How social classes and health considerations in food consumption affect food price concerns

Ruining Jin [1], Tam-Tri Le [2,*], Resti Tito Villarino [3], Adrino Mazenda [4], Minh-Hoang Nguyen [2,6], Quan-Hoang Vuong [2]

[1] Civil, Commercial and Economic Law School, China University of Political Science and Law, Beijing, China
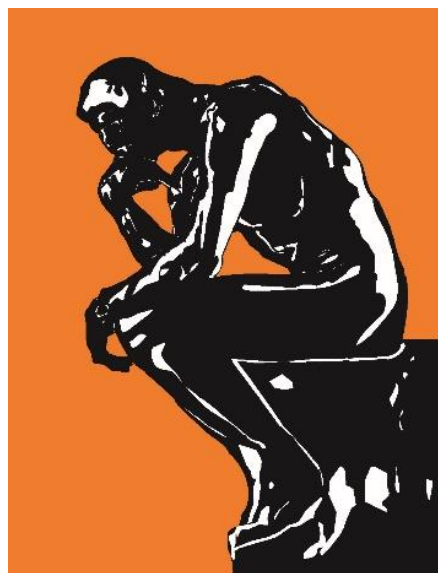
[2] Centre for Interdisciplinary Social Research, Phenikaa University, Hanoi, Vietnam

[3] Cebu Technological University, Cebu, Philippines

[4] School of Public Management and Administration, University of Pretoria, Pretoria, South Africa

[6] A.I. for Social Data Lab (AISDL), Vuong & Associates, Hanoi, Vietnam

* Corresponding: tri.letam@phenikaa-uni.edu.vn (Tam-Tri Le)

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Abstract

Food prices are a daily concern in many households' decision-making, especially when people want to have healthier diets. Employing Bayesian Mindsponge Framework (BMF) analytics on a dataset of 710 Indonesian citizens, we found that people from wealthier households are less likely to have concerns about food prices. However, the degree of health considerations in food consumption was found to moderate against the above association. In other words, people of higher income-based social classes may worry more about food prices if they care more about the health impacts of their food choices. These findings provide more insights for policymakers on the psychological aspects of promoting the balance between finance and health in food consumption.

Keywords: food price; social class; health consideration; Indonesia; Bayesian Mindsponge Framework

"— Wherever there is food, there is freedom!"

In "Dream"; *The Kingfisher Story Collection* (2022)

1. Introduction

As a rapidly growing developing nation facing globalization, urbanization, and economic growth, Indonesia is undertaking a nutrition transition where people's dietary habit is changing (Kusin et al., 1991; Labiba et al., 2020; Lestari et al., 2018). One study found that Indonesian workers' dietary intake consisted of unhealthy nutrients, such as high amounts of fat, particularly saturated fat, and cholesterol, with a low intake of dietary fiber (Zahra & Chandra, 2021). Another study on Indonesian high school students warned of a similar unhealthy food pattern, in which Indonesian adolescents consumed inadequate amounts of fruits and vegetables, and excessive amounts of food rich in sugar, fat, and salt (Dwijayanti et al., 2021). When a trend like this has been noticed, it is worthwhile to examine the health implications associated.

The health implications of unhealthy diets involve physical health risks as well as mental ones. The increased consumption of energy-dense foods, high in added sugars, unhealthy fats, and sodium, has contributed to a surge in diet-related health issues, such as obesity, diabetes, and cardiovascular diseases (Oddo et al., 2019). In addition to physical health issues, people's mental health conditions can also deteriorate when their food choices involve unhealthy nutrients and suffer from physical health deterioration (Collins et al., 2022; Jin et al., 2023; Rossa-Roccor et al., 2021; Wattick et al., 2018). These health concerns highlight the urgent need for a deeper understanding of who is most likely to be involved in this trend and the negative health outcomes associated. To this end, the role of social class should be examined in influencing people's food decision-making, as social class categorization significantly shapes individuals' concerns about food prices and their ability to access proper nutrition in Indonesia (Anyanwu et al., 2022; Rasyid et al., 2020).

For people of lower social classes, economic concerns are probably one of the main factors that caused people to have unhealthy food choices based on the current landscape of food consumption in Indonesia (Chin, 2010; Lestari et al., 2018). The soaring prices of staple foods and income disparities have posed substantial barriers to the accessibility of nutritious food options for a significant portion of the population. In other words, people with lower socioeconomic status are often associated with poorer diets characterized by lower intake of fruits, vegetables, and whole grains and higher consumption of processed and fast foods (Foroozanfar et al., 2022; Gustafson, 2013). As a result, these people tend to risk their health conditions to purchase more affordable products such as calorie-dense, processed foods rather than fresh food. Having said this, however, are there any other social groups that are less likely to be impacted by food prices and economic concerns?

Upper-class Indonesians' food choices, on the other hand, are the ones who are less likely to include price and economic concerns; rather, they are likely to be influenced by health concerns and cultural influence. Studies conducted by Adelina and Seda (Adelina et al., 2021; Seda et al., 2020) have highlighted the influence of social class categorization on people's concerns about food prices in Indonesia. Extant studies reached a consensus that higher-income individuals tend to have greater purchasing power and are less affected by fluctuations in food prices, enabling them to prioritize food quality over affordability, while individuals from lower social classes, often facing economic constraints, are more sensitive to price fluctuations and tend to prioritize cheaper, calorie-dense food options.

