International Journal of Agriculture, Food and Innovation–MIYR
2026, Volume 1, Issue 1, pp.1~11
https://doi.org/10.53468/ijafi.2026.1.1.1

Factors associated with food purchase frequency among urban consumers in Ulaanbaatar, Mongolia

Tuul Damdinsuren[1], Undrakh Zagarkhorloo[2*], Byambajargal Gansukh[3]

[1,2,3]Department of Marketing, School of Economics and Business, Mongolian University of Life Sciences, Mongolia
*Corresponding author: Undrakh Zagarkhorloo, undrakh@muls.edu.mn

CITATION

Tuul Damdinsuren, Undrakh Zagarkhorloo, Byambajargal Gansukh. Factors associated with food purchase frequency among urban consumers in Ulaanbaatar, Mongolia. International Journal of Agriculture, Food and Innovation-MIYR, 2026, 1(1), 1~11.

https://doi.org/10.53468/ijafi.2026.1.1.1

ARTICLE INFO

Received: 23 August 2026
Revised: 28 August 2026
Accepted: 15 September 2026
Available online: 30 September 2026

COPYRIGHT

Copyright © 2026 by author(s). International Journal of Agriculture, Food and Innovation-MIYR is published by MIYR Press. This work is licensed under the Creative Commons Attribution (CC BY 4.0) license.
https://creativecommons.org/licenses/by/4.0/

Abstract - This study investigates whether product evaluations and social influences are associated with the frequency of purchasing six food categories among urban consumers in Ulaanbaatar, Mongolia. Design/methodology: A cross-sectional convenience survey obtained 850 responses; adjusted analyses used 844 complete cases. The analysis operationalized Product Evaluation (taste, quality, nutritional value and health impact) and Social Influence (friends, colleagues, online groups and influencers) as two exploratory four-item observed composites. Category specific ordinal logistic regressions controlled for demographic characteristics, and false-discovery-rate adjustment addressed multiple testing. Findings: Internal consistency was high. Product Evaluation was inversely associated with frequent meat purchasing (OR = 0.732) and positively associated with frequent egg purchasing (OR = 1.206). Social Influence was positively associated with meat purchasing (OR = 1.206) and inversely associated with milk purchasing (OR = 0.824). Respondent-clustered interaction tests indicated significant differences in both associations across food categories ($p < .001$). Originality/value: The study distinguishes purchase frequency from dietary intake, identifies category dependent associations in an underexamined urban food market, and demonstrates why a single aggregate food choice relationship may obscure contrasting product level patterns. The observational design and modest model fit preclude causal or nationally representative claims.

Keywords - Food purchase frequency; Product evaluation; Social influence; Ordinal logistic regression; Urban consumers

1. INTRODUCTION

Food purchasing is a recurring consumer decision with implications for diet quality, food-system demand, and the design of nutrition and marketing interventions. Food choice is widely understood as a multidimensional process in which sensory appeal, perceived quality and healthfulness, social norms, information, access, and economic constraints interact rather than operate independently [1~3]. For the present study, the focal behavioural outcome is defined more narrowly as self-reported food purchase frequency. This distinction is important because purchase frequency captures how often consumers acquire a food category, whereas food choice and consumption behaviour are broader constructs that also encompass preference, selection, quantity, and intake. Two theoretical pathways are especially relevant to the revised analysis. First, evaluative theories of consumer behaviour propose that behavioural decisions are preceded by judgments about the attributes and expected consequences of an option. The Theory of Planned Behaviour identifies attitude as a proximal antecedent of behavioural intention [4], while food-choice research shows that taste, sensory appeal, health, and nutritional considerations are recurrent motives

