Information, Preferences, and Adoption Decisions: Three Essays in Applied and Behavioral Economics

by

Pathmanathan Sivashankar

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Approved by

Dr. Samir Huseynov, Chair, Assistant Professor,
Department of Agricultural Economics and Rural Sociology (AERS)
Dr. Joshua M. Duke, Professor, AERS
Dr. Mykel Taylor, Professor, AERS
Dr. Wenying Li, Associate Professor, AERS
Dr. Wendiam Sawadgo, Assistant Professor, AERS
Dr. Sungeun Cho, Associate Professor, Poultry Science (University Reader)

Abstract

This dissertation, through three chapters, explores preference heterogeneity among college students, investigates the consistency between stated and observed food choices, and evaluates barriers to agricultural technology adoption among U.S. agribusiness firms. These studies provide insights into the factors that shape decision-making across different contexts within the agricultural food system.

In the first chapter, we survey college students to understand their food consumption preferences and infer their future food decisions. Using the latent class analysis method, we classify survey participants based on food temptation feelings and food taste ratings. Our analyses identify two latent groups of students: Tempted Indulgers and Temptation Restrainers. Tempted Indulgers are health conscious but overweight and succumb to temptation. Temptation restrainers are also health conscious but have normal BMI scores and exercise self-control in food decisions. Latent classes' correlation with BMI and self-control measures validate our findings. We conclude that the food preferences of young adults are primarily driven by menu-dependent preferences rather than knowledge of food diet quality. Our findings explain why most nudge-based health interventions fail, and we show the importance of addressing menu dependent visceral feelings in designing health policies.

The second chapter studies whether the decision makers exhibit consistent food choices in a dynamic setting. There is limited knowledge about the consistency of food choices in dynamic decision-making contexts. We conducted an incentivized food choice

experiment in a field setting. Around 77% of food decisions are dynamically consistent, and most inconsistencies occur in choice switches from high to low-calorie meal options. Our results bear good news for policymakers, as food decisions are moderately consistent, and desired preference shifts can be sustained over time. However, shifting food preferences poses a significant challenge to health policies, as information and behavioral nudges do not influence food preferences and their consistency.

Chapter three investigates how economic, environmental, technical, political, and socio-cultural barriers shape innovation outcomes of openness, effort and success among US agribusiness firms. Drawing from perception-based survey data from agribusiness employees, the analysis employs a sequential modeling strategy combining ordered probit and triple hurdle probit estimation. The results reveal that environmental barriers are the most significant obstacle to innovation across all innovation stages, indicating regulatory and sustainability pressures can stimulate adaptive innovation. Economic barriers exhibit dual effect, reducing openness and effort but positively influencing innovation success once firms commit to adoption. Technical barriers hinder progress in specific contexts, especially for smaller firms and food related enterprises. Findings reveal heterogeneity across subsectors and firm sizes, highlighting that innovation in agribusiness often emerges as a strategic adaptation to constraints.

Artificial Intelligence (AI) Use Disclosure Statement

In the preparation of this dissertation, the following Artificial Intelligence (AI) tools were used: ChatGPT and Claude Ai. These tools were used primarily to generate and modify some codes for regression results. The codes thus generated were cross-checked with the software manuals for accuracy and applicability. The author acknowledges full responsibility for the intellectual content of this work and has ensured that all AI-assisted sections have been reviewed and revised for accuracy and appropriate academic style. All AI-generated content was reviewed and validated for relevance, appropriateness, and accuracy before incorporation into the final document to maintain scholarly integrity of this research.

Digital Accessibility Disclosure Statement

In the preparation of this dissertation, the following digital accessibility tools were used to ensure that this document complies with federal requirements: Microsoft Word Accessibility Checker and Adobe Acrobat Pro Accessibility Checker. The author acknowledges full responsibility for the intellectual content of this work and has made a good-faith effort to comply with digital accessibility requirements in publishing, wherein the nature of the content does not significantly change in order to do so. Furthermore, all content has been reviewed and revised to meet these requirements prior to final publication.

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Chapter One

Informed but Tempted: A Latent Class Analysis of College Students' Food Preferences[1]

2.1 Introduction

The prevalence of high-calorie food intake has become a severe public health issue in many developed as well as developing countries. In the United States, this problem manifests as a dramatic increase in state obesity rates across the country (Delgado, 2020; CDC, 2022a). It has been documented that an easily accessible, extensive array of available tempting food choices is one of the primary factors driving excessive calorie intake (Lee et al., 2022; Pancer et al., 2022). Increasing availability of high-calorie diet options in food swamps is associated with the prevalence of unhealthy eating habits and consequent obesity (Cooksey-Stowers et al., 2017; Goodman et al., 2020). Previous studies have also shown that the presence of high-calorie unhealthy items in the menu drains the self-control resources of consumers by exposing them to menu-dependent temptation and visceral feelings, and consequently, this decision environment leads to welfare-reducing food choices (Sadoff et al., 2020).

A plethora of studies and primary public policy measures focus on improving population health with the help of designing informational nudges that incentivize consumers to obtain food product-related information and make educated diet decisions. The primary purpose of these initiatives is to make consumers better informed about the product characteristics and improve the quality of food choices. However, previous

[1] Co-authored with Joshua Duke and Samir Huseynov

research shows that information nudges have a limited impact on the quality of consumed food (Stran et al., 2016; Gustafson and Zeballos, 2018). Though calorie labeling laws were designed to inform consumers about the nutritional content of food products and nudge them to reduce their calorie intakes, a vast literature investigating the effectiveness of legislative labeling initiatives shows that the provided information does not improve the quality of food consumption (Cawley et al., 2020; Gustafson and Zeballos, 2018). Studies also find that calorie information does not affect the food selection among consumers, especially among those who are less dedicated to a healthy diet (Girz et al., 2012; Tapper et al., 2022). Thus, the current state of the literature on food nudges and education does not provide conclusive evidence about why informational nudges and knowledge on healthy diet do not improve food decision quality (Moore et al., 2022).

This study investigates the role of knowledge about diet quality and visceral feelings in the formation of food preferences. In particular, our focus is on determining the relative importance of food diet quality knowledge and menu-dependent cues in identifying latent consumer preference profiles. We conduct a survey with college students and map different dimensions of food preferences using a representative sample of diet alternatives appealing to young consumers. We build on emerging menu-dependent preferences and elicit participants' multi-faceted attitudes toward food alternatives. Survey participants separately assess presented food options based on taste, health, temptation, and satiety characteristics. Our study also constructs different measures of subjective knowledge of diet quality, health consciousness, subjective prediction of self-control, and temptation issues. Using the finite normal mixture modeling approach and measures on menu-dependent visceral feelings, we identify two latent classes of students: *Tempted Indulgers* and *Temptation Restrainers*. We find that the identified latent preference classes of students cannot be predicted based on knowledge of food quality, consciousness about healthy diet, and income. Instead, our results show that food preferences are primarily driven by menu-dependent temptation feelings, self-assessed future temptation issues, and satiety characteristics of food items. We also find that, in our study sample, Tempted Indulgers are primarily overweight but Temptation Restrainers have normal BMI indicating that elicited preferences have external validity in terms of predicting consumers' health and daily eating habits. In fact, an overwhelming number of studies show that higher BMI values are informative of unhealthy eating habits (Lloyd-Richardson et al., 2008; Guti´errez-Pliego et al., 2016; Varela et al., 2020). Our findings suggest that food preferences are formed based on the taste characteristics of diet alternatives and temptation feelings of consumers. Health consciousness and food quality knowledge are not robust determinants of food preferences. Therefore, our results offer new insight into why information nudges and knowledge of food diet quality do not induce healthy food decisions.

This paper's contribution is threefold. First, using the recent advancements in the finite normal mixture models, we identify two latent classes of students based on their menu dependent preferences. The classification results show that food-related visceral feelings are more helpful in identifying consumer profiles compared to subjective knowledge about a healthy diet. Second, we test our classifications using self-control and temptation measures of Ameriks et al. (2007), which have been well-accepted in the food decisions literature. Our study shows that coarse measures eliciting temptation cues are as predictive as the well validated measures of Ameriks et al. (2007). Third, we focus on students and investigate their food preferences when facing low, middle, and high tempted food alternatives that constitute their usual diet options amid the busy college life. In the era where the average consumers are becoming overweight and obese, understanding the underlying patterns of young consumers will help to develop better nudges to improve the quality of food decisions. We rely on non-choice data showing how widespread internet food ratings can be used to reliably construct consumer preferences. For instance, Bernheim et al. (2013) show that non-choice data can be sufficient to predict actual choice outcomes.

The paper is organized as follows. The previous section presented motivation for the study. The succeeding section discusses the debate in the literature on healthy-unhealthy eating and discusses experimental evidence which has used the concepts of temptation and self-control and their effects on food choices. Section three discusses the survey method and the empirical model used. This section sequentially outlines how the study was performed and how the food choices were selected. In addition to that, this section paves the explanation for the use of the finite mixture model for latent class identification and justifies the use of the probit model to identify the impact of explanatory variables on the identified classes. Section four presents the findings of the study and mainly explains the findings based on the identified two latent class groups. Section five presents the discussion and conclusion of the study while signaling future directions.

2.2 Review of Literature

Understanding food decision dynamics has always been a concern for researchers. Both economists and psychologists have tried to understand human decision-making with respect to consumption. As studies point out, it is not a single factor that affects food consumption, but a range of factors affect the food consumption decision and their interactions. These factors include both external environmental factors as well as food-related internal factors. On the other hand, psychologists have been working on human decision-making based on dual systems approach (Frankish, 2010). Dual systems play an important role as food decision-making is a routine exercise, thus there may not be much thought while making decisions as opposed to other important, expensive, and rare decision-making instances (e.g., buying a car, education, trip).

Empirical discourse on healthy-unhealthy eating

Unhealthy food consumption patterns have raised concern among policymakers. Unhealthy eating leads to negative repercussions in many aspects of social life, be it for an individual or for society and the relevant governmental institutions. Generally, many studies have dealt with the negative effects of unhealthy food consumption on individuals (Rodrigues et al., 2017; Almutairi et al., 2018; Pujia et al., 2021). However, more of the studies center around the adolescent or nearby age cohorts as food consumption habits in the early stage of life can significantly affect future food diet decisions and health outcomes (Martin et al., 1999; Barbosa Filho et al., 2014; Rodrigues et al., 2017; Voracova et al., 2018; Siu et al., 2019; Pujia et al., 2021). A few of them specifically deal with unhealthy food consumption of university students (Yahia et al., 2008; Afshin et al., 2019; Llanaj et al., 2018; Abraham et al., 2018), and some studies focus on individuals in middle age categories (Katagiri et al., 2014; Afshin et al., 2019; Schnabel et al., 2019).

There has been a growing literature about over consumption, obesity, and unhealthy eating habits in the United States (Cutler et al., 2003; Jia et al., 2019; Sanyaolu et al., 2019; Mathew Joseph et al., 2020). All these studies denote the magnitude of the need for a health policy to counter raising obesity rates and associated health issues. Ruhm (2012) suggests that rising obesity is due to the encouragement of overeating by food producers through incentives to engineer food products that stimulate the affective decision systems. It has also been shown that the affective state of mind can cause unconscious over-eating (Evers et al., 2013).

Traditionally, our focus was on single food consumption decisions based on different attributes of the same food. It is important to look at how individuals make food decisions when they have an array of food choices. Menu-dependent preferences play an important role over here, and this justifies why we should opt for menu-dependent preferences to understand food decision-making (Kozup et al., 2003; Bacon and Krpan, 2018). Here the menu would have several food items with different attributes, and hence the decision maker will have to make decisions based on all these factors employing both systems. So the decision maker compares all the options relative to others and finally decides depending on the options available. Self-control studies based on menu-dependent preferences in a food choice context are rare. Thus, understanding the heterogeneity in self-control among the students would be indicative of which factors they succumbing to temptation.

This study enables us to understand and profile young consumers based on their food decision-making and other characteristics. We focused on students from a southern public university in the United States and investigated their food choice behavior and classify them based on their preferences for food items. Classification of students based on their ratings and preferences for food items would help to understand their eating habits. By understanding these preferences and categories, we identify for which factors students give more prominence in selecting food items. Also, we employ a sophisticated measure of self-control (Ameriks et al., 2007).

2.3 Survey Methods

We conducted the survey in April of 2022 with undergraduate students at a university in the Southeastern United States. The survey questions and instruments were compiled in Qualtrics. The Qualtrics link was disseminated among students using departmental mailing lists. The email invitations were sent to undergraduates of the colleges of agriculture (N=1,069) and Liberal Arts (N= 4,391). The recruitment email stated that decision-making take approximately 20 minutes to complete. Participation in the survey was incentivized with a $20 Amazon gift card reward for randomly selected ten respondents. Before starting the study, students were informed that after the completion of the survey, the research team would randomly determine the ten participants out of the respondents who completed all survey questions.

We received 267 responses to our survey request. This accounts for a response rate of 4 %. Five participants did not complete the primary part of the study eliciting food preferences. Therefore, we excluded their responses from our analysis. The average respondent is white and approximately 70% of the participants partially or entirely rely on their parents for funding their education. Our study sample is over-represented with female students (80.15%), and most participants were between 19 and 21 years old. Appendix A offers a more detailed analysis on sample statistics. Though, the response rate is low, we were still able to get an adequate number of participants. Also, it should be noted that we did our survey in the latter weeks of April just before the end of the semester. Further, we only provided incentives for 10 participants based on a raffle draw. These reasons might have been also a reason for lower response apart from the factors which are beyond the scope of the study. In terms of sample bias, we limited the study only to two colleges in the university mainly due to administrative issues, but among the 6,460 students, they all received the email invitations and only those who are interested took part in the study. So, all 6,460 students had the same opportunity to take part in the survey time periods.

The survey had two blocks. In the first block, participants were separately shown nine menus containing one food alternative. Individual menus also posed four Likert scale questions to measure respondents' attitudes toward the presented option. Table 1.1 presents the details of food options in the survey menus. We selected three food categories appealing to students considering their busy schedules: salads, burritos, and pizzas. The food alternatives were available either in the university campus cafeteria or close restaurants within walking distance. This design feature allowed us to elicit students' food preferences using familiar food choices available amid busy class schedules.

Table 1.1: Presented Food Menu Options

Menu Category	Food Option	Serving Size	Calorie Content
Salad	Elevated cobb Salad	1 bowl	300
Salad	Chicken-Avocado Salad	1 bowl	305
Salad	Customized Chicken Salad	1 bowl	315
Burrito	Chicken Burrito -Chipotle	1 wrap	600
Burrito	Chicken Burrito	1 wrap	605
Burrito	Black Beans-Rice Burrito	1 wrap	625
Pizza	Backyard BBQ Chicken - large (14”)	3 slices	900
Pizza	Chicken-Bacon-Parmersan Large (14”)	3 slices	930
Pizza	Buffalo-Chicken -Large (14”)	3 slices	960

Note: The table shows the food options presented and provides information about serving size, calorie content and price of menu alternatives. Pizza alternatives were presented as the whole pizza, respondents were informed that the serving size was three slices out of eight slices.

The food alternatives were selected in a manner to cover a wide range of calories. Salad choices covered the 300-315 calorie range, including different nutrition ingredients. The first salad menu had 300 calories with no protein ingredients. The second salad menu included avocado, and only the third menu contained chicken meat. The purpose of gradually enriching food contents from the first salad menu to the last alternative was to make food items taste-wise appealing and nutritionally sufficient. Put differently, a health-conscious survey participant facing the meal options in the first category had access to a healthy salad choice with rich nutritional content and appealing taste. For instance, Customized Chicken Salad offered a tastier and nutritionally richer content compared to Elevated Cobb Salad. The structure of the first menu category enabled us to document food preferences when the health-taste trade-off was minimal. Moreover, having three different food alternatives representative of salad options on the first menu provided flexibility in calibrating a wide array of homegrown food preferences.

The second food category included burrito options. Food alternatives contained a broader spectrum of calorie and taste features in this category. The calorie contents of menu options were almost double of salad items ranging from 600 to 625 calories. Moreover, taste-wise, the second category offered more appealing flavors. Relatively health-conscious consumers might prefer the second category of food alternatives due to being tastier than the salad category and healthier than a pizza. The third menu category presented pizza options containing from 900 to 965 calories. This category exposed survey respondents to the study's tastier but the least healthy food alternatives. A relatively health-conscious individual with self-control issues can prefer food items in the second category compared to pizza options. The contrast between the second and third menu categories allowed our study to elicit food preference trade-offs when a decision-maker faced relatively healthier options but not as tasty as pizza offerings.

In each menu scenario, participants were asked four questions investigating the food item's perceived taste, health, satiety, and temptation features. The questions allowed us to document the health consciousness of respondents and link their preferences to visceral feelings (i.e., taste and temptation aspects of food options). We also asked students to report to what extent the presented food alternatives were appealing in terms of feeling full. This question enabled the study to identify whether respondents' food preferences were driven to maximize calorie-per-dollar considering the limited consumption budget of students.

The second block of the study contained questions analyzing the demographic characteristics of survey respondents. Apart from the conventional demographic question, we also asked for their funding sources (as a proxy to identify those who are in financial support). Also, information regarding BMI measures and factors they consider when making food purchasing decisions was also included. This block also elicited respondents' self-assessed temptation and self-control issues as well as their health consciousness. Self-assessed temptation and self-control issues were measured using the well-accepted survey instruments developed by Ameriks et al. (2007). This includes a hypothetical scenario where participants receive free food coupons for dinner and how the participants spend them across time. It captures the ideal spending, expecting to spend, and spending under temptation. Using these we come up with two measures of self-control, the Expectation-Ideal gap, and Temptation-Ideal gap.

2.4 Empirical Model

We employ a model-based clustering approach as opposed to the traditional clustering approaches, in identifying primary food preference groups in our study sample. The traditional clustering approaches (hierarchical clustering and k-means clustering) are primarily not based on formal models. These are different statistical approaches to cluster the data using observable individual characteristics. Hierarchical Clustering Analysis (HCA) includes different algorithms assigning individual observations to multiple groups to determine the optimal latent groups (Kozak and Scaman, 2008). For instance, the iterative relocation method assumes that the data set is partitioned into a certain number of groups, and the optimal group structure is determined by moving single data points from one group to another one until no improvement of the selected statistical criterion can be achieved (Fraley and Raftery, 2002). The k-means clustering method uses sum of squares criterion to determine the optimal states of identified clusters (MacQueen, 1967). However, in general, HCA analysis lacks model-based approach and primarily relies on heuristic algorithms.

In contrast, the model-based latent class analysis focuses on the conditional probability distributions embedded in data (Scrucca et al., 2016). Here the data is considered to be coming from a mixture of densities. In the model-based approach, each cluster is modeled by normal or Gaussian distribution shaped by mean, covariance, and associated probability in the mixture (Fraley and Raftery, 2002). So each data point has the probability of belonging to any cluster. Specifically, it has been shown that finite-mixture models provide a flexible framework to identify distributional properties of latent classes (McLachlan et al., 2019). The primary assumption behind this approach is that the observed data set is the outcome of mixture of multivariate normal distributions representing individual groups (Plaehn, 2019). This approach has been extensively used to determine latent preference groups in the consumer economics literature (Plaehn, 2019; Lacroix and Gifford, 2020).

We prefer the model-based finite-mixture method to identify latent preference groups in our data, as this approach explicitly models different data-generating processes in the observed study sample. This method also overlaps with our study assumptions relying on the existence of distinctive food preference distributions within our student sample. Our primary approach is that surveyed individuals represent different preference groups from the population of interest, and each latent preference group generates an independent distribution with different means and variances (Scrucca et al., 2016). But the latent distributions are unidentified in the data and together they generate finite-mixture (Kozak and Scaman, 2008; McLachlan et al., 2019).

We follow Scrucca et al. (2016) and describe the primary building blocks of finite-mixture latent class analysis method. We assume that our data *x* contains independent identically distributed (iid) responses of *n* survey participants: $x = x_1, x_2, \ldots x_n$. We also assume that answers to survey questions are connected to individual preferences, and the responses of each participant can be modeled using a probability density function with a finite mixture model of *G* components:

$$f(x_i \Psi) = \sum_{k=1}^{G} \pi_k f_k(x_i; \theta_k)$$

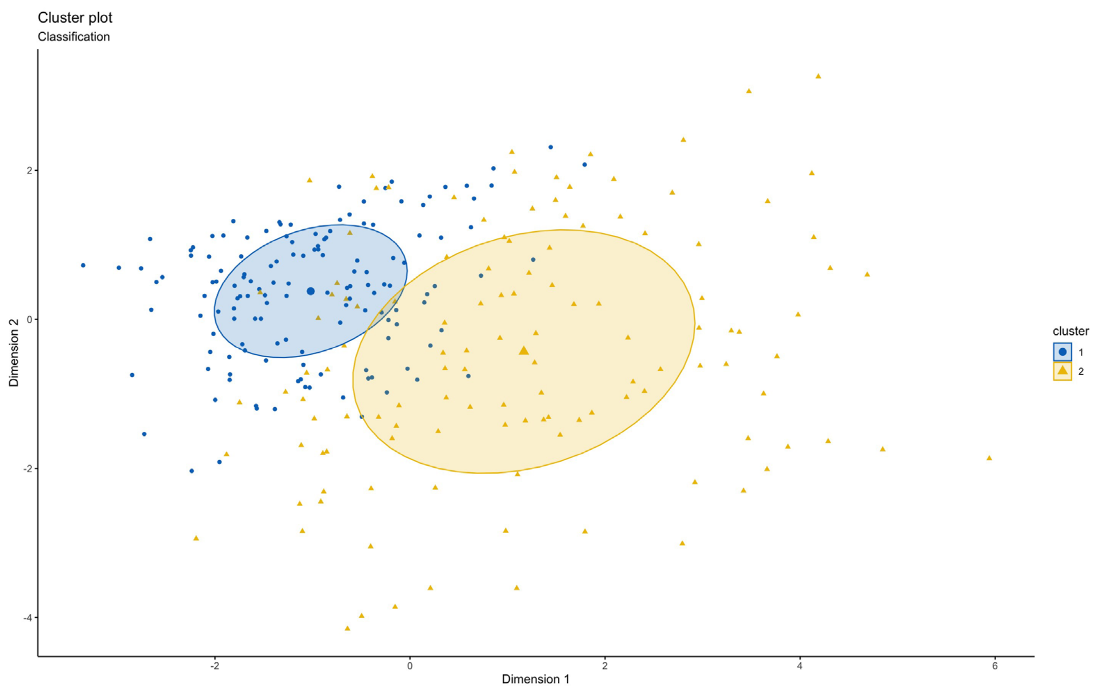
where $\Psi = \{\pi_1, \ldots \pi_{G-1}, \theta_1, \ldots, \theta_G\}$ are the characteristics parameters of the mixture model. The k-th component density for respondent x_i is represented with $f_k(x_i; \theta_k)$. Our method calibrates $G - 1$ number of probability weights $(\pi_1, \ldots \pi_{G-1})$ of the mixture model component densities for each individual. Model parameters Ψ are determined using individual log-likelihood function $\sum_{i=1}^{n} \log\big((x_i;\ \Psi)\big)$ using EM computation algorithm. The number of *G* components represent latent groups in the data. the

Our method uses Gaussian mixture model (GMM) assuming a (multivariate) Gaussian distribution for each latent group k (i.e., each latent group's distribution and the associated probability density function $f_k(x_i; \Psi_k)$ has $N(\mu_k, \Sigma_k)$. Identified latent groups or clusters also have geometric features of for their distributions, such as volume and shape.

We also performed a sensitivity analysis using alternative posterior probability thresholds (0.45 and 0.55) and the results are presented in Appendix Table A1.8. The primary findings were therefore based on the conventional probability assignment

2.5 Results

We start discussing the results of our study by scrutinizing our latent class analysis. Our latent class estimations rely on the role of menu-dependent preferences to identify preference groups among surveyed students. We used taste and temptation feeling measures toward presented food menu options to conduct preference finite mixture model calculations. In our survey, each subject revealed subjective taste and temptation values of each food category identifying individual menu-dependent preferences. We averaged those self-assessed taste and temptation values of each food menu category at the individual level. For instance, assessed taste values of subject *i* for salad menu alternatives averaged and the result was coded as *salad taste*$_i$. In the same manner, we calculated *burrito taste*$_i$ and *pizza taste*$_i$ for individual *i*. Since we presented food alternatives with different characteristics in each food menu category, averaging within-menu self-assessed preference values allowed us to find mean individual attitude toward the menu categories. The same exercise was repeated for subjective temptation feeling values for each menu category yielding *salad temptation*$_i$, *burrito temptation*$_i$ and *pizza temptation*$_i$. These six measures were used to conduct finite mixture latent class analysis to identify preference groups in our study sample.



Visualization of Latent Classes in two-dimensional space

Figure 1.1: The results of Finite Mixture Latent Class analysis

Notes: Figure shows the two identified latent classes.

Figure 1.1 presents the identified latent classes in a two-dimensional space where the dimensions are constructed using the study data[2]. The dimensions are composite of our input data values and allow us to split our data into latent classes. Figure 1.1 panel (b) shows that our identified latent classes are spatially distinct, and this result indicates that preference groups represent different sub-populations in our study.

Table 1.2 shows the results of the balance test for the identified two latent preference classes. Tempted Indulgers (class 1) and Temptation Restrainers (class 2) constitute 57.85% and 42.15% of survey respondents, respectively. As the name implies,

[2] See Fraley et al. (2012) for the details of the procedures of constructing these dimension values.

the Tempted Indulgers preference group exhibits a higher level of temptation feelings toward presented food alternatives compared to the Temptation Restrainers consumer type. The outcome of the balance test also reveals that the gender compositions of identified preference types are not statistically different. However, on average, Tempted Indulgers are over-weight, and they have a higher BMI than Temptation Restrainers. In its turn, Temptation Restrainers report

BMI values falling in the range of normal BMI (i.e., between 18.5 and 25) (CDC, 2022a). It should be noted that the BMI measure was not included in the classification method to identify latent food preference groups. However, our balance test shows that the intensity of temptation feelings is positively correlated with high BMI values, as Tempted Indulgers report being over-weight. This evidence suggests that our latent class analysis exclusively using menu-dependent preference measures can robustly predict BMI types. This overlap also indicates that menu-dependent preference measures can reliably predict true consumption habits and they have external validity.

Table 1.2: Sample Characteristics and Mechanisms for Treatment Conditions

Variables	N	Tempted Indulgers N = 140	Temptation Restrainers N = 122	p-value	p-value adjusted
BMI	243	25.8 (5.9)	23.6 (5.7)	0.00	0.00
Male	262	28 (20%)	20 (16%)	0.45	0.62
Salad Satiety	262	6.63 (1.92)	5.81 (2.39)	0.01	0.01
Burrito Satiety	262	8.02 (1.60)	6.91 (2.28)	0.00	0.00
Pizza Satiety	262	8.62 (1.47)	7.60 (1.99)	0.00	0.00
Salad Health	262	3.46 (1.22)	3.21 (1.41)	0.12	0.23
Burrito Health	262	1.98 (1.63)	1.82 (1.65)	0.53	0.62
Pizza Health	262	-2.74 (1.59)	-2.88 (1.62)	0.47	0.62
Salad Taste	262	2.54 (1.53)	0.19 (2.93)	0.00	0.00
Burrito Taste	262	2.75 (1.61)	0.67 (2.66)	0.00	0.00
Pizza Taste	262	3.22 (1.45)	0.69 (2.83)	0.00	0.00
Salad Temptation	262	1.59 (1.79)	-0.48 (2.81)	0.00	0.00
Burrito Temptation	262	2.07 (1.64)	-0.36 (2.47)	0.00	0.00
Pizza Temptation	262	2.72 (1.56)	-0.20 (2.79)	0.00	0.00
Parent Funding	262	98 (70%)	83 (68%)	0.73	0.77
Funding with Scholarships	262	83 (59%)	79 (65%)	0.36	0.59
Funding with Loans	262	45 (32%)	40 (33%)	0.91	0.91
Funding with Pell Grant	262	17 (12%)	23 (19%)	0.13	0.23
Funding with Other Sources	262	24 (17%)	17 (14%)	0.48	0.62
General Health Consciousness	262	0.98 (0.63)	0.92 (0.71)	0.52	0.62
Subjective Knowledge on Food	262	0.00 (0.90)	-0.01 (1.00)	0.71	0.77

Notes: Statistics: Mean (SD) for non-categorical variables; Count (Proportion) for categorical variables. Tests: Kruskal-Wallis rank sum test; Benjamini & Hochberg correction for multiple testing. Satiety ranged from 0 (Does not makes me full to 10 (Makes me full). Temptation, Taste, and Health ranged from -5 (Very low) to +5 (Very high). Health consciousness and Subjective Knowledge on food ranged from 1 (strongly disagree) to 5 (strongly agree).

Table 1.2 also reports satiety ratings of survey participants evaluating to what extent presented food options would ”make them feel full.” Tempted Indulgers consistently evaluate the satiety of food choices with higher Likert scale ratings compared to Temptation Restrainers. Previous studies show that income constraints might induce consumers to maximize the amount of calorie intake per dollar spent (Drewnowski and

Specter, 2004). This suggests that food alternatives that help “feeling full” might also be attractive to student population who typically face budget limitations.

Asking for income information directly from college students may create disturbances and create noisier data as many are reluctant to reveal the income information. To counter this, we used a proxy variable and asked survey respondents to report the funding sources of their education. However, Table 1.2 reports that in terms of funding sources Tempted Indulgers are not statistically different than Temptation Restrainers. This outcome signals that income is informative for identifying latent food preference groups.

Evaluation of this pair of evidence about satiety and education funding sources suggests that Tempted Indulgers are more conscious about the calorie-per-dollar features of food options compared to Temptation Restrainers, and this difference cannot be explained by income differences. We conclude that the satiety characteristics of food items are more salient for students who are more vulnerable to visceral feelings during food decisions, and this effect is tied to menu-dependent preferences rather than income profile of decisionmakers. A geographic analysis of fast-food consumption and SES reveal that low-income people consume energy dense unhealthy food at the cost of healthy diets (Block et al., 2004). However, the study finds that low-income black neighborhoods have more fast-food restaurants per square mile than white neighborhoods. On the other hand, Dave and Kelly (2012) show that unemployed people have greater tendency to consume unhealthy diets compared to employed people.

It is important to note that the latent food preference groups do not show differences in healthy consciousness and knowledge of food. Students in both preference profiles, on average, report the same Likert score ratings when evaluating healthiness of menu options. This evidence suggests that differential consumption habits of students are not driven by knowledge or health consciousness, but primarily by menu-dependent preferences. This result overlaps with a plethora of evidence accumulated by interdisciplinary studies investigating the ineffectiveness of informational nudges and calorie information labels in reducing calorie intake and alleviating the obesity pandemic (Ellison et al., 2013; Dumoitier et al., 2019; Neuhofer et al., 2020).

Table 1.3 presents the results of the probit analysis for the identified two latent preference groups. Table 1.3 column (1) shows the probit regression estimates when temptation and satiety are the independent variables. According to Table 3, Satiety measures do not affect the likelihood of belonging to the Tempted Indulgers preference group. However, an increase in temptation assessments of the presented menu alternatives increases the likelihood of being in the Tempted Indulgers class. Table 1.3 column (2) shows the results when the independent variables are satiety and taste. Similar to the model specification in Table 1.3 column (1), column (2) also shows that satiety measures do not explain being in our identified preference groups, but taste values are informative as the temptation values. Subjects assessing the menu options with higher taste values are more likely to be in the Tempted Indulgers class.

Table 1.3 column (3), we control satiety, taste, and temptation measure values and find that temptation is more predictive in identifying the latent preference groups. Table 1.3 column (4) also control the BMI measure of study participants and reveals that higher BMI values also increase the likelihood of being in the Tempted Indulgers class. It should be noted that in table 1.3, in model 1 and 2 the taste and temptation were significant in isolation, but when put together in the same model (model 3) the strong statistical significance fades off, indicating a multicollinearity problem. However the taste and temptation visceral feelings are distinct though related and have been discussed in studies separately. Due to this issue, both the variables are retained in the model, also it gives a lower AIC value than model 1 and 2. Table 1.3 column (5) presents the marginal effects in terms of the calculated percentage point estimates based on the model specification from column (4). Marginal effects serve as an easier and useful explanation of the probit model for interpretation, as the change in likelihood is described in percentage points. For instance, one Likert scale value increase in assessed temptation values of pizza menu alternatives raises the probability of being in the Tempted Indulgers preference group by 26 percentage points (p.p.). In the same manner, one Likert scale value increase in perceived temptation value of the burrito menu raises the likelihood of being in Tempted Indulgers by 19 p.p.

Table 1.3: Probit Analysis of Tempted Indulgers

Variable	(1)	(2)	(3)	(4)	(5)
Intercept	-1.79** (0.62)	-2.45*** (0.61)	-2.21** (0.74)	-4.58*** (1.28)	
Salad Satiety	0.07 (0.08)	-0.05 (0.06)	0.08 (0.08)	0.04 (0.10)	0.02 (0.04)
Burrito Satiety	-0.09 (0.07)	0.03 (0.07)	-0.08 (0.09)	-0.05 (0.11)	-0.02 (0.04)
Pizza Satiety	0.09 (0.07)	0.13 (0.07)	0.10 (0.07)	0.16* (0.08)	0.06* (0.03)
Salad Temptation	0.31*** (0.07)		0.02 (0.17)	0.08 (0.19)	0.03 (0.07)
Burrito Temptation	0.35*** (0.07)		0.51* (0.20)	0.47* (0.22)	0.19* (0.08)
Pizza Temptation	0.51*** (0.07)		0.67*** (0.14)	0.66*** (0.14)	0.26*** (0.06)
Salad Taste		0.28*** (0.05)	0.42* (0.19)	0.40 (0.22)	0.16 (0.09)
Burrito Taste		0.18** (0.05)	-0.20 (0.16)	-0.18 (0.17)	-0.07 (0.07)
Pizza Taste		0.35*** (0.06)	-0.14 (0.12)	-0.09 (0.13)	-0.04 (0.05)
BMI				0.07*** (0.02)	0.03*** (0.01)
N	264	264	264	243	243
Log Likelihood	-84.64	-105.40	-75.20	-64.30	-64.30
AIC	183.27	224.81	170.39	150.61	150.61
BIC	208.30	249.84	206.15	189.03	189.03

Notes: The dependent variable is a binary variable, and it is "1" if an observation comes from a subject classified as "Tempted Indulger."

We also find that one value increase in BMI measure also elevates the probability of being a Tempted Indulger. Interestingly, our combined model also shows that subjects evaluating pizza with high satiety scores are more likely to be in this preference group. The health measure values were not considered in Table 1.3 models as Table 1.1 shows there is no difference between the two identified latent preference groups in terms of this aspect of food decisions. Moreover, all models in Table 1.3 reveal that satiety was not significant, implying that satiety or the feeling of making full by the food item does not significantly impact the probability of being in a particular group classification in our study sample. Our analysis in Table 1.3 also informs that taste and temptation preference measures are correlated, but temptation better explains the variation in our outcome variable rendering satiety insignificant in Table 1.3 column (3). Previous studies suggest that the existence of a correlation between the taste and temptation variables (Haynes et al., 2015; Huseynov et al., 2021).

Table 1.4 presents probit analyses with a binary dependent variable indicating if the survey participant is in the Tempted Indulgers group. Table 1.4 column (1) controls the significant variables from the combined model specification from Table 1.3 column (4). All independent variable exhibit qualitatively the same results except the satiety measure values. The model specification in Table 1.4 column (1) shows that Temptation and BMI measures are robust predictors of latent food preference groups. Table 3 columns (2), (3), and (4) controls in a stepwise addition manner workout frequency, self-assesses self-control and temptation issues by Ameriks et al. (2007) and importance of food characteristics, respectively. This stepwise addition of variables in the regression models provides more power and information in the addition of independent variables. Table 1.4 columns (4) shows that survey respondents ranking the nutritional characteristics of food alternatives higher are less likely to be in the Tempted Indulgers group. Moreover, subjects who predict food-related temptation issues are more likely to be one of Tempted Indulgers. The results also show that burrito temptation and Pizza temptation values are significant and positively affect the likelihood to be included in the class of Tempted Indulgers group.