While social class is so important that it can significantly alter people's priorities when making food choices, it can also reshape people's attitudes toward food concerns, such as food quality. Specifically, social class identities in Indonesia can also influence people's perceptions of food quality and ability to access proper nutrition (Long et al., 2022; Rozi et al., 2023; United Nations, 2018). Studies have indicated that individuals from higher social classes tend to be more health-conscious and place greater importance on the nutritional content, freshness, and origin of the food; thus, they are more likely to make informed choices, favoring organic, locally sourced, and nutrient-dense options (Adelina et al., 2021; Anyanwu et al., 2022; Karanja et al., 2022). However, individuals from lower social classes, constrained by limited financial resources, may face challenges accessing nutritious food options and prioritizing affordability over nutritional quality. This disparity in food quality perceptions and access to proper nutrition can contribute to health inequalities and increase the risk of diet-related diseases among disadvantaged groups (Niven et al., 2022).

To address the discrepancy between social-class-based food affordability and food literacy, promote healthy eating behaviors, and mitigate disparities in nutritional well-being (United Nations, 2018), some theoretical frameworks have been proposed. The economic theory of consumer behavior suggests that individuals make rational decisions based on their income, prices of goods, and preferences (Szalonka et al., 2021; United Nations, 2018). Price elasticity of demand theory posits that changes in food prices can significantly influence consumption patterns, with individuals more likely to opt for lower-cost options, especially in low-income populations (Szalonka et al., 2021). Additionally, the social-ecological model emphasizes the influence of environmental and social factors, including income, education, and access to healthy food environments, on shaping individuals' dietary choices (Anyanwu et al., 2022; Szalonka et al., 2021).

Based on the background previously presented, it is essential to probe the psychological pathways of citizens in different social classes, ascertaining the factors when they are making their food-choice decisions. Thus, this article will employ Bayesian Mindsponge Framework (BMF) analytics (Q.-H. Vuong et al., 2022) to shed light on Indonesia's intricate food consumption dynamics. By examining the financial capability and health aspects, this study aims to provide more insights into the challenges faced by policymakers and potential strategies to address the issues of affordability and nutrition in the country's food system.

2. Methodology

2.1. Materials and variables

This study employs secondary data. We use a dataset of 710 Indonesian citizens, retrieved from the open data article "Dataset on The Cultural Dimension of Urban Society Food Consumption in Indonesia" (Seda et al., 2020). Respondents were from five cities: Jakarta (n=174), Bandung (n=150), Surabaya (n=118), Makassar (n=120), and Denpasar (n=148). In the sample, the average age of participants was 41.3 years. Males and females accounted for 42.1%, and 57.9%, respectively. Data collection was approved by Direktorat Riset dan Pengabdian Masyarakat (Directorate of Research and Community Service) Universitas Indonesia (2015). During the data collection process, the original research team (Seda et al., 2020) conducted face-to-face interviews with respondents assisted by local enumerators. Data collection was done through stratified random sampling based on social class. The questionnaire was developed based on indicators of cultural aspects of food consumption at the household level (Beagan et al., 2015). Items related to price and health considerations in food consumption were measured with single questions, using a five-point Likert scale, with answers ranging from 1 (strongly disagree) to 5 (strongly agree). Social classes were categorized by the original research team based on official national statistics (Seda et al., 2020). In the sample, the percentage of lower, middle, and upper social classes are 34.5%, 36.2%, and 29.3%, respectively.

Table 1 shows the variables used in this study taken from the dataset. Rationales for variable selection are presented in the model construction subsection below.

Table 1. Variable description

Variable	Meaning	Type of variable	Value
Price	Whether prices are a major consideration in the food consumption of one's family	Ordinal	From 1 (strongly disagree) to 5 (strongly agree)
SocialClass	The social class of the respondent's household	Ordinal	1 is lower class, 2 is middle class, and 3 is upper class
Health	Whether health is a major consideration in the food consumption of one's family	Ordinal	From 1 (strongly disagree) to 5 (strongly agree)

2.2. Model construction

Investigation into the possible information processes of price considerations in food consumption requires a suitable conceptual framework. Mindsponge is a theory of the human mind's dynamic information-processing mechanisms, which helps explain how subjective values are filtered based on past experiences and current living conditions (Q. H. Vuong & Napier, 2015; Q.-H. Vuong, 2023). The Mindsponge Theory has been effectively employed to study financial and health factors evaluations in decision-making in households (Q.-H. Vuong, Le, Jin, et al., 2023; Q.-H. Vuong, Le, La, et al., 2023), psychological difficulties in dietary changes (Jin et al., 2023), as well as mental optimization of perceived influences (M.-H. Nguyen et al., 2023). In the context of this study, the aspect of subjective cost-benefit judgments in the information filtering system is focused (M.-H. Nguyen et al., 2022).

