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Exploring a Refined MOA Operationalization for Food Waste: Structural Context, Physical Opportunity, and Cognitive-Capacity Indicators in University Cafeterias

Shikun Wei [1], Zhongya Ji [2], Chi Cheng [3], Bang Qiao [1], Jianan Wang [1], Xiaobin Liu [1], Min Zhao [1,*] and Zhi Chen [4,*]

[1] College of Agricultural Economics and Management, Shanxi Agricultural University, No. 1 Mingxian South Road, Taigu District, Jinzhong 030810, China
[2] Jiangsu Key Laboratory of Crop Genetics and Physiology, Agricultural College of Yangzhou University, Yangzhou 225009, China; zyji@yzu.edu.cn
[3] College of Resources and Environment, Shanxi Agricultural University, No. 1 Mingxian South Road, Taigu District, Jinzhong 030810, China
[4] College of Animal Science and Technology, Yangzhou University, Yangzhou 225009, China
* Correspondence: zmin99@sxau.edu.cn (M.Z.); zhichen@yzu.edu.cn (Z.C.)

Abstract

Food waste research often applies the Motivation–Opportunity–Ability (MOA) framework, yet conventional aggregate measures may obscure the distinct roles of physical context and cognition-related capacity. Using a macro-contextual, micro-primary dual-layer design, this study first uses World Bank data from 176 countries to provide structural context; this macro layer is not statistically linked to the student-level model. The main behavioral inference comes from matched plate-weighing and questionnaire data from 170 students across two purposively selected ordinary higher education institutions in northern and southern China. Within this exploratory and context-specific micro-level sample, the baseline three-dimensional MOA model explains only 4.1% of variance in log-transformed plate waste, whereas decomposing Opportunity into social and physical components and representing the Ability extension through behavioral ability and a two-item cognitive-capacity proxy improves model fit. The five-dimensional model explains 44.1% of variance ($F = 26.2$, $p < 0.001$). Johnson relative weight analysis indicates that Physical Opportunity (51.1%) and the two-item cognitive-capacity proxy (46.3%) account for most explained MOA variance in this sample. Item-level sensitivity checks further suggest that portion estimation and nutrition knowledge should be interpreted as distinct cognition-related indicators rather than as a validated latent scale. Robustness checks across raw, log-transformed, winsorized, logistic, and quantile specifications indicate consistent positive associations for Physical Opportunity and consistent negative associations for cognition-related indicators. Because the design is cross-sectional, these findings identify associations rather than causal effects; physical-environment redesign and cognitive-capacity support should therefore be treated as candidate directions for future intervention testing rather than as confirmed intervention effects. By linking objectively measured plate waste to institutional dining conditions, the study contributes to sustainability research on responsible consumption, resource efficiency, low-carbon campus operations, and practical pathways for reducing avoidable food-related environmental burdens in university settings.

Keywords: food waste; MOA framework; dimension refinement; physical opportunity; cognitive-capacity proxy; plate weighing; structural determinants; responsible consumption

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1. Introduction

1.1. University Cafeteria Food Waste as a Responsible Consumption Challenge

Food waste remains a major sustainability concern because it links food security, environmental burden, and resource efficiency. Approximately one-third of food produced globally is lost or wasted annually, generating roughly 3.3 Gt CO_2eq of greenhouse gas emissions [1–3]. In China, food organic waste accounts for 61.2% of municipal solid waste by weight—substantially exceeding global averages [4,5]. Reducing food waste has become a priority in national sustainability governance, exemplified by China's "Dual Carbon" objectives and the "Clean Plate" campaign.

The relevance of this issue to sustainability is both environmental and managerial. At the global level, food-waste reduction is directly connected to responsible consumption and production, particularly Sustainable Development Goal 12.3, which calls for halving per-capita food waste and reducing food losses along supply chains [6]. At the institutional level, university cafeterias are not only places of consumption but also managed socio-technical systems in which procurement, portioning, serving rules, dining infrastructure, and student behavior jointly shape resource efficiency and avoidable environmental burdens. Understanding plate waste in this setting therefore contributes to sustainability scholarship by connecting behavioral evidence with campus sustainability management, low-carbon operations, and practical governance of everyday consumption.

University cafeterias provide a useful institutional setting for examining responsible food consumption under standardized dining conditions. These institutional dining environments serve large populations daily under standardized conditions that differ in several operational respects from household or restaurant settings [7–9]. In cafeterias, portion sizes are determined by staff rather than diners, menu options are standardized, dining periods are time-constrained, and the physical environment is not under individual control. These structural constraints mean that observed waste behavior reflects not only individual dispositions but also environmental affordances that limit behavioral autonomy [10,11].

Prior research documents that plate waste in institutional settings ranges from 15% to 45% depending on meal type and conditions, with large-scale Chinese university surveys reporting 74% of students generate plate waste averaging 61 g per meal [12–14]. However, the psychological mechanisms driving this waste—and their relative importance in constrained institutional environments—remain insufficiently understood. This gap makes it difficult to identify which behavioral levers should be prioritized in cafeteria-based interventions, which often default to motivation-centered campaigns.

1.2. The MOA Framework: Potential and Limitations

The Motivation–Opportunity–Ability (MOA) framework provides a theoretically grounded lens for understanding food waste behavior [15–17]. The framework posits that behavior is jointly determined by: (1) Motivation—the desire or willingness to act; (2) Opportunity—the environmental conditions that enable or constrain action; and (3) Ability—the skills and capacity to perform the behavior [18].

MOA is not the only behavioral framework used in food waste research. The Theory of Planned Behavior emphasizes attitudes, subjective norms, and perceived behavioral control as antecedents of intention and behavior [19]; Norm Activation Theory foregrounds personal norms, awareness of consequences, and responsibility attribution [20]; and COM-B conceptualizes behavior as a function of capability, opportunity, and motivation [21]. In food-waste studies, TPB-based applications have commonly emphasized intention formation, perceived behavioral control, and subjective norms [22,23], whereas norm- and emotion-oriented approaches highlight moral obligation, guilt, responsibility attribution, and competing household routines [24–27]. COM-B is particularly useful for connecting

individual capability and environmental opportunity to intervention design. These approaches overlap with MOA but differ in emphasis: TPB and Norm Activation Theory are especially useful for intention and moral-norm pathways, whereas COM-B and MOA place greater analytical weight on capability and opportunity. The present study therefore does not claim that MOA is theoretically superior to these alternatives; rather, it asks whether a more granular MOA operationalization can provide useful exploratory evidence in a constrained cafeteria setting.

Empirical applications of MOA to food waste have produced valuable insights [22,25,28]. However, conventional operationalizations of the framework face an important measurement limitation: they typically treat Opportunity and Ability as unitary, aggregate constructs. In the context of institutional dining, this aggregation may obscure distinct mechanisms that differentially influence waste outcomes. Specifically:

Opportunity is conventionally measured via perceived social norms and convenience, but cafeteria environments also present physical constraints (portion flexibility, serving autonomy, disposal infrastructure) that may operate independently of social perceptions. Ability is typically assessed as self-reported behavioral confidence, yet food waste reduction also requires cognitive capacities (portion estimation knowledge, food management skills) that may be poorly captured by general agency measures.

This measurement coarseness has led to inconsistent findings. Some studies report significant MOA effects on self-reported waste intentions [24,29], while others find weak or null associations with objectively measured waste [8,17]. These inconsistencies may partly reflect limitations in how MOA dimensions have been operationalized; the framework's explanatory power may have been underestimated due to insufficient dimensional granularity.

1.3. Research Gap: From Aggregate MOA to Refined Dimensions

Building on these observations, two interrelated gaps motivate the present study.

First, prior research has tended to focus more on motivational factors than on distinctions within opportunity and ability. Survey-based food waste studies frequently find that attitudes and intentions explain substantial variance in self-reported behavior, leading to intervention recommendations focused on awareness campaigns and moral appeals [30,31]. Yet these motivation-centered approaches may have limited efficacy in institutional dining, where structural constraints override individual preferences. The relative importance of different MOA dimensions in such constrained environments remains empirically unresolved.

Second, the distinct roles of physical opportunity and cognition-related capacity remain less explicitly theorized and measured. Physical opportunity—environmental affordances such as portion adjustability, serving autonomy, and disposal convenience—represents a separate pathway from social opportunity (norms, peer influence). Similarly, cognition-related capacity—knowledge and skills for food management—differs from behavioral ability (general confidence and assertiveness). Conflating these sub-dimensions into aggregate scales may produce misleading conclusions about which intervention targets are most impactful.

We therefore advance the following proposition: in institutional dining contexts, decomposing MOA into finer-grained dimensions—specifically distinguishing physical from social opportunity, and cognitive from behavioral ability—may improve explanatory power for objectively measured plate waste. This proposed refinement is treated as preliminary and sample-specific rather than as a definitive reformulation of MOA theory. It shifts the analytical focus from "whether MOA matters" to "which components of MOA matter under structural constraints."

1.4. Research Objectives and Hypotheses

This study aims to refine the MOA framework for university cafeteria food waste by decomposing Opportunity and Ability into theoretically meaningful sub-dimensions and testing their relative predictive power against objectively measured behavioral outcomes within the present two-campus sample. To provide structural context, we first establish macro-level evidence on national waste composition patterns using global open data, then focus analytical attention on the micro-level MOA mechanisms. By doing so, the study positions university cafeteria plate waste as a sustainability problem of responsible consumption, institutional resource governance, and behaviorally informed waste reduction rather than only as an individual attitude problem.

Research Questions:

RQ1 To what extent do economic development, infrastructure, and governance explain cross-national variation in organic waste composition, providing contextual grounding for institutional food waste research?

RQ2 Does a refined five-dimensional MOA operationalization (Motivation, Social Opportunity, Physical Opportunity, Behavioral Ability, and a two-item cognitive-capacity proxy) explain objectively measured cafeteria plate waste better than the conventional three-dimensional aggregate model in this sample?

RQ3 Which MOA sub-dimensions or proxy indicators contribute most to plate-waste variance, and what do the patterns tentatively imply for intervention design in institutional dining?

Hypotheses:

Hypothesis 1. *The baseline aggregate MOA model will explain limited variance in objectively measured plate waste ($R^2 < 0.10$), consistent with prior null findings in institutional settings.*

Hypothesis 2. *Decomposing Opportunity into Social and Physical components, and Ability into Behavioral Ability and a two-item cognitive-capacity proxy, will significantly improve model fit ($\Delta R^2 > 0.20$, $p < 0.001$).*

Hypothesis 3. *Physical Opportunity and cognition-related indicators are expected to account for a large share of explained plate-waste variance in the refined model.*

Hypothesis 4. *The associations of Physical Opportunity and the cognition-related indicators will remain robust across alternative model specifications (raw waste, log-transformed, winsorized, logistic, and quantile regression).*

1.5. Contributions

This study makes three contributions to the responsible consumption and sustainability literature. First, it provides preliminary evidence that dimensional refinement—specifically distinguishing physical opportunity and cognition-related capacity—can improve MOA's empirical performance in this two-campus setting. This finding qualifies previous concerns about the limited performance of aggregate MOA measures in institutional settings and redirects theoretical attention toward measurement granularity, while remaining subject to replication. Second, it provides evidence using objectively weighed plate waste as the behavioral outcome, addressing a persistent limitation of self-report-based food waste research and supporting more reliable sustainability assessment in institutional dining. Third, it offers exploratory implications for intervention design: physical-environment redesign and cognition-related capacity development are framed as candidate directions for future testing, not as established causal interventions. These directions are relevant to

sustainable campus management because they target avoidable waste, resource inefficiency, and the translation of sustainability awareness into everyday consumption practice. The weak incremental role of motivation in this sample is interpreted as a ceiling-effect pattern rather than as evidence that motivation is generally unimportant.

