calorie-dense, nutrient-poor options, reinforcing structural barriers to healthy eating. The strong positive association between EFE interaction and the NCD-Risk score highlights that, in Laos, the expansion of food markets does not necessarily improve dietary quality but instead facilitates increased consumption of ultra-processed and energy-dense foods. This raises critical concerns about the unintended public health consequences of food market expansion, particularly in regions where regulatory mechanisms to promote healthy diets are weak and public health messaging limited. This finding aligns with research indicating that food swamps are a growing concern in many low- and middle-income settings (Feng et al., 2010; Zenk et al., 2011).

These findings constitute an important empirical advancement of the broader literature on FEs, which suggests that access alone does not necessarily translate into improved dietary outcomes (Caspi et al., 2012; Turner et al., 2018). This perspective is consistent with Downs et al. (2020), who emphasise that food environment interventions should consider the interplay between formal and informal systems of food provisioning. This challenges the assumption that simply increasing engagement with food markets will enhance dietary diversity and quality (Mattioni et al., 2020). Rather, the variation in findings between Thailand and Laos highlights the complex interplay between individual food choices and the structure of FEs. While individual behaviours play a significant role in shaping dietary patterns, supply-side drivers remain critical. (Mattioni et al., 2020). The composition of available foods in the market, pricing structures, and consumer awareness thus influence dietary choices. Studies have shown that even when healthier options are available, price and promotional strategies often favour less nutritious foods, leading to suboptimal dietary patterns (Glanz et al., 2007; Herforth and Ahmed, 2015).

The findings highlight important pathways through which participation in the EFE influences households' dietary quality, i.e., through effects on consumption NCD-Protect and NCD-Risk foods. The magnitude and direction of these effects appear to depend on the stage of development of the EFE (with later stages of development associated with greater availability of NDC-Risk products, e.g., processed foods and sweetened beverages) and the stage of transition of communities to complete reliance on the EFE for food acquisition. In communities (e.g., in Laos) that retain substantial reliance on subsistence farming or non-market sources for NCD-Protect foods, the main effect of EFE engagement on dietary quality appears to arise from the increased opportunity to consume NCD-Risk foods. However, in communities (e.g., in Thailand) that have transitioned further towards complete reliance on the EFE for food acquisition, the principal effect of interaction with the EFE appears to arise from reduced consumption of NCD-Protect foods (e.g., wholegrains), that may be replaced by NCD-Risk options (e.g., polished grain).

These findings highlight the need for a more strategic approach to food system interventions that not only improve access but also ensure that the nutritional composition of market-available foods supports healthier diets. In Thailand, strategies should focus on strengthening the availability and affordability of nutrient-dense foods while safeguarding traditional dietary practices that may be at risk of displacement due to greater market integration. In Laos, policy efforts should prioritise regulatory mechanisms to counteract the proliferation of unhealthy foods, including taxation on sugar-sweetened beverages, restrictions on ultra-processed food marketing, and improved front-of-pack nutrition labelling. Without such targeted interventions, greater EFE participation may continue to reinforce dietary patterns that heighten the risk of nutrition-related chronic diseases.

A crucial implication of these findings is the need for policies that improve the availability and affordability of healthy food options within the EFE while simultaneously promoting education and awareness about healthy eating practices. In food deserts, policies could focus on enhancing the supply of nutrient-dense foods through improved food retail planning (Shaw et al., 2020) and incentivising vendors to stock healthier options (Kaur, 2023). In food swamps, regulatory measures such as taxation of sugar-sweetened beverages (Niebylski et al., 2015), front-of-pack nutrition labelling (Champagne et al., 2020), and restrictions on unhealthy food marketing (Taillie et al., 2019) could help curb the overconsumption of processed and unhealthy foods.

Additionally, reformulating food products to reduce unhealthy ingredients, improving food labelling clarity, and marketing healthier options remain critical strategies for guiding consumer choices. Studies have shown that clearer nutrition labels and targeted public health campaigns can positively influence dietary behaviours, particularly in settings where unhealthy foods are aggressively marketed (Moore et al., 2008; Wilkins et al., 2017). Furthermore, engaging local food vendors and retailers in healthier food provisioning through financial and technical support may help bridge the gap between food availability and healthier consumer choices. Ultimately, these findings reinforce the need for a holistic approach to food policy, one that ensures that increasing market participation translates into improved dietary patterns rather than exacerbating nutritional inequalities.

6. Conclusion

This study contributes to the growing body of research on FEs by introducing a novel index to assess the extent of household interaction with the EFE. The findings show that greater interaction with the EFE is generally associated with lower dietary quality, although the mechanisms through which this occurs vary between Thailand and Laos, possibly reflecting the different stages in their transitions towards market reliance.