A household has a certain level of financial power, which is used for multiple tasks in life activities according to context-specific demands. While each household has its own way of deciding its expenditures, the patterns of cost-benefit optimization serve as the base of their rationalization. People from wealthy households are expected to care less about food prices since food-related expenditures are less likely to compete with other demands compared to those from poor households who have to strictly balance their spending. In other words, those from higher social classes may subjectively perceive food prices as less of a cost in their household expenditure calculations. That being said, high-quality nutrition can be costly, even for wealthy people. Those who desire to consume higher-quality foods for health reasons may view food prices as more of a perceived cost. Thus, health considerations of foods can be a potential moderator in the relationship between food price considerations and social classes.

To construct the analytical model from the conceptualization presented above, we use Bayesian Mindsponge Framework (BMF) analytics (Q.-H. Vuong et al., 2022). A parsimonious model has high predictive power, and prediction accuracy is enhanced with MCMC-aided Bayesian analysis (Q.-H. Vuong et al., 2022). The equations of the model are as follows.

$$Price \sim normal(\mu, \sigma) \tag{1}$$

$$\mu_i = \beta_0 + \beta_{SocialClass} * SocialClass_i + \beta_{Health*SocialClass} * Health_i * SocialClass_i \tag{2}$$

$$\beta \sim normal(M, S) \tag{3}$$

The probability around mean value μ is in the form of normal distribution, with the standard deviation value σ. The degree of price consideration in food consumption of participant i's family is indicated by μ_i. $SocialClass_i$ is the social class of participant i's household. $Health_i$ is the degree of health consideration in food consumption of participant i's family. The model has an intercept β_0 and coefficients $\beta_{SocialClass}$ and $\beta_{Health*SocialClass}$. The probability around mean value M is in the form of normal distribution, with the standard deviation value S. Figure 1 visualizes the logical network of the constructed analytical model.
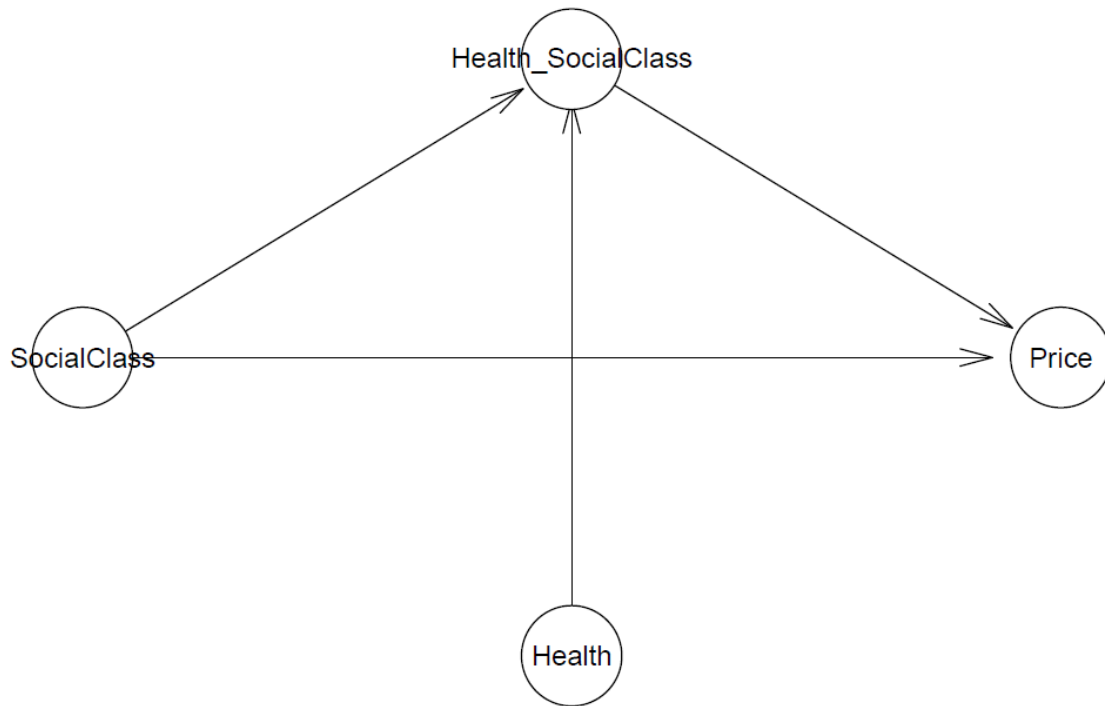
Figure 1. The analytical model's logical network

2.3. Analysis procedure

Using supported MCMC algorithms, we conduct Bayesian analysis in accordance with BMF analytics protocols (M.-H. Nguyen et al., 2022; Q.-H. Vuong et al., 2022). By iteratively generating large samples of serially correlated parameters, MCMC algorithms increase the predictive power and accuracy of Bayesian inference, especially for small sample sizes (V. H. Nguyen et al., 2005; Van Huu & Hoang, 2007). Bayesian inference considers all properties, including unknown parameters, in terms of probabilities, which works well with constructing parsimonious models for higher predictive power (Csilléry et al., 2010; Dunson, 2001; Gill, 2014). In the Bayesian approach, examining the credible range of parameters with

the highest occurrence probability helps improve the accuracy of result interpretation without affecting statistical integrity.