Table 1.4 Probit analysis of Tempted Indulgers with Self-Control Measures

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Intercept	-2.83*** (0.74)	-2.66*** (0.73)	-2.75*** (0.76)	-2.38 (1.25)	
Pizza Satiety	0.08 (0.06)	0.08 (0.06)	0.09 (0.06)	0.09 (0.07)	0.03 (0.03)
Burrito Temptation	0.38*** (0.07)	0.39*** (0.08)	0.40*** (0.08)	0.41*** (0.08)	0.16*** (0.03)
Pizza Temptation	0.37*** (0.06)	0.37*** (0.06)	0.35*** (0.06)	0.40*** (0.06)	0.16*** (0.02)
BMI	0.05** (0.02)	0.05** (0.02)	0.05** (0.02)	0.06** (0.02)	0.02*** (0.01)
Workout		-0.05 (0.06)	-0.06 (0.06)	-0.11 (0.07)	-0.04 (0.03)
EI Gap			0.07 (0.11)	0.07 (0.11)	0.03 (0.04)
TI Gap			0.26 (0.14)	0.31* (0.13)	0.12* (0.05)
Price Rank				0.10 (0.14)	0.04 (0.06)
Safety Rank				-0.01 (0.11)	-0.00 (0.04)
Nutrition Rank				-0.23* (0.12)	-0.09* (0.05)
Calorie Rank				-0.01 (0.11)	-0.01 (0.04)
N	243	243	236	236	236
Log Likelihood	-90.76	-90.48	-85.31	-81.80	-81.80
AIC	191.52	192.97	186.63	187.59	187.59
BIC	208.98	213.93	214.34	229.16	229.16

$p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

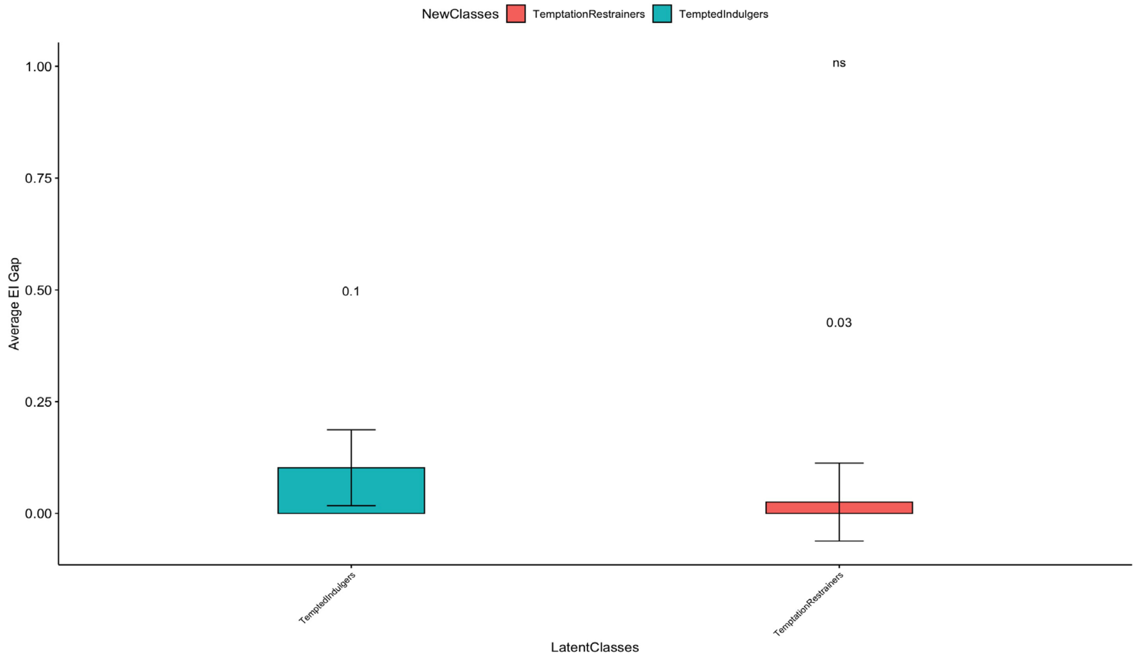
Notes: $p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. The dependent variable is a binary variable and it is "1" if an observation comes from a subject classified as "Tempted Indulger." Work out measures how many times a subject did work out per week. EI Gap and TI Gap is between 0 and 6 which refers to the number of food certificates that can be used for dinner.

In Table 1.4, the positive significance of the TI gap variable re-validates that the Ameriks et al. (2007) measure and indicates that our classification of the latent food preference classes has external validity. Put it differently, subjects assessing presented food alternatives with higher temptation values are more likely to be categorized as the Tempted Indulgers.

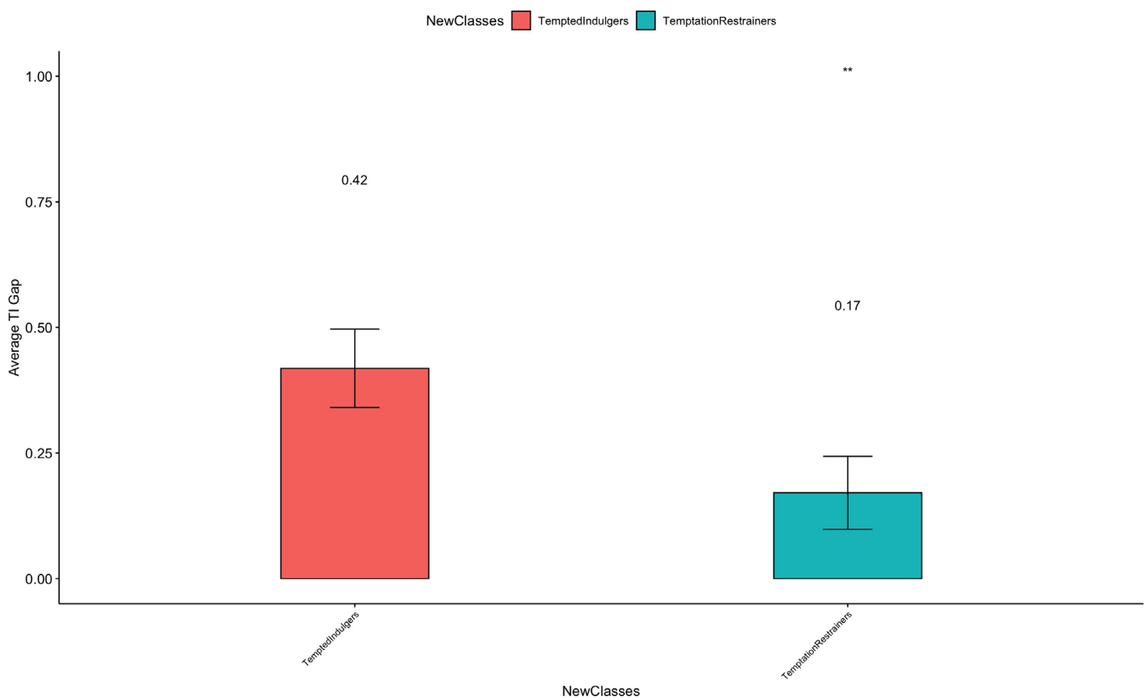
Table 1.4 column (5) convert the estimated coefficients in column (4) into percentage point values, i.e marginal effects of the column 4. Results show that one Likert scale value increase in pizza temptation and burrito temptation measures raises the probability of being in the Tempted Indulgers group by 16%. The corresponding percentage for BMI is 2%. Higher the nutrition ranking, there is less likelihood for that individual to be categorized into the group of Tempted Indulgers by 9%. Nutrition, receiving a higher ranking means the subjects are more concerned about a healthy and balanced diet. Thus, a nutrition conscious person would not succumb to temptation. S/he would have self-control over the food consumption decisions. In fact, this nutrition-temptation discourse is the base of many foods related interdisciplinary studies. And, lack of understanding of the nutrition-temptation disparity is the primary direction for studies (Kemp et al., 2013; Mazzola et al., 2017). Further, our findings partially overlap with the unhealthy-tasty discourse in the literature (Mai and Hoffmann, 2015; Garaus and Lalicic, 2021; Briers et al., 2020).

Figure 1.2 presents the comparison of the identified latent preference groups along the self-assessed self-control and temptation measures developed by Ameriks et al. (2007). The result in Figure 1.2 panel (a) confirms the outcomes of Table 1.4 and we conclude that Tempted Indulgers and Temptation Resisters are not different in terms of perceived self-control issues. However, these groups show differences along the self-assessed temptation issues. Specifically, Tempted Indulgers are predicting a higher magnitude of temptation issues compared to the Temptation Restrainers and this difference is statistically significant ($two - sided - Wilcoxon - test, z - score = 1.854982, p = 0.03$).

Robustness check based on probability thresholds for profile classifications: To assess the sensitivity of the latent profiles identified, alternative posterior probability thresholds of 0.45 and 0.55 were examined. A threshold of 0.45 retained 71 of the 267 respondents (26.6%), whereas a threshold of 0.55 retained only 36 respondents (13.5%). The higher threshold eliminated one of the major latent profiles because respondents assigned to that profile exhibited overlap in posterior membership probabilities. Further, the reduced samples did not hold the original five-profile structure. Thus, the main analyses are based on the conventional maximum posterior probability assignment, which retains all respondents while assigning everyone to the profile with the highest posterior probability.



(a) Comparison of Latent Preference Groups along the EI measure



(b) Comparison of Latent Preference Groups along the EI measure

Figure 1.2: Comparison of Latent Preference Groups along the Ameriks et al. (2007) measures.

2.6 Discussion

This study investigates the role of knowledge about diet quality and visceral feelings in the formation of food preferences. In particular, our focus is on determining the relative importance of food diet quality knowledge and menu-dependent cues in identifying latent consumer preference profiles. We mainly identify two latent consumer preference groups: Tempted indulgers versus temptation restrainers. This finding is in line with literature on temptation and self-control or commitment in different contexts. Many studies have used the latent classes approach to identify the latent classes in similar contexts (Segovia and Palma, 2016; Palma et al., 2017; Huh et al., 2011; Sands et al., 2019; Peschel et al., 2016). Our identification of the two latent groups is also supported by the balanced test and our usage of self-control measures (Ameriks et al., 2007). Our classification shows significant differences in temptation scores, BMI values and body weight. Though self-reported BMI was obtained from the subjects, BMI was not used in the identification of the two latent classes. But when the latent classes are compared with BMI values, the classes support the BMI variations, which indicates latent classes using menu-dependent preference measures can robustly predict BMI categories. At a time when self-reported BMI values are in question, this classification is useful to get an indication of the BMI classifications. This is useful in cases where BMI values cannot be directly measured or when the subjects are not sure about their height and weight. A similar classification has been done by Segovia and Palma (2016) using latent class analysis for a vegetable preference study: health conscious and health redeemers. The former was the cohort who are very health conscious with healthy lifestyles and were willing to pay a premium for the products, but they were not willing to pay a premium for the health benefits. On the contrary, the health redeemers are the ones who had unhealthy lifestyles but were willing to pay for healthy food products. This has an analogy to our findings too. Here too health redeemers were having a bad lifestyle but were willing to pay for health attributes. In our study, Temptation indulgers also have higher health scores and health consciousness but they succumb to temptation. It would have been interesting if we saw whether they are willing to pay more for the health features of the product. But still they were presented with a menu of different products with healthy and unhealthy products. Thus, this implies the tempted indulgers would have paid more, but only by identifying the unobserved heterogeneity may we have some direction.

Though income was informative for identifying the latent preference groups, many socioeconomic covariates did not show much difference. But in a study with children, the latent classes were predicted mostly by socio-economic factors and demographics as opposed to behavioral factors (Huh et al., 2011). It can be inferred that using behavioral factors or questions might be difficult with children. So more sensible variables were used. But in our case, the study is based on adults, who are mostly making their independent food consumption decisions without the interference of their family members, thus behavioral and food-related internal and external factors play an important role. But in our case, we find that the differential consumption habits are not driven by knowledge or health consciousness but primarily by menu-dependent preferences. This indicates that alternatives matter for food consumption habits irrespective of knowledge and health consciousness. Temptation indulgers succumb to their temptations when more alternatives and unhealthy foods are present. Temptations restrainers, though they are tempted they show self-control. So, they do not fall for temptation. On the contrary, a study finds that the more you control yourself, you consume more of that good, at a less frequent interval whereas those who are tempted consume the good frequently but in a lesser amount (Sasso et al., 2022).In a study based on alcohol consumption, Sasso et al. (2022) finds that the group with high self-control strategy consumes alcohol less frequently in a week, but they consume a high amount of alcohol. On the other hand, those who consume very frequently consume less alcohol each time. This indicates those who are having commitment strategies for self-control tend to consume more when they consume alcohol. This may also have implications for healthy eating, sugar consumption, and daily calorie budgets. A consumer with self-control may tend to consume less unhealthy food, but when she consumes, she may consume a greater amount, while temptation indulgers may consume little unhealthy food daily, but may consume less. But this cannot be tested in our study. To test this we need to check for consistency in the temptation-self-control discourse. This issue also warrants further studies to check on the consistency of food decisions over time.

We justify our young sample as it is important for young adults to have healthy eating habits as this will also shape their future eating habits and health outcomes plus literature (Jindahra and Phumpradab, 2023; Le et al., 2023). This is one reason why most of the food/healthy eating studies are conducted with children, adolescents, and young adults. The notable feature of young adults is that they make their food choice independently, without any influence from the family. Thus it is important to look at these independent food consumption decisions. Some studies have very specific samples being considered. SotresAlvarez et al. (2010) studied the food consumption patterns of pregnant women with LCA. They recommend LCA is useful in predicting food consumption patterns for pregnant women. The study uses quite an extensive array of food types and nutrients. Keane et al. (2014) studies the dietary patterns of older consumers in Ireland, using data that captures 10 years. They recommend LCA even to study the patterns of dietary transitions. Further, some studies limit their scope to a particular food or beverage: Alcohol (Sasso et al., 2022), Broiler meat (Pouta et al., 2010), plant-based protein (Vainio et al., 2016). Whereas our study focuses on general meal products. Thus, the general temptation may have a greater role than a particular niche product. Further apart from health consciousness and subjective knowledge on food, we did not test any other social motives or environmental concerns (Pouta et al., 2010). We realize though these may shape the food preference behavior, given our cohort of subjects considered, and the food available around the university, these concerns may not be plausible in this context. But those studies also found that their latent classes were impacted by health and weight concerns as well.

Both the measures of health consciousness (Michaelidou and Hassan, 2008) and subjective knowledge on food (Pieniak et al., 2010), did not show any difference between the two latent groups. This again confirms their menu rankings based on the health aspect of the food items. There too, there was no difference. From this, we can infer that both groups are knowledgeable about the healthiness of the food and in general health consciousness aspects. The only features that they tend to differ are taste and temptations features. These findings also confirm the literature that knowledge and information do not matter for food choice (Insch and Jackson, 2014), but there are other behavioral factors involved. Further in our analysis, the positive significance of the TI gap revalidates the self-control measures of Ameriks et al. (2007). This proves that our classification of latent food preference classes has external validity. But this may differ if there is a heterogeneity in the sample. Since our sample is less heterogeneous as we focus on young adults in an academic setting.

Our study positions with literature, using LCA to identify consumer groups. Latent classes have been used in literature abundantly, and there has been increasing evidence of the robustness of this approach in behavioral economics studies. The application of latent class analysis in many consumer studies validates that latent class analysis is very useful for predicting classification groups (Sotres-Alvarez et al., 2010; Keane et al., 2014; Pouta et al., 2010; Vainio et al., 2016). Further, it has to be also noted the differences between food preferences and food choices. They are related but have different terms. Food choice is a complex concept that cannot be measured easily. It depends on many factors. Though many studies have dealt with this aspect, most of the studies coincide with the main factors described by Shepherd’s approach (1989). According to this, factors affecting food choices can be broadly categorized into 1) food-related/product-related factors, 2) consumer-related factors and 3) the environment, while some studies have a broader variation of these factors. Food preferences originate mainly from the consumer’s point of view (i.e. factor 2 in the above). Some argue preferences are the habits of consumers given past experiences with food choices (Wadalowska et al., 2008). Thus, these habits affect food choices through food preferences. Studies also highlight that food preferences key determinants of dietary intake which can persist into the later life of individuals (Beckerman et al., 2017; Liem and Russell, 2019; Glabska et al., 2021). Also, conventional economics literature has mostly favored choice data which was decided by the consumer, but recently there has been a development in the use of non-choice data which measures the choices of consumers indirectly through various means (Halko et al., 2021). Having said that, this study also needs some consideration of limitations. Our study focuses on 262 undergrads in a southern-eastern public university, mostly a homogeneous sample. In addition, female participants were overrepresented in the sample, and the study population consisted primarily of college students with relatively limited income variation. These sample characteristics may limit the generalizability of the findings to populations with different gender distributions and broader socioeconomic backgrounds. It would be better to extend the study in a much more heterogeneous sample with a larger sample size. This would alleviate any systematic bias that arises from sample size and selection. However, it is noteworthy to mention that this age cohort of respondents is important in understanding the food preferences of young adults, as this is the time period when they make their own food consumption decisions away from home. Another aspect of the limitations arise from the empirics of the analysis. This study's main focus is on the classification of food preferences of the college students. However, though we discuss some theoretical underpinnings, the findings serve as an entry point for further studies based on theory. The classifications and the probit models that we have used only use the variables based on the data collected. However, food choices and preferences can be affected by internal and external factors. These factors can be food-related factors as well as environment-related factors. Thus, while modeling food preferences of food choice many factors come into play. Thus, variable selection and omitted variables has to be considered while generalizing the findings. In addition to that, in general, categorical regressions usually provide a lesser explanation of the variance than the usual OLS regressions.

Having said that, our analysis provides a direction for future work about analyzing the profile of tempted indulgers and how policies can target these food preference groups. Since classification has been identified and those classification correlates with BMI and self-control measures, the study finds validity. The class of tempted indulgers are crucial for designing policies and nudges to control their temptation. This classification can also be generalizable; thus the nudges and policies may also be generalizable for the greater populace. Further, it is important to see how these respondents in two classes behave over time. Do the temptation restrainers fall for temptation over time. If so, what strategies can be used to control their temptations. Though the study is limited to college students, the main classifications have broader implications.

2.7 Conclusion

Healthy food consumption habits are important, as they serve as a predictor of future health, apart from physical activities. Understanding the college students' consumption preferences and patterns is important to know, as this would be the first time for most of the students, who will be making individual food decisions being away from home. Thus, their eating habits may affect their health in the future, or during their working age. It is crucial that they have healthier eating habits, so that they will follow these habits in future too, on average. Also, it is important to note that, apart from the socio-economic backgrounds and demographics, it has been well established that cognitive aspects also have a say in food consumption and preference. Hence, recent studies have been mostly focusing on the behavioral aspects of food decision making. This points out that there is much unobserved heterogeneity involved in food decision making and consideration has to be given to these unobserved factors in food decision making for any food related policies to be effective.

Drawing from the survey of data from college students from a Southern university, based on scores of temptations, and taste scores of food menu alternatives, two distinct latent classes were identified: Tempted indulgers and Temptation Restrainers. Both groups, however, did not show any difference between health consciousness measures and measures on subjective knowledge on food. This implies that the identified preference groups are equally informed about the healthiness of the food products, but one group fails when dealing with food related temptation, whereas the other group do not succumb to temptation. This is also confirmed by the health scores of the balanced test between two groups. This leads to the inference that both groups are well informed, but one group is tempted. The use of the Ameriks et al. (2007) measure also concludes the same finding for the two classes. We show that both classes do not show a difference between the Expected-Ideal gap (Self-control expectation). But tempted indulgers show a significantly lower value for the Temptation Ideal gap (succumbs to temptation).

The probit analysis for the tempted indulgers with the variables on the latent class analysis shows that temptation, tastes, satiety (Pizza) and BMI significantly predict the likelihood of the tempted indulgers. Extending the probit for other explanatory variables, such as workout, TI gap, EI gap, and Ranking factors, reveals that, in addition to temptation, BMI variables, TI gap increases the likelihood of being a tempted indulger. On the other hand, the higher the rank for nutrition, the lesser the likelihood of that person to be a tempted indulger. It is interesting to see how the difference measures strengthen the main findings of this study. The study has many policy implications, mainly study supports that for college students, awareness based behavioral approaches would not be plausible. Their weakness is temptation, and hence behavioral approaches that target temptation would be the most effective ones and any policy that targets this would be a more meaningful one.

Further, looking at what underlying factors make the tempted indulgers class distinct, and investigating how this cohort of people can be approached for better and improved eating habits and a better prediction of their future health. In addition to this, this cohort would be also useful in understanding what types of behavioral strategies are more effective for them. It is also recommended that the study be more extended towards more colleges with a greater number of subjects. Then more unobserved behavioral heterogeneity can be captured.

As further extensions of this study, this study can be extended to evaluate how the subjects would behave in a two-period two selves' model. Mainly to which extent their consumption decisions are consistent. There is also scope for experimental studies with various information treatments and potential policy proxies. Specifically, how would a paternalistic policy or treatment would impact the food decisions of young consumers.

Their commitment strategies can also be identified towards consumption of unhealthy food.

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2.8 Appendix A

Table A1.1: Sample profile

Characteristic	%	Characteristic	%
Gender		**Academic Major**	
Female	80.15	Agriculture	19.85
Male	18.32	Liberal Arts	72.90
Third gender/non-binary	1.53	Engineering	5.34
		Education	0.38
Race/Ethnicity		**Age**	
Asian	4.58	18 years	8.02
Black/African American	4.58	19 years	25.19
Hispanic/Latino	2.67	20 years	21.37
White	86.26	21 years	27.86
Other	1.53	22 years	9.54
Prefer not to say	0.38	23 years	3.44
		24 years	0.76
		25 years or above	3.82
Funding Source*		**Exercise Frequency**	
Through parents	20.23	Once a week	12.21
Loans	4.20	Twice a week	21.37
Pell grants	0.76	Three times a week	21.37
Scholarship/sponsor	6.11	Four times a week	10.69
Other means	1.91	Five or more times a week	16.79
Parents & scholarship/sponsor	25.19	Does not exercise	16.79
Multiple means other than above	40.47	Prefer not to say	0.76
Prefer not to say	1.15		
Employment Status		**Food Allergy**	
Full-time	4.96	Yes	20.61
Part-time	56.11	No	79.39
Not employed	38.17		
Prefer not to say	0.76		

*Multiple selections do not equal 100

Table A1.2: Important factors affecting food decision making

Food Decision Factors	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Price	33.97	30.53	18.70	11.45	5.34
Nutrition	19.85	22.90	24.81	27.10	5.34
Convenience	19.08	26.72	21.76	19.85	12.60
Safety	18.70	8.40	19.47	16.79	36.64
Calorie content	8.40	11.45	15.27	24.81	40.08

Table A1.3: Perceptions on health consciousness

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I reflect about my health a lot	49.24	7.63	18.70	23.66	0.76
I'm very self-conscious about my health	41.60	13.74	14.50	28.24	1.91
I'm alert to changes in my health	48.85	8.78	13.36	27.86	1.15
I'm usually aware of my health	55.73	5.73	9.92	26.72	1.91
I take responsibility for the state of my health	48.47	2.67	11.45	36.64	0.76
I'm aware of the state of my health as I go through the day	44.66	9.92	14.89	29.01	1.53

Table A1.4: Perceptions of subjective knowledge of food

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Compared with an average person I know a lot about healthy food products	2.67	19.85	31.68	32.82	12.98
I know a lot about how to evaluate the quality of healthy food products	2.29	20.61	25.19	39.31	12.60
People who know me, consider me as an expert in the field of healthy food products	30.15	34.73	19.85	9.92	5.34

Table A1.5: Ideal and Actual allocation of dinner vouchers

	0	1	2	3	4	5	6
Ideal		2.33	11.28	68.09	12.06		6.23
Actual	0.39	2.75	14.12	55.69	18.04	2.75	6.27
Temptation (n=115)		4.35	15.65	13.91	31.30	12.17	22.61

Table A1.6: Students who might give in for temptation

Actual _ Expectation	Percent
I would be somewhat/strongly tempted to use more certificates in the first month than would be ideal	24.90
I would be strongly/somewhat tempted to keep more certificates for use in the second month than would be ideal	20.62
I would have no temptation in either direction	54.47

Table A1.7: Variable description for LCA and Probit regression

Variable	Description	Unit	Variable type	Q-Number
Dependent Variable	1 if *tempted indulgers*; 0 otherwise	1 or 0	binary	-
Salad Satiety	Likert scale	0 - doesn't make me full 10 - makes me full	scale	Menu 1 to 3
Burrito Satiety	Likert scale	0 - doesn't make me full 10 - makes me full	scale	Menu 4 to 6
Pizza Satiety	Likert scale	0 - doesn't make me full 10 - makes me full	scale	Menu 7 to 9
Salad Temptation	Likert scale	-5 not tempting +5 very tempting	scale	Menu 1 to 3
Burrito Temptation	Likert scale	-5 not tempting +5 very tempting	scale	Menu 4 to 6
Pizza Temptation	Likert scale	-5 not tempting +5 very tempting	scale	Menu 7 to 9

Salad Taste	Likert scale	-5 not tasty +5 very tasty	scale	Menu 1 to 3
Burrito Taste	Likert scale	-5 not tasty +5 very tasty	scale	Menu 4 to 6
Pizza Taste	Likert scale	-5 not tasty +5 very tasty	scale	Menu 7 to 9
BMI	Body mass index calculated from subjects height and weight	index	Continuous within a Range	D7, D8, D9
Workout	Weekly frequency	Weekly frequency	categorical	D6
EI Gap	Difference between expected and ideal certificate usage	Number of certificates	continuous	SC4SC1
TI Gap	Difference between under temptation and ideal certificate usage	Number of certificates	continuous	SC3SC1
Price Rank	Ranking for price	Rank 1 to 5	ordinal	D12
Safety Rank	Ranking for safety	Rank 1 to 5	ordinal	D12
Nutrition Rank	Ranking for nutrition	Rank 1 to 5	ordinal	D12
Calorie Rank	Ranking for calorie	Rank 1 to 5	ordinal	D12
Gender	Gender of the subjects	1- Male 2- Female	binary	D1
Funding	Types of funding for college education (Parents, loans, pell grants, scholarship/sponsor, other)	Multiple selection	categorical	D11

Health consciousness	Average of general health consciousness related six question- Likert scale	1- strongly disagree to 5- strongly agree	ordinal	HC1
Subjective Knowledge on food	Average of Subjective knowledge on food and food ingredients and preparation related three questions- likert scale	1- strongly disagree to 5- strongly agree	ordinal	SKF1

Table A1.8 Sensitivity analysis of latent profile classification using alternative posterior probability thresholds

Classification Criterion	Respondents Retained	Percent Retained
Maximum posterior probability assignment (primary analysis)	267	100.0
Posterior probability ≥ 0.45	71	26.6
Posterior probability ≥ 0.55	36	13.5

Note: The primary analysis assigns each respondent to the latent profile with the highest posterior probability. Alternative posterior probability thresholds were evaluated as a sensitivity analysis. Increasing the threshold substantially reduced the effective sample size because several respondents exhibited overlapping posterior membership probabilities across profiles. Under the 0.55 threshold, one of the major latent profiles was no longer represented in the retained sample.

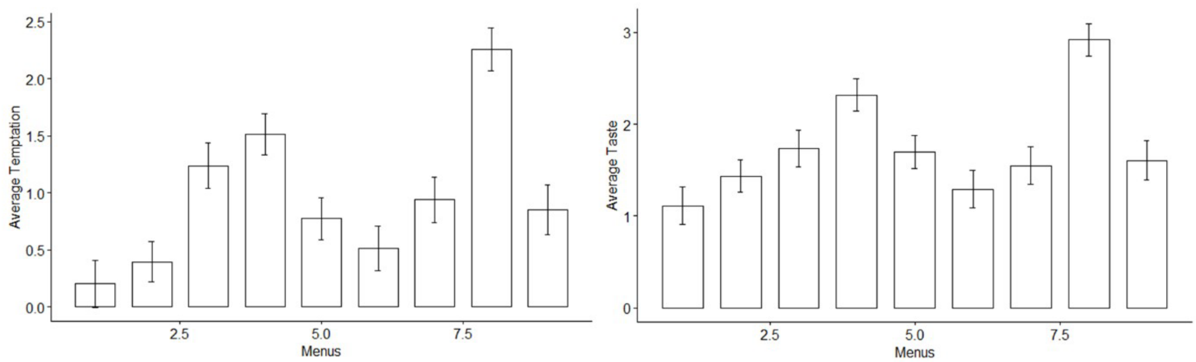


Figure A1.1: Average scores for taste (a) and temptation (b)

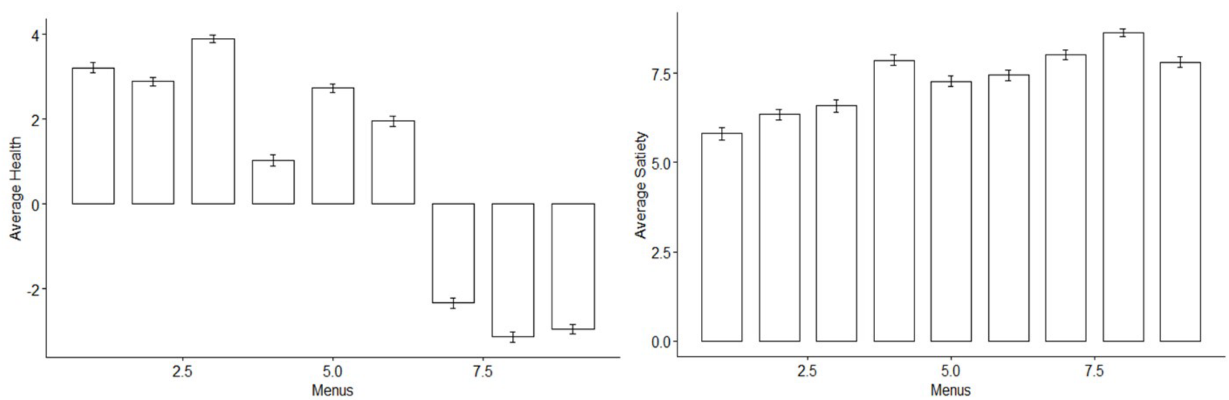


Figure A1.2: Average scores for Health (a) and Satiety (b)

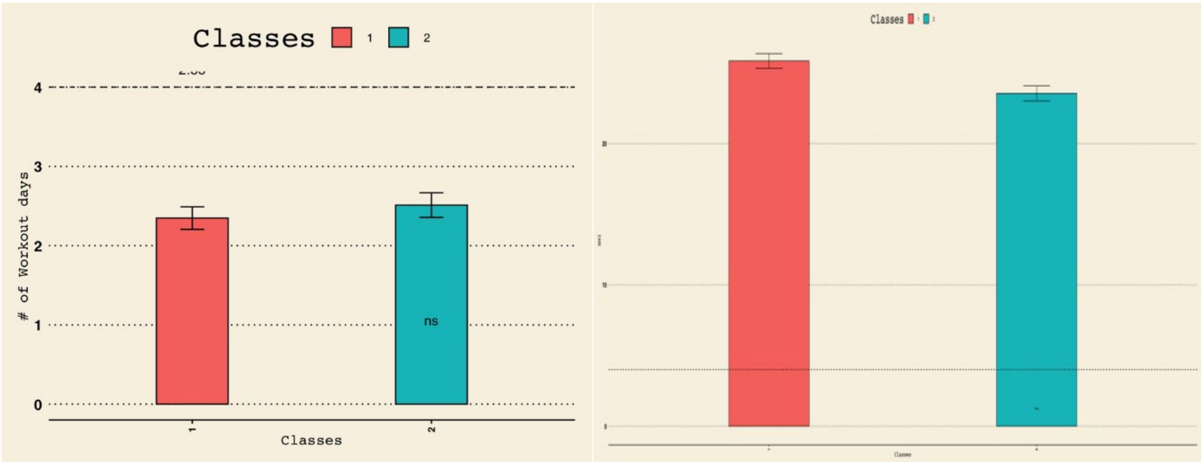


Figure A1.3: Latent class comparison for workout days (a) and BMI (b)

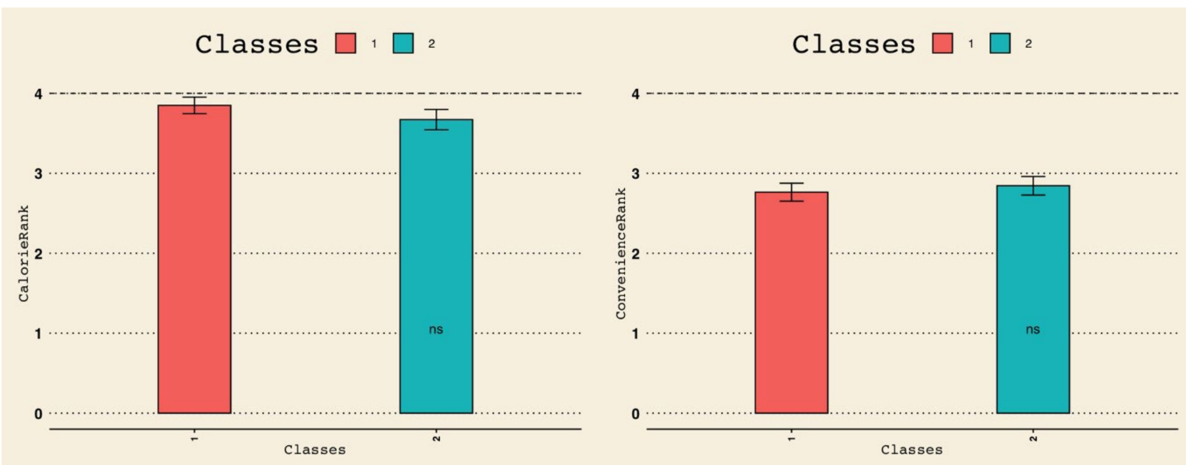


Figure A1.4: Latent class comparison for calorie rank (a) and convenience rank (b)

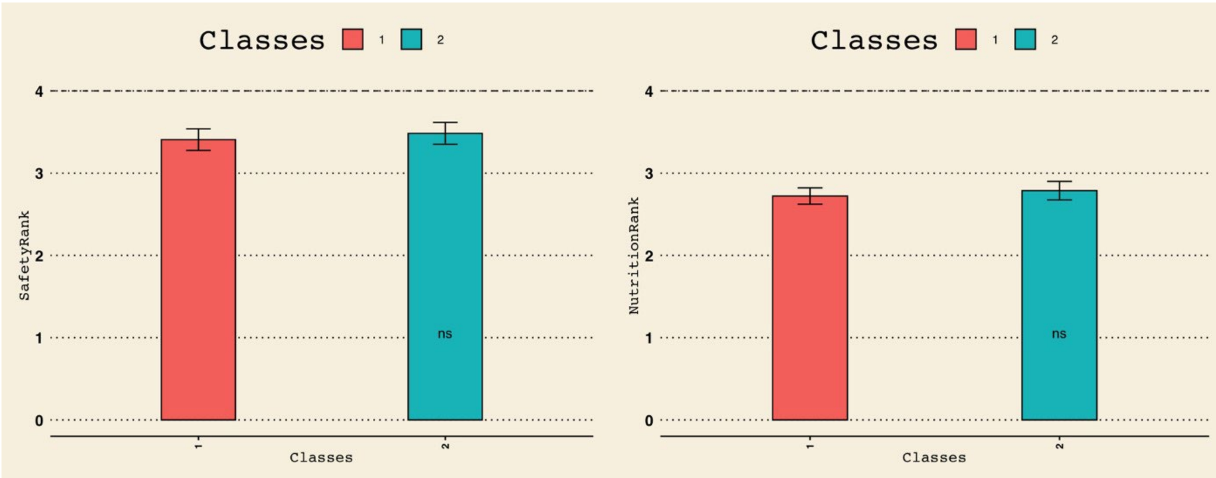


Figure A1.5: Latent class comparison for safety rank (a) and nutrition rank (b)

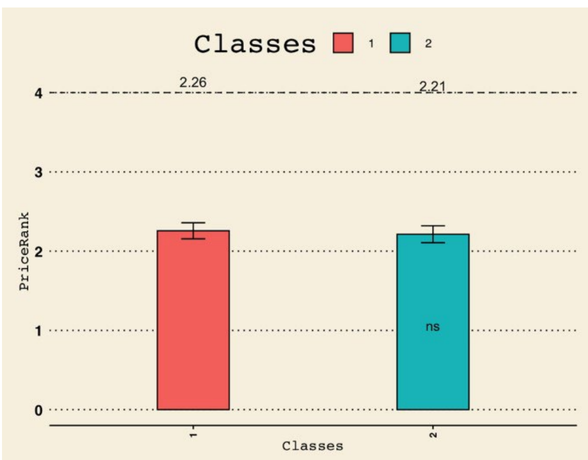
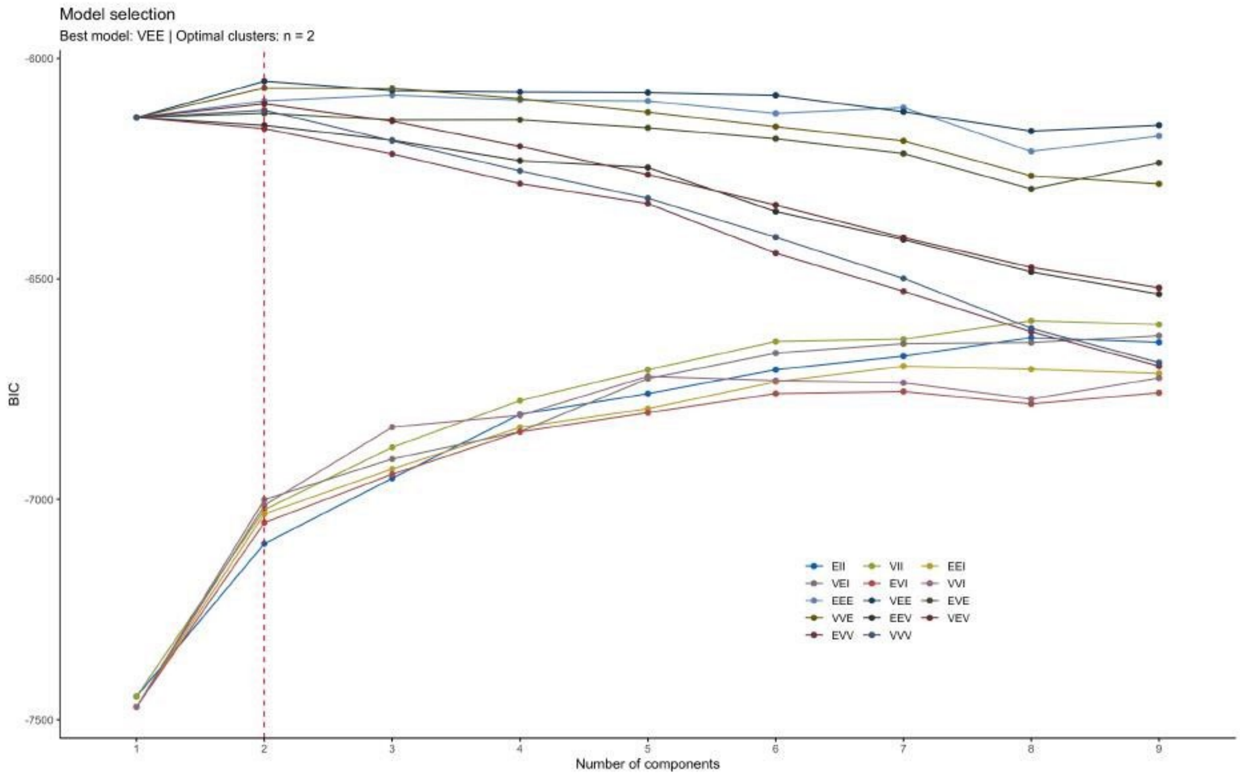


Figure A1.6: Latent class comparison for price rank



(a) Determination of the Best Classification Model

Figure A1.7: Determination of the Best Classification Model

Chapter Two

Dynamic Food Decision (In)Consistency: Evidence from the Field[3]

3.1 Introduction

Primary public health policies mostly nudge low-calorie diets when consumers are at the final stage of food decision-making. Mandatory nutritional panel laws, which require transparent and easily accessible calorie information for packaged food items and chain restaurant menus, aim to promote healthy eating when consumers conclude their food decisions (Barahona et al., 2023). However, there is weak evidence regarding the effectiveness of this information provision on low-calorie food intake (Bollinger et al., 2011; Avery et al., 2023). Previous research extensively demonstrates how the final food choice stage, abundant with temptation cues, can diminish the expected impact of calorie information (Huseynov et al., 2021). Temptation, the desire for food indulgence, and similar visceral feelings may reduce the effectiveness of food information, especially when consumers are hungry and make food choices in a restaurant environment that inhibits their self-control (Downs et al., 2009). The documented low effectiveness of calorie labeling laws suggests that food information may be more beneficial when consumers plan their food choices. Recent theoretical models suggest that food planning (a "cold state") and actual food choice (a "hot state") can trigger different preferences (Noor and Takeoka, 2015; Liang et al., 2020). In a cold state, consumers are more likely to make

[3] This chapter is reproduced from Sivashankar, P., & Huseynov, S. (2026). Dynamic Food Decision (In)Consistency: Evidence from the Field. Journal of Agricultural and Resource Economics, Preprint. https://doi.org/10.22004/ag.econ.376280. Reproduced with permission of the authors.

rational and informed food decisions to improve their health (Yang et al., 2012). Moreover, cold-state food decisions may be more malleable and could enhance the effectiveness of public health policies that rely on information provision. This article investigates how food information affects food planning in a *cold state*, where consumers do not face intense feelings of temptation. We also contrast planned food decisions with actual food choices in a *hot state*, identifying dynamic decision inconsistencies and their determinants.