1.6. Theoretical Framework

Figure 1 presents a simplified framework guiding this study. The figure separates the macro contextual layer from the micro behavioral layer to make clear that the main behavioral inference is based on the student-level cafeteria data. Conventional three-dimensional MOA provides the baseline specification, while the refined model decomposes Opportunity into Social Opportunity and Physical Opportunity and represents the Ability extension through Behavioral Ability and a two-item cognitive-capacity proxy. Physical Opportunity and cognition-related indicators are treated as candidate predictors whose associations require replication and future intervention testing.

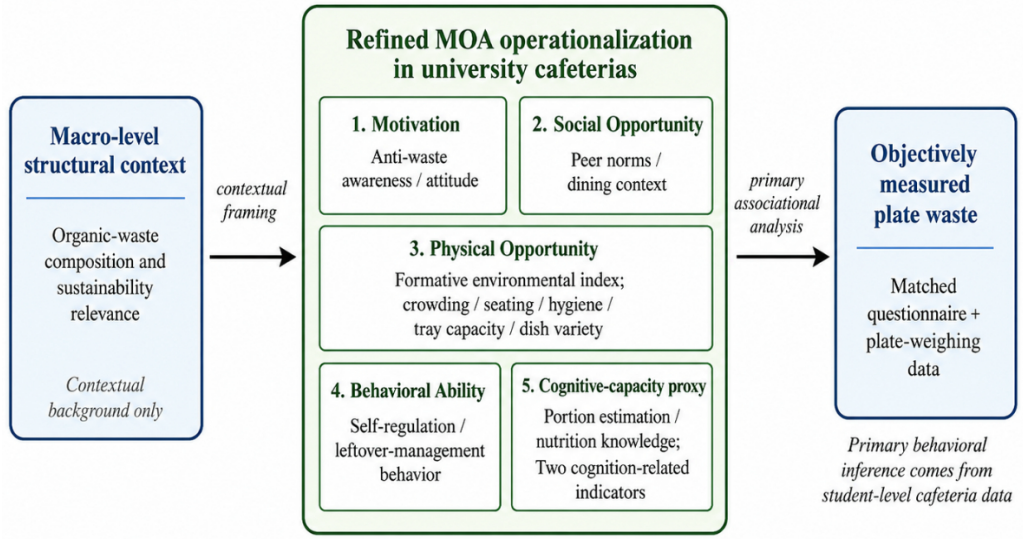


Figure 1. Simplified study framework. The macro layer uses cross-national World Bank data ($N = 176$ countries) only to establish structural context. The micro layer is the primary behavioral analysis and uses matched plate-weighing and questionnaire data from two purposively selected university cafeterias ($N = 170$ students). The refined MOA specification distinguishes Social Opportunity from Physical Opportunity and Behavioral Ability from a two-item cognitive-capacity proxy; all reported micro-level estimates are interpreted as context-specific associations.

2. Methods

2.1. Research Design and Overview

This study uses a macro-contextual, micro-primary design. The macro layer provides contextual background on national organic-waste composition using open-source cross-national data; it is not modeled as a Level-2 predictor of the student observations and is not used to estimate individual-level behavioral effects. The micro layer is the primary inferential component and tests whether a more granular MOA operationalization explains objectively weighed cafeteria plate waste in the present two-campus sample. Accordingly, all behavioral interpretations in the manuscript refer to the micro-level cafeteria data. Figure 1 summarizes this design logic.

The analytical workflow has four steps: (1) macro-level contextual analysis using World Bank and related open data from 176 countries; (2) micro-level plate-weighing and questionnaire measurement across two ordinary higher education institutions in northern and southern China ($N = 170$ final analytic cases); (3) hierarchical regression

and relative-weight analysis comparing aggregate and refined MOA specifications; and (4) robustness and sensitivity checks across alternative outcome specifications and model forms. Figure 2 is included only to document the macro-level context that motivated the campus study.

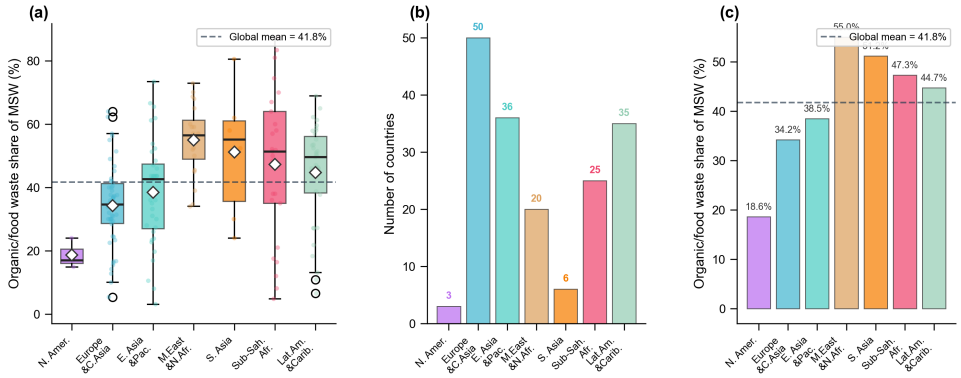


Figure 2. Regional distribution of organic/food waste share in municipal solid waste. (**a**) Box plots showing median, IQR, and range with individual country points; (**b**) sample sizes by region; (**c**) mean organic waste percentages by region with global mean reference line. MEA, SAS, and SSF exhibit the highest shares, while NAC shows the lowest.

Ethical approval was obtained from the Agricultural College of Yangzhou University Ethics Committee (ethics approval number NXY-L-2026-001; review number 2026-008; approval date 7 January 2026), and informed consent was obtained from all participants.

2.2. Part 1: Macro-Level Structural Context

Cross-national data were obtained from the World Bank's "What a Waste 2.0" database [32], supplemented with World Development Indicators [33] and EDGAR emissions data [34]. The dependent variable is *organic waste percentage of total municipal solid waste (MSW)*—a structural indicator of waste composition at the national level.

Independent variables include: log-transformed GDP per capita (economic development), World Bank income classification, waste collection coverage (% of population with formal services), recycling rate (technology proxy), and six Worldwide Governance Indicators dimensions [35,36] (Voice and Accountability, Political Stability, Government Effectiveness, Regulatory Quality, Rule of Law, Control of Corruption).

Missing data in the macro layer were addressed using Multiple Imputation by Chained Equations (MICE) under Missing at Random (MAR) assumptions. The imputation model included organic waste share, log GDP per capita, income classification, collection coverage, recycling rate, regional indicators, and governance variables; 20 imputed datasets were generated and pooled for the hierarchical macro regression. Complete case analysis ($N = 46$ for the most restrictive macro specification) was conducted as a robustness check. This layer provides contextual framing rather than direct behavioral inference.

2.3. Part 2: Micro-Level MOA Measurement

2.3.1. Data Collection Procedures

Micro-level data collection began with a preparatory pilot survey in November 2024, followed by formal investigation from January to May 2026. The study sites were purposively selected from two ordinary higher education institutions located in two Chinese provinces, one in northern China and one in southern China. Both sites used conventional staffed cafeteria service rather than buffet-only or restaurant-style ordering; data were collected during regular lunch and dinner meal periods with standard mixed staple, veg-

etable, and protein menus. Participants were recruited on site after completing their meals, and trained assistants matched questionnaire IDs to plate-weighing records. Because the institutions were purposively selected and not randomly sampled, the micro-level evidence should not be generalized beyond similar campus cafeteria contexts without replication.

Food waste measurement: Trained research assistants weighed food waste at the table level using calibrated digital scales ($\pm$1 g accuracy) immediately after each student completed their meal. Waste was defined as all uneaten food remaining on the plate. A conservative zero-waste threshold of $\leq$5 g was adopted following field weighing conventions.

Questionnaire and sample matching: During fieldwork, objective plate-weighing data and questionnaire data were collected in parallel, yielding 216 weighing observations and 204 questionnaire responses. Reconciliation against the source files showed that the final Questionnaire Star export contained 170 valid questionnaire records, and the cleaned matched analysis file also contained 170 observations with measured food waste and five MOA dimension scores. Earlier working sheets contained 171–172 rows because they included intermediate matching rows or header/working records; these were not used as the final analytic denominator. One respondent had a missing A3c item but a valid A4c response, so the two-item cognitive-capacity proxy was computed from available item information. Gender was missing for 3 cases (1.8%) and academic year for 25 cases (14.7%); the primary model retained $N = 170$ by using a female indicator coded 0 when gender was missing and median-imputed academic year, while complete-case sensitivity analyses are reported at $N = 145$.

2.3.2. Refined MOA Operationalization

Table 1 summarizes the measurement approach for each MOA dimension. We distinguish between reflective scales (where items are interchangeable indicators of a latent construct) and formative indices (where items represent distinct components that jointly define the construct).

Table 1. MOA dimension measurement summary.

Dimension	Type	Items	Analytical Treatment
Motivation	Reflective scale	5 items: moral guilt, duty, principle, self-regulation, finishing behavior	Cronbach's α reported
Opportunity–social	Reflective scale	6 items: portion flexibility, social norms, peer influence, authority attitudes	Cronbach's α reported
Opportunity–physical	Formative index	5 items: crowding, seating availability, hygiene, tray capacity, dish variety	No internal consistency expected; items represent distinct affordances
Ability–behavioral	Two-item scale	2 items: portion request confidence, feedback willingness	Item correlation reported
Ability–cognitive-capacity proxy	Composite indicator	2 items: portion estimation knowledge, nutrition awareness	Treated as cognition-related indicators; item-level robustness checked

Motivation (5 items, reflective scale) was measured using five items adapted from MacInnis and Jaworski [15] and Visschers et al. [24]: moral guilt when wasting food, sense

of duty to reduce waste, personal principle against wasting, self-regulation even when unsupervised, and willingness to finish food despite poor taste. All items used 5-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree). Cronbach's $\alpha = 0.885$ indicates excellent internal consistency.

Social Opportunity (6 items, reflective scale) was measured via six items capturing perceived social norms and institutional arrangements: perceived flexibility of portion sizes, comfort level with intervening when others over-order, awareness of scholarship policies regarding waste, and perceived attitudes of peers, family, and teachers/managers toward food waste. Cronbach's $\alpha = 0.742$ indicates acceptable reliability.

Physical Opportunity (5 items, formative index) was conceptualized as a formative index capturing distinct environmental affordances rather than interchangeable reflective indicators [37–40]. The five items were: (1) cafeteria crowding during peak hours, (2) seating availability, (3) perceived hygiene conditions, (4) tray capacity appropriateness, and (5) variety of bowl/dish sizes. These items represent non-interchangeable physical constraints; low internal consistency is expected and does not indicate measurement failure. Instead, each item contributes uniquely to the environmental opportunity structure. To strengthen construct transparency without overstating validation, we added a content-domain mapping audit in Appendix A Table A2. This audit documents the intended environmental domain covered by each physical-opportunity item and clarifies that the index has not been externally validated against independent expert CVI ratings or objective cafeteria-environment observations. The present study therefore treats Physical Opportunity as a theoretically grounded and diagnostically useful formative index, not as a fully externally validated environmental measure.

Behavioral Ability (2 items) was measured with two items capturing self-reported confidence in requesting smaller portions and willingness to provide feedback to cafeteria staff. With only two items, traditional α is not appropriate; the Pearson correlation between items was $r = 0.508$ ($p < 0.001$).