To check whether simulated data fit the real data, we use Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) diagnostics (Vehtari et al., 2017; Vehtari & Gabry, 2019) to check the goodness-of-fit of the analytical model. To check whether the Markov property is held (iterative samples within a chain are independent), we check the convergence using the effective sample size (*n_eff*) and the Gelman-Rubin shrink factor (*Rhat*). The *n_eff* value indicates the number of non-autocorrelated iterative samples during the stochastic simulation process. *n_eff* values should be above 1000 for reliable inference (McElreath, 2020). The *Rhat* value is the indicator of the iterative simulations' convergence and should equal 1 (Brooks & Gelman, 1998). A *Rhat* value of 1.1 or higher is considered problematic.

The analysis is performed in R using the **bayesvl** open-access package (La & Vuong, 2019). Uninformative prior values, default as a mean of 0 and a standard deviation of 10, are used to reduce subjective influences toward the estimation. The MCMC setup is as follows: 4 chains, 5000 iterations including 2000 warm-up iterations. Considering the importance of transparency and cost management in data usage (Q.-H. Vuong, 2018, 2020), all data and code snippets of this study were deposited at the Open Science Framework repository (https://osf.io/cwpf9/).

3. Results

The latest model fitting run was on August 2, 2023, R version 4.2.1, Windows 11. The total elapsed time was 81.2 seconds.

PSIS-LOO diagnostics (see Figure 2) shows that all *k* values are below 0.5. This diagnostic result indicates that the simulated data fit well with real data.
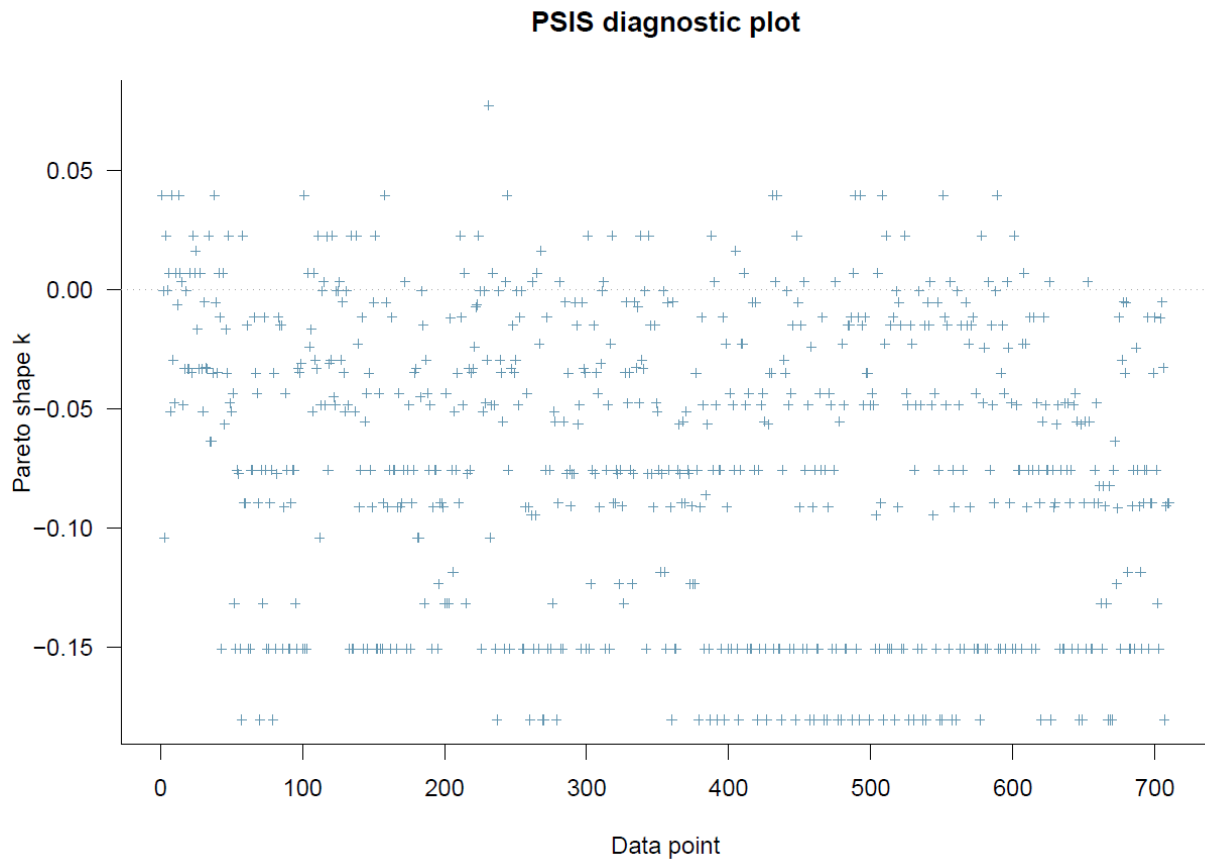
**Figure 2.** PSIS-LOO diagnostic plot for the model

Table 2 shows the estimated posteriors of the analytical model's parameters. All *n_eff* values are above 1000 and all *Rhat* values equal 1, which shows that the model is convergent.