in food evaluation [1, 5, 6]. Second, social-cognitive and normative perspectives emphasise that behaviour is embedded in interpersonal environments. Subjective norms in the Theory of Planned Behaviour and observational/social learning processes in Social Cognitive Theory provide complementary explanations for why peers, reference groups, and mediated social actors may be associated with food-related decisions [4, 7, 8]. These pathways are particularly relevant in Mongolia, where traditional food practices coexist with rapid urban and dietary transition. A national nutritional assessment reported high consumption of red meat, refined grains, and whole-fat dairy alongside relatively low consumption of fruits, non-tuberous vegetables, eggs, fish, and whole grains; it also identified distinct urban, transitional, and nomadic dietary patterns [9]. Analysis of Mongolia's 2019 Household Socio-Economic Survey similarly found red-meat intake far above, and fruit and vegetable intake far below, planetary-health benchmarks, with meaningful urban–rural and seasonal differences [10]. More recent longitudinal evidence from migrants to Ulaanbaatar shows that drivers of food choice and dietary patterns can change during urban adaptation, reinforcing the need to examine food choice in its specific urban and social context [11]. Although product attributes and social context are often discussed together in food-choice research, purchase frequency is a distinct behavioural indicator. A household may purchase a food infrequently because of bulk buying, storage practices or budget timing while consuming it regularly; conversely, repeated small purchases may reflect perishability and shopping access rather than higher intake. The distinction motivates an explicitly purchase-based outcome and discourages interpreting observed associations as dietary adequacy [2, 4]. The broader urban food-system context also extends beyond purchasing decisions to the management of food related waste. Research conducted in Ulaanbaatar has highlighted the importance of household food-waste management as a growing urban sustainability concern [12]. The research question is particularly relevant to urban Mongolia because the coexistence of established meat- and dairy-centred preferences with changing retail and communication environments may produce product-specific associations. Existing studies of dietary patterns offer essential context, but evidence on reported purchasing episodes and the roles of product evaluation and mediated social cues remains less developed [8, 10]. This study responds by estimating associations separately for six selected categories and formally testing heterogeneity rather than treating food purchasing as one homogeneous outcome. Against this background, the study focuses on six frequently purchased food categories identified for analysis from the survey meat, fruit, milk, eggs, vegetables, and vegetable oil among urban consumers in Ulaanbaatar. Rather than assuming that the same predictor has the same meaning or direction for every food, the revised study treats category heterogeneity as a substantive theoretical expectation. This approach is consistent with evidence that Mongolian diets differ markedly by food group and context [11, 10]. The study therefore asks whether two theoretically interpretable dimensions, product evaluation and social influence, are associated with purchase frequency and whether those associations vary across food categories. The study contributes in three ways. It adds consumer-level purchasing evidence from an underrepresented Central Asian setting; it separates the operational outcome of purchase frequency from the broader concepts of food choice and consumption; and it combines theory-led construct interpretation with a reproducible measurement-validation process and ordinal modelling appropriate to the ordered outcome. Because the design is cross-sectional and the sample is non-probabilistic, the study evaluates associations rather than causal effects and restricts inference to the surveyed urban context.

2. THEORETICAL BACKGROUND

2.1 Food Purchase Behavior

Food purchase behavior can be situated at the intersection of evaluative, motivational, and social theories. The Theory of Planned Behavior (TPB) proposes that behavioral intentions arise from attitudes, subjective norms, and perceived behavioral control [4]. Although the present study does not measure the complete TPB sequence and therefore does not claim to test TPB as a full structural model, two of its mechanisms are directly relevant: evaluative judgments about food attributes correspond conceptually to the attitudinal pathway, while perceived influence from other people corresponds to the normative pathway. Social Cognitive Theory complements this perspective by emphasizing

observational learning, social reinforcement, and reciprocal interaction between individuals and their social environment [7].

The distinction between behavioral antecedents and observed purchase frequency is central to the conceptual model. In the Theory of Planned Behavior, attitudes and subjective norms influence intentions, while perceived control and contextual constraints condition behavior [4]. Product Evaluation and Social Influence therefore represent partial operational analogues of evaluative and normative processes, not measurements of all TPB constructs. A significant coefficient in the present models should be interpreted as a cross-sectional association, not as evidence of a completed intention–behavior pathway.

Social Cognitive Theory additionally emphasizes reciprocal relations between personal beliefs, observed behavior and social environments [7]. This perspective helps motivate attention to peers and digital reference groups, but it also highlights the possibility of reverse influence: people who purchase a product frequently may become more attentive to recommendations about it. The design cannot separate these directions.

2.2 Product Evaluation: Sensory, Quality, Nutrition, and Health Judgments

Food-choice research consistently identifies sensory appeal and health-related evaluation as central motives. The Food Choice Questionnaire established sensory appeal and health among the recurring dimensions underlying food selection [4], and subsequent work has shown that taste is a particularly salient determinant of food preference [13]. Sensory cues such as color and appearance can shape expectations of flavor and quality [14, 15], while perceived quality and value integrate both intrinsic and extrinsic product information [16, 17]. Health consciousness and perceived nutritional properties likewise contribute to food related evaluations [5, 18]. In the revised measurement model, taste, product quality, nutritional value, and health impact therefore form a coherent product evaluation construct. This construct is interpreted as an evaluative orientation toward the food category, not as a direct causal mechanism. The four Product Evaluation indicators were retained as a pragmatic summary of distinct but related assessments. Taste captures immediate sensory desirability; perceived quality captures expectations about overall product standards; nutritional value reflects beliefs about nutrient contribution; and health impact captures perceived consequences of repeated use. These judgments need not have the same association with purchasing across meat, eggs, dairy and plant foods. Food Choice Questionnaire research provides a foundation for differentiating sensory and health motives, while perceived value theory emphasizes that product judgments are context dependent [1, 16, 5].