In Thailand, greater households' interaction with the EFE is associated with a reduced intake of healthier food options, a pattern that had historically been observed in the study of 'food deserts'. This pattern suggests a transition stage where traditional dietary staples remain, but the reliance on market-based sources decreases the consumption of nutrient-rich traditional foods, rather than promoting dietary diversity. Instead, in Laos, increased interaction with the EFE corresponds significantly with higher consumption of ultra-processed and unhealthy foods, indicative of 'food swamps'. This aligns with an earlier transition stage, marked by the initial introduction of processed products into diets traditionally dominated by locally sourced staples. These distinct pathways highlight that the effects of low and high interaction from market-based food environments depend substantially on the stage of the community's market transition. Although our cross-sectional data limits the ability to definitively establish causality or to fully characterise the stages of dietary transition, the findings are indicative of ongoing processes within agricultural and rural communities towards greater market dependence.

While the study is grounded in two Southeast Asian countries, the insights it generates have broader relevance at regional and global level. Poor diet quality is now a leading contributor to morbidity and mortality worldwide and is increasingly recognised as a threat to health system sustainability. Understanding how households navigate and utilise food environments offers a more nuanced and behaviourally grounded perspective than exposure-based metrics alone and the findings suggest that household-level patterns of food acquisition provide valuable indicators of how structural food system changes manifest in everyday dietary practices.

The implications of these findings also underscore the need for policy interventions that extend beyond increasing food availability. While improving physical access to food sources is necessary, it is not sufficient to promote healthier dietary choices. Policies should focus on enhancing the affordability and accessibility of nutritious foods while simultaneously curbing the prevalence and appeal of unhealthy options. Regulatory measures, such as product reformulation (Fanzo et al., 2023; Federici et al., 2019), front-of-pack labelling (Champagne et al., 2020), taxation of unhealthy food (Niebylski et al., 2015), and restrictions on unhealthy food marketing (Taillie et al., 2019), could play a critical role in mitigating the adverse effects of market developments. Additionally, consumer education initiatives should be strengthened to improve dietary literacy and encourage informed food choices.

Addressing dietary quality requires a comprehensive and context-sensitive approach that considers the complex interplay between FEs, consumer preferences, and economic constraints. Ensuring that healthier dietary choices are not only available but also accessible, affordable, and culturally acceptable remains a critical challenge for policymakers. By integrating FE research with broader public health and agricultural policies, more effective and sustainable strategies can be developed to improve dietary outcomes in diverse settings.

Ethical approval

The research had been reviewed and approved by the University of Reading School of Agriculture, Policy and Development Ethics Committee (ref. 1961D) and the Lao PDR University of Health Sciences Research Ethics Committee (ref. 395/REC). Chiang Mai University Research Ethic Committee waived separate review requirements following approval from the University of Reading.

Funding sources

This research was funded by Innovative Methods and Metrics for Agriculture and Nutrition Actions (IMMANA, ref. 3.03), which is co-funded with UK Aid from the UK government and the Bill & Melinda Gates Foundation, and is led by the London School of Hygiene and Tropical Medicine (LSHTM), in partnership with Tufts University and the University of Sheffield. The funders had no role in study design; in the collection, analysis and interpretation of data; in the writing of the report; and in the decision to submit the article for publication.

CRediT authorship contribution statement

Giacomo Zanello: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Marco J. Haenssgen:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Prasit Leepreecha:** Conceptualization, Investigation, Supervision, Writing – review & editing. **Eric Deharo:** Conceptualization, Investigation, Supervision, Writing – review & editing. **Chittur S. Srinivasan:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gfs.2026.100916.

Appendix

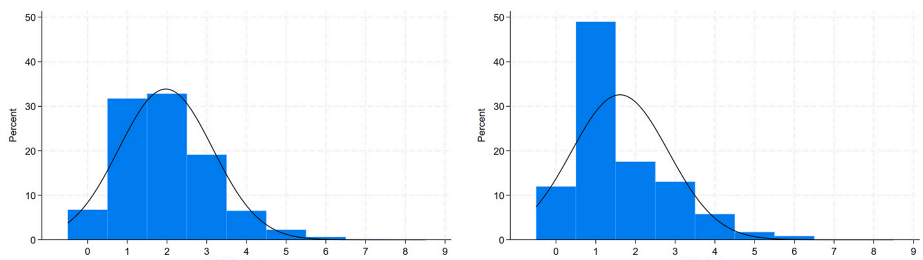


Fig. A.1. Distribution of outcome variables (NCD-Protect and NCD-Risk), in Thailand.