Table 2. Estimated posteriors

Parameters	Mean	SD	n_eff	Rhat
Constant	4.03	0.10	5444	1
SocialClass	-0.81	0.09	4643	1
*Health*SocialClass*	0.10	0.02	5300	1

The convergence of the Markov chains is also visually checked using the trace plots (Figure 3). The trace plots show that after the warm-up period, the chains fluctuate around central equilibriums and do not deviate in certain directions. In the Gelman-Rubin-Brooks plots (Figure 4), we can see that *Rhat* values drop to 1 during the warm-up period, also indicating good convergence. The autocorrelation plots (Figure 5) show that autocorrelation is eliminated quickly and thus does not have problematic influences on the simulation.
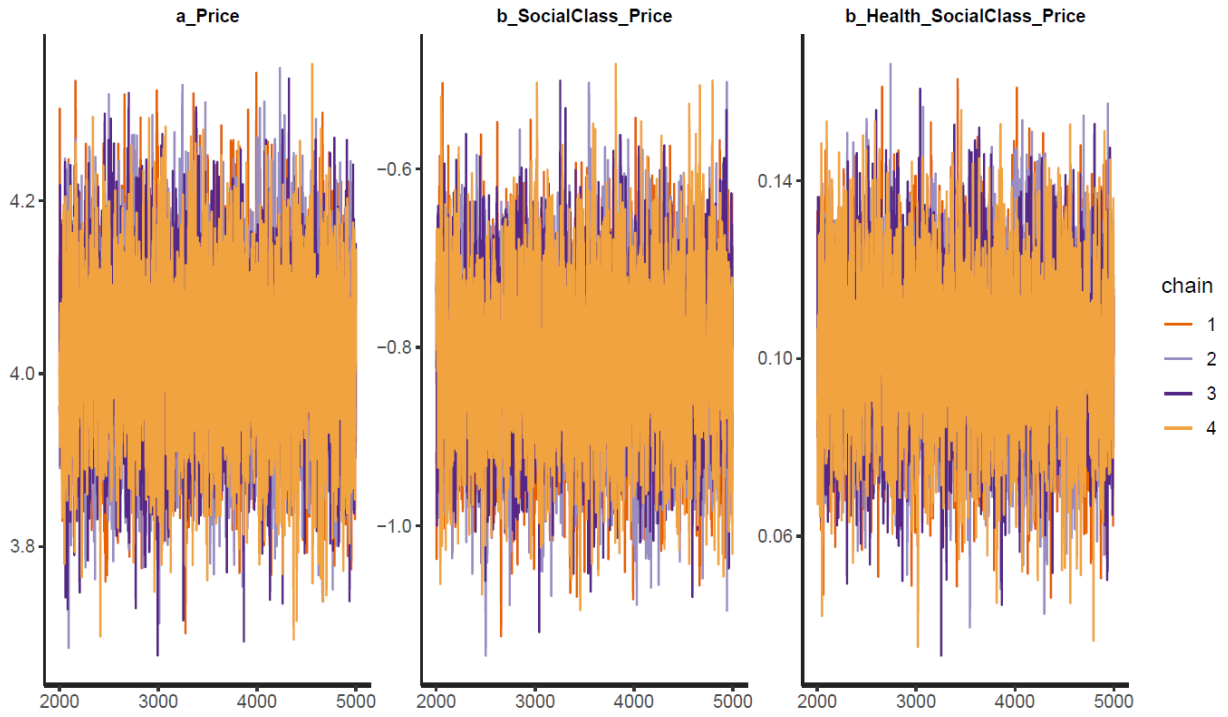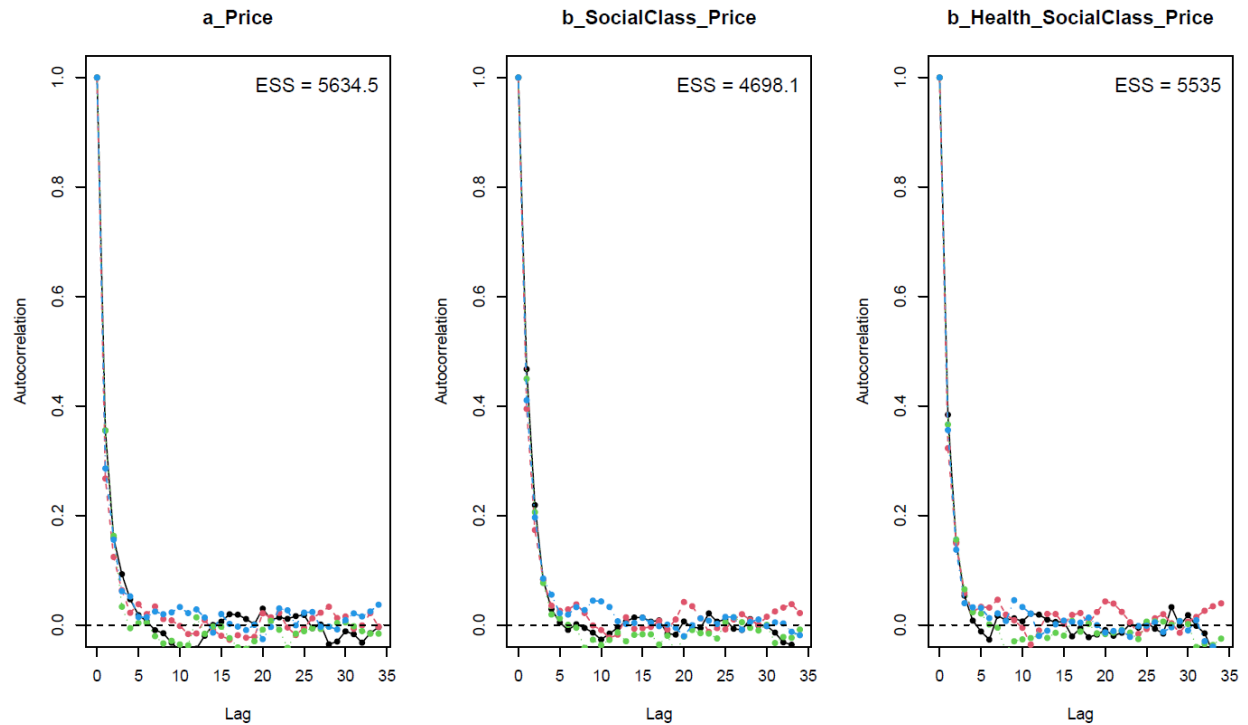
Figure 3. Trace plots for the model
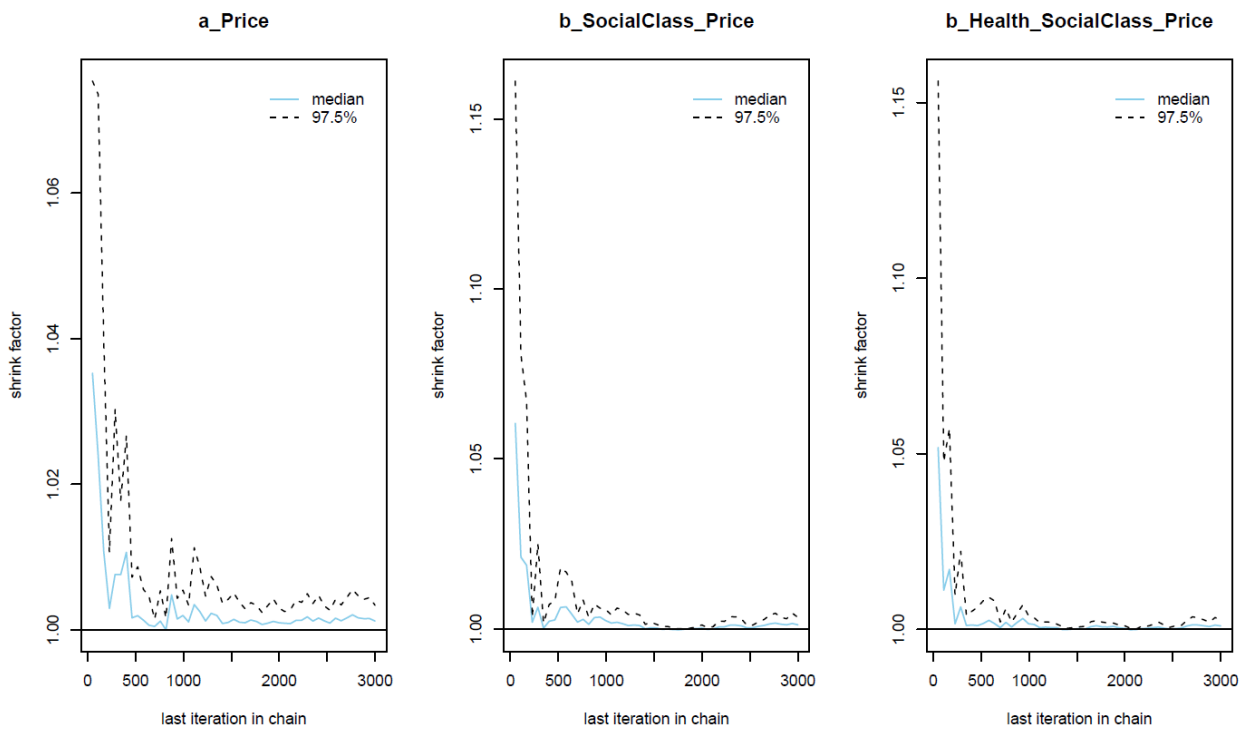
**Figure 4.** Gelman-Rubin-Brooks plots for the model