2.3 Social Influence in Food Purchasing

Food-related behavior is socially embedded. Family, peers, and reference groups contribute to the formation and reinforcement of eating norms and preferences [19, 20, 8]. Digital environments extend these processes beyond face-to-face relationships: experimental evidence shows that social-media influencer exposure can alter food intake, demonstrating that mediated social actors can function as salient food-related cues [21]. In the current instrument, the most stable indicators of this domain were influence from friends, colleagues, online groups, and public figures/influencers. These indicators capture interpersonal and digitally mediated social influence and align with the normative and observational pathways described by Ajzen [4] and Bandura [7]. The Social Influence composite captures two interpersonal sources (friends and colleagues) and two mediated sources (online groups and influencers). These channels may transmit descriptive norms, perceived credibility and product information, yet their effects can vary by product visibility, shopping habits and the social meaning of a food. Evidence that social modelling shapes eating decisions motivates the mechanism but cannot be transferred directly to purchasing frequency without testing it [8, 21]. Unlike a reflective latent factor that is confirmed to account for shared variance, the observed composite is an arithmetic summary of the four reported influence ratings. Internal consistency is reported as a diagnostic, not as proof that all four channels are interchangeable or that the construct has been externally validated. This distinction is important given the imperfect CFA fit of the eight-item measurement structure.

2.4 Mongolian Food Context and Category Heterogeneity

Mongolia's dietary context provides a strong rationale for category-specific analysis. Bromage et al. [9] documented high intake of red meat and whole-fat dairy and comparatively low intake of several plant foods, together with urban, transitional, and nomadic dietary patterns. Delgermaa et al. [10], using national household data, reported particularly high red-meat intake and low fruit and vegetable intake and showed that these patterns differed between urban and rural areas and across seasons. A longitudinal study of recent urban migrants in Ulaanbaatar further demonstrated that drivers of food choice and diet-related indicators change during urban adaptation [11]. These findings imply that meat, dairy, eggs, fruit, vegetables, and oils occupy different nutritional, cultural, seasonal, and purchasing roles. Consequently, a uniform coefficient across food categories is not theoretically necessary; category-specific heterogeneity is an expected feature of the food purchase process. Category heterogeneity follows from differences in perishability, storage, customary use and the social salience of foods. Meat may be bought in larger quantities and stored, while fresh produce may require more frequent shopping trips. These mechanisms are plausible interpretations rather than variables directly observed in the survey. They motivate a formal comparison of slopes across categories and a cautious discussion of the observed differences [9, 10].

2.5 Research Gap

Existing Mongolian research has made important contributions to understanding dietary intake, nutritional status, sustainability, and nutrition transition, but evidence on consumer-level purchase frequency and its evaluative and social correlates remains limited. The present study addresses this narrower behavioral gap. It does not attempt to explain total dietary intake or test a comprehensive causal model of food choice. Instead, it evaluates whether theoretically grounded product evaluation and social influence dimensions are associated with ordered purchase frequency across six food categories and whether those associations differ formally by category.

3. RESEARCH METHODOLOGY

This analysis examines the associations of product related evaluations and selected social influences with reported food purchase frequency. Product Evaluation reflects taste, quality, nutritional value, and health impact. Social Influence reflects friends, colleagues, online groups, and influencers. These are observed item group scores, not confirmed latent constructs.

3.1 Research questions and design

RQ1. Is the observed Product Evaluation composite associated with food purchase frequency?
RQ2. Is the observed Social Influence composite associated with food purchase frequency?
RQ3. Do these associations differ across the six food categories?
The research questions concern statistical associations rather than causal effects.