The difference between cold and hot state preferences and food decisions can be illustrated with a typical dynamic food choice example. Consider a consumer who strives to adhere to a healthy diet. In the morning (i.e., cold state), the health-conscious consumer might plan to eat a salad for lunch. However, when lunchtime arrives (i.e., hot state), they may reverse their decision and choose a burger when making the actual choice at a restaurant. Cold-state *normative* food preferences often lead to choosing low-calorie items, typically compromising on taste (Huseynov et al., 2021). In contrast, hot-state *temptation* preferences lead to maximizing food indulgence at the expense of health. Previous studies show that these conflicting preferences collide during the conclusion of the decision-making process, and temptation-driven preferences can override normative ones, leading to high-calorie food intake (Gul and Pesendorfer, 2001; Noor, 2007; Huseynov et al., 2021). Therefore, a sophisticated consumer might anticipate this potential decision reversal and limit their future choices by going to a salad bar and avoiding restaurants that also serve burgers (Gul and Pesendorfer, 2001).

We use a novel experimental paradigm to map cold state preferences and decisions. We build our experimental design on Toussaert (2018, 2019), where study participants face a decision trade-off between low-, middle-, and high-calorie meal options across seven different menus in a cold state. Participants rank the presented menus based on their preferences. With their seminal work, Gul and Pesendorfer (2001) show that menu ranking can reveal temptation preferences and detect self-control issues. In our study, a lower ranking order increases the realization chance of the menu based on the known probability distribution. This probabilistic menu-ranking design resembles lunch planning in the cold state and enables us to measure i) the commitment demand for a meal item and ii) the Global Avoidance Index (GAI) when the decision-maker constantly down-ranks the menus with a particular meal. We also design two treatment conditions to investigate how behavioral nudges and calorie information affect cold-state decisions and the dynamic consistency of food choices later in a hot state. In the control condition, we display meal options with their calorie contents. In the *Calorie Coloring* treatment, we use green, orange, and red font colors when displaying the calorie counts of the meal options. In the *Information Nudge* condition, we inform subjects about the importance of building healthy eating habits. We randomly assign subjects to study conditions using a between-subject design framework.

Our study proceeds over two consecutive days. On Day 1 (the cold state), participants are randomly assigned to one of three study conditions: Control, Calorie-Coloring, or Information Nudge. In each condition, they are presented with three food items of varying calorie counts from a well-known campus food vendor. In the Control condition, we only show the food items, their calorie contents, and ingredients. In contrast, the Calorie-Coloring treatment displays calorie counts using green, yellow, and red to indicate low-, medium-, and high-calorie foods, respectively. Prior research shows that traffic-light labels increase the cognitive accessibility of numeric information and encourage lower-calorie choices (Scott and Sesmero, 2022; Ellison et al., 2014). In the Information Nudge condition, we append a brief informational piece to the description of food alternatives that emphasizes the importance of developing healthy dietary habits early in life and highlights the potential health risks associated with high-calorie food consumption in later stages of life. Participants are then shown seven possible menus, representing all non-empty combinations of the three food items. They rank these menus according to their preferences, knowing that low-ranked menus are more likely to become binding than high-ranked ones. At the end of Day 1, we randomly select the binding menu and determine which meal alternative the participant will receive on Day 2. On Day 2 (the hot state), we "surprise" participants before ordering their meal and inform them that they can change their Day 1 meal choice to another meal alternative. Participants decide on their Day 2 final meal choices and then order their meals through the food vendor's website/mobile app. We mark food decisions as dynamically inconsistent if participants change their Day-1 meal decisions in the hot state.

Our contribution to the relevant literature is threefold. First, previous studies primarily investigate food decision inconsistencies in a laboratory setting, where study participants make a series of diet choices in a laboratory environment (Villacis, 2023; Fraser et al., 2021; Segovia and Palma, 2021; Huseynov and Palma, 2021; Agranov and Ortoleva, 2017; Scarpa et al., 2007). In a typical research design, decision inconsistencies are usually identified by contrasting decision-makers' early-stage laboratory choices with their late-stage revealed preferences (Fraser et al., 2021).[4] The primary limitation of mimicking inter-temporal decisions with sequential laboratory tasks is that the time lapse between study *periods* may be too short to meaningfully account for the dynamics of real-life choices. We complement this literature by conducting a two-day study. This setup allows us to minimize the experimenter demand effect and capture food diet preferences and choices in the *wild*, closely mimicking real-life decisions (Camerer et al., 2004).

Second, our research design is built on the latest advancements in economic theory, linking food decision inconsistencies to *menu-dependent preferences* and dynamic choice settings (Gul and Pesendorfer, 2001; Noor, 2007; Noor and Takeoka, 2010, 2015). Specifically, we use probabilistic menu-ranking choice situations to reveal menu-dependent visceral feelings and commitment demand in real-life food decisions (Toussaert, 2018; Sadoff et al., 2020; Toussaert, 2019). Finally, we test the predictions of recent theoretical models suggesting that information may be more effective in a cold state (Noor and Takeoka, 2015; Liang et al., 2020). Psychological studies have also made similar predictions, highlighting differences between cold and hot state food decisions (Hoch and Loewenstein, 1991; Petit et al., 2016). Additionally, previous research shows that nutritional education aimed at promoting healthy eating can be more effective in early life stages when food preferences are more malleable (Lai et al., 2020). Therefore, our

[4] Some studies strive to address this caveat by designing follow-up experimental choices or survey waves to measure dynamic decision inconsistencies (Rigby et al., 2016; Liebe et al., 2012; Bryan et al., 2000; San Miguel et al., 2002). However, in studies with multiple survey waves, the attrition rate in participation, uncontrolled information acquisition by subjects, and potential preference shifts limit only attributing changes in intertemporal choices to decision inconsistencies (Rigby et al., 2016).

study contributes to this body of literature by providing evidence on how calorie information and nudges for healthy eating influence food preferences in a cold state.

We find that study participants primarily prefer committing to the low-calorie meal option in the cold state. The second most preferred commitment is for the high-calorie meal in our sample. Our results also reveal that between 68% and 83% of subjects exhibit dynamically consistent food decisions over two consecutive days, depending on their Day 1 meal choices. We calculate Cohen's Kappa for the entire study sample and find that overall dynamic consistency is 65%, while the raw mean consistency is 77%. Based on Cohen's Kappa estimate, we conclude that our study participants show *moderate* dynamic consistency (McHugh, 2012). We differentiate between two dynamic inconsistencies. Positive (negative) inconsistency happens when the decision-maker switches from a higher-calorie (lower-calorie) meal alternative to a lower-calorie (higher-calorie) meal option on Day 2. We find that most of the Day 2 inconsistencies are positive inconsistencies.

Moderate dynamic consistency and positive inconsistency findings indicate a favorable environment for policies that aim to improve the diet quality of consumers and, consequently, address food intake-related health issues. However, one important caveat is that food preferences may not be malleable enough with information nudges. We find that our treatment conditions neither influence food menu rankings nor have any impact on food decision consistency. It suggests that, while desirable diet changes can be sustained in the short term, moving the needle and shifting food preferences with information nudges is challenging.

The rest of the article is organized as follows. We lay out our modeling framework in Section 2.2. Section 2.3 explains our experimental design and empirical approach. Section 2.4 discusses the results. Section 2.5 highlights the policy implications of our findings. The final section concludes the article.

3.2 Modeling Framework

Individual *i* faces a set of food alternatives denoted by *Z* = {*green, orange, red*}. Let $\mathbb{Z}$ be the space of menus that are non-empty subsets of *Z*. Our modeling primitive is a preference structure $\gtrsim$ over menus in $\mathbb{Z}$ and reflects ex-ante choice intentions (Noor and Takeoka, 2010). Based on Gul and Pesendorfer (2001), our agent *i* with this preference structure maximizes their utility by choosing the optimal menu $\mathcal{M} \in \mathbb{Z}$ as follows:

$$V(\mathcal{M}) = \max_{x \in \mathcal{M}}[u(x) + v(x)] - \max_{y \in \mathcal{M}} v(y) \quad \ldots\ldots\ldots\ldots(1)$$

where, *x* is the chosen normatively superior item from the menu $\mathcal{M}$ and *y* is the tempting alternative; *u* represents derived normative utility, while *v* is for temptation utility. Suppose that $\mathcal{M}_1$ = {*green*} and $\mathcal{M}_2$ = {*green, red*}, where *green* is a low-calorie healthy meal, while *red* is a high-calorie tempting and unhealthy alternative. Suppose individual *i* is tempted to *red* and is conscious that the meal *green* is normatively superior to *red*. Then, choosing $\mathcal{M}_1$ and consuming *green* yields utility as follows:

$$V(\mathcal{M}_1) = u(green) + v(green) - v(green) = u(green) \quad \text{...............(2)}$$

In Equation 2, *u*(*green*) + *v*(*green*) denotes the combined normative and temptation utilities from consuming *green*. The third term, −*v*(*green*), represents the highest foregone temptation utility in the menu. Since *green* is the only item in $\mathcal{M}_1$, derived and foregone temptation utilities cancel each other, netting with the normative *u*(*green*) utility. However, for the same individual *i*, consuming *green* from $\mathcal{M}_2$ yields:

$$V(\mathcal{M}_2) = u(green) + v(green) - v(red) = u(green) - \underbrace{[v(red) - v(green)]}_{Self-Control\ Cost\ (c)} \quad \text{.........(3)}$$

In Equation 3, individual *i* derives the normative utility *u*(*green*) by consuming *green* from $\mathcal{M}_2$. However, in this case, the highest forgone temptation utility comes from *red*. The difference between the temptation utilities of *red* and *green* is positive: *v*(*red*)−*v*(*green*) > 0. If *red* is more tempting than *green*, then choosing *green* from $\mathcal{M}_2$ yields lower net utility. Hence, *v*(*red*) − *v*(*green*) is the self-control cost individual *i* incurs when they choose the normatively superior food item from $\mathcal{M}_2$.

Based on Gul and Pesendorfer (2001), even when individual *i* is dedicated to always choosing *green*, they should prefer menu $\mathcal{M}_1$ to $\mathcal{M}_2$. Thus, we should observe that {*green*} is ranked higher than {*green, red*}, i.e., {*green*} $\succ$ {*green, red*}.[5]2 Preferring

[5] In our context, "ranked higher" means decision-makers assign lower rank numbers to a menu. For instance, if M1 is ranked as the first menu, it indicates that the decision-maker prefers this menu to any other menu alternatives.

$\mathcal{M}_1$ over $\mathcal{M}_2$, also indicates that individual *i* demands commitment to *green* by restricting the choice set, as $\mathcal{M}_1$ only contains *green*. Therefore, our modeling framework allows us to capture demand for commitments.

Since *Z* = {*green, orange, red*}, our menu space has seven menus: Z = {$\mathcal{M}_1, .., \mathcal{M}_7$}. Without loss of generality, let's spell out our menus as follows: $\mathcal{M}_1$ = {*green*}, $\mathcal{M}_2$ = {*orange*}, $\mathcal{M}_3$ = {*red*}, $\mathcal{M}_4$ = {*green, orange*}, $\mathcal{M}_5$ = {*green, red*}, $\mathcal{M}_6$ = {*orange, red*}, and $\mathcal{M}_7$. = {*green, orange, red*}. If the individual *i* ranks $\mathcal{M}_1$. higher than all other six menus, then they demand commitment for *green* in our entire menu space Z.

Suppose that the individual *i* exhibits this ranking order in menu space Z: $\mathcal{M}_1 \succ \mathcal{M}_4 \succ \mathcal{M}_5 \succ \mathcal{M}_7 \succ \mathcal{M}_2 \succ \mathcal{M}_6 \succ \mathcal{M}_3$. Notice that, in this preference ordering, the individual *i* indicates that for them choosing *green* is easier in $\mathcal{M}_4$ than $\mathcal{M}_5$; hence, they find *orange* less tempting than *red*. For instance, within this modeling framework, we can identify the number of cases in which individual *i* avoids *red*. An individual may prefer not facing *red* in up to three cases: {*green*} $\succ$ {*green, red*}, {*orange*} $\succ$ {*orange, red*}, and {*green, orange*} $\succ$ {*green, orange, red*}.

These cases arise from pairwise comparisons of preferences between menus containing *red* and the corresponding menus obtained by dropping *red*. When an individual is indifferent between {*green*} and {*green, red*} (i.e., {*green*} $\sim$ {*green, red*}), it suggests that their preference for *green* is strong enough that the presence of *red* does not affect the net utility of choosing *green*. In contrast, when {*green*} $\succ$ {*green, red*}, the individual reveals that the inclusion of *red* reduces their utility from choosing *green*, and therefore they prefer to avoid *red*. Since the ranking order determines whether the menu will be binding at the end of Day 1, we interpret such avoidance as a sign of temptation by *red*. In this sense, the individual restricts their future choice set (i.e., shows a preference for commitment) by ranking menus without *red* more favorably.

It is also possible that the individual exhibits two menu preferences, such as {*orange*} $\succ$ {*orange, red*} and {*green*} $\sim$ {*green, red*}. This indicates that the preference for *green* is strong enough that *red* does not reduce the utility of choosing it. However, the preference for *orange* is weaker, and the inclusion of *red* in the menu lowers the utility of choosing *orange*. Thus, the individual actively avoids *red* when the alternative is *orange* but shows only indifference toward *red* when the alternative is *green*.

Based on this reasoning, we construct the Global Avoidance Index (GAI) for *red* as follows:

$$\sum_{\{M_r\}} \mathbf{1}_{\{\{\mathcal{M}_r \backslash red \succ M\}\}}$$

where we pairwise compare preferences over menus containing *red* with those formed by dropping *red*. The GAI counts the number of pairwise menu comparisons in which the individual preferred a menu without *red*. Only three such pairwise comparisons fit this description. By construction, the GAI can take four values, $GAI \in \{0, 1, 2, 3\}$. The GAI index reveals to what extent the individual avoids a particular meal option due to visceral feelings. A higher GAI value hints that the individual "globally" avoids *red*. In general terms, we use *Global Avoidance Index* (GAI) for each meal alternative, tracking the number of menu comparison instances, where *GAIc* = $\sum_{\{M_c\}} \mathbf{1}_{\{\{\mathcal{M}_c \backslash c \succ M\}\}}$

Our discussion uses the low-calorie food item *green* as a healthier alternative to the high-calorie food item *red*. It is important to note, however, that our menu-ranking procedure does not depend on this classification to identify revealed temptation. We construct temptation measures solely from individuals' menu rankings and our menu-dependent preference assumptions. Thus, these measures are not influenced or contaminated by our own prior views about the relative healthiness of the food alternatives.

Dynamics of Decisions

Without loss of generality, assume that agent *i*'s decision problem spans two periods $t \in \{1, 2\}$, where they choose a menu in $t = 1$ and select an alternative from the menu in $t = 2$. At $t = 1$, the agent faces a menu ranking decision between $\mathcal{M}_a$ = {*green*} and $\mathcal{M}_b$ = {*green, red*}. Following Noor (2011), we assume that preferences over menus are not directly affected by temptation; hence, $t = 1$ is the cold state. Agent *i* intends to choose alternative *green* and regards *red* as an inferior but tempting option. They predict ex ante that the expected utility from choosing *green* will depend on the menu. Specifically,

$$EV_{green}\,(\mathcal{M}_a) = U(green),\ EV_{green}\,(\mathcal{M}_b) = U(green) - C(\mathcal{M}_b)$$

where $C(\mathcal{M}_b) > 0$ denotes the self-control cost associated with $\mathcal{M}_b$. It follows immediately that

$$EV_{green}\ (\mathcal{M}_a) > EV_{green}\ (\mathcal{M}_b)$$

so agent *i* strictly prefers M*a* in *t* = 1.

Suppose instead that nature unexpectedly assigns menu $\mathcal{M}_b$ at *t* = 2. This creates the hot state for agent *i* as menu M*b* has a tempting option. Two cases arise depending on the relative magnitudes of $EV_{green}\ (\mathcal{M}_b)$ and $EV_{red}\ (\mathcal{M}_b)$:

Case I: $EV_{green}\ (\mathcal{M}_b) > EV_{red}\ (\mathcal{M}_b)$. In this case, the agent chooses *green*, but suffers a welfare loss relative to commitment, since $EV_{green}\ (\mathcal{M}_a) > EV_{green}\ (\mathcal{M}_b)$. The choice of *green* is sustained because *u*(*green*) > *C*($\mathcal{M}_b$).

Case II: $EV_{red}\ (\mathcal{M}_b) > EV_{green}\ (\mathcal{M}_b)$. In this case, the agent chooses *red*, exhibiting a choice reversal. This occurs precisely when *u*(*green*) < *C*($\mathcal{M}_b$), i.e., when the self-control cost of resisting *red* outweighs the normative value of *green*. Hence, agent *i* exhibits a choice reversal if the self-control cost of resisting *red* when facing M*b* exceeds the normative value of *green*

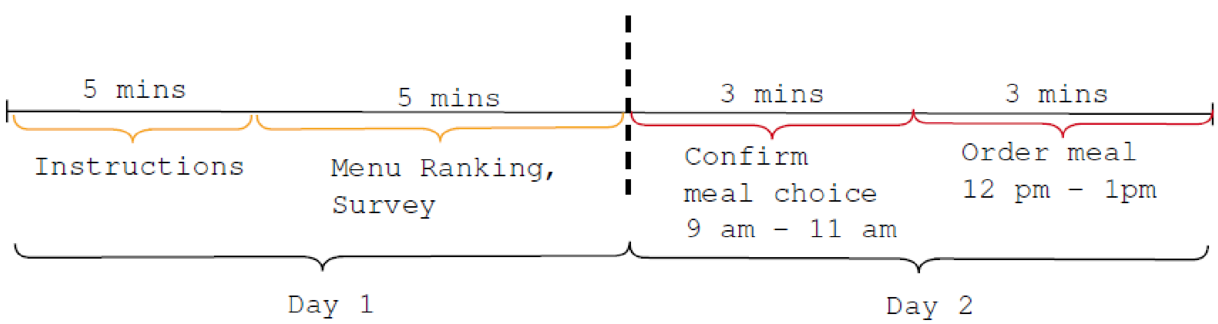
Hypotheses

Our study hypotheses focus on the role of the cold state in shaping food preferences and improving the effectiveness of information nudges.

Hypothesis 1: The literature on menu-dependent preferences extensively shows that food preferences are influenced by the choice environment (Gul and Pesendorfer, 2001; Noor, 2007; Noor and Takeoka, 2010, 2015). In their seminal work, Gul and Pesendorfer

(2001) model how the presence of a relatively tempting food item can diminish the perceived value of healthier but less tasty alternatives. Follow-up studies suggest that decision-makers can reduce their *vulnerability* to tempting food alternatives by distancing themselves from the actual choice time and committing to normatively superior choices (Noor, 2007; Noor and Takeoka, 2010). Therefore, we hypothesize that low- and middle-calorie food alternatives will be more likely to be ranked higher than high-calorie choices.

Hypothesis 2: Studies on menu-dependent preferences also predict that consumers are more likely to be persuaded of the benefits of low-calorie food items (Noor and Takeoka, 2015; Liang et al., 2020). The consumer psychology literature further supports this assertion. For example, Shiv and Fedorikhin (1999) find a strong relationship between cognitive function and susceptibility to temptation by a delicious food alternative. Other studies have also documented that higher cognitive load diminishes the quality of food decisions among university students (Byrd-Bredbenner and Eck, 2020). We predict that because temptation preferences are less prominent in cold states, behavioral nudges, and nutritional information will lead to higher rankings for relatively lower-calorie food items.



Note: Study stages and estimated average time spent for each stage are displayed.
Figure 2.1: Timeline of Experimental Procedures.

Experimental Design

We conducted our incentivized field study on a university campus in the Southeastern United States. We recruited 137 undergraduate students without known allergies via flyers and emails.[6] Potential participants were informed that the study was about food decisions and would proceed over two consecutive days, as shown in Figure 2.1. The study required making food decisions, and the compensation was a meal reimbursement for the chosen meal alternative. Upon signing up for the study, participants were informed they would get an email with a survey link on the specified day.

Recruiting college students for this study is a key part of our research design. Prior work reports mixed evidence on the effectiveness of behavioral nudges in improving diet quality (Stran et al., 2016; Gustafson and Zeballos, 2018). Some studies suggest that nutritional education and behavioral nudges may be particularly effective in early adulthood (Sanyaolu et al., 2019), as this group is more vulnerable to developing unhealthy food habits (Almutairi et al., 2018). By focusing on college students, we are able to examine the drivers of healthy food choices at an early stage of adulthood. In addition, the dynamic setting of our design allows us to track whether food decisions are sustained when young consumers face changes in their decision environment.

On Day 1 of the study, participants received a study link via email. Per instructions, they were required to complete the study's first phase within Day 1 of regular business

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[6] The initial sample size was 141 participants. However, we excluded four subjects from our analyses, as they indicated confusion with our study procedures. Our study protocols have been approved by IRB-22-131-Ex-2204.

hours. After clicking the study link, subjects were introduced to the study procedures and rules. Then, they moved to the menu ranking stage, where they were shown meal options and corresponding menus.[7]

A particular experimental design challenge was determining meal alternatives with different calorie contents. Noor and Takeoka (2015) show that having low-, middle-, and high calorie meal alternatives in the choice sets can help detect preference inconsistencies due to self-control issues. Consumer psychology studies show that stylized low- and high-calorie meal options, such as fruit salad and chocolate cake, can create a choice dilemma, allowing researchers to elicit cognitive and affective determinants of food decisions (Shiv and Fedorikhin, 1999). However, Huseynov et al. (2021) show that designing food choice problems using alternatives from the same meal category helps control home-grown preferences. For instance, the decision trade-off between Oreo Regular Cookies and Oreo Reduced-Fat Cookies is well-tuned to capture preferences for low-calorie food intake while controlling for different home-grown habits, such as brand liking and awareness, as well as general preferences for cookies (Huseynov et al., 2021). We chose a well-known food vendor— Chick-fil-A—which had an accessible location on the campus. We designed three meal menus, as shown in Figure 2.2. All menus had the same Grilled Chicken Sandwich entrée. These design choices allowed us to minimize unobserved heterogeneity due to home-grown preferences. We added different side dishes to each meal option to create calorie count differences: 1) the low-calorie meal (~ 440 calories combined) had a fruit salad, 2) the

[7] Supplementary materials provide screenshots from key study stages.

middle-calorie alternative had a salad mix (~ 620 calories combined), and 3) the high-calorie entrée had mac & cheese (~ 830 calories combined). All meal options also contained a bottle of water. The prices of meal alternatives were very similar, varying around $13.00. Subjects were informed that they would be reimbursed for their meal choices at the end of the study. Therefore, the price was not a determining factor in decisions.

Note: This figure shows designed Chick-fil-A meal alternatives.

Figure 2.2: Meal Alternatives

On Day 1, we randomly assigned subjects to three experimental treatment conditions using a between-subject design. In the Control condition, we displayed calorie counts. However, in the Calorie Coloring condition, we used green, orange (dark-yellow), and red font colors to display the calorie information. In the Information Nudge treatment, we provided excerpts from previous studies about the importance of building healthy eating habits (see Supplementary Materials for details).[8] We did not remind participants of the treatments on Day 2, as our focus was on understanding the effect of behavioral nudges and calorie information in a cold state.

On Day 1, in the menu-ranking stage, study participants ranked the following menus based on their weak preference ordering: $\mathcal{M}_1$ = {*green*}, $\mathcal{M}_2$ = {*orange*}, $\mathcal{M}_3$ = {*red*}, $\mathcal{M}_4$ = {*green, orange*}, $\mathcal{M}_5$ = {*green, red*}, $\mathcal{M}_6$ = {*orange, red*}, and $\mathcal{M}_7$ = {*green, orange, red*}.[9] We used realization probabilities of Toussaert (2019), where the odds for corresponding ranking orders were as follows: 0.35, 0.30, 0.20, 0.10, 0.03, 0.02, and 0. For instance, the first-ranked menu had a 35% probability of being binding at the end of the Day 1 session. Similarly, the bottom-ranked menu was excluded from being realized on Day 1. After the ranking stage, participants proceeded to a demographic survey, followed by the realization of the binding menu to determine Day 2 meal choice.

If the randomly selected menu was a singleton (i.e., {green}, {orange}, or {red}), then the participant was informed that they would have to buy this meal the next day before lunchtime after receiving a short survey link from experimenters. However, if the

[8] Table S4 shows that our random treatment assignments were balanced across key demographic characteristics.
[9] We used the actual names of the meal options in the study. In the rest of our discussion, we will refer to low-, middle-, and high-calorie meal items using our notation {green}, {orange}, and {red} from the model, respectively.

binding Day 1 menu was {green, orange}, {green, red}, {orange, red}, or {green, orange, red}, participants made one more decision and chose their preferred meal alternative for Day 2. Put differently, if the binding menu included two or three meal options, subjects were required to select one meal out of the available alternatives in the binding menu as their Day 2 meal.

We concluded the Day 1 study by eliciting participants' attitudes and visceral feelings towards the meals, followed by a brief demographic survey. Specifically, we asked subjects to rate how tempting, tasty, healthy, and satisfying they found the presented meal options using an 10-point scale. Table A2.3 compares the meal options across these four dimensions. We found that participants rated meals *green* and *red* as almost equally tempting and tasty. In contrast, they perceived meal *orange* as relatively less tasty and tempting than the other options. In terms of healthiness, meals *green* and *orange* were considered similarly healthy and healthier than meal *red*. Participants also found meal *red* to be more satisfying than the other meal options. To summarize, participants perceived meal *green* as tasty, tempting, healthy, and moderately satisfying. However, meal *red* was considered the least healthy but the most tempting, tasty, and satisfying. Lastly, meal *orange* was perceived as moderately tasty, tempting, and satisfying while being rated highly healthy.

On Day 2, we sent out a follow-up study link to the participants and asked them to complete the survey and finalize their decisions. Once the survey began, using their Day 1 study IDs, we reminded subjects of their Day 1 meal selections. Then, following Sadoff et al. (2020), we offered them the opportunity to revise their meal choices to any option they preferred.[10] This design feature allowed us to measure decision inconsistencies when decision-makers face unconstrained sets. Participants finalized their meal choices and ordered them via Chick-fil-A's website or mobile app during lunch hours. After ordering their food, participants sent experimenters the screenshot or the confirmation email from the vendor showing the paid amount. The Day 2 decisions were made between 9 a.m. and 11 a.m. On Day 1, we also asked subjects to report the number of calories they consumed and would consume during the day. Reported calories enabled us to link the current hunger levels of subjects to food decision (in)consistencies. Subjects collected their meal reimbursements in person from experimenters. Failure to complete any study procedures led to the participant's dismissal from the experiment.

3.3 Results and Discussion

We begin our empirical investigation by examining meal choices over two consecutive days. Table 2.1 presents a 3x3 inner matrix, detailing Day 1 meal decisions in the rows and Day 2 food choice transitions in the columns. Each row's proportions sum to 100%, indicating the distribution of meal choices on Day 1. The columns, representing transitions from Day 1 to Day 2 meals, do not total to 100%. However, the percentages in the outer row and column each add up to 100%.

[10] The primary distinction between our study and Sadoff et al. (2020) is that, in their study design, participants always exerted commitment demand in hot states. In other words, they decided to commit to a certain food bundle while revising their current food decisions. In contrast, in our study, we only elicit commitment demand in the cold state.

On Day 1, the meal *red* emerges as the choice selected by 43% of participants, making it the most frequently chosen option. This is followed by the meal *green* at 34% and the meal *orange* at 23%.[11] On Day 2, food preferences shift, with the *green* and *red* meals both being chosen by 39% of participants. The *green* meal's preference increases by 5%, while that for the *red* meal decreases by 4%. The middle-calorie option remains the least chosen on both days, yet its proportion remains relatively stable.[12] We observe attrition rates from Day 1 meal choices at 17%, 32%, and 22% for *green*, *orange*, and *red* meals, respectively.

Table 2.1: Meal Choice Transition Matrix

	Meal Green	Meal Orange	Meal Red	Overall on Day 1
Meal Green	0.83	0.06	0.11	0.34
Meal Orange	0.22	0.68	0.10	0.23
Meal Red	0.14	0.08	0.78	0.43
Overall on Day 2	0.39	0.22	0.39	

Note: This table shows meal choice switching behaviors. Rows indicate Day 1 meal choices, and columns show meal preferences for Day 2. The outer shaded column and row show the proportion of corresponding meal choices for Day 1 and Day 2, respectively. Dark-shaded cells indicate consistent meal preferences.

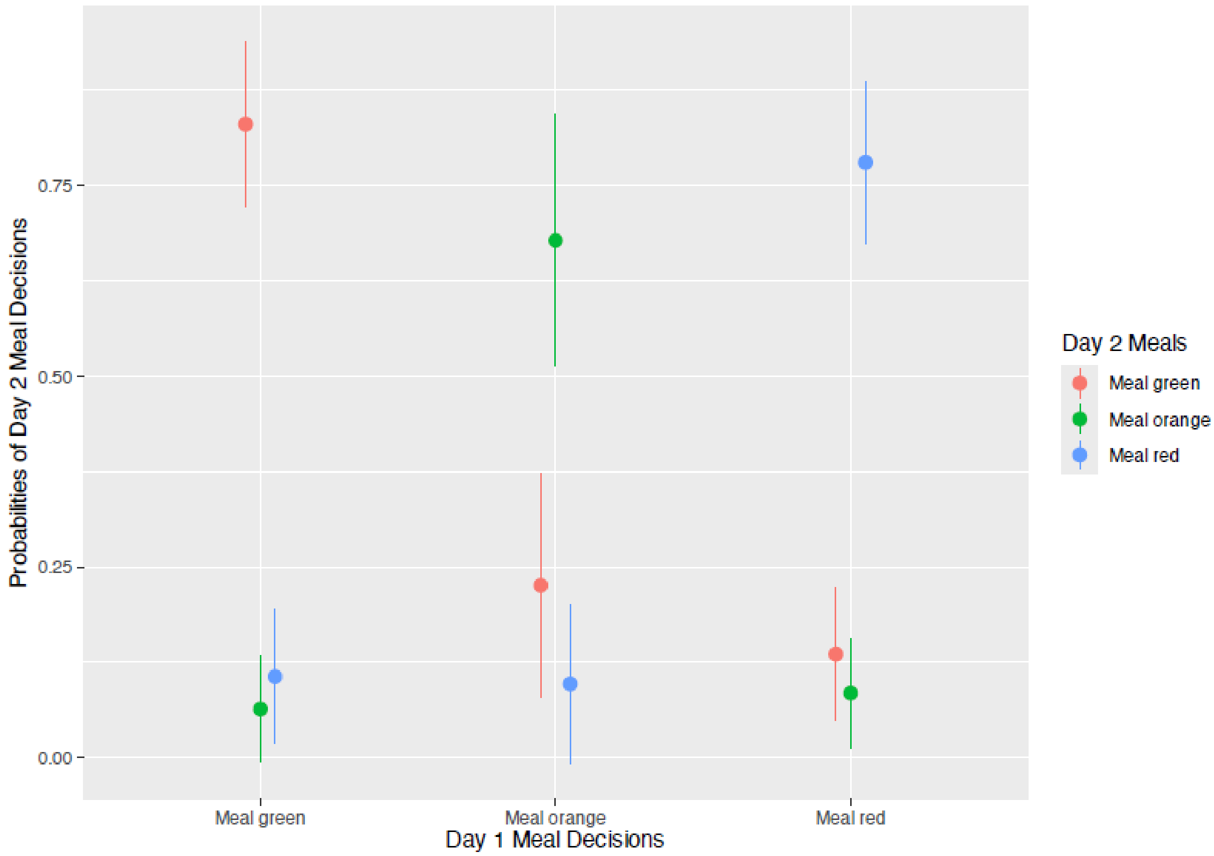
Figure 2.3 presents a more formal analysis of meal decision changes across meal options.[13] Specifically, we display the fitted probabilities obtained from multinomial

[11] We follow Toussaert (2018) and test whether the observed meal choice proportions on Day 1 are statistically different from the random threshold of 33.3%. The chi-square goodness of fit test shows that the observed frequencies are significantly different from the random threshold (p-value = 0.01).