Figure 5. Autocorrelation plots for the model

Analysis results (see Table 2) show that considering a linear relationship, *SocialClass* is negatively associated with *Price* ($M_{SocialClass} = -0.81$ and $SD_{SocialClass} = 0.09$). *Health*SocialClass* was found to have a positive association with *Health* ($M_{Health\_SocialClass} = 0.10$ and $SD_{Health\_SocialClass} = 0.02$). This means *Health* has a moderating effect against the negative association between *SocialClass* and *Price*. Figure 6 shows the posterior distributions for the coefficients of *SocialClass* and *Health*SocialClass*. The distributions of *SocialClass* lie clearly on the negative side and the distributions of *Health*SocialClass* lie clearly on the positive side, suggesting that the analysis result is reliable.
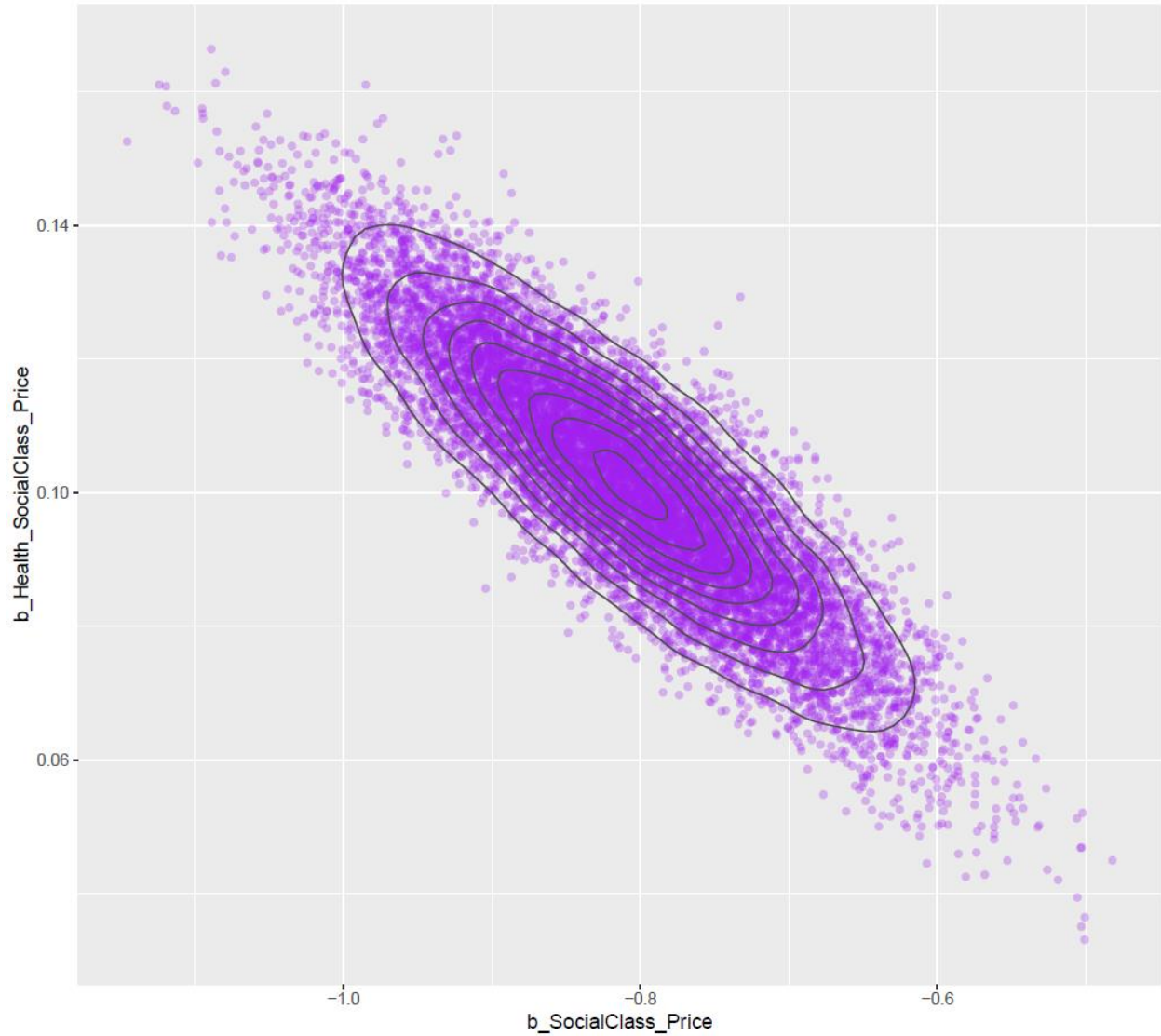
Figure 6. Pairwise posterior distributions of *SocialClass* and *Health*SocialClass*