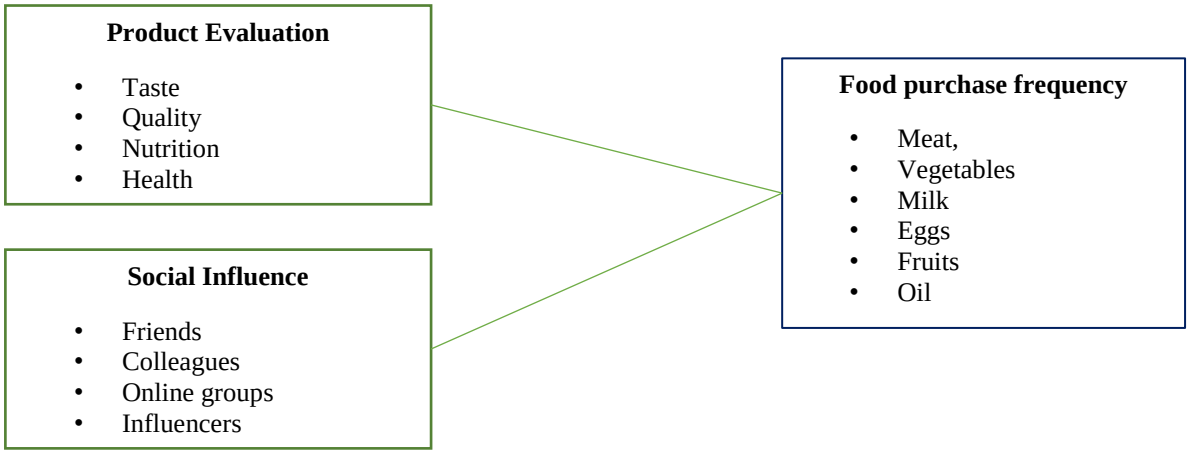


Figure 1. Conceptual framework: observed explanatory composites and food purchase frequency

This study employed a cross-sectional quantitative survey design to examine factors associated with food purchase frequency among urban consumers in Ulaanbaatar, Mongolia. The original survey database contained 850 usable respondent records. Participants were recruited through convenience sampling from supermarkets, local markets, shopping centers, and online channels in Ulaanbaatar. Because the sampling procedure was non-probabilistic and geographically concentrated in Ulaanbaatar, the sample is not interpreted as statistically representative of the entire Mongolian population. Accordingly, the findings are generalized cautiously to the surveyed urban consumer context rather than to all consumers in Mongolia.

3.2 Measurement Instrument and Variable Operationalization

It contained three sections: demographic characteristics, food purchase frequency, and food purchasing determinants. Demographic variables included gender, age, education, income, employment status, and household characteristics. Food purchase frequency was measured on an eight-point ordinal scale ranging from 0 (never purchased) to 7 (purchased daily), with higher scores indicating more frequent food purchasing. Eight purchase-attribute ratings were used to operationalize two observed composites for each food category. Product Evaluation comprised taste, product quality, nutritional value, and health impact; Social Influence comprised friends, colleagues, online groups, and influencers. Each composite was calculated as the mean of its four observed items and standardized for regression analysis. The eight-item structure is exploratory and should not be interpreted as an independently validated latent measurement model. The eight-item, two-group measurement specification was evaluated using continuous-item CFA and, separately, polychoric correlation unweighted least-squares (ULS) diagnostics. The two approaches are not interchangeable. Product Evaluation was calculated as the arithmetic mean of four observed purchase-attribute ratings (taste, quality, nutritional value and health impact); Social Influence was the mean of four ratings (friends, colleagues, online groups and influencers). Each mean was standardized separately within food category. Both variables are observed item-based composites, not CFA-derived factor scores. Cronbach's alpha and polychoric ordinal alpha were estimated for each composite within each food category, and a correlated two-factor ULS model was fitted to the eight-item polychoric correlation matrix for descriptive structural diagnostics. Because food purchase frequency is ordered, proportional-odds ordinal logistic regression was used for the primary analyses across the six food categories. The same demographic adjustments, coding and multiplicity correction were applied across categories. The models quantify associations, not causal effects. Because two focal predictors were evaluated across six food categories, 12 principal coefficient tests were conducted. Benjamini–Hochberg false-discovery-rate (FDR) adjustment was applied to these tests to control the expected proportion of false discoveries across the family of focal comparisons [22]. Cross-category heterogeneity was evaluated in a stacked category level dataset using factor-by-category interactions in ordinal generalized estimating equations, with observations clustered by respondent. Joint Wald tests assessed whether factor associations differed across categories.

4. RESULTS AND DATA ANALYSIS

A total of 850 valid responses were included in the analysis. Table 1 summarizes the respondents' demographic characteristics.

Table 1. Demographic Profile of Respondents (n = 850)

Characteristic	**Category**	**n (%)**
Gender	Female	492 (57.9%)
	Male	358 (42.1%)
Age group	18–24	187 (22.0%)
	25–34	263 (30.9%)
	35–44	218 (25.6%)
	45–54	124 (14.6%)
	55 and above	58 (6.8%)
Education level	Secondary school	68 (8.0%)
	Vocational / technical	134 (15.8%)
	Bachelor's degree	421 (49.5%)
	Master's degree or above	227 (26.7%)

Monthly household income (MNT)	Below 500,000	74 (8.7%)
	500,001–1,000,000	198 (23.3%)
	1,000,001–2,000,000	287 (33.8%)
	2,000,001–3,000,000	184 (21.6%)
	Above 3,000,000	107 (12.6%)
Employment status	Employed full-time	478 (56.2%)
	Employed part-time	121 (14.2%)
	Self-employed	97 (11.4%)
	Student	103 (12.1%)
	Unemployed / other	51 (6.0%)

Women represented 57.9% of the sample, and 56.5% of respondents were aged 25–44 years. Almost half held a bachelor's degree (49.5%), while 26.7% held a master's degree or higher. The largest income group earned MNT 1,000,001–2,000,000 per month (33.8%), and 56.2% of respondents were employed full-time. Given the convenience sampling approach, these characteristics should not be interpreted as representative of the wider Ulaanbaatar population.