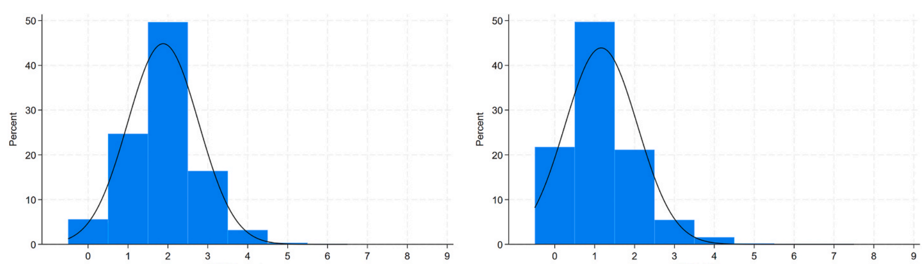


Fig. A.2. Distribution of outcome variables (NCD-Protect and NCD-Risk), in Laos.

Table A.1
Differences between socio-demographic characteristics and dietary outcomes (NCD-Protect and NCD-Risk scores) in Thailand and Laos.

	Thailand (Chiang Mai)			Laos (Vientiane)		
	NCD-Risk score	NCD-Protect score	Obs.	NCD-Risk score	NCD-Protect score	Obs.
Sex						
Male	1.689	1.879	1062	1.211	1.754	1116
Female	1.545	2.041	1361	1.136	1.961	1792
Difference	−0.144**	0.162**		−0.075*	0.206***	
Age						
Younger	1.586	2.154	1272	1.273	1.818	1474
Older	1.633	1.767	1151	1.052	1.947	1434
Difference	0.048	−0.387***		−0.221***	0.129*	
Residence						
Peri-urban	1.656	1.990	1706	1.160	1.883	1776
Rural	1.495	1.923	717	1.171	1.879	1132
Difference	−0.161	−0.067		0.012	−0.004	

(*continued on next page*)

Table A.1 (*continued*)

	Thailand (Chiang Mai)			Laos (Vientiane)		
	NCD-Risk score	NCD-Protect score	Obs.	NCD-Risk score	NCD-Protect score	Obs.
Household size						
Small household	1.466	1.999	852	1.157	1.863	2017
Large household	1.686	1.955	1571	1.181	1.924	891
Difference	0.220**	−0.044		0.024	0.061	
Wealth						
Low wealth	1.838	1.758	1014	1.229	1.891	1739
High wealth	1.443	2.123	1409	1.068	1.868	1169
Difference	−0.395***	0.364***		−0.160***	−0.023	

Note: Household size, asset ownership, and age categories were split at the median. The reported statistics are sample means, while the significance levels of the differences are derived from separate OLS regressions of NCD-Protect and NCD-Risk scores on household and individual characteristics (sex, rural/urban location, household size, asset ownership, and age), run separately for Thailand and Laos. Standard errors are clustered at the household level. Significance levels: *p < 0.10, **p < 0.05, ***p < 0.01.

Table A.2
Multilevel model of NCD-Protect score in Thailand (Chiang Mai), by location. For each location (full sample, peri-urban, and rural), null model, only EFE interaction index, and full model estimations are reported.

	Full Sample			Peri-urban			Rural		
	Null	Market	Full	Null	Market	Full	Null	Market	Full
EFE interaction index		−0.562*	−0.593*		−0.459	−0.371		−0.775**	−1.003**
		(0.324)	(0.336)		(0.456)	(0.460)		(0.363)	(0.420)
Sex (male is baseline)			0.094**			0.123			0.069
			(0.046)			(0.078)			(0.062)
Age			0.002			0.023			−0.028
			(0.012)			(0.021)			(0.024)
Age (squared)			0.000			−0.000			0.000
			(0.000)			(0.000)			(0.000)
Household size			0.004			0.090			−0.000
			(0.033)			(0.068)			(0.033)
Agricultural household			−0.071			−0.007			−0.206
			(0.156)			(0.221)			(0.213)
Wealth index			0.300			−0.520			0.645
			(0.393)			(0.676)			(0.451)
Constant	1.954***	2.295***	1.880***	2.188***	2.457***	1.654*	1.719***	2.202***	2.484***
	(0.132)	(0.229)	(0.482)	(0.100)	(0.285)	(0.863)	(0.0991)	(0.236)	(0.617)
Level 1 variance (village)	0.053***	0.040***	0.019**	0.000	0.000	0.000	0.008**	0.000	0.000
	(0.025)	(0.020)	(0.015)	(0.000)	(0.000)	(0.000)	(0.010)	(0.000)	(0.000)
Level 2 variance (household)	0.419***	0.411***	0.407***	0.528***	0.517***	0.494***	0.256***	0.242***	0.239***
	(0.032)	(0.031)	(0.032)	(0.057)	(0.056)	(0.053)	(0.030)	(0.028)	(0.028)
Level 3 variance (individual)	0.005**	0.005**	0.000	0.039***	0.039***	0.024***	0.000	0.000	0.000
	(0.007)	(0.007)	(0.000)	(0.014)	(0.014)	(0.012)	(0.000)	(0.000)	(0.000)
Residual	0.959	0.959	0.959	0.976	0.976	0.976	0.929*	0.928*	0.925*
	(0.014)	(0.014)	(0.014)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Intraclass correlation coefficient (ICC, Level 1)	0.037	0.028	0.014	0.000	0.000	0.000	0.007	0.000	0.000
Intraclass correlation coefficient (ICC, Level 2)	0.329	0.318	0.308	0.342	0.338	0.331	0.222	0.207	0.206
Intraclass correlation coefficient (ICC, Level 3)	0.332	0.322	0.308	0.367	0.363	0.347	0.222	0.207	0.206
Conditional Nakagawa's R-squared	0.208	0.212	0.199	0.234	0.234	0.215	0.183	0.200	0.174
Marginal Nakagawa's R-squared	0.000	0.005	0.051	0.000	0.002	0.069	0.000	0.011	0.064
Akaike information criterion (AIC)	7056.4	7055.5	7059.2	3753.0	3755.9	3759.6	3293.8	3291.8	3299.2
Sample size	2423	2423	2423	1272	1272	1272	1151	1151	1151