To aid result interpretation, Figure 7 illustrates the estimated outcomes based on the posterior results of the analytical model. The *y*-axis represents food price considerations, the *x*-axis represents health considerations about food, and the line color represents income-based social classes. In general, people in lower social classes are more concerned about food prices, and the concern degrees are enhanced by health considerations in food consumption. This effect of health considerations is stronger in people of higher social classes.
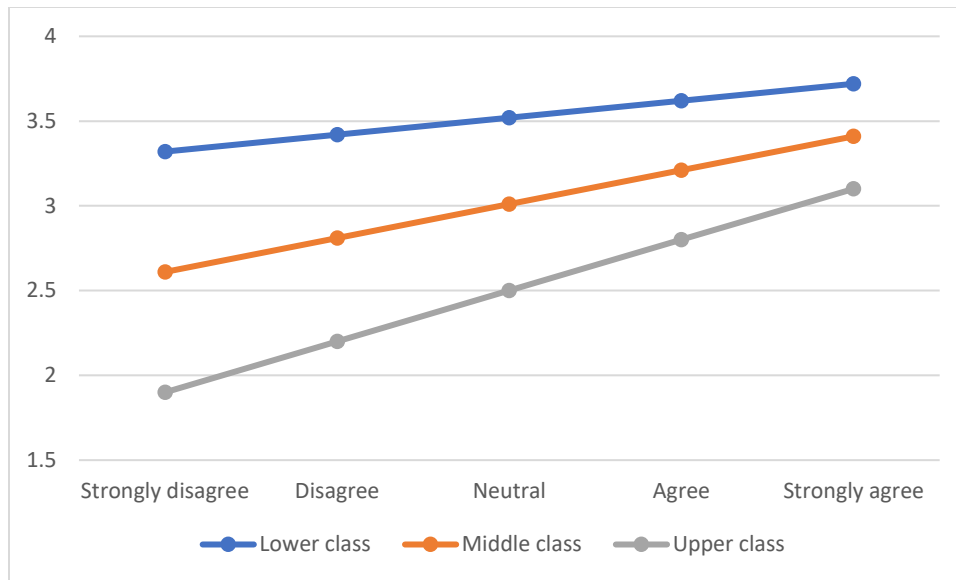
Figure 7. Estimated food price considerations based on social classes and health considerations in food consumption

4. Discussion

Employing BMF analytics on a dataset of 710 Indonesian urban residents, the current study found that people from a higher income-based social class are less likely to think that food price is a main consideration regarding their family's food consumption. However, health considerations about food have a negative moderating effect on this association. Here, "food price is a main consideration" has two implications: (1) for some people, the price of the food must be considered to ensure the family's affordability; (2) for some other people, the price of the food also needs to be considered for quality assurance and health guarantee.

The findings that people from a higher income-based social class are less likely to consider that food price is a main concern regarding their family's food consumption falls in the first implication. According to Engel's Law, as family income increases, the proportion of income spent on food decreases, and people tend to eat a more diverse diet with higher food quality (Choi & Lee, 2019; Clements & Si, 2018). Other studies also support this finding (Hupkens et al., 2000; Iqbal & Anwar, 2014; Khoiriyah et al., 2023; Pechey & Monsivais, 2016). In this case, for lower-income families, money spent on food might take up a major portion of their income, but they also need to pay for other necessities to survive, including healthcare, clothes, rental, etc. Consequently, food price is a major concern for family consumption for lower-class families, because if they overspend their budget on food because of the price hike, there would be a shortage of other necessities; on the other hand, upper-class families don't place food price as a major concern because even the price of food goes higher, they would also be able to cover other expenditures readily.

The finding that upper-class people who are more concerned about the health aspect of their food also have a relatively high level of food price consideration belongs to the second implication of food price concern. In consumer psychology, the term Price-Quality Heuristic describes consumers' tendency to use price as a cue for quality, especially when they lack

other information or experience about a product or service (Wainstein & Sichel, 1976). In this case, it has been corroborated that upper-class people generally have high expectations for nutrition and healthy diets, so they tend to choose better-quality foods (Daniel, 2021). From a mindsponge information-processing perspective, when upper-class people have a mindset focusing on food quality and nutrition, they are more likely to give more perceived benefits on foods that can satisfy their healthy-eating needs, while the perceived costs such as higher price and shorter duration of freshness can be downplayed because of their high income. As a result, they tend to place price as a consideration to distinguish "healthy" and "unhealthy" food due to PQH.

However, the price of food and the level of healthiness are not always positively connected, therefore a higher price does not always indicate a higher level of healthiness, and vice versa. For instance, some foods may cost more due to organic certification, fair trade requirements, or ethical sourcing, but this does not necessarily mean that they are healthier or more nutrient-dense. Similar to how some foods may cost less due to processing, mass production, or subsidies without necessarily being less wholesome or healthy (Grigsby-Duffy et al., 2020). Food prices and healthiness levels may also vary significantly across different regions, countries, and markets, depending on the availability, accessibility, and affordability of different food groups (The World Bank, 2023).

Based on the discussion above, there are two recommendations that can be made. The first one is to offer more affordable food options: Local authorities can offer more affordable food options to low-income families in case of food price fluctuations. By doing so, low-income families can have a relatively fixed portion of expenditure on food, so they don't need to squeeze their budget on other necessities when the price of food goes up. This can help to reduce the negative impact of price fluctuations on low-income families. The second is to increase public promotions and education programs: More public promotions and education programs should be designed to increase the public's food and health literacy. In this way, people can make their infosphere regarding food choices diverse and open, while increasing their information-processing capabilities, so that they could minimize the impacts of PQH. By increasing public awareness of healthy food choices and nutrition, people can make informed decisions about their food choices and focus on buying real healthy food that could meet their individual needs rather than pricy food, which does not necessarily reflect healthiness.

The study is not without limitations. First, the impact of culture is not incorporated into the current study. Since "health consideration" is a subjective norm, future studies can focus on how culture shapes the value and healthiness of food, and how that would impact people's food choices. Second, the current study is based on participants living in urban areas. Future studies can include cross-sectional analysis between rural and urban areas to gain a better understanding of how food choices and health considerations differ between these two populations. This can help to identify any unique challenges faced by rural populations and inform the development of targeted interventions to promote healthy eating habits.

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