Descriptive Statistics of Food Purchase Frequency

Table 2 reports food purchase frequency on a scale ranging from 0 (never purchased) to 7 (purchased daily), with higher scores indicating more frequent food purchasing.

Table 2. Descriptive Statistics of Food Purchase Frequency Among Urban Mongolian Consumers

Food category	Minimum	Maximum	Mean	Std. Deviation
Meat	0	7	6.09	1.490
Vegetable	0	7	5.69	1.377
Milk	0	7	5.65	1.327
Egg	0	7	5.62	1.317
Flour	0	7	5.48	1.433
Fruit	0	7	5.44	1.462
Oil	0	7	5.30	1.279
Fine vegetable	0	7	5.28	1.531
Rice	0	7	5.28	1.379
Flour product	0	7	5.27	1.559
Traditional dairy food	0	7	5.17	1.539
Sugar	0	7	4.95	1.577
Dairy product	0	7	4.84	1.610
Flour, prepared	0	7	4.83	1.657
Chicken	0	7	4.07	1.932
Meat products	0	7	3.90	1.952
Fish	0	7	3.52	2.120

Meat had the highest purchase frequency (M = 6.09, SD = 1.49), followed by vegetables (M = 5.69), milk (M = 5.65), eggs (M = 5.62), flour (M = 5.48), and fruit (M = 5.44). This pattern indicates the continued prominence of livestock-based foods alongside diversification in urban food purchasing patterns. This purchasing pattern is also consistent with research linking urbanisation and retail modernisation to dietary diversification [33; 49]. Fish (M = 3.52, SD = 2.12), meat products (M = 3.90, SD = 1.95), and chicken (M = 4.07, SD = 1.93) had lower mean frequencies and greater dispersion, indicating more heterogeneous purchasing patterns. Meat, vegetables, milk, eggs, fruit, and vegetable oil were selected for the subsequent further analysis because of their behavioural relevance and suitable factor score structures.

Eight-Item Measurement Results

The eight-item continuous-data CFA showed CFI of .930–.952, TLI of .896–.929, RMSEA of .133–.161, and SRMR of .038–.062 across food categories. In particular, elevated RMSEA prevents claims of satisfactory overall model fit. Ordinal polychoric ULS diagnostics are reported separately. High internal consistency supports coherence of the observed item groups but does not establish factorial validity.

Table 3. Eight-item CFA results for the two observed item groups

Food category	CFI	TLI	RMSEA	SRMR	Factor φ	HTMT
Meat	.941	.913	.142	.058	.263	.271
Fruit	.941	.913	.140	.046	.242	.250
Milk	.952	.929	.133	.038	.245	.254
Eggs	.930	.897	.158	.057	.284	.304
Vegetables	.930	.896	.161	.062	.245	.273
Vegetable oil	.946	.920	.139	.050	.273	.292

Across six food categories (N = 850 for the eight-item measurement blocks), Cronbach's alpha ranged from .914 to .937 for Product Evaluation and from .907 to .941 for Social Influence; ordinal alpha ranged from .943 to .961 and from .929 to .957, respectively. The ordinal ULS factor correlation ranged from .270 to .324, and the off-diagonal residual RMS from .038 to .062. Ordinal alpha was based on estimated polychoric correlations, while conventional alpha was based on the observed ordinal item scores. These statistics are descriptive measurement diagnostics and cannot establish confirmatory model fit.

Table 4. Eight-item ordinal polychoric ULS diagnostics and internal consistency, by food category.

Food	α PE	α SI	Ordinal α PE	Ordinal α SI	φ	Residual RMS
Eggs	0.914	0.935	0.944	0.951	0.324	0.051
Fruit	0.920	0.920	0.949	0.940	0.270	0.046
Meat	0.937	0.907	0.961	0.929	0.279	0.062
Milk	0.927	0.936	0.956	0.953	0.278	0.038
Vegetable oil	0.928	0.929	0.953	0.946	0.305	0.049
Vegetables	0.915	0.941	0.943	0.957	0.288	0.058

The continuous-data CFA and ordinal polychoric ULS estimates are not directly interchangeable. The ULS residual RMS is an off-diagonal correlation discrepancy measure rather than robust SRMR. Because the item groups were selected using the same sample, the reported measurement checks are exploratory rather than independent confirmation.