Cognitive-capacity proxy (2 items, composite indicator) was measured as a composite indicator capturing complementary knowledge-related capacities: (1) ability to accurately estimate personal food needs, and (2) knowledge of food nutrition and calories. These items represent distinct cognitive competencies rather than homogeneous reflective indicators. Because the two items showed near-zero correlation ($r = -0.071$), the composite is retained in Model C primarily for comparability with the proposed five-dimensional MOA operationalization, but substantive interpretation emphasizes item-level cognition-related indicators reported in Model D and the robustness checks.

2.3.3. Dimensional Scoring

Dimension scores were computed as simple averages of constituent items, consistent with conventional MOA operationalization. All items were coded such that higher scores indicate: higher motivation to reduce waste, more favorable social opportunity, more constrained physical environment (note: for physical opportunity, higher scores indicate worse conditions—greater crowding, lower perceived seating adequacy, poorer hygiene, less appropriate tray capacity, and less suitable bowl/dish variety), higher behavioral ability, and higher cognition-related capacity. The physical opportunity block was additionally inspected through inter-item correlations, formative-indicator VIFs, item-level regressions, and leave-one-out index tests.

2.4. Analytical Strategy

2.4.1. Hierarchical Regression Models

We estimated a sequence of nested regression models to test the incremental explanatory value of dimensional refinement:

Model A (Baseline): Aggregate MOA with three dimensions (Motivation, Opportunity, Ability) using conventional measurement. Model B (+Physical Opportunity): Model A plus the decomposed Physical Opportunity dimension, testing the incremental contribution of physical environmental affordances. Model C (Five-Dimensional): Full specification with five dimensions (Motivation, Social Opportunity, Physical Opportunity, Behavioral Ability, and a two-item cognitive-capacity proxy). Model D (Item-Level): All 20 individual items as predictors, testing whether dimensional aggregation loses predictive information. Model E (+Interactions): Model C plus two-way interaction terms (Motivation × Social Opportunity, Motivation × cognitive-capacity proxy, Physical Opportunity × cognitive-capacity proxy).

All models used log-transformed food waste ($\log(1 + \text{FW})$) as the dependent variable due to zero-inflation and extreme right-skewness (skewness = 3.12, kurtosis = 18.12; 25.3% of respondents left $\leq$5 g waste). HC1 heteroskedasticity-robust standard errors were employed throughout. Control variables included gender and academic year; because missingness occurred only in these controls, complete-case and MICE sensitivity analyses were used to evaluate whether the substantive coefficients changed when controls were imputed more formally. For the micro-level MICE sensitivity analysis, we generated 20 imputed datasets using chained equations with Bayesian Ridge posterior sampling. The imputation model included the outcome variable ($\log(1 + \text{FW})$), the five MOA dimension scores, gender, and academic year, so that predictor–outcome associations were preserved during imputation. Gender was rounded back to the nearest valid binary category after imputation, and academic year was treated as an ordered numeric control. Because micro-level missingness was limited to controls (3 missing gender values and 25 missing academic-year values), MICE was used only as a sensitivity check rather than as the primary basis for inference; complete-case results are reported at $N = 145$ and compared with the imputed-control results in Appendix A Table A3.

2.4.2. Relative Importance Analysis

Johnson Relative Weights Analysis (RWA) [41] was used to decompose the dimension-only R^2 into contributions from each MOA dimension, providing a multicollinearity-robust measure of relative importance. Raw relative weights are reported together with percentages of the explained MOA variance; by construction, the raw weights sum to the dimension-only model R^2. RWA is interpreted as an associational variance-decomposition method, not as evidence of causal priority.

2.4.3. Robustness-Check Specifications

We conducted a set of robustness checks to assess whether findings were sensitive to specification choices:

DV transformations: Raw waste (OLS-HC1), $\log(1 + \text{FW})$, winsorized waste (99th percentile ceiling), and binary waste (>5 g; logistic regression). Quantile regression: Estimates at $\tau = 0.10, 0.25, 0.50, 0.75, 0.90$ with bootstrapped standard errors (1000 replications) to examine distributional heterogeneity. Sensitivity analyses: Six alternative model specifications testing coefficient stability for the cognitive-capacity proxy, including leave-one-dimension-out analyses and a parsimonious two-predictor model (Physical Opportunity + cognitive-capacity proxy only). Multicollinearity diagnostics: Variance Inflation Factors (VIFs) for all models.

2.4.4. Statistical Power

Post-hoc power analysis using Cohen's f^2 with non-central F approximation indicated that the sample was sufficient to detect medium-to-large effects ($f^2 \geq 0.15$) at conventional power levels, but underpowered for small effects. The observed effect size in the refined model was large ($f^2 = 0.790$); however, null findings for weaker MOA dimensions (e.g., Social Opportunity, Behavioral Ability) should be interpreted cautiously given the limited power to detect small effects in this sample ($N = 170$).

All analyses were conducted using Python 3.11.5 (statsmodels 0.14+, scipy 1.12+, pandas 2.0+). Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3. Results

This section reports findings from the dual-layer analytical framework. Consistent with the macro-contextual, micro-primary design, Part 1 (cross-national open-data analysis) provides structural context on correlates of national organic waste composition. Part 2 (campus cafeteria study) constitutes the primary inferential analysis, testing whether the refined MOA model improves explanatory power for objectively measured plate waste.

3.1. Part 1: Structural Drivers of Food Waste Composition (Contextual Analysis)

3.1.1. Descriptive Overview

Table 2 presents summary statistics for the macro-level sample. Across 176 countries, organic waste constituted a mean of 41.78% of total MSW (SD = 17.87), ranging from 3.10% (highly industrialized economies with advanced source separation) to 87.60% (low-income economies where organics dominate unsorted waste streams). Per capita GDP averaged $25,191 (SD = $23,464), reflecting substantial global inequality in economic development.

Figure 2 visualizes the regional distribution of organic waste shares, revealing pronounced heterogeneity across World Bank regions.

Table 2. Macro-level descriptive statistics: cross-national waste indicators.

Variable	*N*	Mean	SD	Min	Median	Max
Organic Waste % of MSW	176	41.78	17.87	3.10	43.20	87.60
GDP per capita ($)	175	25,190.9	23,464.4	839.8	16,147.7	117,335.6
Income Level (1–4)	176	3.01	1.02	1.00	3.00	4.00
MSW per Capita (kg/year)	174	394.75	250.22	50.35	351.78	1384.90
Collection Coverage (%)	80	76.55	26.09	8.00	83.92	100.00
Recycling Rate (%)	112	17.20	14.28	0.18	15.00	64.60
Open Dump Rate (%)	60	50.98	30.86	0.00	54.10	100.00

Note: Income Level: 1 = Low, 2 = Lower-Middle, 3 = Upper-Middle, 4 = High income. Source: World Bank What a Waste 2.0 Database.

Figure 2 presents the regional distribution of organic waste shares. Pronounced heterogeneity across World Bank regions motivates the macro-level contextual grounding analysis below.

3.1.2. Macro-Level Bivariate Associations

Bivariate correlations among core macro variables (Table 3) revealed a theoretically consistent pattern: per capita GDP was negatively correlated with organic waste share ($r = -0.44$, $p < 0.001$), indicating that economically developed nations exhibit lower proportional organic waste. This association is consistent with the possibility that higher-income countries have more developed waste-sorting systems. GDP was also positively associated with collection coverage ($r = 0.50$) and recycling rate ($r = 0.64$).

The bivariate relationship between economic development (log GDP per capita) and organic waste share was negative ($r = -0.44$, $p < 0.001$), representing the most robust struc-

tural finding in the macro-level analysis. Additional bivariate associations for collection coverage and recycling rate were examined as descriptive diagnostics.

The correlation between organic waste share and collection coverage was modestly negative ($r = -0.16$), suggesting that infrastructure expansion alone does not fully explain cross-national variation—other factors such as dietary patterns, urbanization, and cultural norms around food likely contribute additional explanatory power.

Table 3. Macro-level correlation matrix: core structural variables.

	(1)	(2)	(3)	(4)	(5)
(1) Organic Waste %	1.00				
(2) log(GDP pc)	−0.44 ***	1.00			
(3) Income Level	−0.40 ***	0.74 ***	1.00		
(4) Collection Coverage	−0.16	0.50 ***	0.72 ***	1.00	
(5) MSW per Capita	−0.38 ***	0.64 ***	0.66 ***	0.50 ***	1.00

Note: *** $p < 0.001$. N varies by variable availability (see Table 2).

3.1.3. Governance Indicators (WGI) Results

We obtained the Worldwide Governance Indicators (WGI) 2024 dataset, which provides six nuanced governance dimensions for 210–215 countries. Table 4 reports correlations between WGI dimensions and organic waste percentage.

Table 4. WGI governance dimensions vs. organic waste % (primary analysis).

WGI Dimension	*r*	*p*
Voice and Accountability (VA)	−0.431 ***	<0.001
Political Stability (PV)	−0.425 ***	<0.001
Government Effectiveness (GE)	−0.419 ***	<0.001
Regulatory Quality (RQ)	−0.433 ***	<0.001
Rule of Law (RL)	−0.480 ***	<0.001
Control of Corruption (CC)	−0.479 ***	<0.001

Note: *** $p < 0.001$. $N = 168$–170. All six dimensions show significant negative correlations.

All six WGI dimensions exhibit significant negative correlations with organic waste share ($p < 0.001$; Table 4), suggesting that governance quality is consistently associated with organic waste share. Rule of Law (RL) and Control of Corruption (CC) show the strongest effects ($r \approx -0.48$). WGI dimensions are also positively correlated with collection coverage and recycling rate, indicating that governance enables waste management infrastructure, which in turn reduces organic waste shares.

3.1.4. Pre-Imputation Exploratory Analysis

Before addressing missing data, we examined hierarchical OLS regression on available complete cases. Log-transformed GDP per capita showed a consistent negative coefficient across specifications ($b = -6.62$ to -9.29, $p < 0.05$), while collection coverage and recycling rate showed unstable coefficients as N attrited from 175 to 46 due to missing data—consistent with selection bias rather than true null effects. Full results for the complete-case exploratory models are reported in Supplementary Table S2.

3.1.5. Primary Results: MICE-Imputed Structural Model

To address severe N-attrition (collection coverage: 54% missing; recycling rate: 36% missing), we employed MICE imputation, increasing effective N from 80–112 to 175. Imputation diagnostics are provided in Appendix A Figure A1. Table 5 reports hierarchical regression results.

After MICE, GDP shows the largest and most stable association, while recycling rate reaches marginal significance ($b = -0.17$, $p = 0.05$). Region dummies increase R^2 from 20.3% to 35.8%, indicating regional heterogeneity. A complete-case robustness check ($N = 46$) confirmed GDP as the strongest predictor ($r = -0.519$, $p < 0.001$), providing mutual validation with the MICE estimates.

Table 5. Primary results: hierarchical regression with MICE imputation ($N = 175$).

	M1: Economic	M2: +Infra	M3: +Tech	M4: Full
(Intercept)	105.45 ***	99.48 ***	102.35 ***	68.67 ***
log(GDP pc)	−6.62 ***	−5.80 ***	−5.80 ***	−5.80 ***
Collection coverage (%)	–	0.02	0.02	0.02
Recycling rate (%)	–	–	−0.17 *	−0.17 *
Region dummies	No	No	No	Yes
N	175	175	175	175
R^2	0.173	0.203	0.358	0.358
Adj. R^2	0.168	0.192	0.315	0.315

Note: *** $p < 0.001$, * $p < 0.05$. HC1 robust SEs. Region dummies significantly improve model fit ($p < 0.001$).