[12] We also test whether the observed meal choice proportions on Day 2 are statistically different from the random threshold of 33.3%. The chi-square goodness of fit test shows that the observed frequencies are significantly different from the random threshold (p-value = 0.01).

[13] See Table S6 for regression outputs.

regressions for meal choice switches across study days. Figure 3 confirms our previous discussion, showing that approximately 77% of meal decisions exhibit dynamic consistency on Day 2. Additionally, cross-meal switches constitute around 10%. For instance, about 20% of Day 1 meal *green* decisions switch to meal *orange* (green) or meal *red* (blue) on Day 2. However, the proportions of meal switches from Day 1 meal *green* and meal *orange* to Day 2 meal *red* are not statistically different (Benjamini & Hochberg corrected $p-value = 0.89$). Similarly, the proportions of meal switches from Day 1 meal *green* and meal *red* to Day 2 meal *orange* are not statistically different (Benjamini & Hochberg corrected $p - value = 0.82$). These findings suggest that Day 2 meal *red* and meal *orange* choices have the same probability of attracting switches from other meals. Interestingly, participants who preferred meal *orange* on Day 1 were more likely to switch to meal *green* than those who chose meal *red* on Day 1 (Benjamini & Hochberg corrected p-value < 0.01). We conclude that participants selecting the middle-calorie meal alternative (i.e., meal *orange*) on Day 1 were more likely to exhibit dynamic inconsistency by switching to meal *green* on Day 2 rather than to meal *red*. Moreover, the results of the proportion tests indicate that consistent decisions for meals *green*, *orange*, and *red* are not statistically different.

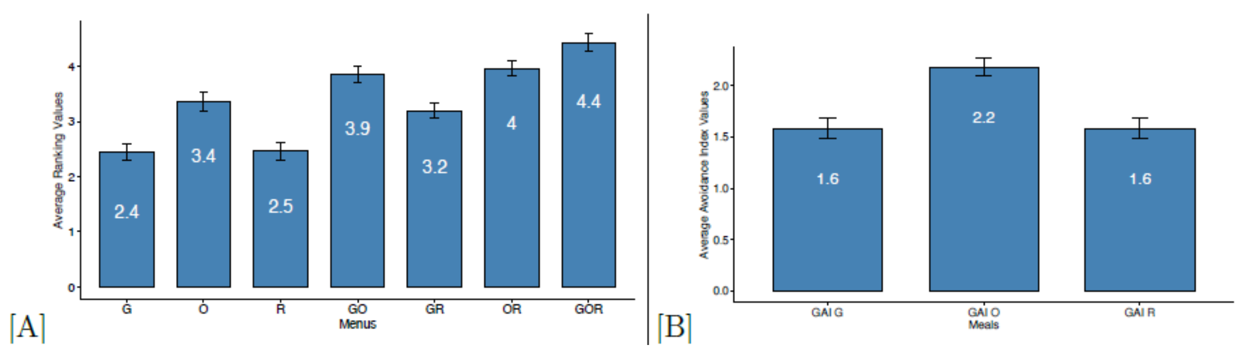


Note: This figure shows the fitted probabilities of meal choices on Day 2 (y-axis) with respect to Day 1 meal decisions (x-axis). The probabilities were obtained using multinomial logistic regressions.

Figure 2.3: Fitted Probabilities for Day 2 meal choices.

Menu Rankings: Figure 2.4, Panel A, presents the average ranking values for the experimental menus. Singleton menus {*green*} and {*red*} receive the highest preference. This corroborates our finding that most participants concentrate around two preference types, favoring either meal *green* or meal *red* as their top choice. Another important observation is that the most extensive choice set {*green, orange, red*} ranks as the least preferred menu. Studies by Toussaert (2019) and Huseynov et al. (2023) suggest that a preference for larger choice sets, without restricting any meal options, indicates a preference for flexibility. However, our sample, on average, seems not to favor flexibility, showing a tendency to commit to either the *green* or *red* meals.

Table 2.2 provides a detailed analysis of the ranking values for all menus using an ordinal logit model. Columns 1, 3, and 4 of Table 2 illustrate that our treatment conditions do not significantly impact menu rankings when compared to the control condition. This documented null effect may stem from the relatively small calorie differences between meal options. Huseynov et al. (2021) show that calorie differences provide a good proxy for self control costs, and that visceral responses are more likely to arise when the differences are large. It is possible that the calorie differences in our study were not substantial enough to trigger self-control concerns among participants, or that participants perceived the differences as minor, thereby reducing the effectiveness of our treatments.



Panel A depicts the average rankings of menus in Day 1 (a lower ranking order indicates a higher preference level). Panel B shows the average Global Avoidance Index (GAI) values of the meals. Note: G, O, and R stand for Green, Orange, and Red, respectively.

Figure 2.4: Menu Ranking and Global Avoidance Index for Day 1

Column 2 of Table 2.2 indicates that the ranking of a menu is lower (i.e., higher in nominal value but lower in qualitative terms) if it includes the *orange* meal as opposed to the *green* meal. Similarly, the inclusion of the *red* meal tends to reduce a menu's ranking compared to the *green* meal, with the *orange* meal having a more pronounced negative impact on the ranking than the *red* meal. We conclude that, on average, participants rank menus featuring the *green* meal as the highest. This preference is followed by menus with the *red* and then the *orange* meals, confirming that the least favored option among our subjects was the middle-calorie food item.

Tables A2.2 and A2.3 in the Supplementary Materials reveal that neither behavioral nor information nudges significantly impact individual menu rankings and meal GAI (Global Avoidance Index) values. This result is consistent with previous research that highlights the challenges in nudging consumers towards low-calorie food intake (Galizzi, 2014). Addition ally, this finding implies that the influence of food-related information can be minimal and highly dependent on the context, as suggested by (Messer et al., 2017).

Table 2.2: Experimental Treatments and Menu Rankings

	Dependent variable: Menu rankings			
	(1)	(2)	(3)	(4)
Calorie Coloring	-0.10		-0.08	-0.11
	(0.16)		(0.18)	(0.18)
Information Nudge	0.09		0.10	0.07
	(0.18)		(0.19)	(0.20)
Orange Meal		1.42***	1.42***	1.42***
		(0.13)	(0.13)	(0.13)
Red Meal		0.57***	0.57***	0.57***
		(0.12)	(0.12)	(0.12)
μ_1	0.95***	1.08***	1.08***	1.08***
	(0.07)	(0.08)	(0.08)	(0.08)
μ_2	1.69***	1.91***	1.91***	1.91***
	(0.08)	(0.09)	(0.09)	(0.09)
μ_3	2.35***	2.66***	2.66***	2.66***
	(0.10)	(0.11)	(0.11)	(0.11)
μ_4	3.05***	3.41***	3.41***	3.41***
	(0.11)	(0.13)	(0.13)	(0.13)
μ_5	4.03***	4.43***	4.43***	4.43***
	(0.15)	(0.16)	(0.16)	(0.16)
sigma	0.65***	0.80***	0.80***	0.79***
	(0.13)	(0.13)	(0.13)	(0.13)
AIC	3644.67	3505.97	3509.07	3514.01
Pseudo-Rsq	0.000	0.039	0.039	0.039
N	959	959	959	959

Note: The table reports the results of Ordinal Logit regression analyses for menu rankings. The dataset is formatted in a panel structure. The estimated cutpoints are presented with $\mu 1$, $\mu 2$, $\mu 3$, $\mu 4$, and $\mu 5$. All estimated cutpoints are statistically greater than zero, validating the core Ordinal Logit model assumptions. The estimated sigma shows the estimated panel-level variance. Model 4 also includes controls: Male, BMI, Weekly Budget and Workout intensity; none is statistically significant. $*$p<0.1; $**$p<0.05; $***$p<0.01

We display the average values of the GAI for the *green*, *orange*, and *red* meal options in Figure 2.4, Panel B. Consistent with our earlier findings, the GAI values for the *green* and *red* meals are identical and lower than that of *orange*. According to Gul and Pesendorfer (2001), the primary driver of the avoidance behavior represented by the GAI index is temptation. Unlike psychological models, economic preference structures identify temptation through menu exclusion. To investigate this, we asked participants in the exit survey to rate their level of temptation towards the *green*, *orange*, and *red* meals using a Likert scale. Additionally, they were requested to evaluate how satisfying, tasty, and healthy each meal alternative was. Table S1 in the Supplementary Materials demonstrates that GAI values are inversely correlated with the perceived tastiness of a meal. A similar pattern is observed with temptation levels towards different meals. Specifically, subjects show lower GAI values for meals they consider more tempting. No significant correlation is found between GAI values and the “Healthy” and “Satisfying” attributes of the meals. Therefore, we infer that participants are more likely to avoid a meal item when they perceive it as less tempting and/or tasty. Therefore, contrary to our modeling framework, the GAI index is higher when consumers find a meal option less tasty or less tempting.

Table 2.3: Meal Choice Inconsistency on Day 2

	Dependent Variable		
Variables	Inconsistency (1)	Inconsistency (2)	Inconsistency (3)
Calorie coloring	0.12		-0.14
	(0.08)		(0.08)
Calorie Coloring &	-0.001		-0.001
Information Nudge	(0.10)		(0.10)
GAI Green		0.005	0.01
		(0.03)	(0.03)
GAI Orange		0.004	-0.0005
		(0.04)	(0.04)
GAI Red		0.06*	0.07**
		(0.03)	(0.03)
Constant	0.27***	0.11	0.16
	(0.06)	(0.10)	(0.12)
N	*137*	*137*	*137*
R^2	0.02	0.03	0.06

Note: The table shows the results of OLS regression analyses for meal choice inconsistency on Day 2 with respect to Day 1 meal decisions. Robust HC1 standard errors are reported. $*$p<0.1; $**$p<0.05; $***$p<0.01

Decision In(Consistency)**:** Table 3 presents linear regressions to scrutinize the factors influencing food decision inconsistency across the study days. Columns 1 and 3 of Table 2.3 indicate that our treatment conditions do not significantly impact the consistency of food decisions on Day 2. Additionally, we find no statistically significant correlation between the GAI values for the *green* and *orange* meals and decision inconsistency. However, as shown in Columns 2 and 3 of Table 2.3, decision-makers who exclude the *red* meal from their menu (i.e., M\ *red* $\succ$M) are observed to be 7% more likely to exhibit inconsistency in their Day 2 food choices.

Table 2.4: Determinants of Meal Choice Inconsistency on Day 2

	Dependent Variable					
	Inconsistency		$Inconsistency_{negative}$		$Inconsistency_{positive}$	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
GAI Green	0.005	0.01	-0.01	-0.01	0.01	0.02
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
GAI Orange	0.004	-0.004	0.001	0.005	0.003	-0.01
	(0.04)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)
GAI Red	0.06*	0.06*	0.001	0.01	0.06**	0.05**
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Constant	0.11	0.14	0.09	-0.01	0.02	0.15
	(0.10)	(0.15)	(0.08)	(0.09)	(0.08)	(0.12)
N	137	137	137	137	137	137
R^2	0.032	0.042	0.001	0.015	0.049	0.083

Note: The table shows the results of OLS regression analyses for meal choice inconsistency on Day 2 with respect to Day 1 meal decisions. Columns 2, 4, and 6 also control for High BMI, High Workout intensity, and High Food Budget binary variables. We also control for the reported total number of breakfast and brunch calories consumed. We also controlled for the planned number of dinner calories, ensuring that observed effects were not driven by participants' anticipated evening calorie intake. None of the controlled variables is significant. See Table S4 for the overall sample characteristics of the control variables. Robust HC1 standard errors are reported. $*$p<0.1; $**$p<0.05; $***$p<0.01

Table 2.4 continues our investigation of the determinants of food decision inconsistency, expanding our empirical inquiry to positive and negative inconsistencies. Table 2.4 Columns 5 and 6 demonstrate that the relationship between GAI values of *red* meal and food inconsistency stems from decision switches from high- to low-calorie meals. Put differently, study participants avoiding *red* meal on Day 1 are more likely to double down and reduce their calorie intake at the expense of being inconsistent.

Table 2.4 Columns 2, 4, and 6 offer a more thorough investigation of decision inconsistencies via controlling for a range of demographic and behavioral characteristics. We do not detect any effect of the controlled variables on food decision inconsistencies.

Potential Influence of Other Factors**:** Although our modeling framework does not depend on classifying low-calorie foods as healthier than their high-calorie alternatives, our treatment conditions are grounded in this normative distinction. Specifically, they either highlight the health benefits of low-calorie consumption or employ traffic-light symbols to reduce calorie intake through visual nudging. Still, certain subject groups (e.g., bodybuilders) may deliberately prefer high-calorie items to support high-intensity workout routines. Consistent with this, Table A2.5 shows that participants, on average, rated the low-calorie option as healthier but less satisfying than its high-calorie counterpart.

In Table 2.4, we control for reported calorie intake at breakfast and brunch, as well as planned dinner calorie intake. We also include weekly workout intensity as a control. None of these controls is statistically significant.[14] Moreover, Table A2.4 confirms that our treatments are balanced with respect to BMI and workout intensity. Taken together, these results suggest that alternative diet habits are unlikely to be driving our findings.

One important limitation of our study is that while the designed low- and medium-calorie meal options differ in calorie content, participants did not perceive them as significantly different in terms of the "Healthy" and "Satisfying" attributes. As Table A2.5 shows, meals *green* and *orange* received almost identical "Healthy" and "Satisfying" scores, although meal *green* was rated higher on "Tasty" and "Tempting," perhaps due to its higher sugar content. The higher sugar content might also make meal *green* a less

[14] Similar results are reported in Table A2.6.

preferred option for individuals following special diets (e.g., keto). This suggests that calorie content can be a noisy measure and may fail to capture the full range of nutritional aspects of food items. Future studies could benefit from incorporating participants' perceived characteristics of food options alongside calorie counts when designing food choice scenarios.

Not observing compliance is also a noteworthy limitation of our study. Subjects may selectively consume parts of the meals, leading to differences between assigned and actual calorie intake. For instance, a subject might choose not to eat the buns of a sandwich, or while eating meal *orange*, might omit the salad dressing. Not consuming the dressing could even reduce the calorie intake of meal *orange* below that of meal *green*. Because this is a field study, subjects could also purchase additional meals or food items to accompany their study meals. Future studies might employ biomarker-based measures to better account for these factors.

3.4 Policy Implications

Evidence-based public health policies rely on studies documenting crucial behaviors of the target population. Suppose an investigation reveals that a particular behavioral nudge can induce low-calorie food consumption, potentially alleviating obesity-related public health issues (Laiou et al., 2021; Lai et al., 2020; McCluskey et al., 2012). From policymakers' perspective, if a nudge induces an intention to consume low-calorie food, promoting this behavioral approach can enhance the effectiveness of public education programs encouraging healthy eating habits (Caputo and Just, 2022).

However, food decision *inconsistencies* in dynamic settings can reduce the effectiveness of policies, as the behavioral apparatus of public health programs may change food choice intentions but not necessarily actual consumption decisions (Palma, 2022). Understanding crucial factors affecting decision consistency over time can enhance the effectiveness of public policy actions, leading to improved health outcomes (Caputo and Just, 2022; Palma, 2022). This article investigates the behavioral foundations of diet choices in an incentivized field study setting, revealing the critical determinants of dynamic (in)consistency of food decisions. Overall, we find that food decisions are moderately consistent over a short horizon, and the desired preference shifts can be sustained over time.

Our findings align with previous studies that examine individual and environmental factors influencing food decision reversals. For instance, Chandon (2013) emphasizes the importance of considering environmental factors during the food purchase and consumption stages to prevent the obesity pandemic. We build on this approach by demonstrating that food planning in a cold state does not necessarily align with food choices made in a hot state. Future studies could scrutinize the differences between these two states, particularly in promoting low-calorie intake. We suggest that hot states, characterized by visceral feelings, significantly diminish the positive effects of calorie information. In fact, Liu et al. (2014) also argue that self-control issues may be a key factor behind the moderate effectiveness of food information-provision measures.

Our study also highlights the role of visceral feelings in the effectiveness of public policies. Conventional economics assumes that individuals have the willpower to resist tempting *bads* and consume normatively superior *goods*. The primary building blocks of economic models and preference structures typically omit self-control issues (Strotz, 1955; O'Donoghue and Rabin, 1999). This omission is particularly problematic in policy-making, as many policy actions focus on educating the target population by informing them about the benefits of goods or the harms of bads. Under standard preference assumptions, wanting goods translates directly into consuming them. However, extensive evidence shows that preference and choice reversals occur, even when decision-makers prefer consuming goods but change their choices in favor of bads at the moment of final decisions (Sadoff et al., 2020; Toussaert, 2018). Gul and Pesendorfer (2001) introduced an extension to the utility maximization problem, demonstrating that agents with self-control issues experience reduced utility when they choose goods from a set that also includes bads. Thus, decision inconsistencies often arise from the incompatibility between the current self's plans and the future self's decisions, primarily due to self-control issues (Fudenberg and Levine, 2006). Our study distinguishes between the food planning and choice stages, revealing that visceral feelings can hinder the realization of normatively superior food consumption plans. Future policy actions might achieve better outcomes by focusing on individual and environmental factors enhancing food decision consistency.

We also demonstrate that shifting preferences with behavioral nudges is not an easy task. Previous work shows that front-of-package nutritional labels are cost-effective policy tools, as their public health benefits significantly outweigh their implementation costs (Dupuis et al., 2024). However, the literature remains inconclusive on how to design the most effective labels. Evidence suggests that simple numerical calorie information may not be cognitively accessible to consumers, and even traffic-light labeling may be insufficient to reduce calorie intake (White-Barrow et al., 2023). Some studies show that pairing nutritional information with behavioral nudges can improve effectiveness (Falbe et al., 2021). Consistent with this literature, we find that numerical information and traffic-light colors did not significantly influence food preferences or their consistency. This null finding suggests that food preferences are complex and highly individual-specific, indicating that a one-size-fits-all approach may be insufficient to improve diet quality. Recent studies also show that simply exposing students to health campaign banners is ineffective unless "healthy" food labels are coupled with price reductions (Kirchoff et al., 2024). Therefore, public policies may benefit from developing more comprehensive nutritional labels that account for the psychological processes of food decision-making while also making healthy food alternatives both cognitively and economically accessible.

3.5 Conclusion

Public health policies aim to improve food diet preferences to enhance society's health outcomes. The implicit assumption in policy-making is that desired preference shifts can be sustained over some periods; thus, policies rely on the dynamic consistency of decisions. Previous studies investigate food decision inconsistency using a laboratory setting or follow-up survey waves (Agranov and Ortoleva, 2017; Rigby et al., 2016). However, both approaches have limitations. Laboratory studies are limited in creating meaningful time lapses between study tasks to reasonably mimic real-life decisions. On the other hand, follow-up survey waves might be confounded by uncontrolled information acquisitions and preference shifts.

In this article, we use an “intermediate” approach and conduct an incentivized food choice study over two consecutive days in a field setting. Hence, our study tests the (in)consistency of decisions over a more reasonable time span and in the *wild*. We build our study using the latest advancements in economic theory and experimental design paradigms. We find that, on average, 77% of food decisions are dynamically consistent, and most inconsistencies occur in terms of choice switches from high- to low-calorie meal items. Our results bear *good news* for policymakers, as food decisions are moderately consistent and desired preference shifts can be sustained over time. However, the *bad news* is that food preferences are not malleable enough. We find that information and behavioral nudges do not significantly influence food preferences and their consistency. While desirable diet changes can be sustained in the short term, shifting food preferences poses a significant challenge to health policies.

We employed meal alternatives from one of the busiest food vendors on campus to increase the external validity of our conclusions. Nevertheless, some factors can potentially offer alternative explanations for our results. The low-calorie meal option can be considered the only “dessert” option in our choice set. Thus, the green menu can be considered a low calorie but not so “healthy” alternative in our setting. While acknowledging this limitation, our conclusions rely on revealed preferences (temptation and avoidance behavior via the menu-ranking stage) and choice inconsistency. Moreover, our study approach offers new perspectives in mapping different food preferences. Future studies might consider partnering with local food vendors and customizing menu alternatives to better capture “health” vs. “taste” trade-offs in food decisions.

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Supplementary Materials

Table A2.1: Global Avoidance Index and Its Correlates

Variable	***GAI Green***	***GAI Orange***	***GAI Red***	***GAI Green***	***GAI Orange***	***GAI Red***	***GAI Green***	***GAI Orange***	***GAI Red***	***GAI Green***	***GAI Orange***	***GAI Red***
Green Tempting	*-0.09* (0.05)*											
Orange Tempting		*-0.11*** (0.03)*										
Red Tempting			*-0.18*** (0.03)*									
Green Tasty				*-0.21*** (0.06)*								
Orange Tasty					*-0.11** (0.04)*							
Red Tasty						*-0.19*** (0.04)*						
Green Healthy							*0.04 (0.06)*					
Orange Healthy								*0.08 (0.05)*				
Red Healthy									*-0.05 (0.04)*			
Green Satisfying										*-0.01 (0.04)*		
Orange Satisfying											*0.01 (0.03)*	
Red Satisfying												*-0.01 (0.05)*
Constant	*1.76*** (0.14)*	*2.25*** (0.08)*	*2.00*** (0.11)*	*2.27*** (0.22)*	*2.36*** (0.10)*	*2.21*** (0.16)*	*1.47*** (0.20)*	*1.93*** (0.19)*	*1.56*** (0.10)*	*1.68*** (0.31)*	*2.13*** (0.25)*	*1.64*** (0.47)*
N	*137*	*137*	*137*	*137*	*137*	*137*	*137*	*137*	*137*	*137*	*137*	*137*

Note: The table shows the results of OLS regression analyses for GAI values.
Robust HC1 standard errors are reported. $*p<0.1$; $**p<0.05$; $***p<0.01$

Table A2.2: Experimental Treatments and Menu Rankings

Variable	Dependent Variable						
	Menu {Green}	Menu {Orange}	Menu {Red}	Menu {Green, Orange}	Menu {Green, Red}	Menu {Orange, Red}	Menu {Green, Orange, Red}
Calorie Coloring	0.11	-0.48	0.06	-0.42	0.04	-0.19	0.41
	(0.34)	(0.38)	(0.38)	(0.32)	(0.32)	(0.30)	(0.37)
Information Nudge	0.11	0.27	-0.23	0.20	-0.03	0.21	0.40
	(0.40)	(0.46)	(0.38)	(0.38)	(0.38)	(0.33)	(0.38)
Constant	2.38***	3.46***	2.50***	3.96***	3.19***	3.98***	4.17***
	(0.24)	(0.29)	(0.26)	(0.22)	(0.25)	(0.20)	(0.22)
N	137	137	137	137	137	137	137
Adjusted R^2	0.00	0.01	0.00	0.01	0.00	0.00	0.00

Note: The table shows the results of OLS regression analyses for assigned rankings for different menus. Robust HC1 standard errors are reported. ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01

Table A2.3: Experimental Treatments and Global Avoidance Index

Variable	Dependent Variable		
	GAI Green	GAI Orange	GAI Red
Calorie Coloring	0.27	-0.09	0.25
	(0.22)	(0.20)	(0.23)
Information Nudge	-0.14	0.08	0.03
	(0.25)	(0.22)	(0.25)
Constant	1.52***	2.19***	1.48***
	(0.15)	(0.15)	(0.16)
N	137	137	137
Adjusted R^2	0.01	0.00	0.00

Note: The table shows the results of OLS regression analyses for Global Avoidance Index values. Robust HC1 standard errors are reported. ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01

Table A2.4: The Comparison of Primary Demographic Characteristics across Study Treatments

Variable	N	Control (N = 48)	Calorie Coloring (N = 52)	Information Nudge (N = 37)	p-value	Adjusted p-value
Male	137	17 (35%)	17 (33%)	8 (22%)	0.36	0.54
High BMI	137	30 (62%)	23 (44%)	16 (43%)	0.11	0.45
High Workout Intensity	137	25 (52%)	25 (48%)	17 (46%)	0.84	0.84
High Food Budget	137	26 (54%)	22 (42%)	20 (54%)	0.41	0.54

Note: The table presents the primary demographic characteristics of the recruited participants. The reported statistics are n (percentage), representing counts and proportions. We conducted Pearson's Chisquared test to compare proportions across groups. The Benjamini & Hochberg correction for multiple testing was applied to compute the adjusted p-values. All indicators are binary. The binary variables for High BMI, High Workout Intensity, and High Food Budget were constructed by splitting the overall study sample based on the median values of the respective indicators.

Table A2.5: The Comparison of Primary Meal Characteristics

Attribute	Meal Green (N = 137)	Meal Orange (N = 137)	Meal Red (N = 137)	p-value	Adjusted p-value
Tasty	8.28 (1.45)	6.69 (2.34)	8.25 (2.22)	<0.001	<0.001
Tempting	7.01 (2.08)	5.63 (2.80)	7.27 (2.59)	<0.001	<0.001
Healthy	7.94 (1.47)	7.98 (1.69)	4.58 (2.20)	<0.001	<0.001
Satisfying	7.11 (2.32)	7.11 (2.35)	8.46 (1.74)	<0.001	<0.001

Note: The table presents how study participants perceive various characteristics of meal options. Participants evaluated the characteristics using an 11-point scale ranging from 0 to 10 (with 0 being the least and 10 being the most). The reported statistics are the mean (standard deviation). We conducted a Kruskal- Wallis rank sum test to compare the mean values. The Benjamini & Hochberg correction for multiple testing was applied to compute the adjusted p-values.

Table A2.6: Food Decision Switches Across Study Days

Variable	Dependent variable			
	Meal Orange (1)	Meal Red (2)	Meal Orange (3)	Meal Red (4)
Day 1 Meal Orange	3.664***	1.207	3.767***	1.212
	(0.741)	(0.838)	(0.767)	(0.889)
Day 1 Meal Red	2.095**	3.803***	2.059**	4.193***
	(0.827)	(0.610)	(0.851)	(0.695)
Male			0.019	1.362**
			(0.705)	(0.650)
High BMI			0.544	0.758
			(0.628)	(0.581)
High Workout Intensity			0.468	0.532
			(0.622)	(0.585)
High Food Budget			0.107	-0.910
			(0.612)	(0.565)
Total Pre-Lunch Calories			-7.600	0.988
			(9.126)	(6.953)
Constant	-2.565***	-2.054***	-2.839***	-2.911***
	(0.599)	(0.475)	(0.916)	(0.813)
Akaike Information Criterion (AIC)	196.222	196.222	205.037	205.037

Note: The table shows the results of multinomial regression analyses.
∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01

Screenshots of the Experiment

Instruction

This survey will include the following stages:

1. Your rankings of the seven combined meal menus
2. Information about you and your food consumption habits.
3. Email address for the follow-up study and for compensation.

Please note that there are no right or wrong answers in the study. You should make decisions based on your preferences.

The survey would take about 10-15 minutes to complete.

War Eagle!

In the next question, you will be asked to rank 7 combined food menus.

You will have 7 boxes ranging from rank 1 to rank 7. On the left pane, you will be given 7 combinations of food menus. They either may include one or more meal options. Your task is to drag the menus from the left pane into boxes on the right.

You should rank combined menus based on your food preferences. The ranking orders will determine which meal option will be realized at the end of the study. You will only receive the realized meal option at the end of the study.

Your ranking order of combined menus will determine the realization probabilities of menus as shown below:

Ranking 1	Ranking 2	Ranking 3	Ranking 4	Ranking 5	Ranking 6	Ranking 7
35%	30%	20%	10%	3%	2%	0

On the next 4 screens, we will be shown different examples to make this part of the study clear. Please pay attention and spend as much time as needed to grasp how ranking orderings determine the realization probabilities of combined menus.

There are 7 menu combinations using the three menus. Please rank the menus according to your preference. If you are indifferent between any food menus, you may assign them under the same ranking. You may drag and drop the food items into the rank boxes. There are 7 rank boxes.

Menu 1: Sandwich + Fruit cup
Menu 2: Sandwich + Side Salad
Menu 3: Sandwich + Mac & Cheese

To move forward you have to place all the menus in any of the boxes. The weights of rankings are (0.35, 0.3, 0.2, 0.1, 0.03, 0.02, 0) where 0.35 = P{rank 1} and 0 = P{rank 7}. For any indifferent rankings, the weights will be randomly assigned.

Items

{Menu 1}
{Menu 2}
{Menu 3}
{Menu 1,Menu 2}
{Menu 1,Menu 3}
{Menu 2,Menu 3}
{Menu 1,Menu 2,Menu 3}

Rank 1 | Rank 2 | Rank 3 | Rank 4 | Rank 5 | Rank 6 | Rank 7

Menu Ranking Stage

Menu 1 (~440 cal)

Grilled Chicken Sandwich with no extras: Multigrain bun, Chicken, lettuce, tomato, BBQ sauce
Side: Medium fruit cup (apples, orange, strawberry, blueberry)
Dasani water bottle

Menu 2 (~620 cal)

Grilled Chicken Sandwich with no extras: Multigrain bun, Chicken, lettuce, tomato, BBQ sauce
Side: Side salad (mixed greens, tomato, cheese, Balsamic vinaigrette dressing
Dasani water bottle

Menu 3 (~830 cal)

Grilled Chicken Sandwich with no extras: Multigrain bun, Chicken, lettuce, tomato, BBQ sauce
Side: Medium Mac & Cheese (Macaroni & cheese blend)
Dasani water bottle

Food Items Displayed in the Control Condition

Menu 1 (~440 cal)	Menu 2 (~620 cal)	Menu 3 (~830 cal)
Grilled Chicken Sandwich with no extras: Multigrain bun, Chicken, lettuce, tomato, BBQ sauce **Side:** Medium fruit cup (apples, orange, strawberry, blueberry) Dasani water bottle	**Grilled Chicken Sandwich with no extras:** Multigrain bun, Chicken, lettuce, tomato, BBQ sauce **Side:** Side salad (mixed greens, tomato, cheese, Balsamic vinaigrette dressing Dasani water bottle	**Grilled Chicken Sandwich with no extras:** Multigrain bun, Chicken, lettuce, tomato, BBQ sauce **Side:** Medium Mac & Cheese (Macaroni & cheese blend) Dasani water bottle

Food Items Displayed in the Calorie Coloring Condition

Food Items Displayed in the Information Nudge Condition

Information Nudge: Many studies have shown that people often establish tastes and habits while they are relatively young. Evidence suggests the early establishment of habits and preferences occurs for a variety of behaviors including food choice. An especially important time of life for food choice is when people step out independently for the first time and begin to make all of their own food decisions. The transition to college or university is a critical period for young adults, who are often facing their first opportunity to make their own food decisions. If they can develop better eating habits which transfer to a future lifestyle, resulting in good health later on. Poor eating habits and limited physical activity can likely increase the risk for osteoporosis, obesity, hyperlipidemia, diabetes, and cancer later in life. Such an unhealthy lifestyle is further linked to health-related quality of life, which is related to an individual's nutritional status. All of these associations suggest that it is important to establish good eating habits at an early age.

Example for the cases when the binding menu has mor than two meal alternatives:

Based on your ranking order your realized menu is shown below. Please select meal that you prefer to receive at the end of the study.
Note: If you have one meal option on the screen, you still have to select it.

- ○ Menu 1
- ○ Menu 3

The Likert scale questions to measure stated preferences for each meal option:
Day 2

How tasty or not tasty do you consider this product, where -5 is "Not tasty" and 5 is "Very tasty"?

Not tasty					Neither "Not tasty" nor "Tasty"					Very tasty
-5	-4	-3	-2	-1	0	1	2	3	4	5

Please answer

How healthy or unhealthy do you consider this product, where -5 is "Very unhealthy" and 5 is "Very healthy"?

Very unhealthy					Neither "Unhealthy nor "Healthy"					Very healthy
-5	-4	-3	-2	-1	0	1	2	3	4	5

Please answer

How tempting do you consider this product, where -5 is "Not tempting" and 5 is "Very tempting"?

Not tempting					Neither "Not tempting" nor "Tempting"					Very tempting
-5	-4	-3	-2	-1	0	1	2	3	4	5

Please answer

To which extent does this product make you full, where 0 is "Does not make me full" and 10 is "Makes me full"?

Doesn't make me full										Makes me full
0	1	2	3	4	5	6	7	8	9	10

Please answer

Day 2 survey to measure decision consistency:

Choice *

Today, before ordering Menu 2 you have a chance to change your menu choice. Would you like to keep Menu 2, or would you prefer to order a different menu from the available alternatives?

- ○ I prefer to keep Menu 2
- ○ I prefer to choose other menu

You chose to change the food item you selected yesterday. To which item would you like to switch for today?

- ○ Menu 1
- ○ Menu 2
- ○ Menu 3

Planned calorie intakes

We would like to know what did you eat or you are planning to eat today in terms of calories? Please provide the calorie estimates to best of your knowledge.

0 200 400 600 800 1000 1200 1400 1600 1800 2000

How many calories you consumed or plan to consume for Breakfast

How many calories you consumed or plan to consume for Brunch

How many calories you consumed or plan to consume for Lunch

How many calories you consumed or plan to consume for Dinner

Chapter Three

Understanding Barriers to Agricultural Technology Adoption: Evidence from U.S. Agribusiness Firms[15]

4.1 Introduction

Technology adoption in agriculture encompasses a wide range of practices and technologies to enhance crop productivity, animal husbandry, and the overall well-being of humanity. As these advancements are integrated into agricultural systems, they become crucial drivers in achieving sustainable development goals, playing a pivotal role in fostering environmental, economic, and social sustainability (Pretty et al., 2018; Ladha et al., 2020; FAO, 2020; Yin et al., 2022). Agricultural innovation contributes to the conservation of natural resources and mitigates ecological degradation by promoting sustainable farming practices and enhancing resource efficiency (Shiferaw et al., 2009; Ren et al., 2023; Balmford et al., 2018; Lobell et al., 2020). Tilman et al. (2011) demonstrated that innovative agricultural practices, such as precision farming and improved crop genetics, can substantially increase crop yields while reducing environmental impacts (Ray et al., 2013; Tilman et al 2011; Lipper et al., 2014). Moreover, research by Enahoro et al. (2019) emphasized the importance of innovative livestock production systems in meeting the growing demand for animal protein sustainably. Agricultural innovation also contributes to poverty reduction by creating employment opportunities, increasing farm incomes, and fostering rural development (Diao et al., 2017). These findings highlight the crucial role of agricultural innovation and technology

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adoption in addressing the challenges of food security, climate change, and poverty, ultimately improving the well-being of humanity.

Research on agricultural innovation is also important for several reasons. Firstly, they help identify and develop new practices, technologies, and strategies that can enhance agricultural productivity, sustainability, and resilience (Morton et al., 2013). By exploring innovative approaches, researchers can contribute to addressing global challenges such as food security, climate change, and resource scarcity (Pardey et al., 2016). Secondly, these studies provide insights into the economic and social impacts of agricultural innovation, including its potential to improve rural livelihoods, reduce poverty, and promote inclusive growth (Lowder et al., 2016). Furthermore, they help policymakers and stakeholders make informed decisions regarding investment in research, development, and implementation of innovative agricultural practices (Klerkx et al., 2012).

Innovation adoption literature discusses both top-down as well as bottom-up approaches (Imperial, 2021; Harper 2018; Wang et al; 2018). Most of the innovations in agriculture adopts a top-down adoption approach (Allan et al., 2022; de Janvry and Sadoulet, 2002; Van der veen 2010; Zhang et al., 2018). However, in agriculture, it is important to consider the stakeholder's behavior as well, especially farmers (Pagliacci et al., 2020). Farmers' behavior is seen as separate from these technological solutions imparted from the top. Similarly, any agribusiness enterprise faces the problem of a disconnect between the technological solutions introduced and the employees' behavior be it a farm or an agribusiness enterprise. Technology adoption literature in agriculture shows mixed results. Most of these studies are based on top-down approaches where technology is introduced by the firm or the government, but farmers fail to capitalize on this opportunity, the reasons for failures are context-specific (Morris et al., 2017; Awotide et al., 2016). This signals a need for a study based on a bottom-up approach to understand the contextual factors in technology adoption (Pronti et al., 2024). Literature also highlights the need for synchronization of top-down and bottom-up approaches would yield a better adoption of new technology and innovation (Bellone et al., 2023; Chatterjee et al., 2023; Sanga et al., 2023; Srivastava et al., 2016; Rustan et al., 2022; Evans et al., 2017).