Primary Ordinal Logistic Regression

The final purchase-frequency analysis included 844 complete cases. After demographic adjustment and FDR correction across the 12 focal tests, Product Evaluation was associated with lower odds of more frequent meat purchasing (OR = 0.732, 95% CI [0.636, 0.842], q < .001) and higher odds of more frequent egg purchasing (OR = 1.206, 95% CI [1.044, 1.394], q = .033). Social Influence was associated with higher odds of more frequent meat purchasing (OR = 1.206, 95% CI [1.056, 1.379], q = .027) and lower odds of more frequent milk purchasing (OR = 0.824, 95% CI [0.716, 0.948], q = .027). Neither focal predictor remained significant after FDR adjustment for fruit or vegetables. For vegetable oil, Product Evaluation reached nominal significance (OR = 0.862, 95% CI [0.750, 0.990], p = .036) but did not survive multiple-testing correction (q = .086); Social Influence was also non-significant after correction. McFadden pseudo-R^2 ranged from .0173 to .0291. The models therefore identify selective category-specific associations, but their overall explanatory fit remains modest.

Table 5.Category-Specific Ordinal Logistic Regression Results for Food Purchase Frequency

Category	Predictor	OR	95% CI	p	FDR q	Pseudo-R^2
Meat	Product evaluation	0.732	[0.636, 0.842]	<.001	<.001	0.0291
Meat	Social influence	1.206	[1.056, 1.379]	.006	.027	0.0291
Fruit	Product evaluation	1.020	[0.884, 1.178]	.785	.785	0.0235

Fruit	Social influence	0.906	[0.790, 1.039]	.158	.172	0.0235
Milk	Product evaluation	1.111	[0.964, 1.280]	.145	.172	0.0173
Milk	Social influence	0.824	[0.716, 0.948]	.007	.027	0.0173
Eggs	Product evaluation	1.206	[1.044, 1.394]	.011	.033	0.0252
Eggs	Social influence	0.872	[0.758, 1.003]	.056	.112	0.0252
Vegetables	Product evaluation	1.130	[0.984, 1.299]	.084	.125	0.0184
Vegetables	Social influence	0.883	[0.771, 1.012]	.074	.125	0.0184
Vegetable oil	Product evaluation	0.862	[0.750, 0.990]	.036	.086	0.0194
Vegetable oil	Social influence	1.112	[0.974, 1.269]	.115	.153	0.0194

Cross-category Heterogeneity

The repeated-measures analysis confirmed that the associations were not constant across food categories. In the stacked purchase-frequency dataset (5,064 category-level observations from 844 respondents), the Product Evaluation × category interaction was significant (Wald $\chi^2 = 65.586$, df = 5, $p < .001$), as was the Social Influence × category interaction (Wald $\chi^2 = 37.931$, df = 5, $p < .001$). The joint test of all ten interaction terms was also significant (Wald $\chi^2 = 85.107$, df = 10, $p < .001$).

Table 6. Wald Tests of Cross-Category Heterogeneity in Product Evaluation and Social Influence Associations

Joint test	Wald χ^2	df	p
Product evaluation × food category	65.586	5	<.001
Social influence × food category	37.931	5	<.001
All factor × category interactions	85.107	10	<.001

The analyses address three research questions. Product Evaluation and Social Influence were examined as observed composites in adjusted category specific models (RQ1–RQ2). Category-by-composite interaction tests directly assessed heterogeneity across food categories (RQ3). The results do not support claims about other unmodelled purchase attributes.

5. DISCUSSION

Measurement limitations are important for interpretation. The selected eight-item composites showed high internal consistency and modest between group polychoric correlations. Product Evaluation and Social Influence are therefore interpreted as operational item groupings rather than validated latent domains. Product Evaluation was associated with purchase frequency for meat and eggs, but in opposite directions. Higher Product Evaluation scores corresponded to lower odds of frequent meat purchasing and higher odds of frequent egg purchasing. This contrast argues against a single, uniform product-evaluation effect. One possible interpretation is that consumers who scrutinise meat more closely may buy it less often or in more deliberate purchase episodes, whereas evaluations of taste, quality, nutrition, and health may align more closely with routine egg purchasing. The data do not measure purchase quantity, expenditure, or stockpiling, however, so these explanations remain plausible interpretations rather than tested mechanisms. Social Influence also varied by category. It was positively associated with meat purchase frequency but inversely associated with milk purchase frequency. This pattern is consistent with the broader view that food behaviour is socially embedded, while also showing that social influence cannot be assigned one direction across all products [7, 20, 8]. The formal interaction tests reinforce this point: both Product Evaluation and Social Influence changed significantly across food categories.