3.1.6. WGI Governance Regression Results

A supplementary regression incorporating the six WGI governance dimensions confirmed that Control of Corruption exhibits the strongest negative coefficient ($b = -7.04$, $p < 0.001$), while Government Effectiveness shows a positive coefficient likely due to multicollinearity with GDP ($r = 0.805$). The WGI model explains 26.7% of variance, improving on GDP alone ($R^2 = 0.173$). Detailed estimates are reported in Supplementary Table S1.

3.1.7. Exploratory Regional Heterogeneity

A one-way ANOVA revealed significant regional differences ($F(6, 169) = 6.073$, $p < 0.001$), with MEA exhibiting the highest mean organic waste share (55.0%) and NAC the lowest (18.6%). GDP–waste correlations varied across regions: LCN and MEA showed the strongest effects ($r \approx -0.58$ to -0.59, $p < 0.01$); EAS was weaker and marginally significant ($r = -0.32$, $p = 0.055$). These patterns suggest context-specific structural profiles warranting region-sensitive policy approaches. Detailed regional results are reported in Supplementary Table S3.

The macro-level findings establish that structural context—economic development, infrastructure quality, governance capacity, and regional location—is associated with aggregate waste composition. Because these variables were not measured at the campus level, the macro analysis is treated as contextual background rather than as covariates in the micro-level model. The remaining question is whether individual-level MOA constructs are associated with plate waste within the institutional cafeteria setting highlighted by the macro-contextual analysis.

3.2. Part 2: Refined MOA Predictors of Observed Plate Waste (Primary Analysis)

We now turn to the campus-level data ($N = 170$) collected from two ordinary higher education institutions located in northern and southern China. The micro-level survey began with a preparatory pilot stage in November 2024, followed by formal data collection from January to May 2026. Building on the macro-level structural context established in Part 1, this layer tests whether the refined five-dimensional MOA specification—distinguishing Physical Opportunity and the cognitive-capacity proxy from their traditional aggregate counterparts—is associated with objectively measured plate waste in real-world institutional dining settings.

3.2.1. Sample and Dependent Variable Characteristics

During data collection, 216 weighing observations and 204 questionnaire responses were obtained. After data verification, matching, and screening against the source files, the final analytic sample comprised 170 valid respondents with measured food waste and five MOA dimension scores. The dependent variable—plate waste weighed immediately after each meal—exhibited extreme dispersion: mean = 118.0 g, SD = 151.9 g (CV = 128.7%); skewness = 3.12; kurtosis = 18.12. A quarter of respondents left no measurable waste ($\leq$5 g), and 43.5% wasted less than 50 g, producing a zero-inflated distribution. Following established practice, we used $\log(1 + \mathrm{FW})$ as the primary DV in parametric analyses.

Table 6 presents descriptive statistics for all 20 measurement items across five MOA dimensions.

Table 6. Micro-level descriptive statistics: refined five-dimensional MOA measures ($N = 170$).

Variable	Mean	SD	Min	Max	α	Skew
Food Waste (DV)						
Raw (grams)	118.0	151.9	0	1258	–	3.12
log(1 + FW)	3.89	2.20	0.00	7.14	–	−0.64
Motivation (5 items, α = 0.885)						
M1: Moral Guilt	4.04	0.87	1	5		−0.94
M2: Sense of Duty	4.18	0.92	1	5		−1.42
M3: Personal Principle	4.09	0.86	1	5		−0.97
M4: Unsupervised	4.15	0.82	1	5		−1.13
M5: Finish Despite Taste	3.19	1.06	1	5		−0.27
Opportunity–Social (6 items, α = 0.742)						
O1s–O6s: Mean	3.18	0.75	1.33	5.00		–
Opportunity–Physical (5 items, formative)						
O5p: Crowding	2.32	1.58	1	5		0.69
O6p: Seating Availability	2.37	1.48	1	5		0.58
O7p: Hygiene Conditions	2.82	1.34	1	5		0.19
O8p: Tray Capacity	3.25	1.48	1	5		−0.38
O9p: Dish Variety	2.46	1.42	1	5		0.35
Ability–Behavioral (2 items)						
A1b: Portion Request	3.35	1.08	1	5	r_{12} = 0.508	−0.47
A2b: Feedback Willingness	2.85	1.04	1	5		−0.07
Ability–Cognitive-capacity proxy (2 items, composite)						
A3c: Portion Estimation	3.59	1.30	1	5	$r_{12} = -0.071$	−0.53
A4c: Nutrition Knowledge	3.77	1.20	1	5		−0.57

Note: Motivation: α = 0.885 (excellent); Opportunity–Social: α = 0.742 (acceptable); Opportunity–Physical: formative index (α = 0.101 expected; items are non-interchangeable affordances); Ability–Behavioral: 2-item scale (α = 0.673, item r = 0.508); Ability–Cognitive-capacity proxy: composite indicator ($\alpha = -0.153$; items measure distinct cognitive domains).

Three measurement features merit note. Motivation ceiling effect: four of five motivation items exhibited means above 4.0 on a 5-point scale, compressing the variance available for regression; at the scale level, 55.3% of respondents scored at or above 4.0, 25.9% scored at or above 4.5, and 15.3% scored at or above 4.8. Physical Opportunity formative structure: the five physical environment items ($\alpha = 0.101$) capture distinct, non-interchangeable affordances (crowding $\neq$ seating $\neq$ hygiene); low internal consistency is theoretically expected for a formative index but does not by itself validate the construct [37,39,40]. Cognitive-capacity proxy: the two items capture complementary capacities (portion estimation vs. nutrition knowledge; $r = -0.071$) and are retained in the five-dimensional model for comparability, while substantive interpretation relies primarily on item-level cognition-related indicators.

Figure 3 displays the distribution of objectively measured plate waste, which motivates the log-transformation strategy adopted for parametric models.

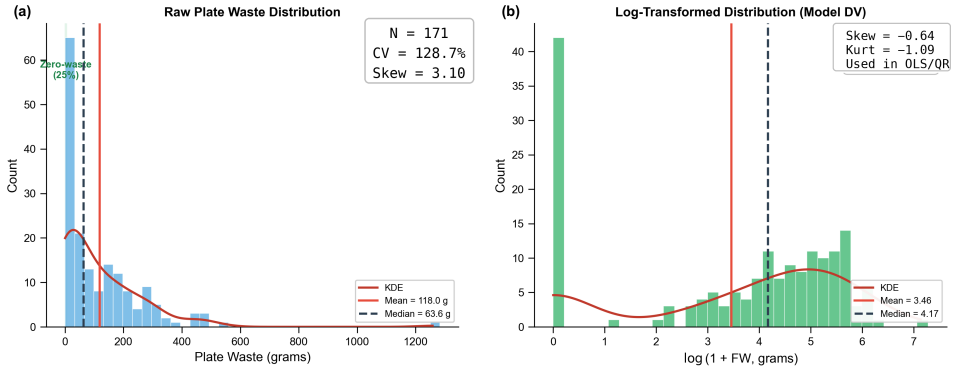


Figure 3. Distribution of measured plate waste and log-transformed model outcome ($N = 170$). Panel (**a**): Raw plate waste (grams) with KDE overlay; red solid line indicates mean, dashed line indicates median, green shaded region marks zero-waste threshold ($\leq$5 g); 25.3% of respondents left $\leq$5 g waste. Panel (**b**): Log-transformed outcome, $\log(1 + \text{plate waste in grams})$, used in the main OLS and quantile regression models. The log transformation accommodates the right-skewed distribution and zero-inflation observed in Panel (**a**).

3.2.2. Correlation Structure

Table 7 reports zero-order correlations among the five MOA dimension scores and food waste. The pattern reveals theoretically meaningful but counterintuitive suppressor relationships.

Table 7. Micro-level correlation matrix: five-dimensional MOA predictors and food waste ($N = 170$).

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Food Waste (g)	1.00					
(2) Motivation	−0.005	1.00				
(3) Opp.–Social	0.023	0.464 ***	1.00			
(4) Physical Opportunity	0.539 ***	−0.002	0.065	1.00		
(5) Ability–Behavioral	0.136	0.308 ***	0.246 ***	0.113	1.00	
(6) cognitive-capacity proxy	−0.440 ***	0.055	−0.057	−0.572 ***	−0.051	1.00

Note: *** $p < 0.001$. The strong negative correlation between Opp.–Physical and Ability–Cognitive-capacity proxy ($r = -0.572$) signals shared variance and potential construct overlap.

At the zero-order level, Physical Opportunity shows the strongest positive correlation with waste ($r = 0.539$, $p < 0.001$): students perceiving more constrained physical environments waste more. The cognitive-capacity proxy shows the strongest negative correlation ($r = -0.440$, $p < 0.001$): students with greater nutritional knowledge waste less. These two important predictors are strongly negatively correlated with each other ($r = -0.572$): students in more physically constrained environments report lower cognitive capacity. This collinearity structure indicates that the two predictors share variance and should be interpreted jointly in multivariate models.

The full correlation structure across all five dimensions showed a strong negative association between Physical Opportunity and the cognitive-capacity proxy ($r = -0.572$), signaling shared variance in multivariate models.

3.2.3. Hierarchical Regression: From Aggregate to Refined MOA

Table 8 reports the hierarchical regression sequence testing whether dimensional refinement improves explanatory power. All models used $\log(1 + \text{FW})$ as the dependent variable with HC1 robust standard errors. Model C is treated as the primary micro-level specification because it directly corresponds to the hypothesized refined MOA operationalization while remaining more parsimonious than the 20-item disaggregation and interaction

models. Model D and Model E are therefore interpreted as sensitivity checks rather than replacement primary models.

Table 8. Hierarchical regression: incremental contribution of dimensional refinement (DV = $\log(1 + \text{FW})$).

	(A) Baseline	(B) +Phys. Op.	(C) Full 5-Dim	(D) 20-Item	(E) +Interact.
Motivation	−0.199	−0.091	0.002	–	−0.108
Social Opportunity	0.081	−0.081	−0.153	–	−0.122
Physical Opportunity	–	1.858 ***	1.223 ***	–	1.295 ***
Behavioral Ability	0.212	0.110	0.114	–	0.106
cognitive-capacity proxy	–	–	−0.908 ***	–	−0.925 ***
N	170	170	170	169	170
R^2	0.041	0.358	0.441	0.569	0.454
Adj. R^2	0.012	0.334	0.417	0.500	0.420
F	1.47	22.0 ***	26.2 ***	12.0 ***	21.8 ***
Max VIF	–	–	1.50	–	–

Note: *** $p < 0.001$. HC1 robust SEs. Model A = conventional 3-dim aggregate MOA; Model B = +Physical Opportunity; Model C = full 5-dimensional; Model D = all 20 individual items; Model E = Model C + interaction terms. Coefficients are associational and should be interpreted alongside RWA and sensitivity analyses.

Model A (Baseline): The conventional three-dimensional aggregate MOA model—Motivation, Opportunity (social only), and Ability (behavioral only)—produced $R^2 = 0.041$ ($F = 1.47$, $p = 0.203$), failing to reach statistical significance. None of the three baseline MOA dimensions reached significance. This baseline result is consistent with H1 and replicates the weak effects commonly reported when MOA is applied to objectively measured waste behavior in institutional settings.

Model B (+Physical Opportunity): Adding the Physical Opportunity dimension was associated with a marked increase in model fit: R^2 jumped from 0.041 to 0.358 ($\Delta R^2 = 0.317$, $\Delta F = 80.4$, $p < 0.001$). The overall model became highly significant ($F = 22.0$, $p < 0.001$), and Physical Opportunity showed a positive coefficient ($b = 1.858$, $p < 0.001$).