Studying grassroots perceptions of innovation and technological adoption offers several benefits for organizations, particularly when situated within broader systems frameworks such as Agricultural Innovation Systems (AIS) and Actor-Network Theory (ANT). The AIS framework (Klerkx et al., 2012) conceptualizes innovation as emerging through interactions among diverse actors including frontline employees, managers, researchers, and institutions, within a specific policy and institutional environment. In agribusiness settings, bottom-up approaches are crucial in facilitating such interactions by emphasizing the direct communication between top managers and frontline workers (Fraser et al., 2016; Viswanathan et al., 2012; McDonough et al., 2015; Leeuwis et al., 2004). When bottom-up learning is weak or delayed, firms often find it difficult to process feedback along the organizational hierarchy and adapt to dynamic market conditions and changing demands (Wei et al., 2011; Leeuwis et al., 2004; Chatterjee et al., 2023; Jansson, 2011). ANT complements these systems thinking by highlighting the co-

construction of innovation through human and non-human actors such as technologies, routines, tools, and regulations, making clear that frontline perspectives are indispensable to understanding how technologies are adopted in real-world, heterogeneous environments (Klerkx et al., 2012).

Agribusiness firm employees, from an AIS and ANT perspective, are not merely passive recipients of top-down technological interventions; rather, they possess rich, experience-based insights that expose practical misalignments in implementation. These include mismatches between technology design and workplace context, usability challenges, and communication breakdowns. Thus, managers must remain open to accessing this information through both formal and informal avenues to effectively diagnose and respond to barriers to adoption (Wei et al., 2011; McDonough et al., 2015; Becker and Bish, 2017). In addition, a bottom-up approach allows managers to identify resource rigidities deeply embedded organizational constraints that inhibit responsiveness to change (Gilbert, 2005; Yi et al., 2017; Khan, 2024). These insights closely align with the structural and behavioral domains outlined by Montes de Oca Munguia et al. (2021), who emphasize the importance of accounting for performance expectations, learning dynamics, external influences, and adopter characteristics in adoption studies. Our work reflects these elements by capturing how barriers manifest at various employment levels in agribusiness firms.

Despite these advantages, bottom-up learning may also present challenges, particularly in terms of integrating feedback from the operational level with strategic decision-making from the top. This tension is well documented in the literature on organizational learning and innovation systems (Katila & Ahuja, 2002; Butler et al., 2015). Nonetheless, in the context of technology adoption, bottom-up engagement remains critical for surfacing frontline issues and gauging employee sentiment. Frontline workers may feel threatened by automation and innovation, especially in agriculture, where technology can displace labor by reducing workforce size or hours worked (Gilbert, 2005; Schroeder et al., 2024). Such emotional and job security concerns often go undetected in top-down models (Hazell et al., 2010; Chatterjee et al., 2023). Therefore, following the logic of both AIS and ANT, bottom-up approaches offer a more holistic understanding of adoption dynamics by illuminating both technical and social frictions. They allow managers and researchers to capture not only the practical challenges but also the affective and attitudinal dimensions of technology uptake in agribusiness enterprises (Leeuwis et al., 2004; McDonough et al., 2015; Schroeder et al., 2024).

Our paper's novelty arises from three interrelated contributions to the literature on innovation adoption in agribusiness enterprises. First, unlike most existing studies that primarily examine barriers, we employ three distinct but interrelated dependent variables: (i) the openness of the firm toward innovation, (ii) the firm's effort in pursuing innovation, and (iii) the firm's perceived success in innovation adoption. This multidimensional focus allows us to capture a more holistic picture of the adoption process. Most prior research operationalizes adoption as a binary or single-dimensional outcome, limiting the ability to understand the progression and internal dynamics of innovation within organizations. By contrast, our tripartite outcome structure reflects the complex and staged nature of innovation adoption processes in practice (Hameed et al., 2012). To model these dynamics, we apply ordered probit regression as the canonical framework, complemented by a triple-hurdle probit model that captures sequential adoption behavior and conditional decision processes across stages of openness, effort, and success. This integrated econometric approach, reinforced by heterogeneity analyses by firm size and industry, enables us to uncover nuanced behavioral mechanisms underlying innovation adoption in agribusiness enterprises.

Second, we categorize barriers to innovation using five broad and well-supported dimensions: economic, technological, socio-cultural, environmental, and political and policy-related. While these categories are widely recognized in the literature, our contribution lies in applying them in a way that is cognitively accessible to frontline employees. This framing facilitates more accurate and meaningful data collection, especially in contexts where participants may lack technical training but possess lived experience with organizational constraints. These are incorporated, not as a theoretical novelty, but as a practical structuring device that enables interpretability by frontline employees and alignment with key adoption constructs, such as those identified in Montes de Oca Munguia et al. (2021). Together, this design bridges conceptual models and empirical implementation, providing an integrated, actor-informed framework for analyzing adoption in U.S. agricultural enterprises.

Third, we incorporate a bottom-up approach by directly surveying agribusiness employees including frontline workers about their perceptions and experiences with innovation. While the bottom-up perspective is not new in itself, its systematic integration into firm-level innovation studies within the agribusiness sector remains limited. Our approach is grounded in the view that frontline insights provide a more context-sensitive understanding of how innovation is experienced and negotiated at the ground level particularly in environments where top-down innovation models may misrepresent grassroots realities. By foregrounding these voices, we aim to contribute to a more democratized and practice-oriented account of innovation processes.

This research focuses on the significance of identifying and comprehending barriers to agricultural innovation and technology adoption among US agricultural enterprises. Firstly, the study identifies the types of barriers and challenges faced by agricultural enterprises in innovation and technology adoption using a comprehensive literature review. Secondly, using the identified barriers, this study assesses the severity of these barriers and the impact of these barriers exert on firms' innovation adoption. By doing so, the research aims to provide valuable insights into the critical obstacles that need to be addressed to facilitate the diffusion of agricultural innovations and promote sustainable development.

While agricultural innovation is often regarded as a pathway to greater sustainability, recent scholarship highlights that not all innovations are unambiguously beneficial (Klerkx & Rose, 2020). Some innovations may generate trade-offs, such as heightened resource use, social inequities, or new ecological risks. Therefore, it is essential to approach the relationship between innovation and sustainability critically, recognizing both potential benefits and unintended negative externalities (Smith et al., 2023).

Our analysis is informed by this nuanced perspective, and acknowledges that innovation outcomes are context-dependent and may involve complex trade-offs. The remainder of the paper is as follows. The review of the literature and the conceptual framework are presented in section 2. The research method that was employed for this study is discussed in section 3. The result and discussion section of the study are presented in section 4. Section 5 concludes the paper with research implications.

4.2 An Overview of the Role of Innovation and Barriers

No matter how crucial agricultural innovation is for sustainable development, it is imperative to ensure widespread dissemination and adoption among farmers to fully leverage its potential and maximize its benefits. To this end, it is essential to understand the potential barriers that prevent the adoption of new practices and technologies. Different innovations create barriers of varying magnitudes and directions. Feder et al. (1985) offer an economically grounded framework that views adoption decisions through a utility-maximization lens. While foundational, this model largely emphasizes individual-level rationality, leaving less room for structural or behavioral explanations that recent studies have prioritized. Feder et al. (1985) discussed factors such as farm size, lack of information, risk aversion, incentives, and ownership, human capital, labor shortage, lack of credit, uncertainty, absence of complementary equipment, lack of infrastructure, and complementary inputs, all of which impact the adoption of new technologies. This study also discusses the issue of simultaneous adoption of other technologies as well as how adoption has been measured.

Wheeler’s (2008) exploration of organic farming barriers highlights how both perceptual (e.g., public misperception) and structural factors (e.g., lack of government support, market profitability) jointly inhibit innovation. This suggests that market and institutional alignment is as critical as technological readiness. Similarly, Weiss and Bonvillion (2013) argue that the U.S. innovation system is structurally bifurcated: one part embracing the rapid innovation, and another, composed of ‘legacy sectors,’ resisting the change. Their work is particularly valuable for agricultural innovation because it shifts the focus from typical “valley of death” concerns to systemic barriers embedded in established technological, institutional, and socio-political paradigms. For example, they highlight how perverse subsidies and regulatory architectures not only discourage new entrants but actively reinforce existing, less sustainable models. This analytical lens is crucial for understanding agricultural sectors globally, where similar legacy dynamics, such as subsidy regimes, path-dependent infrastructure, and export-driven paradigms can limit the adoption of sustainable innovations. Their framework, which integrates economic, political, and socio-cultural obstacles, offers a useful model for dissecting the institutional inertia that prevents even desirable innovations from reaching the market. In doing so, it provides a powerful complement to micro-level adoption studies by emphasizing the structural lock-ins and policy contradictions that must be addressed.

Recent studies have begun to unpack the deeper structural, institutional, and cognitive roots of innovation barriers in agriculture. Long et al. (2016), drawing on cross-national interview data and a synthesized theoretical framework, demonstrate that barriers to climate-smart agriculture adoption are not confined to either the supply or demand side alone; rather, they emerge from a complex interplay between technology providers' limitations and users' hesitations, which are rooted in both institutional design and knowledge asymmetries. Björklund (2018), focusing on the underutilization of sustainable business model innovation in Swedish agriculture, reveals that adoption barriers extend beyond resource constraints to include rooted mindsets, a lack of entrepreneurial orientation, and contextual factors specific to family farms. This finding focusses on the role of internal agency and socio-cultural conditioning in mediating innovation behavior, even when sustainability is normatively desirable. Meanwhile, Dahabieh et al. (2018) bring attention to the food and agricultural biotechnology sector, where innovation is impeded not just by regulatory or cognitive barriers but by more technical and systemic frictions, particularly the dual challenges of "specialized adoption uncertainty" and "complex product-market fit" across value chains.

What unites these studies is a shared emphasis on innovation as a systemically embedded process, shaped by economic structures, socio-cultural norms, technological readiness, and policy and regulatory frameworks. While environmental considerations are often the motivation behind these innovations, they are frequently sidelined in the actual implementation process due to competing priorities across these other dimensions. Collectively, these studies challenge the adequacy of linear adoption models and reinforce the need for a multidimensional framework, such as the one developed in this study, that explicitly integrates economic, socio-cultural, technological, environmental, and policy-related barriers.

Cummings et al. (2021) and Da Silva et al. (2023) both examine barriers to the uptake of technological innovations in agrifood systems but from distinct vantage points: nanotechnology and digital Industry 4.0, respectively. Cummings et al. build a typology of barriers to responsible innovation in nano-agrifood, identifying structural deficits such as the lack of product oversight, insufficient training and workforce capacity, and the absence of critical data; all of which map closely to technological, institutional, and policy-related constraints. Their framing integrates these barriers within the broader stages of innovation, from R&D through commercialization, underscoring the systemic nature of challenges in emerging technologies. Similarly, Da Silva et al. (2023) emphasize how the promise of digital technologies in Agriculture 4.0 is constrained by the knowledge gap among users and the need for advanced technical skills. Yet they also note enabling conditions such as pre-existing technological infrastructure and the role of open innovation in bridging institutional silos. Together, these studies suggest that innovation uptake in agriculture is contingent not just on technological readiness, but on institutional coordination, regulatory clarity, and stakeholder capacity, aligning closely with multidimensional barrier categories such as technological, socio-cultural, economic, and policy domains.

Having screened the literature to the best of our knowledge, it becomes evident that barriers to agricultural innovations are multifaceted and can manifest in diverse dimensions such as economic, technical, socio-cultural, environmental, and political. Understanding and addressing these barriers is crucial for the successful adoption and implementation of agricultural innovations. A holistic approach is necessary, encompassing considerations across these dimensions. Through a comprehensive literature review, factors influencing the diffusion and adoption of agricultural innovations can be categorized into these five distinct groups, economic, technical, socio-cultural, environmental, and political dimensions as it is shown in Table A1 in the appendix A.

The theory of barriers to innovation stems from many studies. However, the seminal paper by Klepper (1996) which proposed that the company's decision to adopt innovation depends on the sum of net profits after adopting innovation and the cost incurred for innovation. This cost for innovation adoption captures many dimensions of cost factors. They range from tangible direct costs to intangible indirect costs. Many studies have tried to investigate these cost factors and obstacles. It is not merely the monetary factors but non-monetary obstacles can also be a huge obstacle for innovation adoption. Thus, the literature on barriers for innovation of firms discusses different factors. Some look at the factors as external and internal factors, some also include contextual factors. Björklund (2018) states that these three barriers are interrelated. Siverstsson and Tell (2015) delve deeper into the contextual factors and propose that the level of barriers for innovation may depend on the size of the firm as well as the type of offering offered by the firm: i.e whether it is high technology firm or low technology firm. They highlight that given where the firm is positioned within this context, the level of innovation adoption and perceived barriers may differ.

Overcoming these barriers requires collaborative efforts involving farmers, researchers, policymakers, and stakeholders. This effort includes targeted investments in research and development, capacity building, and knowledge-sharing platforms. Strengthening policy frameworks, aligning regulations, and providing financial support can establish an enabling environment for agricultural innovation. Addressing socio-cultural norms, promoting awareness and education, and fostering inclusive decision-making processes are crucial for facilitating the adoption of innovative practices on farms. Considering the environmental sustainability of innovations and ensuring equitable access to resources and benefits are also essential.

By addressing these challenges comprehensively, we can unlock the full potential of agricultural innovation. This approach can lead to increased productivity, enhanced resilience, and sustainable agricultural practices that contribute to food security, rural development, and environmental stewardship. Given the literature classified in Table A1 (Appendix A) and our research question the following conceptual framework in Figure 1was built with the hypotheses.

While prior studies provide valuable descriptive and structural explanations for the barriers to innovation in agriculture, most remain fragmented across economic, institutional, and behavioral perspectives. What is still underdeveloped is an integrative account of how firms behave when confronted with these barriers, that is, the mechanisms through which constraints are interpreted and acted upon. Building on the behavioral theory of the firm (Cyert & March, 1963), this study conceptualizes innovation behavior as a form of problemistic search—an adaptive response triggered when performance shortfalls or external constraints challenge existing routines. From this perspective, barriers are not merely obstacles but informational and disciplinary signals that can, under certain conditions, stimulate experimentation and resource reallocation. Some theoretical framework integrate the Porter hypothesis, Induced Innovation theory with the Problemistic search theory (Mazzanti & Zoboli, 2006). In addition, studies argue that environmental constraints can serve as triggers of adaptive search and resource reallocation rather than mere inhibitors of innovation. This mechanism—supported by behavioral perspectives on problemistic search (Cyert & March, 1963; Greve, 2003)—suggests that firms facing regulatory, ecological, or reputational pressures engage in targeted innovation efforts to restore performance and maintain legitimacy. Studies by Miao and Popp (2014) and Miao (2020), specifically finds evidence that environmental barriers can induce technology adoption in agriculture. Further, Moscona and Sastry (2023) provide a theoretical explanation of how constraints like climate change can induce innovation and agricultural technology adoption.[16]

Accordingly, this paper advances a constraint typology model, where five domains of barriers—economic, technical, political, socio-cultural, and environmental—represent distinct forms of constraint that differ in their capacity to suppress or induce innovation.

[16] See Zilberman et al. 2025 for a discussion on innovation and technology adoption in agriculture.

Economic and technical barriers typically deplete organizational slack, reducing firms' ability to search or absorb new knowledge. Political and socio-cultural barriers introduce uncertainty or normative rigidity, dampening risk-taking and strategic openness. In contrast, environmental barriers often generate compliance pressure and reputational incentives that can provoke adaptive innovation, consistent with the induced-innovation and problemistic-search literatures.

Within this behavioral framework, the present study formulates five domain-specific hypotheses (H1–H5), linking each barrier to firms' level of innovation adoption. These hypotheses capture both the constraining and adaptive effects of barriers and guide the empirical analysis that follows.

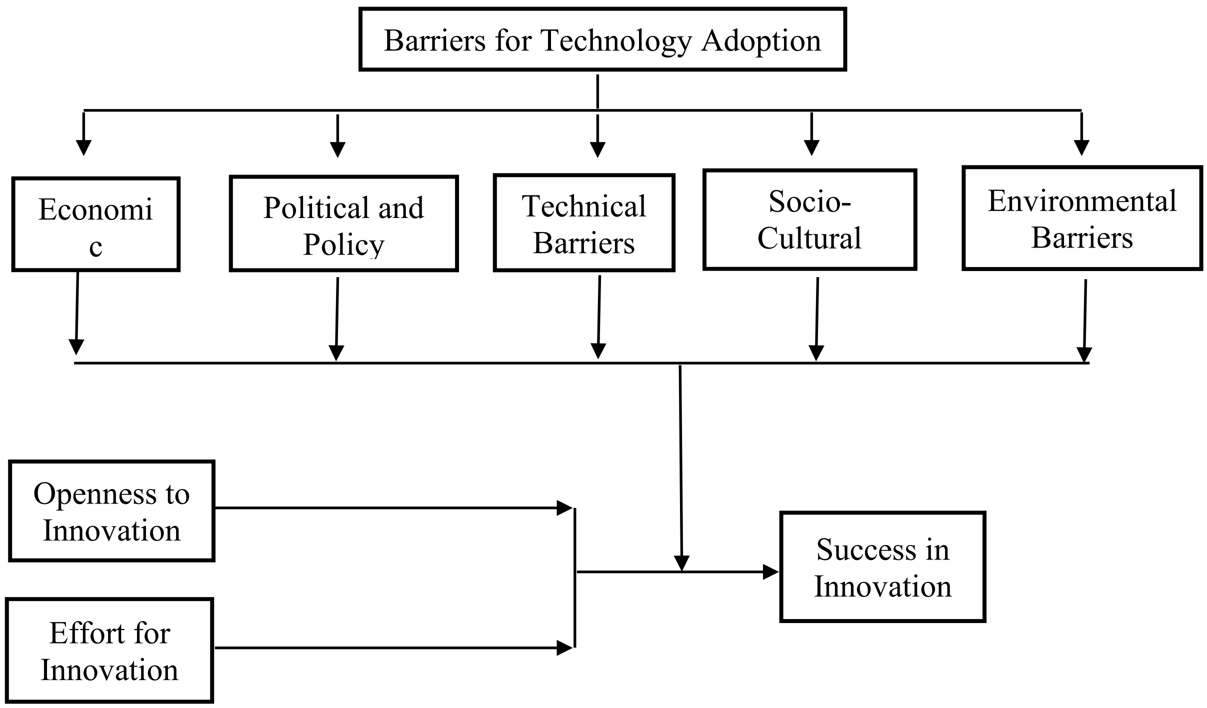

Figure 3.1: Conceptual framework for Barriers for innovation adoption

Hypotheses

Based on the behavioral theory of the firm and problemistic search logic and the conceptual framework developed, we hypothesize that for agricultural enterprises in our sample, deteriorating barriers negatively affect the level of innovation adoption. Specifically:

H1: Economic barriers decrease innovation adoption by constraining available slack and limiting firms' ability to invest in new technologies

H2: Technical barriers decrease innovation adoption by reducing absorptive capacity and the ability to integrate new technologies effectively.

H3: Political and policy barriers reduce or neutralize innovation adoption by creating uncertainty and administrative burden.

H4: Socio-cultural barriers decrease innovation adoption by reinforcing conservative norms and risk aversion

H5: Environmental barriers increase innovation adoption by triggering adaptive search and compliance-oriented innovation.

Table 3.1: Summary of hypotheses and expected signs

Barriers	Mechanism	Expected sign
Economic	Resource depletion due to limited slack	(–)
Technical	Knowledge and capacity deficit	(–)
Political	Uncertainty, compliance cost	(–) / null
Socio-cultural	Normative rigidity, risk aversion	(–)
Environmental	Compliance and stakeholder pressure	+

4.3 Research Methods

Data Collection

To assess the different types of barriers to innovation adoption in agricultural enterprises and their relationship to the level of effort for innovation, openness to innovation, and success in the innovation of these enterprises, we used data collected through an incentivized questionnaire survey administered through prolific.com. We had 374 respondents who are employed in agricultural enterprises and each respondent who completed the study received $2. Eligibility screening required that participants be at least 18 years of age and currently employed in an agribusiness-related firm. The questionnaire included sections on details about the enterprises and the role of the employee, technical barriers, economic barriers, socio-cultural barriers, environmental barriers, policy and political barriers, and a section covering innovation adoption. The final section collected demographic information such as age, gender, income, and work experience to contextualize the responses and control for potential confounding effects. Most of the questions were of Likert scale type. Thus, the questionnaire can be easily completed within 10 minutes. For the barriers, the 5-point Likert scales (1= Extremely limits technological adoption, 2= Very much limits technological adoption, 3= Somewhat limits technological adoption, 4= Slightly limits technological adoption, 5= Not a limitation at all) were used. These barriers were the hypothesized explanatory variables.

More specifically we wanted to study the relationship between perceived barriers and their effect on three outcome variables on innovation adoption. Thus, perceived barriers were measured under five main barrier types and outcome variable.

Barriers for innovation adoption and innovation adoption

Our variable of interest as an independent variable are the perception of different barriers to innovation adoption. The various factors under five dimensions of barriers were considered (Table A3.1 of the appendix A). The main five dimensions are economic barriers (10 factors), technical barriers (11 factors), political and policy-related barriers (12 factors), socio-cultural barriers (11 factors), and environmental barriers (10 factors). Under each of these dimensions, there was a selected list of factors that could be a potential barrier. According to the literature some studies employ dimensions reduction/factor analysis to identify the underlying factors (Valdés et al., 2021; Madrid-Guijarro et al., 2009), whereas most of the studies use the grouped factors approach based on theoretical grounds (Pellegrino and Savona, 2017; Kijek & Angowski, 2014). As per the observations in both strands of literature, it is clear that most of the factors identified through factor analysis are consistent with the theoretical factors (D'Este et al., 2012; Pellegrino and Savona, 2017).

Further, in general, the main 5 dimensions of barriers were also rated using the Likert scale to identify the main barrier. On the survey platform, agricultural workers were asked the following question under each main barrier: "*Please assess how significantly each one hinders the ability of your enterprise to adopt new technologies. Evaluate their impact based on your direct experiences and observations within your role*."

For the outcome variables, we use three outcomes, *viz*, "Openness for innovation", "Effort for innovation", and "Success in innovation" (Madrid-Guijarro, Garcia, and Van Auken, 2009). All three outcome variables were also measured on a 5-point Likert scale (1= Strongly agree, 2= Agree, 3= Neither agree/nor disagree, 4= Disagree, 5= Strongly disagree). For openness, we asked the following statement to rate: *"My organization is open to adopting new and innovative practices or technologies".* To capture the effort the enterprise puts into innovation adoption, we asked the following question: *"My organization proactively invests time and resources to adopt new innovative technologies".* Finally, to capture the level of success in adopting innovation in the organization, we asked the following: *"The innovative technologies that my organization has implemented have generally achieved their intended outcomes".* Innovation adoption is often modeled as a binary or single-scale outcome. However, such approaches risk oversimplifying the processual and behavioral complexity of adoption. Drawing from organizational behavior and innovation diffusion theory, we distinguish between three stages of adoption behavior: (1) openness (attitudinal disposition) (Hameed et al., 2012), (2) effort (behavioral engagement) (Gagnon & Toulouse, 1996; Yu & Tao, 2009), and (3) success (evaluative outcome) (Olshavsky & Spreng, 1996; Kaur Kapoor et al., 2014). This structure allows for a more nuanced analysis of the adoption pathway (Pichlak, 2016).

Controls

In the analysis of the data, we have to control for important control variables. Such control variables in our study are “industry”. Among agriculture what is the specific sub-industry their enterprise falls into. Another important control variable is the size of the enterprise: micro (1-9 employees), small (10-49 employees), medium (50-249 employees), and large (>250 employees). Further, agricultural enterprises can function either in one node or in multiple nodes of the marketing channel. Most of the enterprises may involve at multiple nodes and channels of the marketing channel. Therefore, level of adoption of innovation in the organizations may be dependent on these factors as well.

Analysis Plan

We followed a pre-specified analytical sequence to examine the relationship between perceived innovation barriers and enterprise adoption outcomes. The analysis proceeded through the following stages as depicted in table 3.2. We followed a multi-stage empirical strategy. First, we conducted exploratory diagnostics and descriptive analyses to assess variable distributions and collinearity. Second, we estimated baseline binary and ordered-probit models to establish the direction and strength of associations between perceived barriers and innovation outcomes. Third, we introduced interaction terms between environmental barriers and firm size to test boundary conditions implied by problemistic search and adaptive reallocation theories. Fourth, we estimated triple-hurdle probit models to capture sequential innovation dynamics. Finally, we conducted a set of robustness tests, including industry fixed effects, and alternative codings, to mitigate concerns of reverse causality, and reporting bias.

Table 3.2: Analysis stages of the study

Step	Analysis	Purpose
(i)	Exploratory diagnostics and descriptive summaries	Distributions, correlations, VIFs, internal consistency
(ii)	Baseline binary and ordered probit models	Establish direction and significance of key predictors (esp. environmental barriers)
(iii)	Interaction models: Environmental barriers × Firm size	Test boundary conditions consistent with the problemistic search mechanism
(iv)	Triple-hurdle probit models (sequential dynamics)	Examine adoption intensity across decision stages (if feasible in data)
(v)	Robustness and alternative explanations	Address reverse causality, reporting bias, endogeneity, and scale artifacts

After validating the measurement model and confirming the reliability and independence of all constructs, we proceeded to estimate the relationship between perceived innovation barriers and adoption outcomes.

As the canonical model, we employed an ordered probit regression, modeling how the perceived severity of five barrier dimensions: economic, technological, political, socio-cultural, and environmental, influences three ordered innovation outcomes: openness, effort, and success. Each barrier dimension was operationalized as the mean of its validated item indicators, supported by confirmatory factor and reliability analyses (Appendix B). The ordered probit model specification accounts for the ordinal scaling of responses, estimating the latent propensity for greater innovation engagement as a function of barrier perceptions and firm-level characteristics.

Measurement Validation and Diagnostic Procedures

Prior to estimation, all multi-item constructs were subjected to a series of psychometric and diagnostic evaluations to ensure reliability, validity, and independence. Internal consistency reliability was assessed using Cronbach's α and McDonald's ω for each of the five barrier constructs: economic, technological, political, socio-cultural, and environmental. All scales demonstrated strong reliability (α = 0.88–0.95, ω = 0.89–0.96), exceeding the conventional 0.70 threshold (Nunnally & Bernstein, 1994).

Exploratory factor analysis (EFA) using maximum likelihood extraction and "oblimin" rotation supported a five-factor solution explaining 61% of total variance. Items loaded cleanly onto their respective theoretical dimensions with minimal cross-loadings (RMSR = 0.04, off-diagonal fit = 0.99). Inter-factor correlations ranged from 0.29 to 0.65, indicating related but distinct constructs. Confirmatory factor analysis (CFA) further confirmed this structure, showing good model fit (CFI = 0.92, TLI = 0.92, RMSEA = 0.065, SRMR = 0.064). All standardized factor loadings exceeded 0.60 and were significant at $p < .001$, demonstrating convergent validity. Average variance extracted (AVE = 0.49–0.75) also met recommended thresholds, supporting construct validity.

Since data were self-reported, potential Common method variance (CMV) was evaluated using Harman's single-factor test. The first unrotated factor accounted for 36% of total variance—below the 50% threshold—and the single-factor model showed poor fit (RMSEA = 0.099, TLI = 0.55), indicating that CMV was not a serious concern. Parallel analysis identified seven factors, confirming that observed relationships were substantive rather than methodological artifacts. Polychoric correlations among the 54 ordinal barrier items averaged r = 0.56 (range = 0.30–0.78), indicating adequate inter-item association without redundancy. Mean-centered composite indices were then calculated for each barrier, ranging from 1 ("not at all severe") to 5 ("very severe"), for use in regression analysis. Correlations among the three outcome variables—openness, effort, and success—ranged from 0.38 to 0.48, below the 0.70 cutoff (Gujarati, 2004), confirming that they capture related yet distinct dimensions of innovation behavior. Variance Inflation Factors (VIFs) for all predictors ranged between 1.26 and 2.78 (mean ≈ 1.9), indicating no problematic multicollinearity. The slightly higher VIFs for the environmental, political, and socio-cultural dimensions reflect conceptual overlap typical of attitudinal constructs (See Appendix B for more details).

All validated and mean-centered indices were subsequently used as predictors in the ordered probit and triple-hurdle probit models described below.

The decision to adopt innovation

Due to the properties ordinal scale of the dependent variable, (ordered outcome), we deploy an ordered probit model as specified as follows (Madrid-Guijarro, Garcia, and Van Auken, 2009):

$$Y_i^* = x_i'\beta + \varepsilon_i$$

$$Y_i = 0 \; if \; Y_i^* \leq 0$$

$$Y_i = 1 \; if \; Y_i^* > 0$$

Where Y_i^* is a latent variable implying the level of adoption of innovation related to the *i* th firm. x_i' is a vector of regressors (severity of barriers) and ε_i is the error term that is assumed to be normally distributed.

The ordered probit model is defined as follows:

$$y_i^* = \beta_0 + \beta_1 \mathrm{Econ}_i + \beta_2 \mathrm{Env}_i + \beta_3 \mathrm{Tech}_i + \beta_4 \mathrm{Pol}_i + \beta_5 \mathrm{Soc}_i + \epsilon_i,$$

where $y_i^*$is the latent variable representing firm i's innovation outcome (openness, effort, or success). The observed ordinal response $y_i$takes values $1, 2, 3, 4, 5$ such that:

$$y_i = j \text{ if } \mu_{j-1} < y_i^* \leq \mu_j, j = 1, \dots, 5,$$

with threshold parameters $\mu_j$estimated as part of the model.

All predictors are mean-centered composite indices derived from Likert-scale items (1 = “not at all severe” to 5 = “very severe”), representing the perceived intensity of each barrier dimension. Higher values indicate greater perceived severity.

Most of the innovation and technology adoption studies have either used probit or ordered probit regression models to model the innovation adoption behavior (Ganguly et al., 2010; Tey and Brindal, 2012; Van der Boezem et al., 2015; Birhanu et al., 2017; Barnett et al., 2019; Priyadharshini et al., 2024).

Interaction effect

To examine whether the inducement effect of environmental constraints varies by firm size, we estimated ordered probit models with a probit link function of the form

$$\mathrm{Y}_{ij} = \beta_1 \mathrm{Env}_{ij} + \beta_2 \mathrm{Size}_{ij} + \beta_3 \left(\mathrm{Env}_{ij} \times \mathrm{Size}_{ij}\right) + \mathbf{B}'\mathbf{X}_{ij} + \gamma_j + \varepsilon_{ij},$$

where $\mathbf{X}_{ij}$ denotes controls for economic, technical, political, and social barriers, and γ_j represents industry fixed effects. The inclusion of γ_j absorbs unobserved heterogeneity in regulatory exposure and innovation norms across industries, thereby mitigating potential reverse causality arising from innovative sectors perceiving stronger environmental barriers.

Robustness Checks

To verify the stability of our results, we conducted a series of robustness checks. While our primary analyses employed ordered probit regression, we extended the analysis by estimating ordered probit models to account explicitly for the ordinal nature of the dependent variables. In addition, we applied a triple-hurdle probit model to capture sequential decision processes and potential structural complexity in the data. Finally, we performed a comprehensive set of diagnostic tests, including assessments of multicollinearity, model fit, proportional odds assumptions, and predictive accuracy. These sensitivity analyses confirm that the observed relationships are not driven by a specific model specification and provide additional confidence in the validity of our findings.

The decision-making process of agribusiness firms regarding technology adoption is not static but rather a dynamic, multi-stage process, as suggested by the behavioral stage change theory (Prochaska & DiClemente, 1983). The full decision pathway typically involves multiple stages, ranging from the initial decision of whether to open to innovation, to exert some effort for adoption, and finally determining the degree of success of innovation adoption (Doss, 2010; Chen et al., 2020; Chen et al., 2023). Building on this theoretical framework, the primary probit model was complemented with additional robustness checks to ensure that our findings are not an artifact of model specification. First, we estimated ordered probit models to explicitly account for the ordinal nature of the dependent variable, providing a more appropriate framework for ordered outcomes (Ganguly et al., 2010; Islam et al., 2017; Hassen, 2018). Second, recognizing that farmers' adoption decisions may follow a sequential structure, we employed a Triple-Hurdle probit model, which is particularly suited for analyzing multi-stage behavioral processes. This model allows for the decomposition of the decision-making process into three conditional stages: whether to adopt, how to adopt, and to what extent, while accounting for potential correlation across stages and addressing possible conditionally uncorrelated errors (Burke et al., 2015; Yang et al., 2020). These additional specifications, along with model diagnostics, provide greater confidence that the reported associations are robust across alternative modeling approaches and consistent with the behavioral decision-making theory (Chen et al., 2023).

Triple-Hurdle Probit

To capture the sequential nature of innovation adoption decisions, we further estimated a Triple-Hurdle Probit model (Burke et al., 2015; Yang et al., 2020). This model extends the traditional binary or ordered probit frameworks by decomposing the adoption process into three conditional stages:

(i) openness to innovation,

(ii) effort or investment toward adoption, and

(iii) realized success in implementation.

Each stage represents a distinct latent decision equation with potentially correlated error terms, allowing for flexible interdependence across decision stages. The model is particularly suited for behavioral and technology adoption contexts where participation, intensity, and success are determined sequentially rather than simultaneously.

Formally, the triple-hurdle model estimates three linked binary equations of the form:

$$Y_{1i}^{*} = \mathbf{X_i}\beta_1 + \varepsilon_{1i}, Y_{1i} = 1 \text{ if } Y_{1i}^{*} > 0,$$

$$Y_{2i}^{*} = \mathbf{X_i}\beta_2 + \varepsilon_{2i}, Y_{2i} = 1\text{''} \; if \text{ ``} Y_{2i}^{*} > 0, and\ Y_{1i} = 1,$$

$$Y_{3i}^{*} = \mathbf{X_i}\beta_3 + \varepsilon_{3i}, Y_{3i} = 1 \text{ if } Y_{3i}^{*} > 0, and\ Y_{2i} = 1,$$

where each stage is observed only if the previous stage is passed (e.g., Y_{2i}observed only if $Y_{1i} = 1$).

The joint likelihood accounts for correlation across the error terms $(\varepsilon_{1i}, \varepsilon_{2i}, \varepsilon_{3i})$, estimated via simulated maximum likelihood. This approach provides a theoretically consistent representation of multi-stage decision processes and offers deeper behavioral insight into the conditional determinants of innovation adoption success.

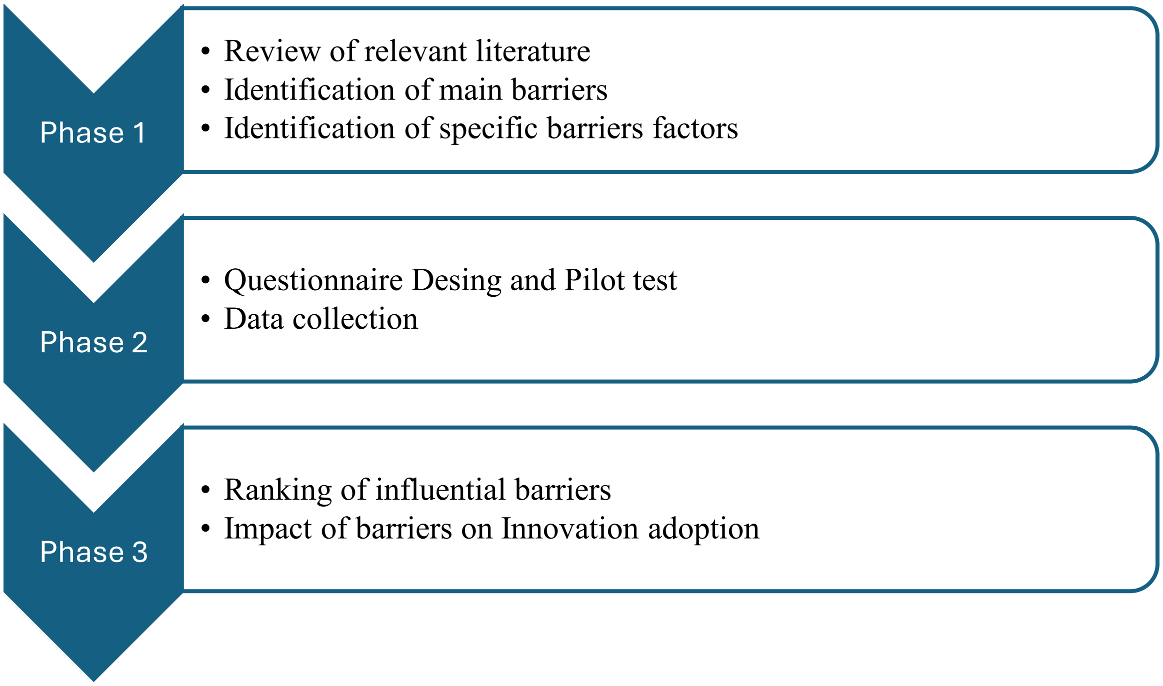

Figure 3.2: Research process

Table 3.3: Descriptive statistics of the Respondents

Variables	N	Frequency (%)
Female	374	195 (52%)
White	374	254 (68%)
Age 45 or older	374	84 (22.5%)
Younger than 45	374	290 (77.5%)
Agricultural (Crop/Livestock/Service/Logistic)	374	131 (35%)
Food production and service	374	171 (46%)
Natural resources/Forestry/Fishing	374	72 (19%)
Enterprise size 1 to 9 employees	374	72 (19%)
Enterprise size 10 to 49 employees	374	111 (30%)
Enterprise size 50 and 249 employees	374	101 (27%)
Enterprise size 250 and more employees	374	90 (24%)
Non managerial position	374	143 (38.2%)
Lower-level management role	374	71 (19%)
Middle-level management role	374	112 (30%)
Top-level management role	374	48 (12.8%)

Note: The table shows the characteristics of recruited employees. Reported statistics in n (%), i.e., counts and proportions

4.4 Results And Discussion

This section examines the impact of various barriers on innovation adoption within U.S. agribusinesses. Understanding these barriers—economic, technical, political, socio-cultural, and environmental - is crucial for identifying obstacles that hinder the successful implementation of new technologies and practices. Through a binary probit regression analysis, we aim to elucidate the relationships between the severity of these barriers and three key dimensions of innovation adoption: openness to innovation, effort invested in innovation, and success achieved in implementing innovative practices. The following results provide insights into how these barriers shape the landscape of innovation in the agricultural sector.