Note: Standard errors are in parentheses. Statistical significance is denoted by asterisks, *p < 0.10, **p < 0.05, ***p < 0.01.

Table A.3
Multilevel model of NCD-Risk score in Thailand (Chiang Mai), by location. For each location (full sample, peri-urban, and rural), null model, only EFE interaction index, and full model estimations are reported.

	Full Sample			Peri-urban			Rural		
	Null	Market	Full	Null	Market	Full	Null	Market	Full
EFE interaction index		0.402	−0.068		0.237	−0.104		0.688	−0.307
		(0.260)	(0.250)		(0.304)	(0.273)		(0.460)	(0.370)
Sex (male is baseline)			−0.091			−0.159**			0.020
			(0.061)			(0.073)			(0.101)
Age			−0.025*			−0.026			−0.066**
			(0.013)			(0.018)			(0.028)
Age (squared)			0.000			0.000			0.000*
			(0.000)			(0.000)			(0.000)
Household size			−0.005			0.026			0.008

(continued on next page)

Table A.3 (*continued*)

	Full Sample			Peri-urban			Rural		
	Null	Market	Full	Null	Market	Full	Null	Market	Full
			(0.024)			(0.040)			(0.029)
Agricultural household			−0.320***			−0.391***			−0.150
			(0.115)			(0.132)			(0.192)
Wealth index			0.185			−0.756*			1.011**
			(0.292)			(0.419)			(0.401)
Constant	1.579***	1.335***	2.810***	1.569***	1.429***	3.779***	1.595***	1.161***	2.882***
	(0.124)	(0.207)	(0.463)	(0.220)	(0.285)	(0.677)	(0.113)	(0.336)	(0.677)
Level 1 variance (village)	0.056***	0.061***	0.031***	0.088**	0.088**	0.055**	0.013**	0.050**	0.000
	(0.022)	(0.025)	(0.015)	(0.049)	(0.049)	(0.031)	(0.013)	(0.035)	(0.000)
Level 2 variance (household)	0.186***	0.179***	0.140***	0.163***	0.160***	0.128***	0.214***	0.194***	0.086***
	(0.021)	(0.020)	(0.017)	(0.026)	(0.025)	(0.019)	(0.034)	(0.033)	(0.026)
Level 3 variance (individual)	0.073***	0.072***	0.048***	0.074***	0.074***	0.015***	0.069***	0.069***	0.091***
	(0.013)	(0.013)	(0.012)	(0.017)	(0.017)	(0.011)	(0.021)	(0.021)	(0.024)
Residual	1.187***	1.187***	1.188***	1.063	1.063	1.064	1.325***	1.325***	1.324***
	(0.018)	(0.018)	(0.018)	(0.022)	(0.022)	(0.022)	(0.029)	(0.029)	(0.029)
Intraclass correlation coefficient (ICC, Level 1)	0.034	0.041	0.022	0.063	0.064	0.043	0.008	0.031	0.000
Intraclass correlation coefficient (ICC, Level 2)	0.159	0.16	0.121	0.181	0.179	0.145	0.14	0.149	0.057
Intraclass correlation coefficient (ICC, Level 3)	0.208	0.208	0.156	0.234	0.233	0.157	0.183	0.191	0.117
Conditional Nakagawa's R-squared	0.208	0.212	0.199	0.234	0.234	0.215	0.183	0.200	0.174
Marginal Nakagawa's R-squared	0.000	0.005	0.051	0.000	0.002	0.069	0.000	0.011	0.064
Akaike information criterion (AIC)	7534.5	7534.2	7509.8	3822.9	3824.3	3800.4	3706.6	3707.0	3699.0
Sample size	2423	2423	2423	1272	1272	1272	1151	1151	1151