Model C (Full Five-Dimensional): Adding the two-item cognitive-capacity proxy further improved model fit to $R^2 = 0.441$ (Adj. $R^2 = 0.417$; ΔR^2 vs. Model A = 0.400, $p < 0.001$). The full five-dimensional model explained 44.1% of the variance, compared with 4.1% in the aggregate baseline. Physical Opportunity showed a positive association ($b = 1.223$, $p < 0.001$), while the cognitive-capacity proxy showed a negative association ($b = -0.908$, $p < 0.001$). Motivation, Social Opportunity, and Behavioral Ability were not significant. VIFs remained below 1.50, indicating that the dimension-level model did not exhibit severe multicollinearity. These results are consistent with H2, but they should be interpreted as exploratory associational evidence rather than theoretical validation.

Model D (Item-Level): Entering all 20 individual items as predictors achieved $R^2 = 0.566$ (Adj. $R^2 = 0.500$), indicating that dimensional aggregation loses some predictive information but also increasing overfitting risk. At the item level, A3c (portion estimation; $b = -0.205$, $p = 0.045$), A4c (nutrition knowledge; $b = -1.168$, $p < 0.001$), and O9p (dish variety; $b = 0.274$, $p = 0.033$) were significant. Accordingly, Model D is used for sensitivity and construct-disaggregation interpretation, not as the primary model. Appendix A Table A4 reports AIC, BIC, and 5-fold cross-validation diagnostics; the parsimonious two-predictor model shows the best cross-validated RMSE, whereas the 20-item model has higher overfitting risk despite its larger in-sample R^2.

Model E (Interactions): Adding two-way interaction terms (Motivation × Social Opportunity, Motivation × cognitive-capacity proxy, Physical Opportunity × cognitive-capacity proxy) yielded negligible improvement ($\Delta R^2 = 0.013$), indicating that the five-dimensional main effects model captures the core predictive structure. H4 is therefore tested primarily through the multi-specification robustness checks below.

Figure 4 visualizes the progressive improvement in explained variance across the five model specifications. Model D has the highest model fit, whereas the interaction model does not further improve explanatory power, suggesting that the main-effect specification provides a more parsimonious representation in this sample.

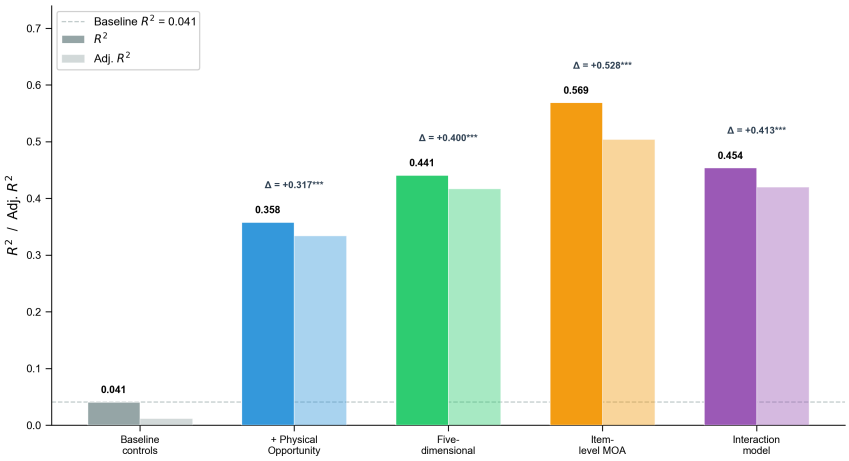


Figure 4. Hierarchical model comparison across MOA specifications. Asterisks indicate *** $p < 0.001$. Model names: Baseline controls = three-dimensional aggregate MOA; + Physical Opportunity = adds decomposed physical environment dimension; Five-dimensional MOA = full refined specification; Item-level MOA = all 20 individual items; Interaction model = five-dimensional plus two-way interaction terms. In-sample R^2 increases across richer specifications, but model comparison should be interpreted alongside adjusted R^2, AIC/BIC, and cross-validation diagnostics because higher in-sample fit does not by itself validate the theoretical structure.

3.2.4. Collinearity, Shared Variance, and Coefficient Interpretation

A notable feature of the revised results is the strong negative association between Physical Opportunity and the cognitive-capacity proxy ($r = -0.572$). At the zero-order level, Physical Opportunity correlates positively with waste ($r = 0.539$), while the cognitive-capacity proxy correlates negatively with waste ($r = -0.440$). In Model C, both associations remain in the same substantive directions: Physical Opportunity is positive ($b = +1.223$, $p < 0.001$), and the cognitive-capacity proxy is negative ($b = -0.908$, $p < 0.001$). Motivation has a near-zero zero-order correlation ($r = -0.005$) and remains non-significant in the multivariate model.

The correlation between Physical Opportunity and the cognitive-capacity proxy nonetheless requires cautious interpretation because partial regression coefficients can redistribute shared variance when predictors are conceptually or empirically related [42,43]. We therefore do not interpret Model C as separating clean causal pathways. Instead, the results indicate that students reporting more constrained physical conditions tend to waste more, whereas students with stronger cognition-related capacity tend to waste less, within this sample and after adjustment for the other MOA dimensions.

For this reason, the results are interpreted jointly across zero-order correlations, partial regression coefficients, relative weights, item-level checks, complete-case/MICE comparisons, and quantile regressions. These estimates address complementary associational quantities and are not treated as causal evidence. The quantile regression results below further support the negative association of the cognition-related indicators and the positive association of Physical Opportunity across the distribution of plate waste.

3.2.5. Relative Weight Analysis: Decomposing Explained Variance

To provide a multicollinearity-robust decomposition of each dimension's contribution, we conducted Johnson Relative Weights Analysis (RWA; Tonidandel and LeBreton [41]).

RWA partitions R^2 into proportions attributable to each predictor, accounting for shared variance through a variable transformation approach.

Physical Opportunity and the cognitive-capacity proxy jointly account for 97.4% of explained MOA variance in the Johnson RWA decomposition (Table 9), providing evidence consistent with H3 but also underscoring that the remaining dimensions contribute little incremental predictive signal in this sample. Motivation—the primary target of many food waste interventions—contributes less than 1% of explained MOA variance in this decomposition. This asymmetry suggests that part of the limited predictive performance observed in prior MOA applications may be attributable to the dimensional granularity of measurement, while also raising the need for replication to rule out sample-specific over-concentration.

Table 9. Relative weight analysis: proportion of explained variance by MOA dimension (dimension-only model, $R^2 = 0.421$).

Dimension	Raw RW	RW %	Rank
Opportunity–Physical	0.215	51.1%	1
Ability–Cognitive-capacity proxy	0.195	46.3%	2
Ability–Behavioral	0.008	1.9%	3
Motivation	0.002	0.4%	4
Opportunity–Social	0.001	0.2%	5
Total	0.421	100%	

Note: RW% sums to 100% of the dimension-only model R^2. Physical Opportunity and the cognitive-capacity proxy jointly account for 97.4% of the explained MOA variance.

Figure 5 visualizes the RWA decomposition. Relative weights indicate each predictor's contribution to explained variance rather than causal effects.

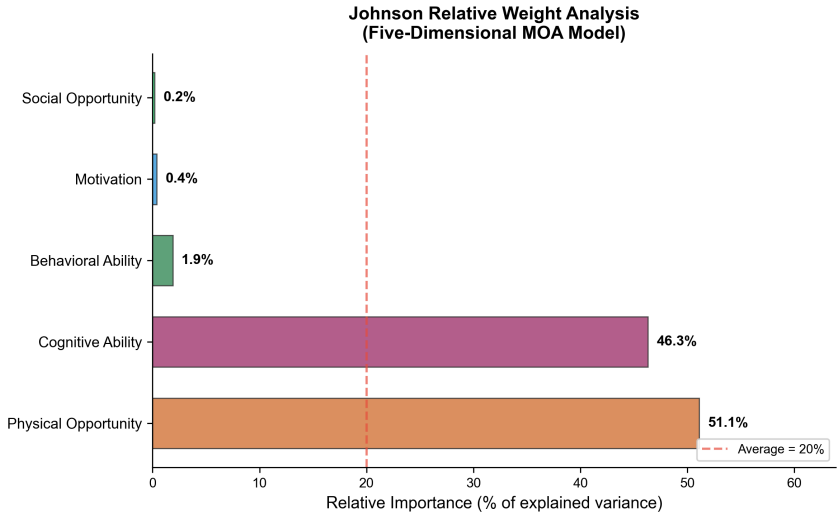


Figure 5. Relative importance of five-dimensional MOA predictors based on Johnson Relative Weight Analysis ($N = 170$, dimension-only model $R^2 = 0.421$). Bars represent the proportion of explained MOA variance attributable to each dimension. Physical Opportunity (51.1%) and the cognitive-capacity proxy (46.3%) account for most explained variance, while the remaining MOA dimensions contribute little in this sample. Relative weights indicate each predictor's contribution to explained variance rather than causal effects.

3.2.6. Robustness and Sensitivity Analyses

Multi-specification robustness. Table 10 reports Model C estimates across four DV transformations. Physical Opportunity and the cognitive-capacity proxy remain the only consistent predictors across all specifications: Physical Opportunity is significant in raw

and winsorized specifications, while the cognitive-capacity proxy is significant in all four specifications ($p < 0.001$ in three of four).

Table 10. Robustness check: five-dimensional MOA model across DV specifications.

	Raw FW OLS-HC1	log(1 + FW) OLS-HC1	Winsorized OLS-HC1	Binary Logit (OR)
Motivation	6.70	0.002	3.75	0.79
Social Opportunity	−7.39	−0.153	−2.78	0.61
Physical Opportunity	90.55 ***	1.223 ***	84.05 ***	4.49 **
Behavioral Ability	7.62	0.114	6.99	1.32
cognitive-capacity proxy	−36.96 ***	−0.908 ***	−35.37 ***	0.19 ***
R^2/Pseudo-R^2	0.351	0.441	0.434	0.328
N	170	170	170	170

Note: *** $p < 0.001$, ** $p < 0.01$. Raw/winsorized coefficients in grams; log coefficients in log-grams; logit coefficients as odds ratios.

Quantile regression. Table 11 reports quantile regression estimates for the five-dimensional model across five quantiles. Physical Opportunity remained significant across all examined quantiles ($p < 0.05$). The cognitive-capacity proxy was significant from $\tau = 0.10$ to $\tau = 0.75$ ($p < 0.05$) and remained marginally significant at $\tau = 0.90$ ($p < 0.10$). This pattern demonstrates that their effects are not localized to specific distributional regions, though the cognitive-capacity proxy weakens at the upper tail.

The quantile regression coefficient trajectories showed that the cognitive-capacity proxy exhibited consistently negative coefficients across all quantiles (aligning with its zero-order correlation of $r = -0.44$), while Physical Opportunity showed consistently positive coefficients throughout the distributional range. This distributional consistency supports interpreting these as consistent associations across the distribution rather than dependence on a single parametric specification. Coefficient estimates are reported in Table 11.

Table 11. Quantile regression: five-dimensional model across food waste distribution (DV = $\log(1 + \text{FW})$, $N = 170$).

	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
Motivation	−0.407	−0.058	−0.177	−0.186	0.163
Social Opportunity	−0.120	−0.404	−0.026	0.180	0.174
Physical Opportunity	2.281 ***	1.765 ***	1.026 ***	0.684 **	0.432 *
Behavioral Ability	0.013	0.186	0.149	0.177	−0.052
cognitive-capacity proxy	−0.679 *	−1.074 ***	−0.649 **	−0.407 *	−0.315 †

Note: Bootstrapped SEs (1000 reps). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

Sensitivity analyses. Six alternative specifications tested the robustness of the cognitive-capacity coefficient: (1) full five-dimensional model, (2) omitting Motivation, (3) omitting Social Opportunity, (4) omitting Physical Opportunity, (5) omitting Behavioral Ability, and (6) a parsimonious two-predictor model (Physical Opportunity + cognitive-capacity proxy only). In all six specifications, the cognitive-capacity proxy remained significant at $p < 0.001$. The most notable result is specification (6): Physical Opportunity and the cognitive-capacity proxy alone achieved $R^2 = 0.438$, accounting for nearly all of the variance explained by the full model.