Overall Assessment of Barriers to Technology Adoption in Agriculture

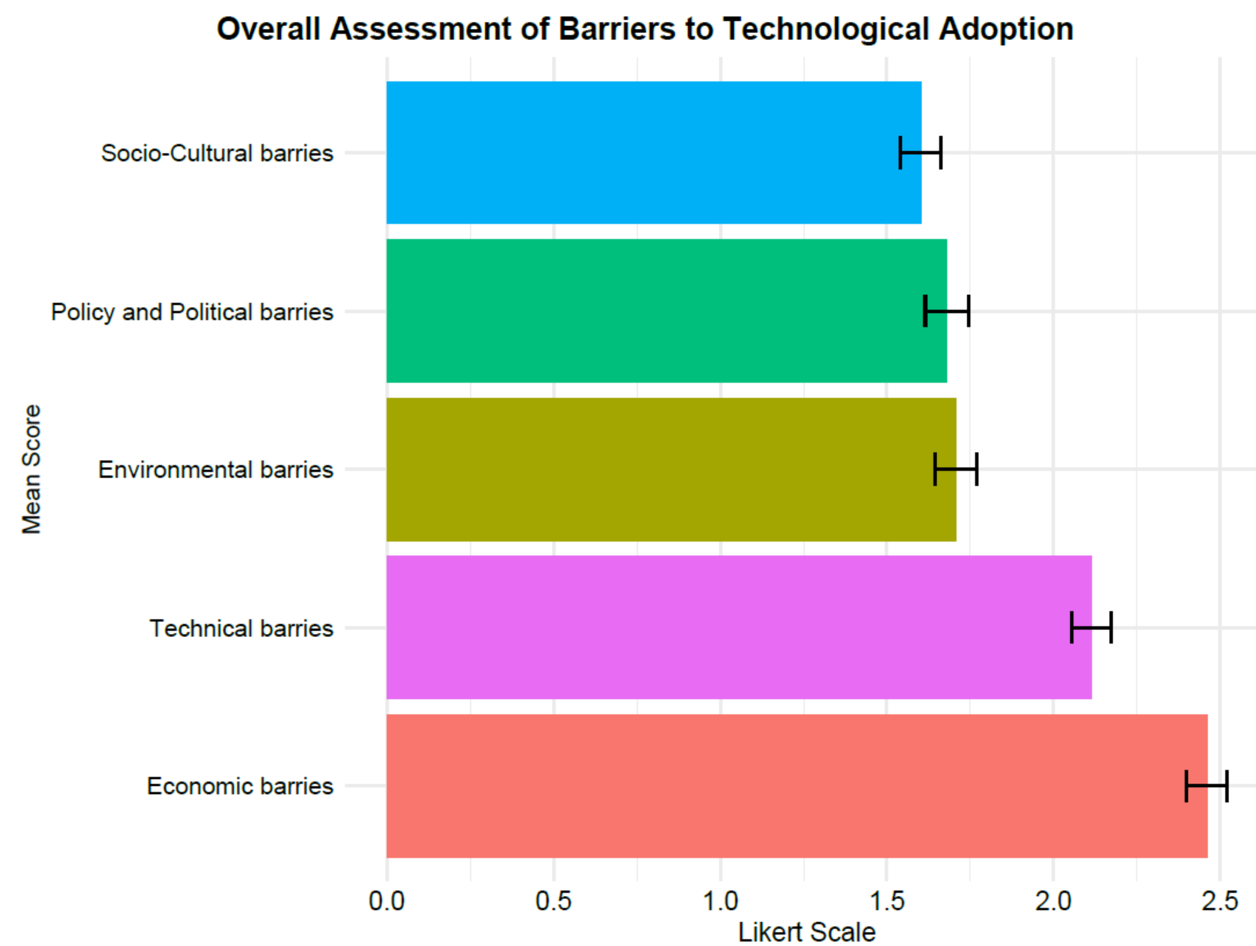

Figure 3.3: Respondents' evaluation of the importance of different barrier types

Figure 3.3 above states the ratings of the overall assessment of barriers to technology adoption in Agriculture. There were five main barriers, namely Socio-cultural barriers, policy and political barriers, Environmental barriers, technical barriers, and economic barriers. The figure clearly shows that the economic barriers are the most important barriers to technology adoption in agriculture as perceived by the respondents. The second most important/rather limiting barrier was the technical barrier. This was followed by environmental barriers, policy and political barriers, and socio-cultural barriers. Given the mean differences, economic barriers and technical barriers are significant barriers whose mean values are also statistically different to each other as well as different from the other barriers. However, the mean values of environmental barriers, policy and political barriers, and socio-cultural barriers are not statistically different to each other. But they are statistically lower than the technical and economic barriers. This confirms the notion that economic barriers are the most important barriers to technology adoption in agricultural enterprises. As the firm is the decision maker, it is obvious that benefits and costs are compared in deciding on technology adoption. Literature also suggests that, in most cases, it is not the case whether the firm adopts a technology or not. Rather a question of when the technology is adopted, sooner or later. The main driving forces for this are the costs incurred. As an individual unit, the firm gauges the cost and benefits of adopting new technology in its production line. It's just not the technology, but the relevant inputs, auxiliary services, and personnel have also to be updated along with technology adoption. Often, a newer technology might be very costly. After economics, the next question is the auxiliary services that need attention and the pertinent costs.

The second most limiting factor is the technical barriers. The availability of technology is just not sufficient for the adoption of that technology. It needs the capacity to handle the technical issues stemming from the adoption of a new technology. Not just the economics of that, but it needs system upgrades, equipment upgrades, technicians, and the latest technological know-how to apply the innovation into context, also the current employees at all levels should have the awareness about how to operate and maximize the potential. Unless the technical skills are matched with the new technology, the firm’s effort to adopt new innovation would be futile. In this context, it is important that other aspect apart from technological barriers are also addressed.

Common barriers in technology adoption are the socio-cultural issues of the stakeholders, especially the firm’s employees and clients. The socio-cultural aspects of the employees and clients must be addressed sufficiently, at the start of the discussion on implementing any technology adoption. As, this aspect might need more time to study the status quo, planning and implementing strategies, and the needed training for the workforce, which has to coincide with the upgrading of technology. It is possible that, once the human dimensions are involved, a greater heterogeneity of knowledge, skills, and attitudes towards the new technology. This further, depends on the cultural background of the community, their education, and previous exposure to technology. As some employees would be motivated, it is possible that some employees may be hostile towards the adoption of new technology due to various reasons. In addition to this, environmental barriers and policy and political barriers can also affect the larger picture of technology adoption. Based on the findings in this study, there is no statistical difference among the mean scores of socio-cultural barriers, policy and political barriers and environmental barriers. A detailed breakdown under each of these main barriers are listed in the appendix.

Barriers and Enterprise Innovation Adoption

Innovation adoption was measured using three dependent variables: Openness to innovation, Effort for innovation and Success in innovation. All these variables were converted to binary variables (i.e. yes if 1 and 0 otherwise). A probit regression was employed to model the decision on innovation variables along with five barriers for innovation and to observe the directionality. In our analysis of the factors influencing innovation adoption, we employed three distinct binary probit regressions. The first regression focused solely on the five identified barriers to innovation - economic, technical, political, socio-cultural, and environmental. This model aimed to assess the direct impact of these barriers on the three dependent variables: openness to innovation, effort for innovation, and success in innovation.

The second regression examined the correlation between each dependent variable and industry type without incorporating additional variables. This analysis aimed to determine whether different agricultural sectors exhibited variations in their innovation adoption based solely on industry classification. Finally, the third regression included barrier scores along with other relevant variables, such as firm size and marketing channel involvement, to validate our findings further. This comprehensive model sought to confirm whether the barriers identified maintained their significance in influencing innovation adoption when controlling these key factors.

Table 3.4 Barriers and Enterprise Innovation Adoption

Variables	Openness to Innovation	Effort for Innovation	Success in Innovation
Severity of Economic Barriers	-0.01 (0.07)	-0.03 (0.07)	0.13* (0.07)
Severity of Socio-Cultural Barriers	-0.11 (0.08)	-0.07 (0.07)	-0.13* (0.08)
Severity of Political and Policy Barriers	0.11 (0.07)	0.17** (0.07)	-0.002 (0.07)
Severity of Environmental Barriers	0.22** (0.08)	0.23***(0.07)	0.01 (0.07)
Severity of Technical Barriers	-0.07 (0.08)	-0.17** (0.08)	0.06 (0.08)
Constant	0.53*** (0.18)	0.07 (0.17)	0.27 (0.17)
Observations:	374	374	374
Log Likelihood:	-197.81	-241.53	-227.43
Akaike Information Criterion	407.61	495.06	466.86

Note: The table shows the results of probit estimations. The independent variables are based on Likert scale values. *p<0.1; **p<0.05; ***p<0.01.

As shown in Table 3.4, we find that environmental barriers are the only variable significantly impacting openness to innovation. This suggests that as the severity of environmental barriers increases, openness to innovation rises by 0.22 percentage points. Firms facing stronger environmental regulations or sustainability pressures may be more inclined to pursue innovative solutions in response.

For the regression analyzing effort for innovation, three barriers emerge as significant: political, environmental, and technical barriers. Specifically, as the severity of political and policy barriers increases, effort toward innovation rises by 0.17 percentage points. This indicates that when the political or regulatory environment becomes more complex, firms tend to invest additional effort in innovation to maintain compliance or competitive advantage. Similarly, as environmental barriers intensify, effort to innovate increases by 0.23 percentage points, highlighting that environmental challenges can serve as external motivators for firms to develop adaptive technologies. In contrast, as technical barriers become more severe, the effort to innovate decreases by 0.17 percentage points, suggesting that technological limitations or inadequate expertise can hinder innovation activity.

With respect to success in innovation, the results show that economic barriers are the only significant factor. An increase in the severity of economic barriers correlates with a rise in firm success in innovation by 0.13 percentage points. This counterintuitive positive effect implies that when firms experience economic constraints, such as higher input costs or limited financial resources, they may focus more intensively on efficiency-enhancing innovations. However, socio-cultural barriers exert a negative and significant effect (-0.13), indicating that cultural resistance or organizational inertia can dampen innovation success.

Overall, the results suggest that while some barriers (such as environmental and political) can stimulate innovation by creating external pressures, others (notably technical and socio-cultural) can constrain firms' ability to translate innovation efforts into tangible success. Building on these findings, the next section examines how these relationships vary across different agricultural and natural resource industries.

Table 3.5 Barriers and Enterprise Innovation Adoption (Comparison across Industries)

Variables	Openness to Innovation	Effort for Innovation	Success in Innovation
Agricultural (Crop/Livestock/Service/Logistic)	0.11 (0.16)	0.09 (0.15)	0.05 (0.15)
Natural resources/Forestry/Fishing	0.57** (0.22)	0.62*** (0.19)	0.40* (0.19)
Constant	0.58** (0.10)	0.05 (0.10)	0.41*** (0.10)
Observations:	374	374	374
Log Likelihood:	-201.47	-248.81	-228.55
Akaike Information Criterion	408.93	503.63	463.10

Note: This table shows the results of probit estimations. Estimates are compared to the responses for “Food production and service." *p<0.1; **p<0.05; ***p<0.01.

As shown in Table 3.5, the innovation-dependent variables are analyzed across various industries, with food production and service serving as the reference category. Compared to the food production industry, the likelihood of openness to innovation is 0.57 units higher in the natural resources, forestry, and fishing industry, a statistically significant relationship at the 5 percent level. Similarly, firms in the agricultural sector, comprising crop, livestock, service, and logistics activities, exhibit a 0.11 unit higher likelihood of being open to innovation compared to their food production counterparts, although this difference is not statistically significant. Additionally, the likelihood of putting forth effort toward innovation increases by 0.62 units for firms in the natural resources, forestry, and fishing industry when compared to those in the food production sector, significant at the 1 percent level. Likewise, firms in the agriculture industry show a 0.09 unit increase relative to the food industry, though this effect is statistically insignificant. With regard to success in innovation, significant differences are observed only for the natural resources, forestry, and fishing industry, where the likelihood of innovation success is 0.40 units higher than that of firms in the food production sector. The agricultural sector, while showing a small positive coefficient (0.05), does not differ significantly from the baseline.

In essence, the findings highlight that enterprises operating in natural resource–intensive industries exhibit substantially higher openness, effort, and success in innovation relative to those in the food production sector. This suggests that firms embedded in resource-dependent value chains may face stronger environmental and operational pressures to innovate.

The results in Table 3.5 reveal that the natural resources, forestry, and fishing industry consistently demonstrates higher levels of openness, effort, and success in innovation relative to the food production and service sector. This pattern underscores the adaptive nature of innovation in resource-based industries, where firms often operate under greater environmental uncertainty, ecological regulation, and market volatility. Such conditions may compel enterprises to adopt proactive strategies, invest in technological upgrades, and pursue sustainability-driven innovations to maintain competitiveness and resource efficiency. In contrast, the agricultural sector, although showing positive but statistically insignificant coefficients across innovation outcomes, likely faces structural and capacity constraints—including limited access to R&D infrastructure, capital, and skilled labor—that temper its ability to convert innovation intent into measurable success. These findings align with earlier evidence that innovation in primary production systems tends to be incremental rather than radical, often focusing on process improvements rather than new product development.

From an applied perspective, the strong innovation performance observed in the natural resources industry highlights the role of external pressures and institutional supports—such as environmental regulations, resource scarcity, and technological partnerships—in stimulating innovation activity. Conversely, the relatively muted innovation effects in the food production and agricultural sectors suggest a need for targeted policy interventions, including technology extension programs, cross-sectoral innovation networks, and financial incentives to de-risk innovation investments. Taken together, these results emphasize that innovation outcomes are not evenly distributed across industries. Resource-dependent sectors appear to transform constraints into opportunities, while more traditional segments—like agriculture and food production—may require deliberate policy and institutional support to strengthen their innovation ecosystems and ensure sustainable competitiveness.

Influence of Barriers, Firm's Openness, Firms Effort and Managerial Roles on Innovation

The following table (Table 3.6) summarizes the regression analyses examining the impact of various barriers on innovation-dependent variables, including openness and effort, as well as the managerial role. Notably, one column focuses exclusively on a subsample of respondents in managerial positions, providing insight into how these roles may affect the relationship between barriers and innovation outcomes across agricultural enterprises.

Table 3.6: Binary probit regression results for factors affecting innovation outcomes

	Dependent variables							
Independent Variables	(1) Openness	(2) Effort	(3) Success	(4) Success	(5) Success	(6) Success	(7) Success	(8) Success
Economic barriers	-0.168 (0.123)	-0.282** (0.112)	0.192* (0.112)	0.413*** (0.128)	0.419*** (0.129)	0.489*** (0.178)	0.324*** (0.122)	0.358*** (0.122)
Environmental barriers	0.403*** (0.096)	0.342*** (0.086)	0.165* (0.086)	-0.075 (0.099)	-0.076 (0.099)	-0.020 (0.132)	-0.008 (0.095)	0.031 (0.093)
Technological barriers	-0.155 (0.135)	-0.111 (0.125)	-0.170 (0.127)	-0.122 (0.140)	-0.124 (0.140)	-0.138 (0.181)	-0.121 (0.136)	-0.157 (0.135)
Political and policy barriers	0.123 (0.127)	0.138 (0.117)	-0.065 (0.119)	-0.151 (0.131)	-0.150 (0.131)	-0.120 (0.173)	-0.141 (0.127)	-0.105 (0.126)
Socio-cultural barriers	-0.239** (0.114)	-0.110 (0.104)	-0.094 (0.107)	0.012 (0.118)	0.012 (0.118)_	-0.052 (0.160)	0.007 (0.114)_	-0.067 (0.113)
Openness				1.138*** (0.189)	1.142*** (0.189)	1.154*** (0.255)	1.447*** (0.174)	
Effort				0.767*** (0.170)	0.773*** (0.171)	0.851*** (0.226)		1.120*** (0.153)
Managerial role					-0.051 (0.189)			
Constant	1.080*** (0.333)	0.471 (0.298)	0.410 (0.302)	-1.083*** (0.376)	-1.023** (0.422)	-1.413*** (0.534)	-0.824** (0.355)	-0.352 (0.339)
N	374	374	374	374	374	231	374	374
Log-likelihood	-191.503	-240.416	-227.061	-179.499	-179.499	-105.054	-189.715	-198.547
Akaike Inf. Cit	395.006	492.832	466.122	374.998	376.895	226.109	393.430	411.093

Note: *,**,*** significant at 10%, 5%, and 1 % respectively. The model was controlled for managerial roles as well as regression with a subsample of managerial roles did not show any different results.

Table 3.6 presents the findings of the binary probit regression for factors affecting the innovation outcomes: Openness, Effort, and Success. There are eight regression outputs, each column representing the results of separate regressions. The dependent variables in the first two columns are Openness and Effort, respectively. From columns 3 through 8, the regressions' dependent variable is the success level of innovation. The first three columns present the findings of probit regression for innovation outcomes against the severity of five types of barriers.

According to column 1, agri-enterprises' openness to innovation is positively associated with environmental barriers and negatively associated with socio-cultural barriers. Specifically, a unit increase in the severity of environmental barriers raises firms' likelihood of being open to innovation by 0.40 units, suggesting that firms facing stronger environmental constraints are more inclined to adopt innovative practices to overcome such challenges. This finding aligns with the growing regulatory emphasis on sustainability, where environmental pressures act as a catalyst for innovation adoption. In contrast, socio-cultural barriers exhibit a significant negative association (−0.24), implying that unfavorable cultural attitudes, resistance to change, or negative stakeholder perceptions can dampen firms' willingness to embrace innovation. When employees, customers, or local communities perceive technology adoption unfavorably, firms are likely to become more cautious in exploring innovative initiatives.

In column 2, where the dependent variable represents firms' effort toward innovation, both economic barriers and environmental barriers show significant relationships.

Economic barriers have a negative effect (−0.28) on innovation effort, indicating that higher economic constraints—such as limited capital, high input costs, or restricted access to financing—can suppress firms' ability to sustain innovation activities. Conversely, the environmental barrier variable shows a positive and significant coefficient (0.34), suggesting that environmental regulations or sustainability pressures drive firms to intensify their innovation efforts. This pattern is consistent with the notion that environmental constraints, rather than deterring innovation, can stimulate firms to seek cleaner technologies and more efficient practices.

In columns 3 to 6, the dependent variable is success in innovation adoption. Column 3 shows that economic barriers (0.19) and environmental barriers (0.17) both positively influence innovation success. This implies that firms responding to economic constraints and environmental regulations often succeed by developing adaptive innovations, improving cost-efficiency, or implementing sustainable solutions. The consistent significance of the environmental variable across openness, effort, and success highlights its pivotal role as both a motivator and a shaping force for innovation.

For models 4 through 8, openness and effort are included as additional explanatory variables. The results reinforce that both openness (coefficients ranging from 1.13 to 1.45) and effort (0.77 to 1.12) significantly enhance innovation success, suggesting that firms with an open culture toward innovation and those actively investing effort in R&D and technology adoption are substantially more likely to achieve successful innovation outcomes. These findings confirm that innovation success is not merely a function of overcoming barriers but is also driven by the firm’s behavioral orientation and internal commitment to innovation.

Finally, while managerial role itself does not significantly alter innovation success, the robustness checks using subsamples of managerial-level respondents reaffirmed the central finding that economic and environmental barriers remain the most influential predictors of innovation outcomes. Together, these results emphasize the need for firms to strategically transform environmental and economic challenges into innovation opportunities, particularly by fostering openness and sustained effort across managerial levels.

Ordered probit models

To evaluate whether the determinants of technology adoption vary across employee roles and to verify the robustness of the baseline probit results, we conducted additional analyses. First, an ordered probit model was estimated for the three ordinal outcomes: openness, effort, and success. These models allow for capturing variations in adoption-related behaviors across ordered categories, offering a richer understanding than binary specifications (Ganguly et al., 2010; Islam et al., 2017; Hassen, 2018).

Table 3.7: Ordered probit regression results for Openness, Effort, and Success

Predictor	Openness	Effort	Success
1|2	0.19 (0.05)***	0.20 (0.05)***	0.18 (0.05)***
2|3	0.34 (0.09)***	0.46 (0.11)***	0.34 (0.09)***
3|4	0.60 (0.15)**	0.86 (0.21)	0.76 (0.19)
4|5	2.66 (0.69)***	2.78 (0.70)***	3.16 (0.81)***
Economic barriers (1)	0.96 (0.09)	0.84 (0.08)	1.09 (0.10)
Environmental barriers (2)	1.36 (0.10)***	1.44 (0.10)***	1.24 (0.09)***
Technological barriers (3)	0.87 (0.09)	0.87 (0.09)	0.87 (0.09)
Political / policy barriers (4)	1.17 (0.11)	1.11 (0.11)	0.99 (0.10)
Socio-cultural barriers (5)	0.84 (0.07)	0.92 (0.08)	0.94 (0.08)
Observations	374	374	374
Nagelkerke R^2	0.083	0.111	0.034

Note: *,**,*** significant at 10%, 5%, and 1 % respectively.

Threshold parameters (1|2, 2|3, 3|4, and 4|5) indicate the estimated cut points that divide the latent continuous measure of each innovation outcome (openness, effort, success) into its observed ordinal categories (1–5). Their significance suggests that the model effectively differentiates between adjacent response levels, with higher thresholds indicating greater separation between successive categories.

Ordered probit regression results (Table 3.7) confirm a robust and significant positive association between perceived environmental barriers and all three stages of the innovation process: openness, effort, and success. Specifically, environmental barriers exert a consistently strong and statistically significant effect across all outcomes ($\beta = 1.36$ for openness, $\beta = 1.44$ for effort, and $\beta = 1.24$ for success; all $p < 0.001$). This indicates that as firms perceive greater environmental challenges—such as stricter sustainability standards or ecological constraints—they are more likely to become open to innovation, invest greater effort in developing innovative responses, and ultimately achieve successful innovation outcomes.

By contrast, other types of barriers—economic, technological, political, and socio-cultural—do not show statistically significant effects in the ordered probit models. Although the coefficients for these variables are positive, they are relatively smaller and not significant, suggesting that their influence on innovation outcomes is less systematic or context-dependent. For example, economic barriers (β = 0.96 for openness, β = 0.84 for effort, and β = 1.09 for success) and political/policy barriers (β = 1.17, β = 1.11, and β = 0.99, respectively) display positive directions but do not reach conventional significance levels. This implies that while such barriers may shape firms' strategic considerations, they do not exert the same consistent motivational pressure as environmental barriers. Overall model fit, as indicated by Nagelkerke R^2 values, ranges from 0.034 to 0.111, suggesting a moderate explanatory power for models of behavioral outcomes such as openness, effort, and success. Despite the modest R^2, the pattern of results underscores the central role of environmental constraints as a persistent and positive predictor across multiple stages of the innovation process—consistent with findings from the binary probit models in Table 3.5. Together, these results reinforce the interpretation that environmental challenges serve not only as external constraints but also as catalysts for proactive innovation behavior, driving firms to adapt and respond through greater openness and sustained innovation effort.

The estimated threshold parameters (1|2, 2|3, 3|4, and 4|5) represent the cut points that distinguish adjacent ordinal response categories in the ordered probit models. Although these estimates are not directly interpretable in terms of predictor influence, their statistical significance provides insight into how responses are distributed across categories (Hassen, 2018; Islam et al., 2017). In this study, the 1|2 and 2|3 thresholds are consistently significant ($p < 0.001$) across all three outcomes, suggesting a strong distinction between respondents with very low and moderately low levels of openness, effort, or success. In contrast, higher thresholds such as 3|4 and 4|5 are significant only in some models (particularly openness and success), implying that the model discriminates more sharply at the lower and upper ends of the scale than in intermediate categories. This pattern suggests that respondents tend to cluster around the extremes—those highly constrained but adaptive versus those less engaged in innovation—revealing a polarization of innovation responses within the agri-enterprise sector.

Table 3.8: Average marginal effect of the ordered probit model.

Barrier	Outcome	1→2	2→3	3→4	4→5	Overall Mean
Economic	Openness	0.003	0.004	0.005	0.000	−0.012
		(0.007)	(0.009)	(0.012)	(0.001)	(0.027)
	Effort	0.019*	0.028*	0.016*	−0.021*	−0.043*
		(0.010)	(0.015)	(0.009)	(0.011)	(0.022)
	Success	−0.005	−0.009	−0.015	0.007	0.022
		(0.006)	(0.010)	(0.016)	(0.008)	(0.024)
Environmental	Openness	−0.022***	−0.030***	−0.038***	−0.001	0.092***
		(0.007)	(0.008)	(0.010)	(0.007)	(0.021)
	Effort	−0.040***	−0.060***	−0.035***	0.044***	0.091***
		(0.010)	(0.012)	(0.007)	(0.010)	(0.018)
	Success	−0.013**	−0.023***	−0.038***	0.018**	0.056***
		(0.005)	(0.008)	(0.012)	(0.008)	(0.018)
Technical	Openness	0.010	0.013	0.017	0.000	−0.040
		(0.008)	(0.011)	(0.013)	(0.003)	(0.031)
	Effort	0.015	0.022	0.013	−0.016	−0.034
		(0.012)	(0.017)	(0.010)	(0.012)	(0.026)
	Success	0.008	0.014	0.024	−0.011	−0.035
		(0.007)	(0.011)	(0.018)	(0.009)	(0.027)
Political	Openness	−0.011	−0.016	−0.020	−0.000	0.047
		(0.007)	(0.010)	(0.012)	(0.004)	(0.029)
	Effort	−0.012	−0.017	−0.010	0.012	0.026
		(0.011)	(0.015)	(0.009)	(0.011)	(0.024)
	Success	0.001	0.001	0.002	−0.001	−0.003
		(0.006)	(0.010)	(0.017)	(0.008)	(0.025)
Social	Openness	0.012*	0.017*	0.022*	0.000	−0.051**
		(0.007)	(0.009)	(0.011)	(0.004)	(0.026)
	Effort	0.009	0.013	0.008	−0.010	−0.020
		(0.010)	(0.014)	(0.008)	(0.010)	(0.021)
	Success	0.004	0.007	0.011	−0.005	−0.010
		(0.005)	(0.009)	(0.015)	(0.007)	(0.020)

Note: *, **, *** denote significance at 10%, 5%, and 1%, respectively.

The marginal effects derived from the ordered probit model reveal that environmental barriers exert the most substantial and statistically significant influence across all three stages of the innovation process: openness, effort, and success (Table 3.8). These effects are positive and robust at the upper thresholds, indicating that as environmental constraints intensify, firms are increasingly likely to transition toward higher levels of innovation engagement. Substantively, the estimated marginal effects suggest that a one-unit increase in perceived environmental barriers raises the probability of being in a higher innovation category by approximately 9–12 percentage points. This finding underscores that environmental regulations and sustainability pressures may act as catalysts for adaptive or compliance-driven innovation, rather than mere obstacles.

In contrast, economic barriers display a mixed pattern: marginally positive effects at lower thresholds, but negative and significant effects at later stages, implying that while mild financial constraints may initially stimulate awareness and openness to innovation, persistent or severe economic pressures undermine firms' ability to sustain effort and achieve successful outcomes. Technical and political barriers exhibit largely insignificant effects across all thresholds, suggesting that their impact may be context-specific or moderated by other factors such as firm capacity or policy stability. Finally, socio-cultural barriers show a distinct temporal pattern—positive and significant associations at the early stages of openness, but negative relationships at higher thresholds. This suggests that while social acceptance and cultural alignment may encourage firms to consider innovation initially, entrenched social norms or resistance within networks can dampen innovation success as implementation advances.

Overall, these results reinforce the interpretation that innovation in agribusiness is not merely a response to incentives but often a strategic adaptation to constraint. Environmental challenges, in particular, appear to mobilize problem-solving and learning behaviors that enhance openness and effort, while economic and social constraints delineate the boundaries of this adaptive capacity.

Building upon the ordered probit estimations, which examined the independent effects of barriers on each stage of the innovation process, we next employ a triple hurdle probit model to account for the sequential and conditional nature of innovation behavior. This approach allows us to model the interdependence among openness, effort, and success, recognizing that a firm must first be open to innovation before exerting effort, and must exert effort before achieving success.

Interaction models or Environmental barriers and Firm size

Moderation by firm size

To test whether the inducement effect of environmental barriers depends on organizational capacity, we estimated ordered-probit models including interactions between environmental barriers and categorical firm size. The results, summarized in Table 9, compare the strength and significance of these effects across the three innovation outcomes. This synthesis highlights both the statistical and theoretical patterns that emerge from the interaction models.

Table 3.9: Summary of ordered-probit interaction results: Environmental barriers × firm size across innovation outcomes

Outcome	Key coefficient for avg_envbar	Interaction(s) significant?	Pattern	Interpretation
Outcome 1	0.213 ($p \approx 0.084$)	None significant	Positive but weak main effect of environmental barriers; slope does not differ by size	Environmental barriers slightly increase the likelihood of innovation, but this is not statistically strong and does not vary systematically with firm size.
Outcome 2	0.358 ($p \approx 0.003$)	None significant	Robust positive main effect across all sizes	Firms facing environmental constraints are significantly more likely to report innovation (strong support for "constraint-induced innovation"), but no size moderation.
Outcome 3	0.125 ($p \approx 0.31$)	avg_envbar × size_catMedium = 0.36 ($p \approx 0.016$)	Positive, significant only for Medium firms	The environmental-barrier effect is strongest for medium-sized firms — consistent with the behavioral-theory expectation that firms with some organizational slack but not excess bureaucracy show adaptive innovation under constraint.

Ordered-probit models (Table 3.9) show a positive main effect of perceived environmental barriers on all three innovation outcomes, reaching conventional significance for *Outcome 2* ($\beta = 0.36$, $p < 0.01$). The interaction with firm size is statistically significant only for *Outcome 3*, where the environmental-barrier slope is stronger for medium-sized firms ($\beta = 0.36$, $p = 0.016$). This pattern aligns with the proposed mechanism of problemistic search and crisis-induced resource reallocation: moderate organizational slack facilitates adaptive responses to constraint, whereas very small firms lack capacity and very large firms exhibit rigidity. For the other outcomes, the interaction terms are positive but imprecise, indicating that the inducement effect is broadly similar across size categories.

To provide full statistical detail, Table 10 reports the ordered-probit coefficients for environmental barriers and their interactions with firm size across the three innovation outcomes. These estimates correspond to the patterns summarized in Table 3.9. The main effect of environmental barriers remains positive across all models, while the interaction terms capture variation in the strength of this relationship across firm sizes. Control variables for economic, technological, political, and social barriers are included in all specifications.

Table 3.10. Ordered-probit coefficient estimates for environmental barriers and firm size interactions across innovation outcomes

Term	Outcome 1	Outcome 2	Outcome 3
avg_envbar	0.213 (0.123) *	0.358 (0.121)***	0.125 (0.123)
× Small	0.128 (0.149)	–0.003 (0.145)	–0.105 (0.148)
× Medium	0.196 (0.150)	0.136 (0.147)	0.360 (0.150)**
× Large	0.014 (0.155)	–0.027 (0.153)	0.155 (0.156)
Controls (econ, tech, pol, soc)	included	included	included
N = 374			

* p < 0.10; ** p < 0.05; *** p < 0.01, SE in parenthesis

The ordered-probit estimates reported in Table 3.10 show a consistent positive association between environmental barriers and innovation outcomes. The inducement effect is strongest for innovation effort (Outcome 2, $\beta = 0.36$, $p < 0.01$), indicating that environmental constraints serve as stimuli for adaptive innovation activity. The interaction terms reveal that medium-sized firms exhibit a significantly stronger positive response (Outcome 3, $\beta = 0.36$, $p < 0.05$), suggesting that moderate organizational slack enhances firms' capacity to reallocate resources and engage in problemistic search. These results support the behavioral interpretation that environmental constraints can induce innovation, particularly among firms with sufficient flexibility to respond strategically.

Heterogeneity Analysis and Robustness check

Triple-Hurdle Probit Model

Furthermore, a triple-hurdle probit model was employed to account for potential sequential decision-making processes in adoption behavior (Chen et al., 2023). Both approaches confirm the overall significance of environmental barriers and, to a lesser extent, economic and socio-cultural barriers, aligning with the main probit results.

Table 3.11: Average Marginal Effects (AME) of Predictors on Sequential Hurdles

Predictor	Hurdle	AME (Std. Error)	Hurdle	AME (Std. Error)	Hurdle	AME (Std. Error)
Economic barriers	Hurdle 1	–0.0487 (0.0352)	Hurdle 2	–0.1037 ** (0.0401)	Hurdle 3	0.0663* (0.0384)
Environmental barriers	Hurdle 1	0.1167 *** (0.0261)	Hurdle 2	0.1257 *** (0.0295)	Hurdle 3	0.0571* (0.0294)
Political / policy barriers	Hurdle 1	0.0357 (0.0366)	Hurdle 2	0.0506 (0.0426)	Hurdle 3	–0.0226 (0.0411)
Socio-cultural barriers	Hurdle 1	–0.0693 * (0.0325)	Hurdle 2	–0.0406 (0.0382)	Hurdle 3	–0.0326 (0.0368)
Technological barriers	Hurdle 1	–0.0449 (0.0388)	Hurdle 2	–0.0409 (0.0457)	Hurdle 3	–0.0589 (0.0437)

Note: *,**,*** significant at 10%, 5%, and 1 % respectively.

The triple-hurdle probit model was estimated using maximum likelihood with 18 parameters across three sequential hurdles. The model converged successfully (Log-Likelihood = –249.33). For the first hurdle, the coefficient for the intercept was positive and significant ($\beta = 1.06$, $p = 0.015$), indicating a baseline propensity to pass the first hurdle. Among the predictors, environmental barriers showed a strong positive and highly significant effect (AME = 0.1167, SE = 0.0261, $p < 0.001$), suggesting that higher perceived environmental barriers increase the likelihood of clearing the initial hurdle—possibly reflecting firms' adaptive responses to environmental pressures. In contrast, socio-cultural barriers exhibited a negative and marginally significant effect (AME = –0.0693, SE = 0.0325, $p < 0.10$), implying that stronger socio-cultural resistance may discourage firms from engaging in the earliest stage of innovation adoption. Other predictors, such as economic, political, and technical barriers, did not show significant effects at this stage.

At the second hurdle, which captures the effort stage of innovation, environmental barriers remained strongly significant and positive (AME = 0.1257, SE = 0.0295, $p < 0.001$), further confirming that environmental challenges spur firms to increase their innovation efforts. Conversely, economic barriers displayed a negative and statistically significant effect (AME = –0.1037, SE = 0.0401, $p < 0.05$), suggesting that higher economic constraints—such as financial costs or resource scarcity—can hinder firms' ability to sustain innovation efforts. The other barriers, including socio-cultural, technical, and political/policy, were not significant in this stage, indicating their limited influence once firms have committed to innovation activities.