Note: Standard errors are in parentheses. Statistical significance is denoted by asterisks, *p < 0.10, **p < 0.05, ***p < 0.01.

Table A.4

Multilevel model of NCD-Protect score in Laos (Vientiane), by location. For each location (full sample, peri-urban, and rural), null model, only EFE interaction index, and full model estimations are reported.

	Full Sample			Peri-urban			Rural		
	Null	Market	Full	Null	Market	Full	Null	Market	Full
EFE interaction index		−0.027	−0.144		−0.487	−0.413		0.379*	0.051
		(0.184)	(0.194)		(0.299)	(0.315)		(0.205)	(0.214)
Sex (male is baseline)			0.192***			0.228***			0.152***
			(0.036)			(0.055)			(0.047)
Age			0.031***			0.010			0.044***
			(0.012)			(0.021)			(0.014)
Age (squared)			−0.000***			−0.000			−0.001***
			(0.000)			(0.000)			(0.000)
Household size			−0.001			0.004			−0.0016
			(0.020)			(0.030)			(0.023)
Agricultural household			0.057			−0.040			0.268
			(0.094)			(0.111)			(0.220)
Wealth index			0.464*			−0.058			0.578**
			(0.240)			(0.534)			(0.226)
Constant	1.880***	1.895***	0.733**	1.814***	2.084***	1.687**	1.943***	1.742***	0.164
	(0.051)	(0.112)	(0.345)	(0.055)	(0.174)	(0.660)	(0.073)	(0.134)	(0.413)
Level 1 variance (village)	0.0055***	0.005***	0.006***	0.000	0.000	0.000	0.007***	0.009***	0.009***
	(0.0037)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)	(0.005)	(0.006)	(0.006)
Level 2 variance (household)	0.105***	0.105***	0.112***	0.138***	0.130***	0.138***	0.063***	0.055***	0.060***
	(0.010)	(0.010)	(0.010)	(0.017)	(0.016)	(0.016)	(0.016)	(0.011)	(0.009)
Level 3 variance (individual)	0.028***	0.028***	0.006***	0.018***	0.018***	0.000***	0.041***	0.041***	0.012***
	(0.0056)	(0.006)	(0.004)	(0.008)	(0.008)	(0.000)	(0.009)	(0.009)	(0.006)
Residual	0.655***	0.655***	0.655***	0.774***	0.774***	0.774***	0.532***	0.533***	0.532***
	(0.009)	(0.009)	(0.009)	(0.015)	(0.015)	(0.015)	(0.0104)	(0.01)	(0.010)
Intraclass correlation coefficient (ICC, Level 1)	0.007	0.007	0.007	0	0	0	0.011	0.014	0.014
Intraclass correlation coefficient (ICC, Level 2)	0.139	0.139	0.151	0.148	0.141	0.151	0.109	0.1	0.113
Intraclass correlation coefficient (ICC, Level 3)	0.174	0.174	0.159	0.168	0.161	0.151	0.172	0.165	0.132
Conditional Nakagawa's R-squared	0.174	0.174	0.179	0.168	0.168	0.169	0.172	0.173	0.180
Marginal Nakagawa's R-squared	0.000	0.000	0.023	0.000	0.008	0.021	0.000	0.009	0.055
Akaike information criterion (AIC)	7281.0	7283.0	7257.4	3931.1	3932.5	3929.0	3304.5	3303.3	3286.8
Sample size	2908	2908	2908	1474	1474	1474	1434	1434	1434

Note: Standard errors are in parentheses. Statistical significance is denoted by asterisks, *p < 0.10, **p < 0.05, ***p < 0.01.

Table A.5
Multilevel model of NCD-Risk score in Laos (Vientiane), by location. For each location (full sample, peri-urban, and rural), null model, only EFE interaction index, and full model estimations are reported.