Coefficient-stability interpretation. The OLS, raw-waste, winsorized, logistic, and quantile specifications all point in the same substantive direction: higher Physical Opportunity constraint is associated with more plate waste, while higher cognition-related capacity is associated with less plate waste. This convergence addresses the reviewer concern that Model C coefficients should not be presented as straightforward evidence. We therefore

treat the pattern as robust association in this sample, not as a causal demonstration of direct mechanisms.

3.3. Cross-Level Synthesis: Structural Context and Refined Individual Mechanisms

Structural embeddedness (from Part 1). At the cross-national level, economic development, infrastructure quality, and regional location systematically differentiate organic waste composition. The strong bivariate correlations ($r_{\text{GDP-OrgWaste}} = -0.44$, $p < 0.001$) and significant regional ANOVA ($F = 6.07$, $p < 0.001$) establish that structural factors shape aggregate waste patterns, providing contextual framing for interpreting individual-level behavior.

Enhanced MOA predictive power (from Part 2). Within the constrained environment of a university cafeteria, the refined five-dimensional MOA model explained 44.1% of variance in objectively measured plate waste ($R^2 = 0.441$, Adj. $R^2 = 0.417$), compared to a non-significant 4.1% for the conventional three-dimensional model. This improvement is attributable primarily to the addition of Physical Opportunity and the cognitive-capacity proxy, which jointly account for most explained MOA variance in the Johnson RWA decomposition. The two cognition-related indicators demonstrated robust negative associations across specifications, but they should be interpreted as separate indicators rather than as a validated latent cognitive-ability scale.

Cross-level synthesis: structural context and individual-level mechanisms. Both layers point to the relevance of structural and environmental factors, but they are not integrated in a formal multilevel model. Part 1 shows that macro-level structural variables (GDP, governance, infrastructure) have the strongest associations with aggregate waste outcomes and therefore provide contextual grounding. Part 2 reveals that the micro-level predictors accounting for the most variance are Physical Opportunity (environmental constraints) and cognition-related indicators (knowledge-related capacities). Motivation, despite being the primary target of many food waste interventions, is compromised by ceiling effects that render it ineffective for differentiation. Taken together, the evidence supports a cautious structure-oriented interpretation: food waste in institutional dining appears to be associated with structural conditions, within which individual cognitive-related capacity retains meaningful predictive validity.

4. Discussion

4.1. Summary of Findings

The dual-layer evidence indicates that dimensional refinement can substantially improve the empirical performance of the MOA framework for food waste behavior in this context, while remaining exploratory. At the macro level, structural factors—economic development ($r = -0.44$), governance quality ($|r| = 0.42$–0.48), and regional location ($F = 6.07$, $p < 0.001$)—differentiate national organic waste composition and provide contextual grounding rather than direct micro-level predictors. The main behavioral inference therefore comes from the micro-level cafeteria data. At this level, the conventional three-dimensional aggregate MOA model failed to reach significance ($R^2 = 0.041$, $p = 0.203$), while the refined five-dimensional model explained 44.1% of variance in objectively measured plate waste ($R^2 = 0.441$, Adj. $R^2 = 0.417$, $F = 26.20$, $p < 0.001$). The improvement was driven primarily by Physical Opportunity and cognition-related indicators, but this pattern is interpreted as preliminary association rather than validation of a new MOA structure.

4.2. From "MOA Fails" to "MOA Was Under-Specified" (Theory Layer)

Prior applications of MOA to food waste have yielded inconsistent results, with some studies reporting significant effects on self-reported intentions [24,29] and others finding weak or null associations with objectively measured behavior [8,17]. These findings have sometimes been interpreted as evidence that aggregate MOA measures perform poorly in institutional settings where structural constraints override individual dispositions [30].

Our results qualify this interpretation. The framework's limited explanatory power may reflect under-specification in measurement rather than a limitation of the framework itself. When Opportunity was decomposed into Social and Physical components, and Ability into Behavioral Ability and a two-item cognitive-capacity proxy, the model's explanatory power increased substantially. This finding redirects theoretical attention from whether MOA applies to institutional food waste, to which components of MOA matter under structural constraints. It should nevertheless be read as preliminary evidence from two campuses rather than as definitive theoretical validation.

The theoretical implication is that Physical Opportunity and cognition-related indicators may represent mechanisms that are conflated—and thus obscured—in conventional aggregate MOA measurement. Physical Opportunity captures perceived environmental affordances (crowding, seating, serving infrastructure) that may enable or constrain waste reduction behavior, independent of social norms. The two cognition-related indicators capture information-processing capacities (nutritional knowledge, portion estimation) that may help individuals translate motivation into effective action. Because the present design is observational and cross-sectional, these mechanisms are interpreted as plausible pathways rather than demonstrated causal processes.

4.3. Collinearity, Measurement Overlap, and Coefficient Interpretation (Measurement Layer)

The revised regression results show no positive cognitive-capacity coefficient in Model C. The cognitive-capacity proxy is negatively correlated with waste at the zero-order level ($r = -0.44$) and remains negative in the five-dimensional OLS model ($b = -0.908$, $p < 0.001$).

Nevertheless, reviewer concerns about suppression and conceptual overlap remain important. Physical Opportunity and the cognitive-capacity proxy are strongly negatively correlated ($r = -0.572$), meaning that the two constructs are empirically entangled. The OLS estimates, complete-case sensitivity analyses, MICE sensitivity analysis, and quantile regressions all retain the same substantive signs: Physical Opportunity is positively associated with waste, while the cognitive-capacity proxy is negatively associated with waste.

The item-level Model D provides additional nuance: A4c (nutrition knowledge) shows a strong negative coefficient ($b = -1.168$, $p < 0.001$), and A3c (portion estimation) also shows a smaller negative coefficient ($b = -0.205$, $p = 0.045$). This supports the decision to retain the composite only for comparability with the five-dimensional MOA specification while interpreting the two cognition-related indicators separately.

The strong negative correlation between Physical Opportunity and the cognitive-capacity proxy itself warrants theoretical attention. It may reflect: (a) a genuine contextual pattern in which constrained dining settings inhibit the use of knowledge; (b) a compositional effect where students with different characteristics self-select into different dining environments; (c) overlap in the way respondents evaluate their cafeteria experience; or (d) limitations in the two-item cognitive-capacity proxy measure. Disentangling these explanations requires longitudinal, experimental, or multilevel designs.

The implication for interpretation is that Model C coefficients should be treated as associational estimates within a small, cross-sectional sample. They are useful for iden-

tifying stable predictive patterns, but they do not establish that physical opportunity or cognition-related capacity causally drives plate waste.

4.4. Physical Opportunity as a Formative Construct: Theoretical and Methodological Implications

The low internal consistency of Physical Opportunity ($\alpha = 0.101$) raises legitimate concerns about construct validity. However, this low reliability is theoretically expected for a formative index [37,38]. The five physical environment items—crowding, seating availability, hygiene conditions, tray capacity, and dish variety—represent distinct, non-interchangeable environmental affordances. Expecting high inter-item correlation is equivalent to expecting that a crowded cafeteria will necessarily have poor hygiene or inappropriate tray sizes—a conflation of distinct structural features.

The formative treatment has two important consequences. First, traditional scale purification procedures (dropping items that reduce α) are inappropriate for formative indices, as each item captures a unique aspect of the construct. Second, the predictive validity of Physical Opportunity (RWA = 51.1% of explained MOA variance; zero-order $r = 0.539$ with waste) provides nomological evidence, but it does not replace content validation. We therefore added a content-domain mapping audit (Appendix A Table A2) to make the theoretical coverage explicit, while acknowledging that formal independent expert CVI was not conducted. Future research should consider alternative validation strategies for formative constructs, including: (a) expert-judged content validity, (b) convergent validity with objective environmental measures, and (c) structural equation modeling with formative measurement specifications.

4.5. Motivation Ceiling Effects: Attitudinal Saturation in Chinese University Contexts

Four of five Motivation items exhibited severe ceiling effects (means > 4.0 on a 5-point scale), reflecting a substantively important phenomenon: China's extensive "Clean Plate" campaigns may have contributed to high stated anti-waste attitudes, while actual waste behavior remains variable. This attitudinal saturation is not merely a measurement nuisance—it represents a genuine ceiling in the effectiveness of motivation-centered interventions.

The RWA finding that Motivation contributes less than 1% of explained MOA variance, despite its theoretical centrality in the MOA framework, is consistent with this interpretation. At the scale level, 55.3% of respondents scored at or above 4.0 and 25.9% at or above 4.5, while motivation showed near-zero correlation with waste ($r = -0.047$, $p = 0.546$) and no significant difference across motivation groups (Kruskal–Wallis $p = 0.853$). When most students agree that wasting food is wrong, additional moral appeals may yield limited marginal gains in this particular high-awareness sample. This pattern should not be read as evidence that motivation is generally unimportant; in populations with lower baseline awareness or wider motivational variation, motivation may play a stronger differentiating role.

4.6. Tentative Implications for Intervention Design

The micro-level evidence suggests three potential intervention directions for future testing in comparable cafeteria settings. Because the study is cross-sectional, these directions should be interpreted as hypotheses for intervention trials rather than as demonstrated causal effects.

Physical-environment redesign. Physical Opportunity is the largest contributor to explained MOA variance (RWA = 51.1%) and shows the strongest zero-order correlation with waste ($r = 0.539$). The specific items in this dimension—crowding, seating, and serving infrastructure—suggest candidate intervention entry points: reducing peak-hour crowding, ensuring adequate seating, and redesigning serving systems to allow portion flexibility. These directions are consistent with field experimental evidence that portion-size

changes can reduce waste [44], but they still require direct testing in the present type of university cafeteria setting.

Cognitive-capacity support. The cognition-related indicators show consistent negative associations across specifications. Their two constituent items—portion estimation and nutrition knowledge—suggest that educational tools targeting accurate self-assessment of food needs and nutritional literacy are plausible candidates for future testing. The two-item composite is interpreted as a cognitive-capacity proxy rather than a validated reflective construct, given its two-item structure and low inter-item correlation ($r = -0.071$).

Motivation as a necessary but saturated condition in this sample. The ceiling effects and very small RWA contribution suggest that motivation functions as a background precondition rather than an active differentiator in this sample. Students are already highly motivated; what varies is their Physical Opportunity to act on that motivation and their cognitive-capacity proxy. Future intervention studies in similar high-awareness settings may therefore test motivation maintenance as a baseline component while focusing experimental variation on physical-environment and cognitive-capacity supports.

4.7. Alternative Explanations and Unmeasured Contextual Factors

Several alternative explanations should be considered before translating these associations into interventions. First, hunger level, prior snacking, meal price, food palatability, and menu-specific preferences may affect both portion choice and leftovers but were not directly measured. Second, meal period and time pressure may confound perceived crowding with students' ability to finish meals. Third, campus-specific serving practices, portion defaults, and cafeteria pricing rules may shape both Physical Opportunity perceptions and observed waste. Because these variables were not measured in the present protocol, we do not introduce post hoc analyses without observed measures; instead, we explicitly frame the findings as context-specific associations and identify these omitted variables as priorities for future cafeteria-level research.