The modest McFadden pseudo-R^2 values for food purchase frequency (.0173–.0291) are an important part of the findings rather than a result to be minimised. They indicate limited improvement in likelihood-based fit over intercept-only models, although pseudo-R^2 should not be read as the percentage of variance explained. The study therefore does not support claims that the retained constructs are dominant determinants of purchasing frequency. Food purchasing is

likely to reflect additional influences that were not represented in the final latent model, including prices, seasonal availability, household budgets, shopping routines, quantities purchased, and supply conditions. Reporting odds ratios, confidence intervals, FDR-adjusted results, and model-fit statistics together provides a more proportionate account of the practical importance of the observed associations. The category interaction results provide the clearest evidence for heterogeneity. Product Evaluation and Social Influence both varied significantly across the six food categories, and the combined interaction test was highly significant. Thus, category differences are not inferred merely because one coefficient is significant and another is not. They are supported by a direct respondent clustered test of factor-by-category interactions.

For urban food marketers and nutrition communicators, these results argue against treating all product categories as equivalent. Product information that emphasises taste and health may align differently with routine purchases of eggs and meat, and peer- or influencer-based messages may not have a uniform relationship with purchasing dairy and meat.

6. CONCLUSION

This study investigated purchase frequency for six frequently purchased food categories among urban consumers surveyed in Ulaanbaatar. The analysis used two exploratory, internally consistent observed four-item composites Product Evaluation and Social Influence. Available CFA and ordinal ULS diagnostics do not establish validated latent constructs; findings are interpreted at the observed composite level. In the adjusted purchase frequency analyses, associations surviving false discovery rate correction were observed for meat, milk, and eggs. Formal interactions indicated that the relationships of both observed composites with purchase frequency differed across food categories. These findings are best interpreted as selective, category-specific associations, not strong determinants of purchasing behaviour. The descriptive purchase frequency table also documents that the six analysed categories differ in the share of respondents reporting frequent purchases. Together with the interaction tests, this supports category specific reporting instead of a single pooled food frequency conclusion. The conceptual contribution lies in combining product evaluation and social influence with an explicitly ordinal purchasing outcome while retaining transparent measurement and sampling limitations. Future studies should independently validate measurement items using an appropriate ordinal CFA estimator and recruit probability-based or more diverse samples. Other purchase related attributes, including informational and retail environment measures, warrant direct evaluation. Transactional or longitudinal data could further clarify category-specific associations.

REFERENCE

[1] Steptoe, A., Pollard, T. M., & Wardle, J. (1995). Development of a measure of the motives underlying the selection of food: The Food Choice Questionnaire. Appetite, 25(3), 267–284. https://doi.org/10.1006/appe.1995.0061
[2] Shepherd, R., & Raats, M. (Eds.). (2006). The psychology of food choice. CABI. https://doi.org/10.1079/9780851990323.0000
[3] Rozin, P. (2006). The integration of biological, social, cultural and psychological influences on food choice. In R. Shepherd & M. Raats (Eds.), The psychology of food choice (pp. 19–39). CABI. https://doi.org/10.1079/9780851990323.0019
[4] Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
[5] Roininen, K., Lähteenmäki, L., & Tuorila, H. (1999). Quantification of consumer attitudes to health and hedonic characteristics of foods. Appetite, 33(1), 71–88. https://doi.org/10.1006/appe.1999.0232
[6] Verbeke, W. (2008). Impact of communication on consumers' food choices. Proceedings of the Nutrition Society, 67(3), 281–288. https://doi.org/10.1017/S0029665108007179
[7] Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.
[8] Higgs, S., & Thomas, J. (2016). Social influences on eating. Current Opinion in Behavioral Sciences, 9, 1–6. https://doi.org/10.1016/j.cobeha.2015.10.005

[9] Bromage, S., Daria, T., Lander, R. L., Tsolmon, S., Houghton, L. A., Tserennadmid, E., Gombo, N., Gibson, R. S., & Ganmaa, D. (2020). Diet and nutrition status of Mongolian adults. Nutrients, 12(5), 1514. https://doi.org/10.3390/nu12051514

[10] Delgermaa, D., Yamaguchi, M., Nomura, M., & Nishi, N. (2023). Assessment of Mongolian dietary intake for planetary and human health. PLOS Global Public Health, 3(3), e0001229. https://doi.org/10.1371/journal.pgph.0001229

[11] Bromage, S., Tazhibayev, S., Zhou, X., Liu, C., Tserenkhuu, E., Dolmatova, O., Khishignemekh, M., Musurepova, L., Wusigale, Tsolmon, S., Tsendjav, E., Enkhmaa, D., Rai, R. K., Enkhbat, B., Menghe, B., & Ganmaa, D. (2025). Longitudinal analysis of lifestyle risk factors, nutrition status and drivers of food choice among urban migrants in Ulaanbaatar, Mongolia, and Almaty, Kazakhstan: A formative study. Public Health Nutrition, 28(1), e33. https://doi.org/10.1017/S136898002400243X