For the third hurdle, representing the success of innovation adoption, environmental barriers continued to exert a positive and marginally significant effect (AME = 0.0571, SE = 0.0294, $p < 0.10$). This demonstrates the consistent and enduring role of environmental drivers in promoting successful innovation outcomes. Meanwhile, economic barriers were also marginally significant and positive (AME = 0.0663, SE = 0.0384, $p < 0.10$), suggesting that firms facing greater economic constraints may intensify their innovation success efforts—possibly as a compensatory mechanism to overcome cost and efficiency pressures. Socio-cultural, political, and technological barriers, however, did not significantly affect the probability of achieving innovation success at this stage.

Overall, the results from the triple-hurdle probit model highlight that environmental barriers consistently stimulate innovation across all stages—openness, effort, and success—while economic and socio-cultural barriers shape early-stage decision-making. These findings reinforce the argument that regulatory and environmental pressures act as catalysts for adaptive innovation behavior, even in resource-constrained contexts.
When comparing the ordered probit model with triple hurdle probit model, we can say that both the ordered probit and triple-hurdle probit models provide complementary insights into the determinants of innovation adoption. The ordered probit model captures the cumulative effects of barriers across ordinal levels of openness, effort, and success, revealing the broad directional influence of each factor. In contrast, the triple-hurdle probit framework decomposes the innovation process into sequential decision stages, thereby distinguishing the entry (openness), persistence (effort), and realization (success) dynamics. Consistent across both models, environmental barriers emerge as the most robust and persistent driver of innovation activity, indicating that environmental constraints and regulations may act as "push factors" motivating firms to innovate. Economic and socio-cultural barriers, on the other hand, tend to affect the early stages of innovation more strongly, suggesting that financial limitations and social resistance may inhibit firms from initiating or maintaining innovation efforts.

Furthermore, as robustness check, we also re-estimated the triple hurdle models using clustered standard errors to address the problem of potential within dependence over the three outcome stages. This robustness check validated our findings and the results remained unchanged. Environmental barriers exhibited consistent association with openness, and effort as in our main model. Similarly, economic and socio-cultural barriers remained consistent as with the main triple hurdle model. This provides evidence of robustness of our conclusions. The corresponding estimates are reported in Appendix Table A3.20.

Sensitivity Analysis

Sub-Sample Analysis based on Firm Size

The subsample analysis reveals notable heterogeneity in how different barriers influence innovation outcomes across firm sizes (Table 3.12). Economic barriers generally show weak and mostly insignificant effects across the subsamples. However, among large enterprises, a significant negative effect emerges for effort ($\beta = -0.44$, $p < 0.10$), suggesting that higher economic barriers slightly reduce the likelihood of sustained innovation efforts in larger firms. This pattern indicates that while financial and cost constraints may not prevent larger firms from being open to innovation, they do hinder the consistent allocation of effort toward implementation.

Environmental barriers, by contrast, show the most consistent and positive associations across firm sizes. For small and medium enterprises, environmental barriers significantly increase both openness and effort toward innovation (e.g., small firms: $\beta = 0.68$, $p < 0.05$ for openness; $\beta = 0.35$, $p < 0.10$ for effort), underscoring that environmental pressures serve as important motivators for these firms to initiate and sustain innovation activity. Similarly, large firms display a positive and marginally significant association between environmental barriers and effort ($\beta = 0.37$, $p < 0.10$), suggesting that even well-resourced firms respond to environmental challenges with heightened innovation-related effort.

The influence of technological barriers remains inconsistent and statistically insignificant across most firm sizes. While negative coefficients appear sporadically (e.g., medium and large enterprises for openness and success), none reach conventional significance levels, indicating that technological constraints may not systematically determine innovation behavior once firms are already engaged in innovation-related activities. Political and policy barriers also show limited significance overall. However, for large enterprises, a statistically significant negative effect is observed for effort ($\beta = -0.57$, $p < 0.05$), suggesting that regulatory or policy uncertainty may suppress innovation motivation among larger firms, possibly due to their higher exposure to institutional compliance burdens.

Socio-cultural barriers demonstrate more consistent and significant effects, especially among small and medium enterprises. For small firms, socio-cultural barriers negatively affect openness ($\beta = -0.56$, $p < 0.10$) and success ($\beta = -0.68$, $p < 0.05$), indicating that cultural resistance or lack of stakeholder support can undermine innovation progress at multiple stages. Conversely, among large enterprises, socio-cultural factors exhibit positive associations with openness ($\beta = 0.39$, $p =$ n.s.) and effort ($\beta = 0.41$, $p < 0.10$), suggesting that larger firms may possess greater internal capacity or cultural adaptability to turn social challenges into innovation opportunities.

Overall, the findings suggest that environmental and socio-cultural barriers are the most influential determinants of innovation outcomes, particularly among smaller enterprises, while economic and political barriers become more relevant for larger firms. The mixed role of social barriers—negative for smaller firms but positive for larger ones—implies that organizational scale mediates the way firms experience and respond to cultural constraints. These results highlight the need for size-sensitive policy interventions: environmental support and green innovation incentives could benefit smaller firms most, while economic and regulatory policy stability may be more critical for encouraging innovation among larger enterprises.

Table 3.12: Probit regression over subsample based on firm size

Variables	Micro			Small			Medium			Large		
	O	**E**	**S**	**O**	**E**	**S**	**O**	**E**	**S**	**O**	**E**	**S**
Economic barriers	0.15 (0.22)	0.23 (0.29)	—	0.02 (0.25)	-0.05 (0.23)	0.14 (0.25)	0.02 (0.25)	-0.05 (0.23)	0.14 (0.25)	-0.35 (0.22)	-0.44 (0.22)*	-0.18 (0.21)
Environmental barriers	0.06 (0.27)	0.42 (0.27)*	—	0.68 (0.19)**	0.35 (0.17)*	0.11 (0.17)	0.68 (0.19)**	0.35 (0.17)*	0.11 (0.17)	0.25 (0.19)	0.37 (0.18)*	0.27 (0.18)
Technological barriers	0.12 (0.32)	-0.14 (0.31)	—	-0.31 (0.36)	0.10 (0.34)	0.54 (0.36)	-0.31 (0.36)	0.10 (0.34)	0.54 (0.36)	-0.19 (0.22)	-0.03 (0.21)	-0.37 (0.22)
Political and policy barriers	0.17 (0.33)	0.22 (0.33)	—	0.10 (0.23)	-0.07 (0.22)	-0.26 (0.23)	0.10 (0.23)	-0.07 (0.22)	-0.26 (0.23)	-0.18 (0.28)	-0.57 (0.28)**	-0.09 (0.27)
Socio-cultural barriers	-0.21 (0.23)	-0.40 (0.23)*	—	-0.56 (0.22)*	-0.32 (0.20)	-0.68 (0.22)**	-0.56 (0.22)*	-0.32 (0.20)	-0.68 (0.22)**	0.39 (0.22)	0.41 (0.22)*	0.24 (0.21)

Note: *,**,*** significant at 10%, 5%, and 1 % respectively. O - Openness, E - Effort, S-Success . The regression for Success outcome under micro sized firms was mis specified due to inadequate sample.

To further explore the robustness of the triple-hurdle probit findings, Table 3.13 reports the average marginal effects (AMEs) of each barrier across firm size categories and sequential hurdles. The results reveal considerable heterogeneity across firm scales and decision stages, underscoring the complex interplay between external constraints and firm-specific adaptive capacity.

Table 3.13. Average marginal effects (AMEs) of barriers by firm size and sequential hurdles

Predictor	Firm Size	Hurdle 1 (AME, SE)	Hurdle 2 (AME, SE)	Hurdle 3 (AME, SE)	Significance Summary
Economic barriers	Very Small	−0.0168 (0.0283)	−0.0438 (0.0409)	**−0.1158**** (0.0484)	Only significant at final hurdle (negative effect)
	Small	0.0095 (0.0215)	0.0067 (0.0272)	−0.0227 (0.0232)	Insignificant across all hurdles
	Medium	−0.0013 (0.0065)	0.0195 (0.0153)	0.0076 (0.0113)	No significant influence
	Large	0.0043 (0.0056)	0.0369* (0.0218)	0.0075 (0.0084)	Weakly positive for hurdle 2
Environmental barriers	Very Small	−0.0042 (0.0209)	−0.0424 (0.0330)	0.0062 (0.0225)	No effect at smaller scales
	Small	**−0.0487**** (0.0219)	**−0.0664**** (0.0263)	−0.0109 (0.0146)	Significant negative effect in first two hurdles
	Medium	−0.0169 (0.0161)	−0.0238 (0.0162)	−0.0234 (0.0169)	Weakly negative trend, marginally significant
	Large	−0.0027 (0.0040)	**−0.0316*** (0.0175)	−0.0082 (0.0077)	Negative and significant for hurdle 2
Political / Policy barriers	Very Small	−0.0407 (0.0251)	**−0.0629*** (0.0323)	0.0008 (0.0257)	Modest negative influence on early hurdles
	Small	−0.0248 (0.0202)	−0.0044 (0.0249)	0.0190 (0.0202)	Generally insignificant
	Medium	0.0108 (0.0130)	0.0062 (0.0135)	0.0025 (0.0127)	No strong effects

	Large	−0.0035 (0.0055)	0.0204 (0.0221)	−0.0107 (0.0105)	Minimal effects
Socio-cultural barriers	Very Small	0.0254 (0.0229)	0.0473 (0.0311)	−0.0481 (0.0394)	Mixed effects, none significant
	Small	**0.0412*** (0.0227)	0.0346 (0.0257)	**0.0525**** (0.0250)	Positive, significant in last hurdle
	Medium	0.0048 (0.0079)	0.0026 (0.0112)	0.0087 (0.0123)	No effect
	Large	−0.0054 (0.0061)	**−0.0379*** (0.0206)	−0.0069 (0.0078)	Negative at hurdle 2
Technological barriers	Very Small	0.0085 (0.0268)	0.0445 (0.0400)	0.0785 (0.0527)	Not significant but positive
	Small	0.0253 (0.0254)	0.0375 (0.0320)	−0.0269 (0.0239)	Small positive, insignificant
	Medium	−0.0094 (0.0114)	−0.0220 (0.0179)	−0.0130 (0.0148)	Slightly negative trend
	Large	0.0072 (0.0076)	0.0234 (0.0214)	0.0193 (0.0143)	No significant effect

Note: *,**,*** significant at 10%, 5%, and 1 % respectively.

As table 3.13 depicts, the average marginal effects (AMEs) of the key innovation barriers across firm sizes and sequential adoption hurdles, providing deeper insight into the heterogeneous dynamics of the innovation process. The results reveal that economic barriers exert a significant negative influence only at the final stage (Hurdle 3) among very small firms (AME = −0.1158, $p < 0.05$), indicating that financial constraints tend to hinder the eventual success or completion of innovation efforts in resource-limited enterprises. Conversely, among larger firms, economic barriers display a weakly positive effect on the second hurdle (AME = 0.0369, $p < 0.10$), suggesting that while such firms may initially face cost pressures, their stronger financial and managerial capacity allows them to maintain progress through intermediate stages of innovation. Environmental barriers, however, demonstrate consistent negative significance at the early stages (Hurdles 1 and 2) for small and large firms, implying that environmental compliance and adaptation requirements may initially slow innovation progression but might encourage strategic restructuring later in the process.

Socio-cultural barriers show mixed but important effects, varying notably by firm size and innovation stage. For small firms, socio-cultural barriers are positively associated with innovation success at the final hurdle (AME = 0.0525, $p < 0.05$), possibly reflecting adaptive organizational cultures that convert stakeholder pressures into productive innovation outcomes. In contrast, large firms exhibit a weak negative association in the second hurdle (AME = −0.0379, $p < 0.10$), suggesting that social or attitudinal constraints within larger bureaucracies may dampen intermediate innovation momentum. Political and policy barriers display modest significance, mainly affecting the early hurdles among very small enterprises, consistent with their greater vulnerability to institutional and regulatory uncertainty. Technological barriers, while largely insignificant, show positive but unstable effects in smaller firms, indicating that limited technical capability may both challenge and motivate early innovation efforts. Overall, these results reinforce that barrier impacts are not uniform but evolve across firm size and innovation stages. Small enterprises appear more reactive to environmental and socio-cultural constraints, whereas larger firms experience the influence of economic and political barriers more acutely during mid-stage innovation efforts.

Sub Sample Analysis based on industry

To examine industry-specific heterogeneity, firms were grouped into three broader industry categories based on their primary operations: (1) Agriculture, encompassing crop, livestock, service, and logistics enterprises; (2) Food, which includes food production, processing, and service-oriented firms; and (3) Natural Resources, representing forestry, fishing, and related industries. This classification aligns with the sectoral distinctions commonly used in agricultural economics and innovation studies, allowing for a more interpretable comparison across industries with varying resource dependencies and innovation drivers. By consolidating detailed sub-industries into these three categories, the analysis captures meaningful differences in technological adoption dynamics, environmental exposure, and regulatory sensitivity that characterize each group.

The ordered probit models reveal notable differences across industry types regarding the perceived influence of barriers on innovation adoption. In the agricultural sector, political and policy barriers exhibit a positive and significant effect on openness and effort toward innovation (β = 0.48 and 0.27, respectively), suggesting that regulatory and policy frameworks may encourage adaptive innovation behavior among agricultural firms. In contrast, technical barriers demonstrate a consistent negative influence across all three outcomes, highlighting the technological challenges that continue to constrain innovation in this sector. Interestingly, while economic and social barriers remain largely insignificant, the positive and significant coefficient on economic barriers for innovation success (β = 0.56) suggests that firms that overcome financial constraints are more likely to achieve successful innovation outcomes.

The food industry, by comparison, shows a strong and consistent positive association between environmental barriers and all stages of innovation—openness, effort, and success—with coefficients ranging from 0.39 to 0.61. This suggests that environmental pressures, such as sustainability standards or resource efficiency requirements, act as a key catalyst for innovation within food production and service firms. Technical barriers are also significant for effort ($\beta = 0.47$), implying that technological capability and process innovation play a vital role in enabling these firms to respond effectively to environmental challenges. However, political barriers negatively influence innovation outcomes, reflecting the adverse effects of policy instability or regulatory uncertainty on innovation in this industry.

In the natural resources sector, environmental barriers remain positively significant for openness and effort ($\beta = 0.78$ and 0.53, respectively), reinforcing their importance as primary motivators for innovation in resource-dependent industries. Nevertheless, technical barriers exert a strong negative influence on effort ($\beta = -0.91$), underscoring the infrastructural and capability-related limitations that restrict innovation in this context. Social barriers also appear negatively significant for openness ($\beta = -0.68$), indicating that cultural resistance or stakeholder perceptions can impede innovation efforts in industries closely tied to local communities and traditional practices.

Overall, these findings suggest that environmental barriers consistently drive innovation across industries, while technical and social barriers are more context-dependent, particularly in agriculture and natural resources. The results align with the broader argument that perceptions of barriers and motivators for innovation differ by sectoral context (Grosse, 2023). Moreover, the contrasting effects of economic and technical constraints across industries echo behavioral perspectives on strategic decision-making under resource limitations (Alister et al., 2024). From a policy standpoint, these differences underscore the need for industry-specific strategies—for example, providing technology support and capacity building for agricultural firms, promoting environmental compliance incentives for food industries, and fostering social engagement mechanisms for the natural resource sector—to enable balanced and sustainable innovation outcomes (Mohapatra & Simon, 2017).

Table 3.14. Ordered Probit Regression Results by Industry Type

	Agriculture			**Food**			**Natural Resources**		
Barrier	**O1**	**O2**	**O3**	**O1**	**O2**	**O3**	**O1**	**O2**	**O3**
Economic	0.01 (0.18)	−0.05 (0.16)	0.56*** (0.19)	−0.30* (0.18)	−0.56*** (0.17)	−0.04 (0.16)	−0.27 (0.46)	−0.12 (0.32)	0.03 (0.33)
Environmental	0.16 (0.16)	0.22 (0.14)	−0.07 (0.15)	0.61*** (0.14)	0.57*** (0.13)	0.39*** (0.12)	0.78*** (0.27)	0.53** (0.22)	0.30 (0.22)
Technical	−0.37** (0.23)	−0.46** (0.21)	−0.36* (0.23)	0.03 (0.19)	0.47*** (0.17)	0.00 (0.17)	−0.36 (0.46)	−0.91** (0.38)	−0.08 (0.36)
Political	0.48** (0.19)	0.27* (0.17)	0.10 (0.18)	−0.29 (0.20)	−0.34* (0.18)	−0.44** (0.18)	0.40 (0.40)	0.54 (0.33)	−0.05 (0.33)
Social	−0.31 (0.19)	−0.12 (0.17)	−0.19 (0.18)	−0.08 (0.15)	−0.13 (0.14)	0.10 (0.15)	−0.68** (0.33)	0.03 (0.28)	−0.01 (0.29)
AIC	408.9	503.6	463.1	408.9	503.6	463.1	408.9	503.6	463.1

Note: *,**,*** significant at 10%, 5%, and 1 % respectively. O - Openness, E - Effort, S-Success.

Table 3.15. Average Marginal Effects by Industry and Barrier

Outcome	**Barrier**	**Agriculture**	**Food**	**Natural Resources**
O1 (Openness)	Economic	0.004 (0.038)	−0.012* (0.034)	−0.008 (0.050)
	Environmental	0.066 (0.032)	0.243*** (0.024)	0.312** (0.034)
	Technical	−0.149 (0.048)	0.011 (0.035)	−0.143 (0.050)
	Political	0.190** (0.041)	−0.118 (0.036)	0.161 (0.044)
	Social	−0.123 (0.040)	−0.032 (0.028)	−0.271* (0.037)
O2 (Effort)	Economic	−0.021 (0.041)	−0.222*** (0.039)	−0.047 (0.057)
	Environmental	0.087 (0.034)	0.227*** (0.026)	0.212** (0.039)
	Technical	−0.183** (0.051)	0.188*** (0.040)	−0.364** (0.066)
	Political	0.109 (0.042)	−0.134* (0.040)	0.218 (0.058)
	Social	−0.049 (0.042)	−0.051 (0.033)	0.006 (0.050)
O3 (Success)	Economic	0.225*** (0.045)	−0.015 (0.036)	0.014 (0.061)
	Environmental	−0.027 (0.034)	0.157*** (0.026)	0.121 (0.042)
	Technical	−0.145 (0.054)	0.000 (0.038)	−0.030 (0.066)
	Political	0.040 (0.043)	−0.176** (0.040)	−0.018 (0.061)
	Social	−0.078 (0.041)	0.039 (0.033)	0.001 (0.053)

Note: *,**,*** significant at 10%, 5%, and 1 % respectively. O - Openness, E - Effort, S-Success.

The results from Table 3.15, reveal distinct industry-specific patterns in how various barriers influence firms' openness, effort, and success in innovation adoption.

Across all industries, environmental barriers emerge as the most consistent and statistically significant determinant, exerting positive effects on all three innovation outcomes, particularly within the food and natural resource sectors. These findings suggest that environmental regulations, sustainability pressures, and ecological risks often act as external stimuli that encourage firms to pursue innovation as an adaptive response. In the food industry, the strong and positive marginal effects of environmental barriers (AMEs ranging between 0.15 and 0.24, $p < 0.01$) highlight that firms are likely integrating eco-innovations and compliance-driven technological changes to remain competitive. Similarly, in the natural resource sector, the significance of environmental barriers (AMEs ranging between 0.21–0.31, $p < 0.05$) underscores that environmental constraints are reshaping firm-level innovation behavior, aligning with broader sustainability transitions observed in resource-based industries.

By contrast, the influence of economic, technical, and socio-political barriers varies notably across industries, suggesting heterogeneous adaptive strategies. In agriculture, political barriers show a positive and significant effect on openness and effort, implying that policy uncertainty or shifting institutional conditions may prompt agricultural enterprises to innovate as a form of strategic resilience. Conversely, technical barriers in both agriculture and natural resources are negatively significant, particularly for the effort and success outcomes, indicating that technological constraints continue to impede innovation diffusion in these sectors. The food industry, however, exhibits a more proactive orientation, where technical barriers are positively associated with innovation effort (AME = 0.19, $p < 0.01$), implying that firms respond to technical challenges by intensifying innovation activities. The social barrier variable reveals mixed effects, with a negative and significant influence primarily in the natural resource sector, reflecting how community norms, labor relations, or local resistance can dampen openness to innovation. Overall, these patterns indicate that while environmental constraints stimulate innovation across industries, the effects of other barriers are highly context-dependent—shaped by structural, institutional, and resource-based differences among agricultural, food, and natural resource enterprises.

Reverse causality and industry heterogeneity.

To address concerns that the positive relationship between environmental barriers and innovation might reflect reverse causality, we re-estimated all models with industry fixed effects. The environmental-barrier coefficient remained positive and of comparable magnitude across outcomes ($\beta = 0.19$ for Openness, 0.33 for Effort, and 0.13 for Success), indicating that the association is not driven by cross-industry differences in regulation or innovation intensity. These results reinforce the interpretation of environmental constraint as a trigger for adaptive innovation rather than a perceptual artifact.

Table 3.16: Ordered Probit Models with Industry Fixed Effects (Reverse-Causality Check)

Variable	Outcome 1 (Openness)	Outcome 2 (Effort)	Outcome 3 (Success)
Environmental barriers (avg_envbar)	0.189 (0.126) [0.134]	0.328 (0.124) [0.008 ***]	0.125 (0.123) [0.311]
× Small firm	0.173 (0.151)	0.007 (0.148)	–0.105 (0.148)
× Medium firm	0.215 (0.154)	0.137 (0.150)	0.360 (0.150 **)
× Large firm	0.025 (0.159)	–0.006 (0.157)	0.155 (0.156)
Controls (Econ, Tech, Pol, Soc)	Included	Included	Included
Industry FE	Yes	Yes	Yes
N	374	374	374
Link	Probit	Probit	Probit

(Std. Errors in parentheses; p-values in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.)

Comparison of Models: Full Sample versus Industry-Type Analyses

To explore sectoral heterogeneity, the ordered probit models were re-estimated separately for the three major industry categories—Agriculture, Food, and Natural Resources—and compared with the full-sample model. In the aggregate results (Table 3.6), environmental barriers emerged as the most robust and consistent predictor, significantly and positively associated with openness, effort, and success in innovation (β = 1.36, 1.44, and 1.24, respectively; $p < 0.01$). This pattern underscores that environmental challenges, such as regulatory pressures or sustainability requirements, serve as key external drivers motivating innovation adoption across the sector. However, when the models were disaggregated by industry type (Table 3.10), important differences became apparent. The effect of environmental barriers remained strongly positive and significant in the food industry ($\beta \approx 0.57$–0.61, $p < 0.01$) and in the natural resources sector ($\beta \approx 0.53$–0.78, $p < 0.05$), but was weaker and statistically insignificant in the agricultural sector. This suggests that firms in environmentally sensitive industries are more responsive to sustainability pressures, while agricultural enterprises may still face structural or resource limitations that dampen their responsiveness.

The effects of other barriers diverged more sharply across industries. Economic barriers, which were positive but non-significant in the full model, turned negative and significant for openness and effort in the food industry ($\beta = -0.30$ and -0.56, respectively), indicating that financial constraints suppress innovation activities where operational costs are high. In contrast, they were positive and significant for success in the agricultural sector ($\beta = 0.56$, $p < 0.01$), implying that agricultural firms may adaptively innovate under financial pressure—potentially through efficiency-driven strategies. Technical barriers showed a split pattern: negative and significant in agriculture and natural resources but positive in food production, suggesting that technical know-how and infrastructure availability are particularly decisive in resource-based industries. Interestingly, political and policy barriers were positive for agriculture but negative for food industries, pointing to sector-specific institutional asymmetries. Social barriers were largely insignificant, except for a negative and significant effect in the natural resources sector ($\beta = -0.68$, $p < 0.05$), reflecting the role of community norms or labor practices in moderating innovation decisions.

Overall, while environmental barriers exert a consistent positive influence across industries, economic and technical barriers exhibit differentiated impacts depending on sectoral context. These results reinforce that innovation drivers are not uniform but shaped by each industry's operational environment and regulatory exposure. From a policy standpoint, promoting innovation in the food sector may require alleviating financial and institutional constraints, whereas for agriculture and natural resources, enhancing technical capacity and addressing socio-cultural limitations could be more effective.

4.5 Discussion

The findings of this study yield three key insights into the innovation dynamics of agribusiness firms in the sample. First, environmental barriers emerge as the most consistent and influential factor, significantly increasing the likelihood of higher levels of openness, effort, and innovation success. Rather than deterring innovation, environmental constraints appear to trigger adaptive responses and strategic adjustments, suggesting that regulatory and sustainability pressures can act as catalysts for technological and organizational change.

Although such findings may appear counterintuitive, they resonate with several established frameworks that view environmental constraints as inducements rather than impediments to innovation. According to the Porter Hypothesis (Porter, 1991; Ashford, 2000), stringent environmental and safety regulations can stimulate innovation by compelling firms to redesign technologies, improve efficiency, and gain competitive advantage—particularly when regulatory standards emphasize performance outcomes rather than prescriptive methods. This notion aligns with Hicks' and Ruttan's Induced Innovation Hypothesis, which argues that shifts in relative scarcities or environmental resource values can redirect scientific and technical effort toward new, more sustainable technological trajectories. Complementing these perspectives, Problemistic Search Theory (Cyert & March, 1963; Greve, 2003) offers a behavioral explanation: when firms face environmental pressures that threaten their performance or compliance goals, they initiate adaptive search processes to restore equilibrium, reallocating resources toward innovative solutions. In this sense, environmental challenges act as “constraint-as-catalyst” mechanisms—triggering innovation-driven responses under crisis or regulatory stress.

The positive marginal effects observed in this study thus reflect firms’ adaptive capabilities rather than measurement artifacts. These effects were strongest among larger firms and those in food and natural resource sectors, suggesting that adequate slack and technical capacity enable firms to convert environmental challenges into opportunities. This pattern also mirrors the evidence from sustainability and regulatory innovation studies (Rennings & Rammer, 2011; Mazzanti & Zoboli, 2006; Tung & Baird, 2023), which demonstrate that stakeholder and regulatory pressures can promote both environmental and financial performance. Future research could further examine the boundary conditions of this adaptive mechanism by incorporating interaction terms for firm size, market turbulence, or slack resources and testing whether environmental constraints continue to predict innovation when such moderating factors are explicitly modeled.

Second, economic barriers exert a dual and stage-dependent effect. While heightened financial constraints tend to dampen openness and effort toward innovation adoption, once firms become engaged, these same pressures are associated with higher probabilities of achieving successful outcomes. This pattern implies that resource scarcity may encourage firms to pursue efficiency-oriented innovations that ultimately enhance performance.

Third, openness and effort remain critical mediating factors in determining innovation success, even when controlling for organizational characteristics such as managerial role or firm size. Together, these results underscore that environmental and economic contexts shape firms' innovation trajectories in distinct ways, requiring differentiated policy and managerial strategies that account for both constraint-driven adaptation and capacity-based limitations.

Beyond these empirical patterns, the results provide theoretical support for the induced innovation hypothesis within a behavioral-theory framework. Across all models, environmental constraints exhibit a positive association with firms' innovation outcomes, indicating that regulatory and stakeholder pressures can serve as external stimuli for adaptive innovation rather than deterrents. Interaction analyses further reveal that this inducement effect is strongest among medium-sized firms, which likely possess sufficient organizational slack to engage in problemistic search and resource reallocation while maintaining the flexibility to respond to environmental uncertainty. This size-contingent pattern aligns with behavioral expectations of constraint-induced adaptation, where moderate resource pressure prompts creative and efficient innovation responses.

Robustness tests incorporating industry fixed effects confirm that this relationship is not an artifact of cross-industry heterogeneity or reverse causality—innovative industries simply perceiving greater regulation—but instead reflects a directional mechanism from constraint to innovation. Collectively, these findings position environmental barriers not merely as obstacles but as disciplinary triggers of adaptive search and innovation, highlighting the contextual conditions under which external pressures catalyze rather than constrain technological change.

Linkages to Existing Literature

Our work aligns with and extends several strands of literature on barriers to innovation. Within the broad domain of empirical research on innovation barriers, we contribute to studies emphasizing the critical role of environmental barriers in triggering innovation adoption (Zhang et al., 2018; Ramanathan et al., 2017; Jiang et al., 2018; Caravella & Crespi, 2020; Liu & Wang, 2017; Lovely & Popp, 2011). For example, Lu et al. (2022) report that environmental regulations enhance green technology adoption among Chinese pig farmers, though effects differ by farm size and are mediated by economic incentives and educational awareness. Similarly, Ediriweera and Wiewiora (2021) show that technological innovation in the Australian mining sector reduces costs and environmental impacts. At the policy level, Lovely and Popp (2011) note that access to technology by early adopters can shape environmental regulations in non-innovating countries. Evidence from Zhong and Yan (2023) further demonstrates that environmental barriers significantly influence Chinese farmers’ adoption of low-carbon technologies. Collectively, these studies underscore that environmental pressures are a pivotal force driving innovation adoption, a conclusion supported by our findings. These findings, along with our results, highlight the importance of embedding environmental considerations into corporate strategy, not only for compliance but also for maintaining competitive advantage in sustainability-driven markets.

However, it has to be noted that, our finding that greater environmental barriers are associated with higher innovation openness and success may appear counterintuitive. One explanation, consistent with the Porter Hypothesis, is that environmental constraints or regulations stimulate firms to search for new processes, products, or markets, thereby triggering greater innovation activity. In addition, such barriers may serve as an external signal or catalyst, compelling firms to demonstrate compliance and progressive capabilities through innovation.

However, this relationship could also reflect unobserved differences in firms' innovation capacity, resources, or market exposure. For example, firms with greater innovative potential might be both more aware of / subject to environmental barriers and more successful in introducing innovations. Alternatively, industries or markets with higher innovation rates may also tend to be more regulated or environmentally conscious. Future research should aim to disentangle these effects by including firm-level measures of innovation capacity, sectoral fixed effects, and more detailed market characteristics.

We also contribute to the literature on economic barriers and their complex influence on firms' innovation efforts. Economic constraints often compel firms to invest additional effort to overcome these challenges for survival and competitiveness. Coad et al. (2016), using UK firm-level data, emphasize that financial costs and availability of capital are major determinants of innovation, particularly for SMEs. Gonzales et al. (2005) show that inadequate effort to overcome cost constraints can push firms below profitability thresholds, leading to negative performance outcomes, especially among smaller firms. Madrid-Guijarro et al. (2009) reach similar conclusions in Spain, reporting that cost barriers have heterogeneous effects across firms and production stages, with smaller firms experiencing greater severity due to limited access to finance. Other studies corroborate these findings, highlighting economic and financial constraints as persistent obstacles to technology adoption (de Oliveira et al., 2022). The consistency of these findings with our results reinforces the significance of addressing economic barriers in innovation policy and practice. Our evidence adds nuance by showing that while economic barriers deter openness and effort at lower levels, top managers interpret them as strategic challenges—indicating that interventions should be role-specific to avoid policy misalignment.

Aggregate vs. Industry-Specific Insights

Our analysis reveals that aggregate models obscure critical industry-specific differences in how firms perceive and respond to innovation barriers. While the full-sample results indicate that environmental barriers consistently drive openness, effort, and success, the disaggregated industry-level models expose meaningful heterogeneity across sectors. Firms in the food industry perceive environmental and technical barriers as catalysts for innovation, viewing regulatory standards, sustainability pressures, and technological demands as strategic opportunities for transformation. In contrast, agricultural enterprises interpret similar challenges more as constraints than as opportunities, particularly where limited financial and technical capacity restricts adaptive responses. The natural resources sector, meanwhile, demonstrates a distinctive social dimension, where local norms and community dependencies influence firms' willingness to innovate.

This pattern aligns with behavioral and institutional theories of innovation, which suggest that organizational responses to barriers are shaped by context-specific risk perceptions, opportunity framing, and resource endowments rather than uniform economic rationality. Consequently, what acts as an incentive in one industry may operate as a deterrent in another.

From a policy and strategic standpoint, these findings underscore the need for sector-tailored innovation frameworks rather than one-size-fits-all interventions. For instance, agricultural firms require targeted financial and technical assistance to overcome operational and infrastructural constraints; food industry firms benefit from stable regulatory guidance and incentives for sustainable technology adoption; and natural resource enterprises need social engagement and community-aligned innovation programs to ensure local legitimacy and diffusion. This nuanced understanding highlights the value of industry-based analysis for designing actionable, context-specific innovation policies and business strategies.

Societal and Policy Implications

Beyond firm-level practices, these findings hold broader societal relevance. Environmental barriers act as external pressures that can accelerate sustainability transitions, aligning with global commitments such as the UN Sustainable Development Goals (SDGs). However, if economic barriers disproportionately constrain SMEs compared to large firms, there is a risk of widening equity gaps in innovation adoption. Policymakers should therefore design inclusive innovation policies, such as subsidized financing for SMEs, green credit schemes, and collaborative platforms for resource sharing, to ensure that sustainability-driven innovation does not become a privilege of large corporations (Rui, 2013; Ruan and Song, 2023; Hardi et al., 2025; Morales et a., 2025) . These interventions can create a more level playing field and foster systemic progress toward green growth given similar contest of agribusiness firms. Numbers of studies also specifically study the interventions in the agriculture sector (Ye et al., 2022; Shah et al., 1995; Miao et al., 2012; Miao and Khanna, 2017).

Openness, Effort, and Innovation Success

Finally, our findings highlight the sequential nature of innovation adoption—where *openness* and *effort* jointly determine success. Openness to innovation exerts the strongest positive influence, indicating that firms willing to engage with external ideas and opportunities are significantly more likely to achieve successful outcomes. Effort further reinforces this relationship by translating openness into tangible results, underscoring the importance of sustained organizational commitment to innovation. This is consistent with prior research linking firms' search strategies to innovation performance. Katila and Ahuja (2002) describe this relationship as an inverted-U curve: broader and deeper search improves performance up to a point, beyond which additional search incurs high costs and diminishing returns. Cohen and Levinthal (1989, 1990) argue that R&D investments create absorptive capacity, enabling firms both to generate new knowledge and leverage existing knowledge in the field. Conversely, the "Not-Invented-Here" syndrome (Laursen & Salter, 2006) illustrates how internal resistance to external ideas can hinder innovation success despite openness efforts.

Empirical evidence supports these theoretical insights. Laursen and Salter (2006), analyzing UK industrial firms, find that external search strategies significantly impact innovative performance but follow a curvilinear pattern. Marullo et al. (2018) demonstrate that startups' success in California strongly correlates with organizational openness and human capital at inception. In agriculture, Gellynck et al. (2015) report that farmers' absorptive capacity enhances innovation adoption, a finding echoed by Priyadharshini et al. (2024) in their study of European SMEs, where resource allocation and sustained effort underpin successful innovation.

Review studies also reinforce these insights. Tey and Brindhal (2012) identify seven key determinants of agricultural technology adoption ranging from socio-economic and institutional factors to behavioral and technological factors, while highlighting the dominance of probit/logit and Tobit models in adoption research. Van der Boezem et al.

(2015), examining Agri-Food sector startups, point to alliance formation, strategic fit, governance, resource access, IP protection, and trust as critical to open innovation success. These factors resonate with our findings, underlining the centrality of openness and effort as core enablers of innovation performance. Together, these findings underline that openness and effort are not only internal determinants of innovation performance but also mediators of how external barriers—environmental or economic—shape adoption outcomes.

Limitations

Despite these important insights, our study has several limitations that warrant consideration. First, while Prolific.com is not a conventional sampling frame for agribusiness research, it has been increasingly used in academic studies requiring targeted samples under time and resource constraints (Peer et al., 2017; Palan & Schitter, 2018). Our recruitment strategy targeted participants with self-identified affiliation to the agri-food sector and employed eligibility screening questions to enhance sample relevance. Nevertheless, the representativeness of the sample across the broader agri-food landscape remains limited, and future research could benefit from broader sampling across subsectors and organizational types to enhance generalizability.

Second, although our sample size (n = 374) may be considered modest, it aligns with accepted thresholds for probit and logit modeling, especially when model parsimony is maintained (Long & Freese, 2014; Cameron & Trivedi, 2022). Similar or smaller perception-based samples have been used in agricultural economics to derive meaningful inferences on technology adoption (e.g., Läpple & Kelley, 2013; Conteh et al., 2016; Wu et al., 2024). Still, larger samples may increase external validity and allow for more robust subgroup analysis.

Third, while the study provides evidence that environmental barriers positively influence innovation adoption, the underlying mechanisms remain unexplored. Behavioral theory suggests that such constraints may trigger problemistic search or crisis-induced innovation responses, which can be empirically examined through interaction effects (e.g., between environmental barriers and organizational characteristics such as perceived opportunity, resource slack, or market turbulence). However, due to data limitations, our survey captured only firm size as a potential moderator, preventing a more comprehensive test of these interaction dynamics. Future research incorporating richer firm-level and perceptual variables could more explicitly identify when and how environmental pressures transform from obstacles into innovation drivers.