4.8. Limitations

Five limitations warrant explicit acknowledgment.

Two-institution, cross-sectional design. Data were collected from two ordinary higher education institutions in one northern and one southern Chinese province ($N = 170$), with a single plate-waste measurement per student. This design cannot separate trait-like dispositional effects from state-like situational fluctuations and cannot support national or cross-cultural generalization. Broader multi-institution replication with repeated measures is essential before generalizing beyond this context.

Construct overlap and coefficient interpretation. Although Model C does not show a cognitive-capacity-proxy sign reversal, the strong correlation between Physical Opportunity and the cognitive-capacity proxy introduces uncertainty about conceptual overlap and shared variance. Definitive separation of direct and indirect effects requires SEM, path modeling, experimental manipulation, or instrumental variable approaches.

Formative construct validation. The low α for Physical Opportunity, while theoretically expected for a formative index, limits the strength of claims about this dimension. The added content-domain mapping audit improves transparency about item coverage, but it is not equivalent to external validation through formal independent expert CVI or objective cafeteria-environment measures. Future research should validate the formative structure using objective environmental observation, expert content-validity ratings, and structural equation modeling with formative indicators.

Cognitive-capacity proxy indicator. The two items forming the cognitive-capacity proxy showed near-zero correlation ($r = -0.071$), indicating they capture distinct cognitive domains rather than a unitary construct. The composite score may obscure differential mechanisms even though both items were negatively associated with waste in Model D. Future research should use comprehensive, objective cognitive assessments.

Missing campus-level structural variables. Although Physical Opportunity captures perceived environmental constraints, the study did not measure objective cafeteria-level variables (portion sizes, menu design, serving systems, pricing mechanisms). This limits the precision of structural intervention recommendations, which would benefit from direct observation of the environmental features that Physical Opportunity items proxy.

Additionally, the macro-level estimates remain associational; MICE does not transform correlation into causation, and WGI dimensions are highly correlated with GDP ($r = 0.805$), introducing multicollinearity in multivariate models.

5. Conclusions

This study employed a dual-layer analytical framework to examine food waste as a sustainability challenge of responsible consumption and institutional resource governance, combining cross-national structural analysis (Part 1, $N_{\text{countries}} = 176$) with campus-level primary MOA analysis (Part 2, $N_{\text{students}} = 170$ across two ordinary higher education institutions in northern and southern China). The main empirical pattern is that a more granular MOA operationalization performs better than the conventional aggregate specification in this sample: the conventional three-dimensional aggregate model explained a non-significant 4.1% of variance in objectively measured plate waste, while the refined five-dimensional model—distinguishing Physical Opportunity and a two-item cognitive-capacity proxy from their aggregate counterparts—explained 44.1%.

5.1. Theoretical Contributions

The study makes three cautious theoretical contributions. First, it suggests that the limited performance reported in some institutional food waste studies may reflect measurement under-specification rather than theoretical inadequacy. When Physical Opportunity and a cognitive-capacity proxy are added to the model, explanatory power increases substantially—a finding that qualifies the interpretation that aggregate MOA measures perform poorly in structurally constrained settings, but does not by itself validate a new theoretical structure.

Second, it identifies Physical Opportunity and cognition-related indicators as the largest contributors to explained MOA variance in the RWA decomposition, while Motivation contributes little once ceiling effects are considered in this high-motivation sample. This asymmetry redirects theoretical attention from attitudinal variables to environmental design and capability development as candidate behavioral levers in institutional dining, but it does not imply that motivation is generally unimportant across populations or contexts.

Third, it documents a strong association between Physical Opportunity and the cognitive-capacity proxy that has both methodological and substantive implications. The zero-order correlation for the proxy ($r = -0.44$) and the partial coefficient ($b = -0.908$) both indicate that students with greater cognitive-related capacity waste less overall. This finding cautions against interpreting any single model coefficient in isolation when predictors are substantially correlated.

5.2. Practical Implications

The evidence suggests three tentative directions for future intervention testing in comparable cafeteria settings. Physical-environment redesign—addressing crowding, seating, and serving infrastructure—is a candidate pathway suggested by the micro-level Physical Opportunity associations. Cognition-related capability development—nutrition education and portion-estimation training—is also suggested by the large relative-weight contribution of the cognition-related indicators, but should be tested with more comprehensive and objective measures. Motivation maintenance, rather than additional motivation enhancement alone, may be appropriate in high-awareness student populations; this conclusion should not be generalized to contexts with lower baseline anti-waste motivation. From a sustainability perspective, these implications indicate that university food-waste reduction may require coordinated changes in infrastructure, behavioral capability, and operational governance, rather than relying only on awareness campaigns.

5.3. Limitations and Future Directions

Five limitations warrant emphasis. Two-institution, cross-sectional design: the micro-level study covered two purposively selected ordinary higher education institutions ($N = 170$), with one observation per student; it cannot separate trait from state effects or support national or cross-cultural generalization. Macro–micro linkage: the cross-national analysis provides structural context but is not statistically linked to the student-level model; the main behavioral inference is therefore micro-level and context-specific. Construct-overlap ambiguity: the strong correlation between Physical Opportunity and the cognitive-capacity proxy introduces interpretive uncertainty; SEM, path modeling, or experimental manipulation is needed for definitive separation of pathways. Formative construct validation: Physical Opportunity's low α (0.101) is expected for a formative index; the added content-domain mapping audit improves transparency but formal expert CVI and objective environmental validation remain necessary. Cognitive-capacity proxy: the two items measure distinct domains (portion estimation vs. nutrition knowledge); future research should employ comprehensive objective assessments. No campus structural variables: portion sizes, menu design, and serving systems were not directly measured, limiting the precision of structural intervention recommendations.

Future research should pursue three directions. Enhanced measurement: expand the cognitive-capacity battery with objective tests, validate Physical Opportunity against observational measures, and replace self-report Motivation with behavioral indicators. Repeated behavioral measures: collect multiple plate-waste observations per participant to reduce situational noise (CV = 128.7%). Formal multilevel design: collect institution-level variables (cafeteria type, meal plan structure, serving systems) and model them as Level-2 predictors, thereby moving beyond the contextual linking used in the present study.

5.4. Closing

Food waste in institutional dining may be better understood as a structurally conditioned behavior, within which cognition-related indicators retain meaningful predictive validity in this sample. The findings suggest that future intervention studies should test whether motivation-based messages can be complemented by environmental design and capacity-building approaches that help students act on the motivation they already possess. In this sense, the study contributes to the sustainability agenda by translating food-waste reduction from a general normative goal into measurable, behaviorally informed, and institutionally actionable pathways for reducing avoidable resource loss in campus dining systems.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su18126134/s1, The Supplementary Information package includes three supplementary tables: governance-regression results using the six WGI dimensions, complete-case exploratory macro-level regression models, and regional heterogeneity statistics for organic-waste share. Table S1: Rotated Component Matrix for the Traditional 13-Item MOA Scale; Table S2: Measurement Items Used in the Refined MOA Model; Table S3: Sensitivity Analysis: Cognitive Ability Coefficient Across Model Specifications; Figure S1: Macro-level bivariate associations between organic waste share of municipal solid waste and key structural predictors across 176 countries. Sample size varies by variable availability; Figure S2: Regional heterogeneity in structural predictors of organic waste share. The figure summarizes variation in associations across World Bank regional groups; Figure S3: Correlation heatmap for five-dimensional MOA predictors and food waste. The negative association between Physical Opportunity and Cognitive Ability is relevant for interpreting the suppression pattern discussed in the manuscript; Figure S4: Mean plate waste by gender. Gender information was available for 167 respondents; this supplementary check is descriptive and does not alter the main analytic sample; Figure S5: Quantile-specific associations between five-dimensional MOA predictors and log-transformed plate waste. Coefficients were estimated with bootstrapped standard errors; Figure S6: Sensitivity check using the conventional aggregated three-dimensional MOA specification.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data supporting this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

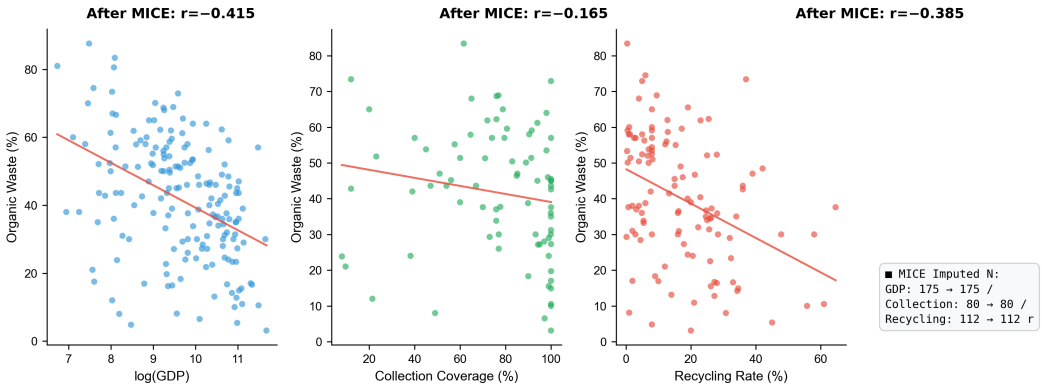


Figure A1. MICE imputation effect: Sample size increase from complete-case baseline ($N = 46$–80 depending on variable set) to MICE-imputed full sample ($N = 175$ for all variables). Shaded areas indicate imputed value distributions.

Table A1. Reliability statistics for refined five-dimensional MOA measures.

Construct	Items	Type	α	Mean	SD
Motivation	5	Reflective	0.885	3.93	0.75
Opportunity–Social	6	Reflective	0.742	3.18	0.75
Opportunity–Physical	5	Formative	0.101 †	2.64	0.58
Ability–Behavioral	2	Scale	0.673 ‡	3.10	0.92
Ability–Cognitive-capacity proxy	2	Composite	−0.153 ‡	3.68	0.98

Note: † Low α is theoretically expected for formative indices where items represent distinct, non-interchangeable affordances. ‡ Two-item scales report item inter-correlation rather than α: Ability–Behavioral $r = 0.508$; Ability–Cognitive-capacity proxy $r = -0.071$ (items measure complementary domains).

Table A2. Content-domain mapping audit for the Physical Opportunity formative index.

Indicator	Environmental Domain	Formative Rationale	Validation Status
O5p Crowding	Spatial and temporal congestion	Captures peak-hour density and queuing pressure that may reduce time and attention available for portion adjustment.	Theoretical/content mapping; formal expert CVI not conducted.
O6p Seating availability	Capacity and access	Captures whether limited seats or turnover pressure constrain meal pace and finishing behavior.	Theoretical/content mapping; formal expert CVI not conducted.
O7p Hygiene conditions	Environmental quality	Captures perceived cleanliness and comfort, a domain not necessarily correlated with crowding or seating.	Theoretical/content mapping; formal expert CVI not conducted.
O8p Tray capacity	Serving infrastructure	Captures whether plate/tray design supports appropriate food selection and carrying capacity.	Theoretical/content mapping; formal expert CVI not conducted.
O9p Dish variety	Portion-size affordance	Captures availability of bowl/dish-size options that may enable smaller or better-matched portions.	Theoretical/content mapping; formal expert CVI not conducted.

Note: This table is an author-team content-domain mapping audit added to clarify construct coverage. It should not be read as an independent expert content-validity index (CVI).

Table A3. Micro-level complete-case and MICE sensitivity comparison.