	Full Sample			Peri-urban			Rural		
	Null	Market	Full	Null	Market	Full	Null	Market	Full
EFE interaction index		0.579***	0.511***		0.683***	0.420*		0.479**	0.492**
		(0.151)	(0.155)		(0.231)	(0.232)		(0.194)	(0.201)
Sex (male is baseline)			−0.120***			−0.187***			−0.066
			(0.038)			(0.059)			(0.045)
Age			−0.008			−0.029			−0.006
			(0.011)			(0.018)			(0.013)
Age (squared)			−0.000			0.000			0.000
			(0.000)			(0.000)			(0.000)
Household size			−0.016			−0.008			−0.0189
			(0.016)			(0.022)			(0.022)
Agricultural household			−0.064			−0.096			0.415**
			(0.074)			(0.081)			(0.206)
Wealth index			−0.197			−0.160			−0.225
			(0.192)			(0.392)			(0.213)
Constant	1.165***	0.851***	1.659***	1.274***	0.894***	2.446***	1.058***	0.803***	0.929**
	(0.0604)	(0.101)	(0.314)	(0.0441)	(0.135)	(0.558)	(0.0484)	(0.117)	(0.385)
Level 1 variance (village)	0.011***	0.0104***	0.0138***	0.000	0.000	0.000	0.001*	0.003***	0.001*
	(0.005)	(0.005)	(0.006)	(0.000)	(0.000)	(0.000)	(0.002)	(0.003)	(0.002)
Level 2 variance (household)	0.065***	0.053***	0.054***	0.054***	0.040***	0.050***	0.075***	0.065***	0.054***
	(0.008)	(0.007)	(0.006)	(0.012)	(0.011)	(0.009)	(0.009)	(0.009)	(0.008)
Level 3 variance (individual)	0.028***	0.027***	0.008***	0.052***	0.051***	0.010***	0.000	0.000	0.000
	(0.050)	(0.006)	(0.005)	(0.011)	(0.011)	(0.007)	(0.000)	(0.000)	(0.000)
Residual	0.721***	0.721***	0.721***	0.827***	0.827***	0.826***	0.613***	0.613***	0.611***
	(0.010)	(0.010)	(0.010)	(0.016)	(0.016)	(0.016)	(0.012)	(0.012)	(0.012)
Intraclass correlation coefficient (ICC, Level 1)	0.013	0.013	0.017	0	0	0	0.002	0.004	0.002
Intraclass correlation coefficient (ICC, Level 2)	0.092	0.079	0.085	0.058	0.044	0.056	0.111	0.1	0.083
Intraclass correlation coefficient (ICC, Level 3)	0.125	0.111	0.096	0.114	0.1	0.068	0.111	0.1	0.083
Conditional Nakagawa's R-squared	0.125	0.125	0.129	0.114	0.114	0.116	0.111	0.112	0.112
Marginal Nakagawa's R-squared	0.000	0.015	0.036	0.000	0.016	0.051	0.000	0.014	0.032
Akaike information criterion (AIC)	7513.8	7501.9	7477.4	4017.9	4011.8	3991.8	3458.7	3455.0	3455.0
Sample size	2908	2908	2908	1474	1474	1474	1434	1434	1434

Note: Standard errors are in parentheses. Statistical significance is denoted by asterisks, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Data availability

Data will be made available on request.

References

Boruff, B.J., Nathan, A., Nijënstein, S., 2012. Using GPS technology to (re)-examine operational definitions of 'neighbourhood'in place-based health research. Int. J. Health Geogr. 11, 1–14.

Caldwell, E.M., Miller Kobayashi, M., DuBow, W.M., Wytinck, S.M., 2009. Perceived access to fruits and vegetables associated with increased consumption. Public Health Nutr. 12 (10), 1743–1750.

Cannuscio, C.C., Hillier, A., Karpyn, A., Glanz, K., 2014. The social dynamics of healthy food shopping and store choice in an urban environment. Soc. Sci. Med. 122, 13–20.

Caspi, C.E., Sorensen, G., Subramanian, S.V., Kawachi, I., 2012. The local food environment and diet: a systematic review. Health Place 18 (5), 1172–1187.

CDC, 2023. Healthy Food Environments. Centers for Disease Control and Prevention.

Cetateanu, A., Jones, A., 2016. How can GPS technology help us better understand exposure to the food environment? A systematic review. SSM Popul. Health 2, 196–205.

Champagne, B., Arora, M., ElSayed, A., Løgstrup, S., Naidoo, P., Shilton, T., Vaca McGhie, D., Armstrong-Walenczak, K., Berteletti, F., Ganesan, S., Popkin, B., 2020. World heart Federation Policy brief: Front-Of-Pack labelling. Global Heart 15 (1). https://doi.org/10.5334/gh.935.

Chen, X., Kwan, M.-P., 2015. Contextual uncertainties, human mobility, and perceived food environment: the uncertain geographic context problem in food access research. Am. J. Publ. Health 105 (9), 1734–1737.