[12] Erdenetsetseg, E., Purevjal, T., Chogsom, A., Munabaatar, T., Erdenejargal, T., & Gansukh, O. (2025). Solutions for food waste management improvement of Ulaanbaatar city. International Journal of Social Science and Humanities Research-MIYR, 5(3), 1–18. https://doi.org/10.53468/ijsshr-miyr.v5i3.9

[13] Drewnowski, A., & Popkin, B. M. (1997). The nutrition transition: New trends in the global diet. Nutrition Reviews, 55(2), 31–43. https://doi.org/10.1111/j.1753-4887.1997.tb01593.x

[14] Deliza, R., & MacFie, H. J. H. (1996). The generation of sensory expectation by external cues and its effect on sensory perception and hedonic ratings: A review. Journal of Sensory Studies, 11(2), 103–128. https://doi.org/10.1111/j.1745-459X.1996.tb00036.x

[15] Spence, C., Levitan, C. A., Shankar, M. U., & Zampini, M. (2010). Does food color influence taste and flavor perception in humans? Chemosensory Perception, 3(1), 68–84. https://doi.org/10.1007/s12078-010-9067-z

[16] Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. Journal of Marketing, 52(3), 2–22. https://doi.org/10.1177/002224298805200302

[17] Fernqvist, F., & Ekelund, L. (2014). Credence and the effect on consumer liking of food: A review. Food Quality and Preference, 32, 340–353. https://doi.org/10.1016/j.foodqual.2013.10.005

[18] Michaelidou, N., & Hassan, L. M. (2008). The role of health consciousness, food safety concern and ethical identity on attitudes and intentions towards organic food. International Journal of Consumer Studies, 32(2), 163–170. https://doi.org/10.1111/j.1470-6431.2007.00619.x

[19] Birch, L. L., & Fisher, J. O. (1998). Development of eating behaviors among children and adolescents. Pediatrics, 101(Supplement 2), 539–549.

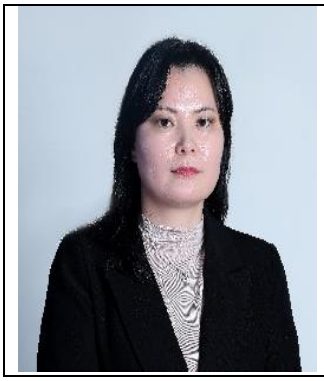
[20] Patrick, H., & Nicklas, T. A. (2005). A review of family and social determinants of children's eating patterns and diet quality. Journal of the American College of Nutrition, 24(2), 83–92. https://doi.org/10.1080/07315724.2005.10719448

[21] Coates, A. E., Hardman, C. A., Halford, J. C. G., Christiansen, P., & Boyland, E. J. (2019). Social media influencer marketing and children's food intake: A randomized trial. Pediatrics, 143(4), e20182554. https://doi.org/10.1542/peds.2018-2554

[22] Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. Journal of the Royal Statistical Society: Series B (Methodological), 57(1), 289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

AUTHOR'S BIOGRAPHY

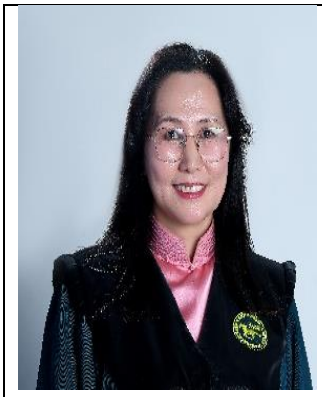
1. First Author



Tuul Damdinsuren tuul.d@muls.edu.mn

Tuul Damdinsuren is a PhD student at the School of Economics and Business, Mongolian University of Life Sciences, Mongolia. Her research specializes in food consumer behavior and sustainable consumption. The article resulted from her PhD research conducted between September and December 2024. She wrote the initial draft of the manuscript.

2. Corresponding Author



Undrakh Zagarkhorloo undrakh@muls.edu.mn

Undrakh Zagarkhorloo is a PhD supervisor and academic researcher at the School of Economics and Business, Mongolian University of Life Sciences, Mongolia. Her research specializes in agricultural marketing and community-based tourism. She supervised the PhD research underlying this article, developed the theoretical framework, and conducted the data analysis.

3. Co Author



Byambajargal Gansukh byambajargal.g@muls.edu.mn

Byambajargal Gansukh is a scholar and lecturer at the School of Economics and Business, Mongolian University of Life Sciences, Mongolia. Her research specializes in agricultural marketing and dairy food value chain management. She contributed to the research by coordinating data collection and conducting data processing.