Predictor	Complete-Case b	Complete-Case p	MICE Mean b	MICE Mean p
Motivation	0.033	0.886	−0.007	0.974
Social Opportunity	−0.165	0.481	−0.161	0.448
Behavioral Ability	0.072	0.646	0.125	0.387
Physical Opportunity	1.280	<0.001	1.223	<0.001
cognitive-capacity proxy	−0.827	<0.001	−0.908	<0.001

Note: Complete-case models use $N = 145$ because academic year is missing for 25 respondents. Micro-level MICE used 20 imputed datasets and is treated as a sensitivity check because missingness occurred only in controls.

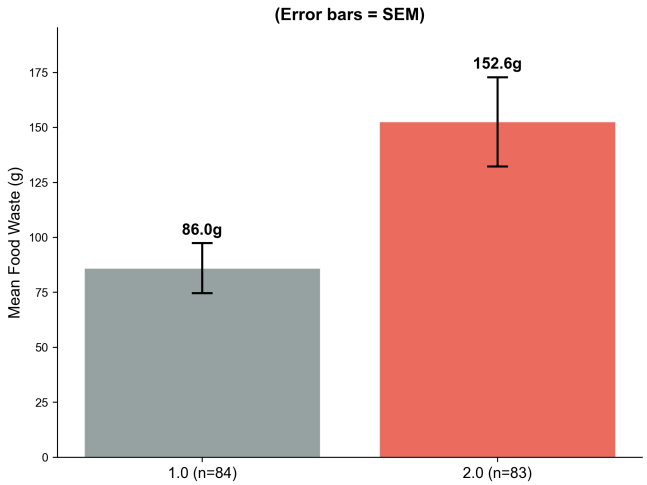


Figure A2. Mean plate waste by gender among respondents with valid gender information ($n = 167$; 3 missing). Gender code 1: $n = 84$, M = 86.0 g, SEM = 11.4 g; gender code 2: $n = 83$, M = 152.6 g, SEM = 20.3 g. The difference is statistically significant in a Welch test ($p = 0.0049$), supporting the inclusion of gender as a control variable.

Table A4. Model parsimony and cross-validation sensitivity for micro-level specifications.

Model	N	k	R^2	Adj. R^2	AIC/BIC	5-Fold CV RMSE
P-1 Classic MOA (3-dim)	145	3	0.058	0.024	642.44/660.30	2.198
P-2 Refined MOA (5-dim)	145	5	0.435	0.406	572.37/596.19	1.742
P-4 Physical + cognitive only	145	2	0.432	0.416	567.09/581.97	1.697
P-5 20-item model	144	20	0.576	0.499	557.05/625.35	1.748

Note: The 20-item model has the lowest AIC and highest in-sample R^2, but the parsimonious two-predictor model has the lowest BIC and best 5-fold cross-validated RMSE. The item-level model is therefore interpreted as a sensitivity/disaggregation model rather than the primary specification.

References

1. Gustavsson, J.; Cederberg, C.; Sonesson, U.; van Otterdijk, R.; Meybeck, A. *Global Food Losses and Food Waste: Extent, Causes and Prevention*; Food and Agriculture Organization: Rome, Italy, 2011.
2. Intergovernmental Panel on Climate Change. *Climate Change 2021: The Physical Science Basis*; Cambridge University Press: Cambridge, UK, 2021. [CrossRef]
3. Corrado, S.; Sala, S. Food waste accounting along global and European food supply chains: State of the art and outlook. *Waste Manag.* **2018**, *79*, 120–131. [CrossRef]
4. United Nations Environment Programme. *Food Waste Index Report 2021*; United Nations Environment Programme: Nairobi, Kenya, 2021.
5. Food and Agriculture Organization of the United Nations. The State of Food and Agriculture 2019: Moving Forward on Food Loss and Waste Reduction. 2019. Available online: https://chooser.crossref.org/?doi=10.4060%2FCA6030EN (accessed on 11 June 2026).
6. United Nations. *Transforming Our World: The 2030 Agenda for Sustainable Development*; United Nations General Assembly Resolution A/RES/70/1; United Nations: New York, NY, USA, 2015.
7. Wu, Y.; Tian, X.; Li, X.; Yuan, H.; Liu, G. Characteristics, influencing factors, and environmental effects of plate waste at university canteens in Beijing, China. *Resour. Conserv. Recycl.* **2019**, *149*, 151–159. [CrossRef]
8. Betz, A.; Buchli, J.; Göbel, C.; Müller, C. Food waste in the Swiss food service industry–Magnitude and potential for reduction. *Waste Manag.* **2015**, *35*, 218–226. [CrossRef] [PubMed]
9. Engström, R.; Carlsson-Kanyama, A. Food losses in food service institutions: Examples from Sweden. *Food Policy* **2004**, *29*, 203–213. [CrossRef]
10. Thaler, R.H.; Sunstein, C.R. *Nudge: Improving Decisions About Health, Wealth, and Happiness*; Penguin Books: New York, NY, USA, 2009.
11. Hebrok, M.; Boks, C. Household food waste: Drivers and potential intervention points for design—An extensive review. *J. Clean. Prod.* **2017**, *151*, 380–392. [CrossRef]
12. Qian, L.; Li, F.; Cao, B.; Wang, L.; Jin, S. Determinants of food waste generation in Chinese university canteens: Evidence from 9192 university students. *Resour. Conserv. Recycl.* **2021**, *167*, 105410. [CrossRef]
13. Liu, Y.; Cheng, S.; Liu, X.; Cao, X.; Xue, L.; Liu, G. Plate waste in school lunch programs in Beijing, China. *Sustainability* **2016**, *8*, 1288. [CrossRef]
14. Qian, L.; Rao, Q.; Liu, H.; McCarthy, B.; Liu, L.X.; Wang, L. Food waste and associated carbon footprint: Evidence from Chinese universities. *Ecosyst. Health Sustain.* **2022**, *8*, 2130094. [CrossRef]
15. MacInnis, D.J.; Jaworski, B.J. Information processing from advertisements: Toward an integrative framework. *J. Mark.* **1989**, *53*, 1–23. [CrossRef]
16. White, K.; Habib, R.; Hardisty, D.J. How to SHIFT consumer behaviors to be more sustainable: A literature review and guiding framework. *J. Mark.* **2019**, *83*, 22–49. [CrossRef]
17. van Geffen, L.; van Herpen, E.; Sijtsema, S.J.; van Trijp, H.C.M. Food waste as the consequence of competing motivations, lack of opportunities, and insufficient abilities. *Sustain. Prod. Consum.* **2020**, *24*, 20–30. [CrossRef]
18. Dibb, S.; Simkin, L.; Pride, W.M.; Ferrell, O.C. *Marketing: Concepts and Strategies*, 7th ed.; Cengage Learning EMEA: Andover, UK, 2016.
19. Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* **1991**, *50*, 179–211. [CrossRef]
20. Schwartz, S.H. Normative influences on altruism. In *Advances in Experimental Social Psychology*; Berkowitz, L., Ed.; Academic Press: Cambridge, MA, USA, 1977; Volume 10, pp. 221–279.
21. Michie, S.; van Stralen, M.M.; West, R. The behaviour change wheel: A new method for characterising and designing behaviour change interventions. *Implement. Sci.* **2011**, *6*, 42. [CrossRef]
22. Graham-Rowe, E.; Jessop, D.C.; Sparks, P. Predicting household food waste reduction using an extended theory of planned behaviour. *Resour. Conserv. Recycl.* **2015**, *101*, 202–217. [CrossRef]

23. Fan, H.; Wang, J.; Lu, X.; Fan, S. Factors influencing food-waste behaviors at university canteens in Beijing, China: An investigation based on the theory of planned behavior. *Front. Agric. Sci. Eng.* **2023**, *10*, 83–94. [CrossRef]
24. Visschers, V.H.M.; Wickli, N.; Siegrist, M. Sorting out food waste behaviour: A survey on the motivators and barriers of self-reported amounts of food waste in households. *J. Environ. Psychol.* **2016**, *45*, 66–78. [CrossRef]
25. Stancu, V.; Haugaard, P.; Lähteenmäki, L. Determinants of consumer food waste behaviour: Two routes to food waste. *Appetite* **2016**, *96*, 7–17. [CrossRef]
26. Russell, S.V.; Young, C.W.; Unsworth, K.L.; Robinson, C. Bringing habits and emotions into food waste behaviour. *Resour. Conserv. Recycl.* **2017**, *125*, 107–114. [CrossRef]
27. Stefan, V.; van Herpen, E.; Tudoran, A.A.; Lähteenmäki, L. Avoiding food waste by Romanian consumers: The importance of planning and shopping routines. *Food Qual. Prefer.* **2013**, *28*, 375–381. [CrossRef]
28. Quested, T.E.; Marsh, E.; Stunell, D.; Parry, A.D. Spaghetti soup: The complex world of food waste behaviours. *Resour. Conserv. Recycl.* **2013**, *79*, 43–51. [CrossRef]
29. Principato, L.; Secondi, L.; Pratesi, C.A. Reducing food waste: An investigation on the behaviour of Italian youths. *Br. Food J.* **2015**, *117*, 731–748. [CrossRef]
30. Kollmuss, A.; Agyeman, J. Mind the gap: Why do people act environmentally and what are the barriers to pro-environmental behavior? *Environ. Educ. Res.* **2002**, *8*, 239–260. [CrossRef]
31. Steg, L.; Vlek, C. Encouraging pro-environmental behaviour: An integrative review and research agenda. *J. Environ. Psychol.* **2009**, *29*, 309–317. [CrossRef]
32. Kaza, S.; Yao, L.C.; Bhada-Tata, P.; Van Woerden, F. *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050*; Technical Report; World Bank: Washington, DC, USA, 2018. [CrossRef]
33. World Bank. *World Development Indicators 2024*; World Bank: Washington, DC, USA, 2024.
34. European Commission Joint Research Centre. *EDGAR GHG Emissions Database 2024*; European Commission Joint Research Centre: Brussels, Belgium, 2024.
35. Kaufmann, D.; Kraay, A.; Mastruzzi, M. The Worldwide Governance Indicators: Methodology and analytical issues. *Hague J. Rule Law* **2011**, *3*, 220–246. [CrossRef]
36. World Bank. *Worldwide Governance Indicators 2024*; World Bank: Washington, DC, USA, 2024.
37. Diamantopoulos, A.; Riefler, P.; Roth, K.P. Advancing formative measurement models. *J. Bus. Res.* **2008**, *61*, 1203–1218. [CrossRef]
38. Jarvis, C.B.; MacKenzie, S.B.; Podsakoff, P.M. A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *J. Consum. Res.* **2003**, *30*, 199–218. [CrossRef]
39. Bollen, K.A.; Lennox, R. Conventional wisdom on measurement: A structural equation perspective. *Psychol. Bull.* **1991**, *110*, 305–314. [CrossRef]
40. Petter, S.; Straub, D.W.; Rai, A. Specifying formative constructs in information systems research. *MIS Q.* **2007**, *31*, 623–656. [CrossRef]
41. Tonidandel, S.; LeBreton, J.M. Relative importance analysis: A useful supplement to regression analysis. *J. Bus. Psychol.* **2011**, *26*, 1–9. [CrossRef]
42. Conger, A.J. A revised definition for suppressor variables: A guide to their identification and interpretation. *Educ. Psychol. Meas.* **1974**, *34*, 35–46. [CrossRef]
43. MacKinnon, D.P.; Krull, J.L.; Lockwood, C.M. Equivalence of the mediation, confounding and suppression effect. *Prev. Sci.* **2000**, *1*, 173–181. [CrossRef] [PubMed]
44. Kallbekken, S.; Sælen, H. "Nudging" hotel guests to reduce food waste as a win–win environmental measure. *Econ. Lett.* **2013**, *119*, 325–327. [CrossRef]

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