Christian, W.J., 2012. Using geospatial technologies to explore activity-based retail food environments. Spatial and Spatio-Temporal Epidemiology 3 (4), 287–295.

Cummins, S., 2007a. Commentary: investigating neighbourhood effects on health-avoiding the local trap. Int. J. Epidemiol. 36 (2), 355–357.

Cummins, S., 2007b. Neighbourhood food environment and diet: time for improved conceptual models? Prev. Med. 44 (3), 196–197.

Downs, S.M., Ahmed, S., Fanzo, J., Herforth, A., 2020. Food environment typology: advancing an expanded definition, framework, and methodological approach for improved characterization of wild, cultivated, and built food environments toward sustainable diets. Foods 9 (4), 532. https://doi.org/10.3390/foods9040532.

Elliston, K.G., Ferguson, S.G., Schüz, N., Schüz, B., 2017. Situational cues and momentary food environment predict everyday eating behavior in adults with overweight and obesity. Health Psychol. 36 (4), 337–345.

European Public Health Alliance, 2019. Government Endorsed front-of-pack Nutrition Label.

Fanzo, J., McLaren, R., Bellows, A., Carducci, B., 2023. Challenges and opportunities for increasing the effectiveness of food reformulation and fortification to improve dietary and nutrition outcomes. Food Policy 119, 102515. https://doi.org/10.1016/j.foodpol.2023.102515.

Federici, C., Detzel, P., Petracca, F., Dainelli, L., Fattore, G., 2019. The impact of food reformulation on nutrient intakes and health, a systematic review of modelling studies. BMC Nutrition 5 (1), 2. https://doi.org/10.1186/s40795-018-0263-6.

Feng, J., Glass, T.A., Curriero, F.C., Stewart, W.F., Schwartz, B.S., 2010. The built environment and obesity: a systematic review of the epidemiologic evidence. Health Place 16 (2), 175–190.

Glanz, K., Sallis, J.F., Saelens, B.E., Frank, L.D., 2007. Nutrition Environment Measures Survey in stores (NEMS-S): development and evaluation. Am. J. Prev. Med. 32 (4), 282–289.

Global Diet Quality Project, 2025a. Diet Quality Questionnaire (DQQ) for Lao PDR. https://www.dietquality.org/countries/lao.

Global Diet Quality Project, 2025b. Diet Quality Questionnaire (DQQ) for Thailand. https://www.dietquality.org/countries/tha.

Gustafson, A., Hankins, S., Jilcott, S., 2012. Measures of the consumer food store environment: a systematic review of the evidence 2000-2011. J. Community Health 37 (4), 897–911.

Haenssgen, M.J., Charoenboon, N., Zanello, G., Mayxay, M., Reed-Tsochas, F., Lubell, Y., Wertheim, H., Lienert, J., Xayavong, T., Khine Zaw, Y., Thepkhamkong, A., Sithongdeng, N., Khamsoukthavong, N., Phanthavong, C., Boualaiseng, S., Vongsavang, S., Wibunjak, K., Chai-In, P., Thavethanutthanawin, P., et al., 2019. Antibiotic knowledge, attitudes and practices: new insights from cross-sectional rural health behaviour surveys in low-income and middle-income South-East Asia. BMJ Open 9 (8). https://doi.org/10.1136/bmjopen-2018-028224.

Herforth, A., Ballard, T., Rzepa, A., 2024. Development of the diet quality questionnaire for measurement of dietary diversity and other diet quality indicators. Curr. Dev. Nutr. 8 (8), 103798. https://doi.org/10.1016/j.cdnut.2024.103798.

Herforth, A., Ahmed, S., 2015. The food environment, its effects on dietary consumption, and potential for measurement within agriculture-nutrition interventions. Food Secur. 7, 505–520.

Hillsdon, M., Coombes, E., Griew, P., Jones, A., 2015. An assessment of the relevance of the home neighbourhood for understanding environmental influences on physical activity: how far from home do people roam? Int. J. Behav. Nutr. Phys. Activ. 12 (1), 100.

Holsten, J.E., 2009. Obesity and the community food environment: a systematic review. Public Health Nutr. 12 (3), 397–405.

Inglis, V., Ball, K., Crawford, D., 2008. Socioeconomic variations in women's diets: what is the role of perceptions of the local food environment? J. Epidemiol. Community Health 62 (3), 191–197.

Jann, B., 2014. Plotting Regression Coefficients and other Estimates. STATA J.: Promoting Communications on Statistics and Stata 14 (4), 708–737. https://doi.org/10.1177/1536867X1401400402.

Kaur, S., 2023. Barriers to consumption of fruits and vegetables and strategies to overcome them in low- and middle-income countries: a narrative review. Nutr. Res. Rev. 36 (2), 420–447. https://doi.org/10.1017/S0954422422000166.

Lartey, A., Hemrich, G., Amoroso, L., Remans, R., Grace, D., Albert, J.L., Garnett, 2016. Influencing food environments for healthy diets. In: Food and Agriculture Organization of the United Nations (Rome, Italy). ISBN: 978-92-5-109518-8. http://www.fao.org/documents/card/en/c/453abfb9-37a8-4569-8d73-c2d699f76503.

MacNell, L., Elliott, S., Hardison-Moody, Annie, Bowen, S., 2017. Black and Latino urban food desert residents' perceptions of their food environment and factors that influence food shopping decisions. J. Hunger Environ. Nutr. 12 (3), 375–393.

Mattioni, D., Loconto, A.M., Brunori, G., 2020. Healthy diets and the retail food environment: a sociological approach. Health Place 61 (102244), 102244.

Moore, L.V., Diez Roux, A.V., Nettleton, J.A., Jacobs, D.R., 2008. Associations of the local food environment with diet quality-a comparison of assessments based on surveys and geographic information systems: the multi-ethnic study of atherosclerosis. Am. J. Epidemiol. 167 (8), 917–924.

Niebylski, M.L., Redburn, K.A., Duhaney, T., Campbell, N.R., 2015. Healthy food subsidies and unhealthy food taxation: a systematic review of the evidence. Nutrition 31 (6), 787–795. https://doi.org/10.1016/j.nut.2014.12.010.

Partington, S.N., Menzies, T.J., Colburn, T.A., Saelens, B.E., Glanz, K., 2015. Reduced-item food audits based on the nutrition Environment Measures surveys. Am. J. Prev. Med. 49 (4), e23–e33.

Popkin, B.M., 2018. The nutrition transition and obesity in the developing world. J. Nutr. 131 (3), 871S–873S. https://doi.org/10.1093/jn/131.3.871s.

Popkin, B.M., 2021. Measuring the nutrition transition and its dynamics. Public Health Nutr. 24 (2), 318–320. https://doi.org/10.1017/S136898002000470X.

Popkin, B.M., Ng, S.W., 2022. The nutrition transition to a stage of high obesity and noncommunicable disease prevalence dominated by ultra-processed foods is not inevitable. Obes. Rev. 23 (1). https://doi.org/10.1111/obr.13366.

Rabe-Hesketh, S., Skrondal, A., 2022. Multilevel and Longitudinal Modeling Using Stata. Stata Press.

Rose, D., Bodor, J.N., Hutchinson, P.L., Swalm, C.M., 2010. The importance of a multi-dimensional approach for studying the links between food access and consumption. J. Nutr. 140 (6), 1170–1174. https://doi.org/10.3945/jn.109.113159.

Sharkey, J.R., Johnson, C.M., Dean, W.R., 2010. Food access and perceptions of the community and household food environment as correlates of fruit and vegetable intake among rural seniors. BMC Geriatr. 10 (1), 32. https://doi.org/10.1186/1471-2318-10-32.

Shaw, S.C., Ntani, G., Baird, J., Vogel, C.A., 2020. A systematic review of the influences of food store product placement on dietary-related outcomes. Nutr. Rev. https://doi.org/10.1093/nutrit/nuaa024.

Taillie, L.S., Busey, E., Stoltze, F.M., Dillman Carpentier, F.R., 2019. Governmental policies to reduce unhealthy food marketing to children. Nutr. Rev. 77 (11), 787–816. https://doi.org/10.1093/nutrit/nuz021.

Turner, C., Aggarwal, A., Walls, H., Herforth, A., Drewnowski, A., Coates, J., Kadiyala, S., 2018. Concepts and critical perspectives for food environment research: a global framework with implications for action in low-and middle-income countries. Global Food Secur. 18, 93–101.

Turner, C., Kalamatianou, S., Drewnowski, A., 2019. Food environment research in low- and middle-income countries: a systematic scoping review. Adv. Nutr. 11 (2), 387–397.

Wilkins, E.L., Morris, M.A., Radley, D., Griffiths, C., 2017. Using Geographic Information Systems to measure retail food environments: discussion of methodological considerations and a proposed reporting checklist (Geo-FERN). Health Place 44, 110–117.

Zenk, S.N., Schulz, A.J., Matthews, S.A., Odoms-Young, A., Wilbur, J., Wegrzyn, L., Gibbs, K., Braunschweig, C., Stokes, C., 2011. Activity space environment and dietary and physical activity behaviors: a pilot study. Health Place 17 (5), 1150–1161.