Finally, our cross-sectional design restricts causal inference. While we capture associations between barriers, internal innovation dynamics, and perceived success, longitudinal or experimental designs would be better suited to establish causal pathways. These limitations provide direction for future research that seeks to build upon and validate our findings in diverse contexts.

4.6 Conclusion

The findings of this study provide valuable insights for agribusiness enterprises and policymakers, particularly those operating in contexts similar to the firms represented in our sample—medium-sized, commercially oriented agricultural, food, and natural resource enterprises. Using ordered probit models and industry-disaggregated analyses, the study reveals that innovation barriers operate in nuanced and context-dependent ways rather than as uniform constraints. Environmental barriers consistently emerge as positive and significant predictors of openness, effort, and success in innovation, while economic and technical barriers exert differentiated effects across industries.

In particular, environmental constraints appear to function as catalysts for innovation in the food and natural resource sectors—where sustainability pressures and regulatory standards encourage adaptive technological responses. Conversely, economic and technical barriers remain the most persistent challenges for agricultural enterprises, emphasizing the dual need for financial accessibility and technical capacity in enabling successful innovation adoption. Political and policy barriers display mixed effects across industries, reflecting sector-specific regulatory environments, while social barriers play a subtler role, particularly in community-embedded natural resource firms.

From a policy perspective, the results suggest that industry-specific innovation strategies are essential. For agriculture, targeted financial and technical support remains critical; for the food industry, incentives aligned with environmental compliance and sustainability may be more effective; and for natural resource enterprises, policies that strengthen technical infrastructure and stakeholder engagement can improve innovation outcomes. However, these implications should be interpreted cautiously, as the data were collected from respondents on the Prolific platform who represent agribusiness-type firms rather than a nationally randomized enterprise sample. Hence, the recommendations are most relevant to firms with similar structural and organizational characteristics to those in our study.

At a broader level, the analysis underscores the importance of addressing economic and technical barriers to ensure equitable innovation diffusion. Without inclusive financing and capability-building initiatives, innovation adoption may remain concentrated among larger, well-capitalized firms. Policy tools such as innovation grants, tax credits, and subsidized credit lines for small and medium enterprises can promote more inclusive, sustainability-driven innovation.

While the study's psychometric validation and multi-dimensional modeling strengthen its internal validity, a key limitation is that interaction effects, such as whether environmental constraints trigger problemistic search or crisis-driven innovation, could not be fully examined due to limited moderating variables beyond firm size. Future research integrating richer firm-level and longitudinal data, along with qualitative inquiry, would clarify when and how environmental pressures act as barriers versus catalysts for innovation.

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Appendix

Appendix A

Table A3.1: Review of Literature on Barriers to Innovation in Agriculture

Dimension	Factors	Authors
Economic	Size of the farm (inadequate farm size), Lack of credit, Cost of the technology, Cost of the credit, Cost of labour, Cost of land, Operation costs, Research costs, Low return on research and development, Payback period of the investment, Lack of consumer demand, The size of the market, Inelastic supply and demand pricing, Low profitability, Economic uncertainty, Price instability, Volatility	Feder et al. (1985), del Río González (2005), Luken & Van Rompaey (2008), Wheeler (2008), Montalvo (2008), Rodriguez et al. (2009), Knutson et al. (2011), McCarthy et al. (2011), Boehlje et al. (2011),Weiss & Bonvillian (2013), Luthra et al. (2014), Goldberger et al. (2015), Läpple et al. (2015), Rijswijk and Percy (2015), Sivertsson & Tell (2015), Long et al. (2016), Johnson et al. (2016), Hammond et al. (2017), Grover & Gruver (2017), Björklund (2018), Dahabieh et al. (2018), Cummings et al. (2021), Barbosa Junior et al. (2022)
Technical	Lack of information, Training needs for agricultural professionals, Insufficient human capital, Lack of R&D, Absence of equipment (complimentary), Labour shortage, Supply chain shortages , Inappropriate transportation, infrastructure, Lack of infrastructure, Post harvesting	Feder et al. (1985), Wheeler (2008), Luken & Van Rompaey (2008), Montalvo (2008), Johnson (2010), Knutson et al. (2011), Boehlje et al. (2011), Weiss & Bonvillian (2013), Luthra et al. (2014), McCarthy et al. (2011), Goldberger et al. (2015), Läpple et al. (2015), Rijswijk and

	losses , Uncertainty of future effects, Uncertainty about the innovation, Higher risk perception, Need for collaboration, Compatibility and Adaptability of Innovation, Communication of scientific info/scientists, Lack of scientific research/proof, Technological complexity, Precautionary principle	Percy (2015), Long et al. (2016), Grover & Gruver (2017), Björklund (2018), Dahabieh et al. (2018), Cummings et al. (2021), da Silva et al. (2023)
Socio-cultural	Prejudices against new technologies, Prejudices against new products , Social networks and peer influence, Negative media, Traditional beliefs and practices, Knowledge and awareness gaps, Lack of consumer care/willingness to pay premiums, Lack of farmer acceptance, Lack of farmer knowledge and negative perceptions, Philosophical/religious/social factors, Public good aspect, Globalization issues, Disinformation about new technologies/products, Misinformation about benefits, Misperception, Ethical concerns, Strong resistance to change	Ratten & Ratten (2007), Wheeler (2008), Montalvo (2008), Luken & Van Rompaey (2008), Rodriguez et al. (2009), Vishwanath (2009), Sneddon et al. (2011), Knutson et al. (2011), Eidt et al. (2012), Weiss & Bonvillian (2013), Meijer et al. (2015), Sivertsson & Tell (2015), Long et al. (2016), Hammond et al. (2017), Björklund (2018), Barbosa Junior et al. (2022)

	habits, Gender disparities and unequal power dynamics	
Political	Inadequate incentives, Lack of subsidy, Regulatory constraints, Weak institutions, Corruption, Bureaucratic procedures, Lack of policy support, Public service announcements, Legal basis or barriers, Lack of regulation/need for extra regulation, Political instability and conflicts, Fragmented governance and coordination, Lack of government support, Property rights issues	Luken & Van Rompaey (2008), Wheeler (2008), Montalvo (2008), Termeer (2009), Knutson et al. (2011), Boehlje et al. (2011), Bogdanski (2012), Eidt et al. (2012), Weiss & Bonvillian (2013), Sivertsson and Tell (2015), Long et al. (2016), Grover & Gruver (2017), Björklund (2018), Dahabieh et al. (2018), Cummings et al. (2021), Lindberg et al. (2023)
Environmental	Climatic change variability, Biological variability, Produce appearance problems, Water scarcity and quality, Pest/disease problems, Biodiversity loss and pest management, Soil degradation and erosion, Lack of nutrients in farmed soils, Land availability and fragmentation, Environmental regulations and compliance, Sustainability concerns, Land access/suitability, Environmental awareness, Externality issues	Fuglie & Kascak (2001) Wheeler (2008), Fleming and Vanclay (2010), Knutson et al. (2011), Weiss and Bonvillian (2013), Goldberger et al. (2015), Sivertsson & Tell (2015), Banson et al. (2016), Grover and Gruver (2017), Björklund (2018), Dahabieh et al. (2018), Apipoonyanon et al. (2021), Barbosa Junior et al. (2022)

Bar chart on barriers for technology adoption

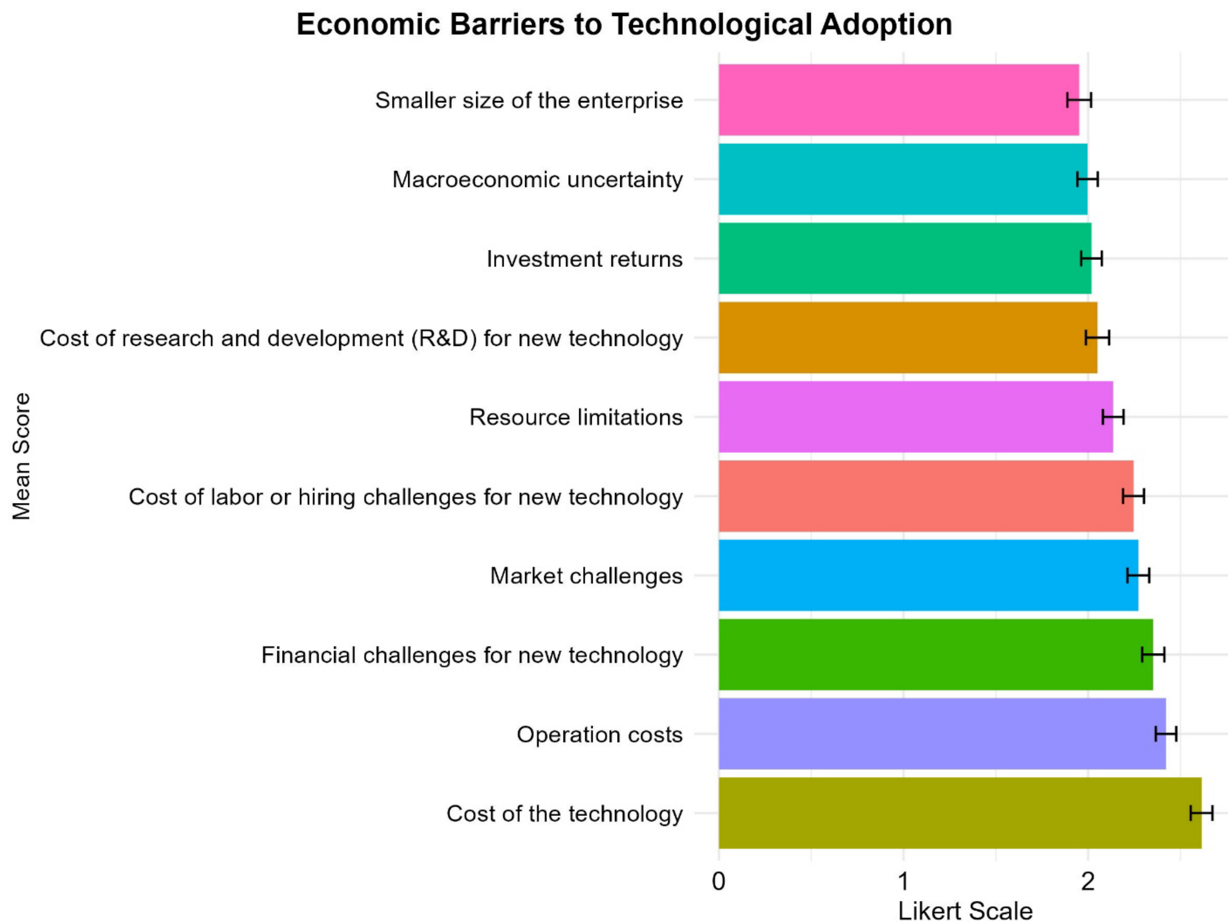

Figure A3.1: Respondents' evaluation of the importance of different economic barriers

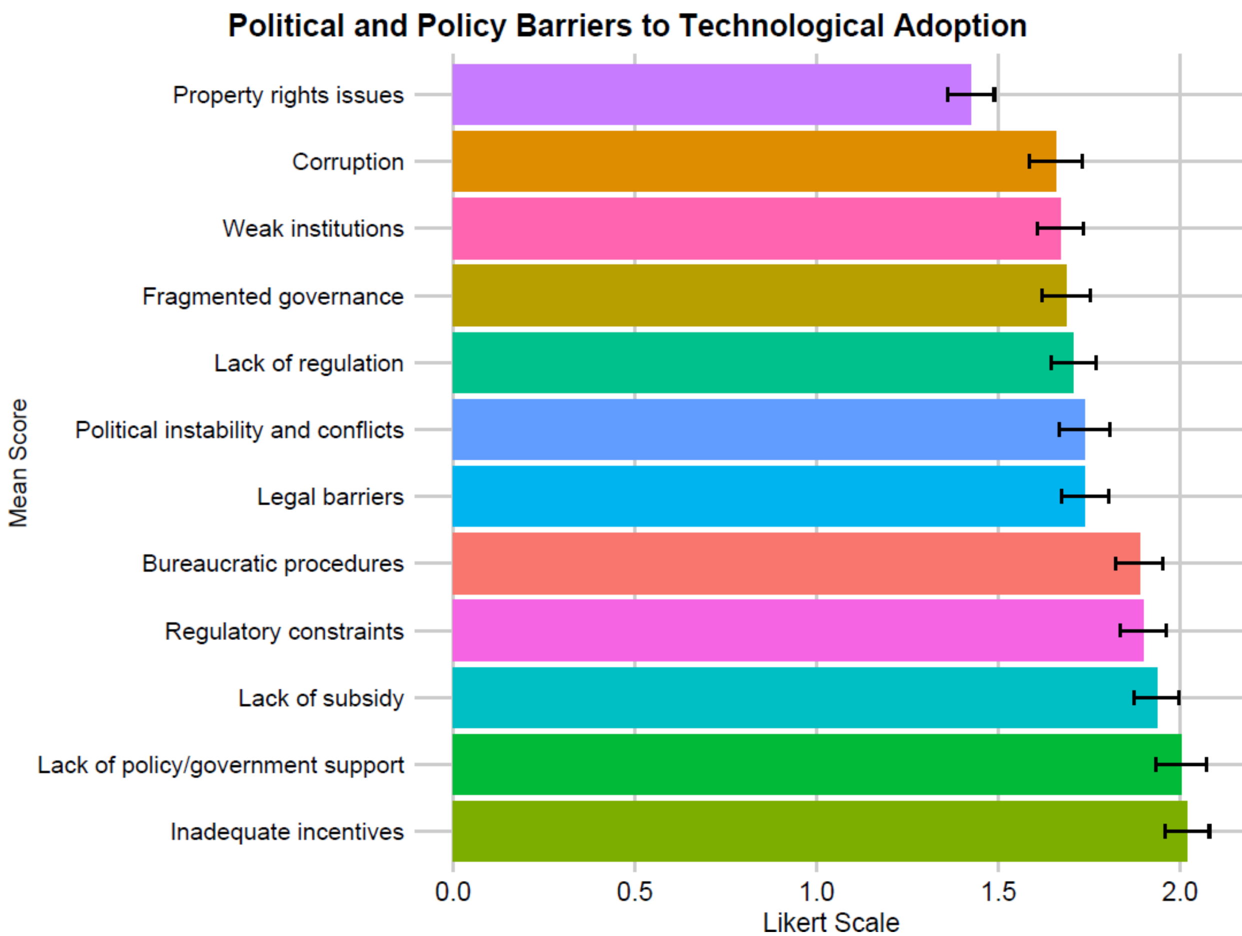

Figure A3.2: Respondents' evaluation of the importance of different political and policy Barriers

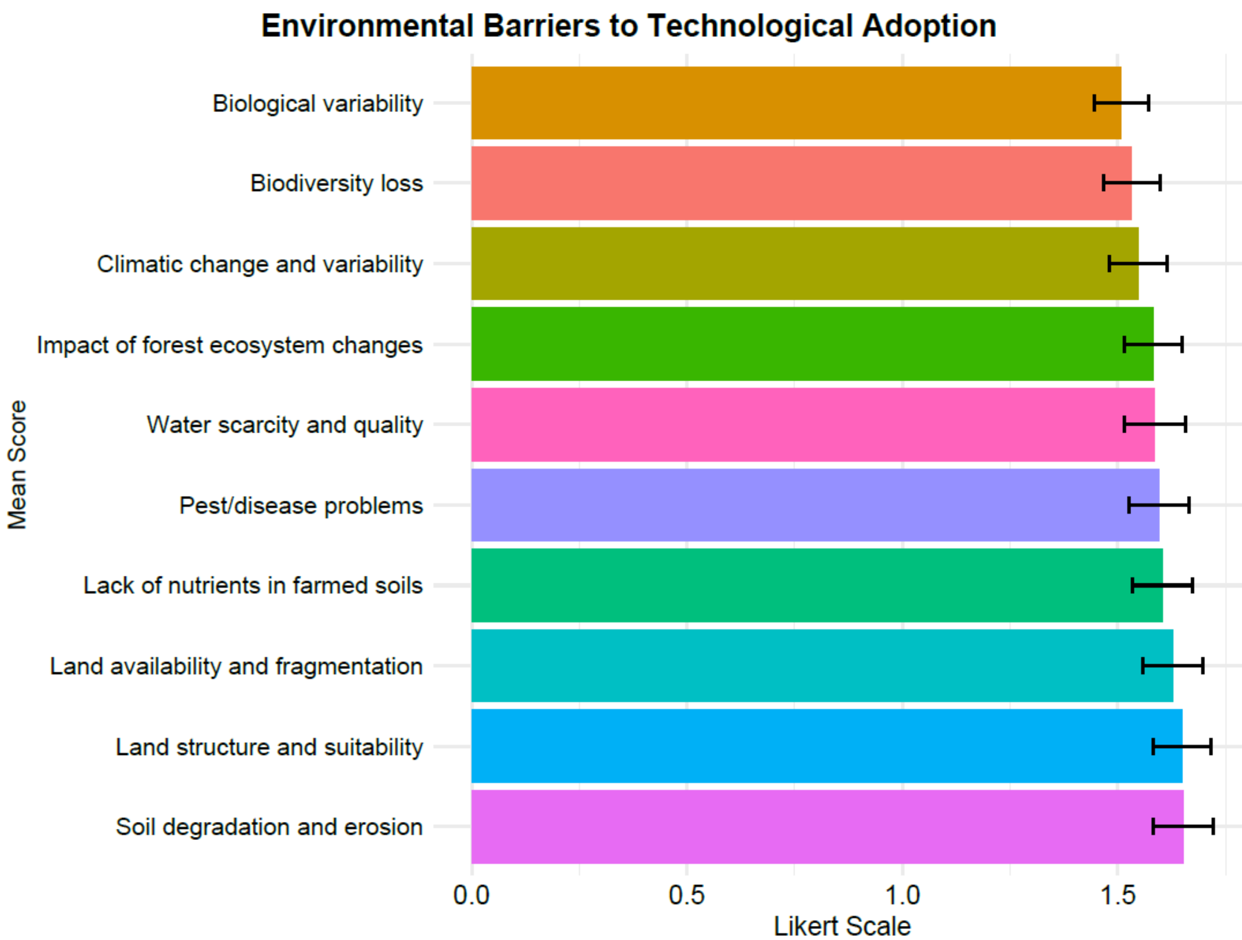

Figure A3.3: Respondents' evaluation of the importance of different environmental barriers

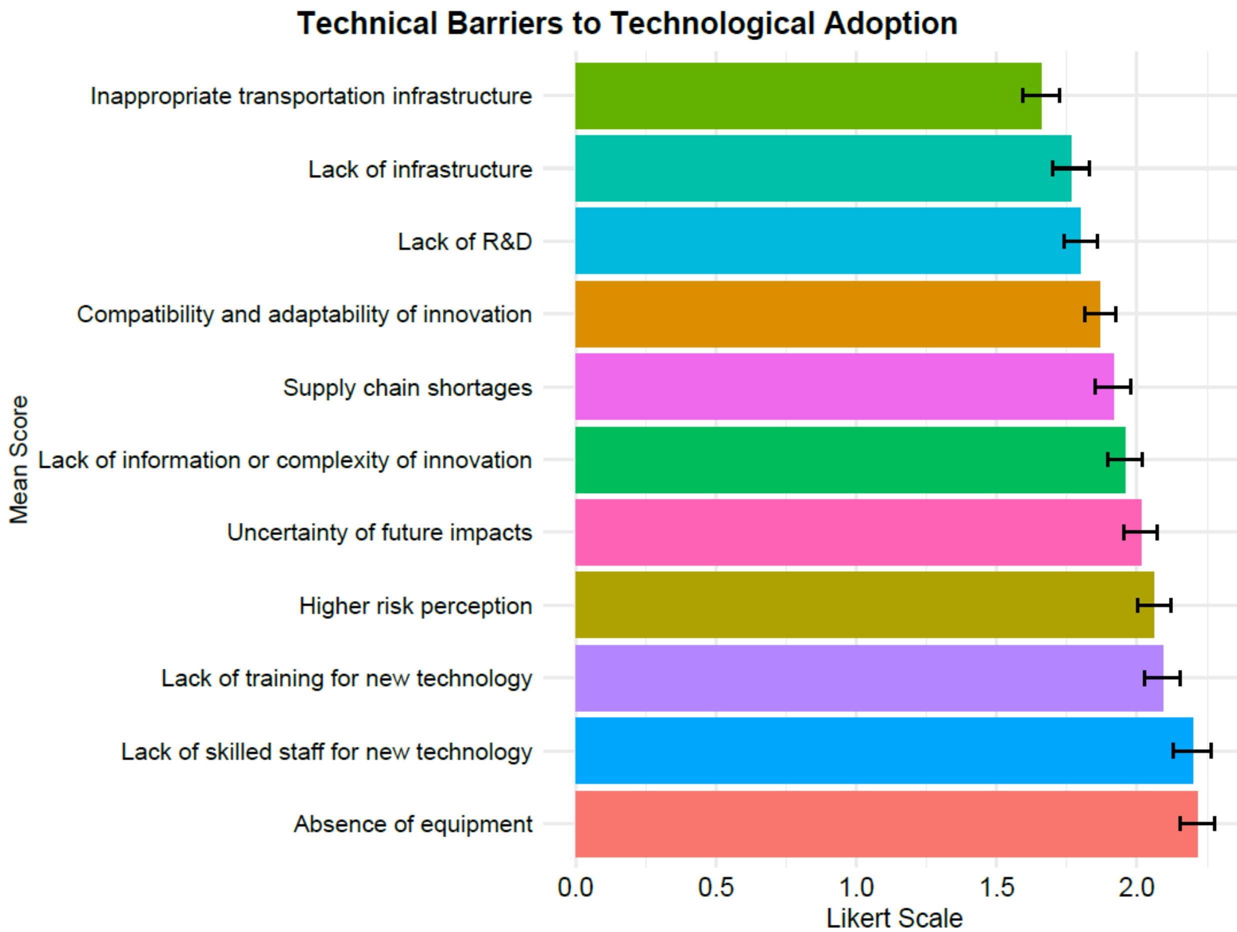

Figure A3.4: Respondents' evaluation of the importance of different technical barriers

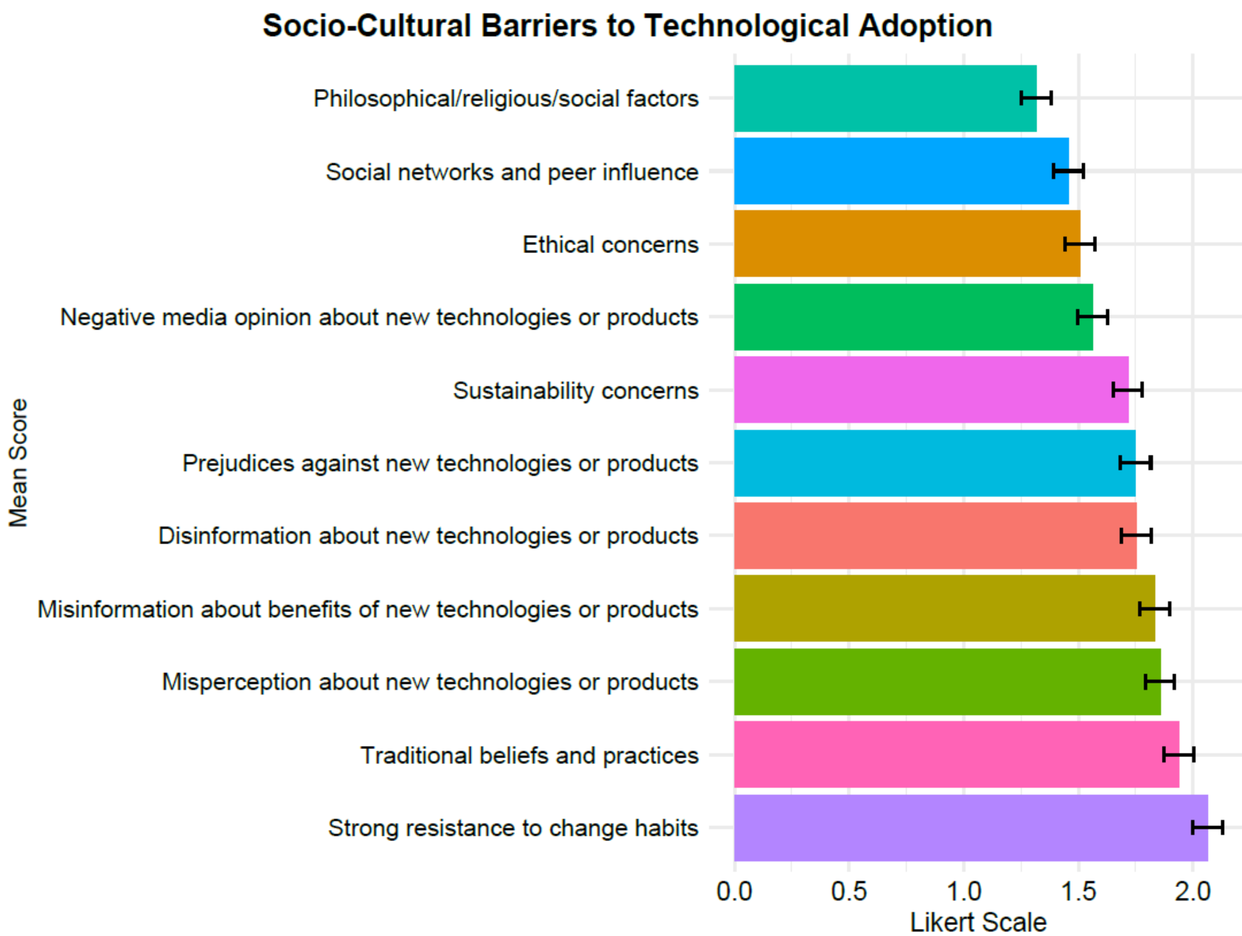

Figure A3.5: Respondents' evaluation of the importance of different socio-cultural barriers

Appendix B

Table A3.2: Variable Definitions

Variable	Description	Measurement	Source/Construction
avg_econbar	Economic barriers	Mean of 10 items	Survey
avg_envbar	Environmental barriers	Mean of 10 items	Survey
avg_techbar	Technological barriers	Mean of 11 items	Survey
avg_polbar	Political/policy barriers	Mean of 12 items	Survey
avg_scbar	Socio-cultural barriers	Mean of 11 items	Survey
outcome_1	Openness to innovation	Ordinal, 1–5	Survey
outcome_2	Effort toward innovation	Ordinal, 1–5	Survey
outcome_3	Success in innovation	Ordinal, 1–5	Survey

Table A3.3: Mean and Standard Deviation of Barriers

Barrier Type	Mean	SD
Economic barriers	3.21	0.78
Technical barriers	2.96	0.86
Political / Policy barriers	2.78	0.96
Social / Cultural barriers	2.70	0.95
Environmental barriers	2.59	1.10

Table A3.4: Outcome variables descriptives

Variable	n	Mean	SD	Median	Trimmed	MAD	Min	Max	Range	Skewness	Kurtosis	SE
Openness (outcome_1)	374	3.86	0.97	4	4.00	0.00	1	5	4	−1.08	1.05	0.05
Effort (outcome_2)	374	3.49	1.13	4	3.56	1.48	1	5	4	−0.52	−0.56	0.06
Success (outcome_3)	374	3.75	0.93	4	3.85	0.00	1	5	4	−0.83	0.70	0.05

Table A3.5: Correlations of barriers and outcomes

Variables	avg_econbar	avg_techbar	avg_polbar	avg_scbar	avg_envbar	outcome_1	outcome_2	outcome_3
avg_econbar	1.00	0.60	0.54	0.45	0.37	−0.01	−0.05	0.04
avg_techbar	0.60	1.00	0.71	0.64	0.54	0.00	0.02	−0.01
avg_polbar	0.54	0.71	1.00	0.67	0.64	0.12	0.12	0.03
avg_scbar	0.45	0.64	0.67	1.00	0.61	0.02	0.08	0.02
avg_envbar	0.37	0.54	0.64	0.61	1.00	0.22	0.26	0.13
outcome_1 (Openness)	−0.01	0.00	0.12	0.02	0.22	1.00	0.69	0.59
outcome_2 (Effort)	−0.05	0.02	0.12	0.08	0.26	0.69	1.00	0.53
outcome_3 (Success)	0.04	−0.01	0.03	0.02	0.13	0.59	0.53	1.00

Table A3.6: Interpretation of correlations

Pattern	Observation	Interpretation
Barrier–Barrier correlations	Moderate to high (0.37–0.71)	Some shared variance: plausible because all represent perceived barriers (conceptually related). Not alarmingly high, so not a strong CMV concern.
Barrier–Outcome correlations	Mostly weak (−0.05 to 0.26)	This reduces the concern about CMV, since if CMV were strong, you'd expect all positive and large correlations.
Outcome–Outcome correlations	High (0.53–0.69)	Acceptable and theoretically consistent: openness, effort, and success should be sequentially related. Not necessarily a bias indicator.

Note: CMV is possible but unlikely to severely distort your findings. The correlation pattern shows: no uniformly high correlations, both positive and negative relationships, and differentiation across constructs: all indicating that respondents discriminated between barriers and outcomes.

Table A3.7: Harmen Single factor test for common method variance

Result	Meaning
SS loadings (First factor) = 22.39	This is the eigenvalue of the first unrotated factor.
Proportion Var = 0.36	The first factor explains 36% of the total variance.
RMSEA = 0.099 (poor fit for a one-factor model)	Indicates that the single-factor model fits the data poorly.
Parallel analysis suggests 7 factors	There are multiple underlying constructs, not just one general factor.
High residuals and χ^2 significant ($p < 0$)	Confirms that the one-factor solution cannot account for the covariance among items.

Note: Correlation analysis shows moderate associations among the five barrier constructs ($r = 0.37–0.71$) and relatively weak relationships between barriers and outcomes ($r = −0.05$ to 0.26), suggesting that common method variance is unlikely to dominate the observed patterns. This interpretation was further supported by a post hoc Harman's single-factor test, which indicated that no single factor accounted for the majority of variance across items, implying that the findings reflect substantive relationships rather than methodological artifacts.

Table A3.8 Variance Inflation Factors (VIF) for Predictors

Predictor	VIF
avg_econbar	1.72
avg_envbar	2.07
avg_techbar	2.50
avg_polbar	2.78
avg_scbar	2.13
outcome_2B	1.26
outcome_1B	1.26

Note: All VIFs fall well below the conventional thresholds (5 or 10), confirming the absence of multicollinearity among predictors. The slightly higher VIFs observed for environmental, political, and socio-cultural barriers (≈2–3) are typical for attitudinal constructs that naturally exhibit conceptual proximity. Overall, these diagnostics indicate that the regression coefficients are stable and not inflated by shared variance among explanatory variables.

Table A3.9: Results of the exploratory factor analysis

Statistic	Result	Interpretation
Extraction method	Maximum Likelihood (unrotated, 1-factor model)	—
Number of items included	68 barrier items + 3 outcomes	All perception-based measures included
Eigenvalue of 1st factor (SS loadings)	22.39	—
Proportion of variance explained (1st factor)	36%	Below 50%, indicates low CMV risk
RMSEA	0.099	Poor fit for one-factor model
Tucker–Lewis Index (TLI)	0.554	Below acceptable threshold (<0.90)
χ^2 (df = 1829)	8544.13, $p < 0.001$	Significant misfit of single-factor model
Parallel analysis suggested factors	7	Confirms multi-dimensional structure
Residual RMSR	0.10	Indicates moderate unexplained variance

Note: Exploratory factor analysis using maximum likelihood estimation was conducted on all measurement items to assess common method variance (CMV). The first unrotated factor accounted for 36% of total variance, well below the 50% threshold typically associated with substantial CMV. Model fit indices (RMSEA = 0.099, TLI = 0.55) indicated poor fit for the single-factor model, and parallel analysis identified seven distinct factors. These results suggest that CMV is unlikely to bias the findings materially.

Scree plot

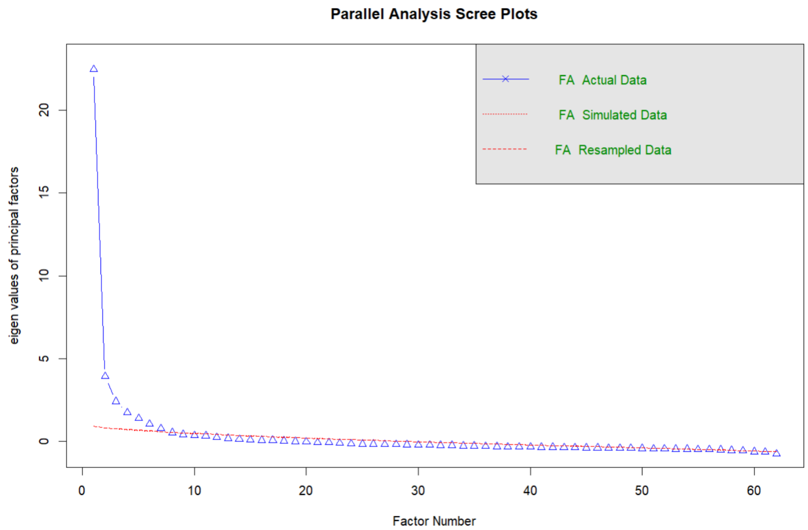

Figure A3.6: Scree plot for exploratory factor analysis

Table A3.10. Polychoric Correlation Summary for Barrier Items

Statistic	Description	Value / Summary
Input items	Total number of Likert-scale barrier items analyzed	54
Sample size	Number of complete observations used in the correlation matrix	374
Mean inter-item correlation (approx.)	Average correlation among 54 items	≈ 0.56
Range of correlations (min–max)	Weak to strong inter-item associations	0.30 – 0.78
Correlation matrix dimensions (ρ)	54 × 54	Each cell represents a pairwise polychoric correlation
Threshold matrix (τ)	54 × 4	Estimated thresholds for transforming ordinal responses into continuous latent scores
Method	Maximum likelihood estimation (ML)	psych::polychoric()

Note: Polychoric correlations were computed among the 54 ordinal barrier items to account for the categorical nature of the Likert responses. The average inter-item correlation was approximately 0.56 (range 0.30–0.78), suggesting moderate to strong internal consistency among items while avoiding redundancy. These results support proceeding with reliability and factor analyses using these indicators. None of the correlations approach 1.00, suggesting no multicollinearity concerns.

Table A3.11: Reliability and Convergent Validity Indices

Construct	Cronbach's α	Ordinal α	ω (Omega)	AVE	Interpretation
Economic (10 items)	0.878	0.898	0.886	0.487	Reliable; AVE ≈ 0.50 borderline
Technological (11 items)	0.909	0.923	0.923	0.563	Strong reliability, adequate AVE
Political (12 items)	0.936	0.948	0.944	0.634	Excellent reliability and validity
Socio-Cultural (11 items)	0.928	0.942	0.942	0.650	Excellent reliability and validity
Environmental (10 items)	0.952	0.964	0.958	0.752	Outstanding reliability and validity

Note: Reliability and convergent validity were assessed using Cronbach's α, ordinal α, McDonald's ω, and Average Variance Extracted (AVE). All constructs exceeded the recommended reliability thresholds (α ≥ 0.70; ω ≥ 0.70). AVE values ranged from 0.49 to 0.75, indicating that the latent constructs explain, on average, more than half of the variance in their observed indicators. The Economic barrier dimension's AVE (0.487) was slightly below the 0.50 threshold but considered acceptable given its high reliability (α = 0.88; ω = 0.89) and theoretical coherence. Together, these results confirm that the five barrier constructs demonstrate strong internal consistency and adequate convergent validity.

Table A3.12. Factor Loadings from EFA (Oblimin Rotation, ML Extraction)

Factor	Dominant Items (Highest Loadings ≥ 0.50)	Construct Interpretation	Variance Explained	Reliability (α)
ML1	envbar_1 – envbar_10	Environmental Barriers	17%	0.952
ML4	polbar_1 – polbar_12	Political / Policy Barriers	15%	0.936
ML3	scbar_1 – scbar_11	Socio-Cultural Barriers	12%	0.928
ML2	econbar_1 – econbar_10	Economic Barriers	10%	0.878
ML5	techbar_1 – techbar_11	Technological Barriers	8%	0.909

Total Variance Explained: 61%
Root Mean Square Residual (RMSR): 0.04 (excellent fit)
Fit based on off-diagonal values: 0.99 (strong factorial fit)
Factor Intercorrelations: 0.29–0.65 (moderate, expected for related barrier dimensions)

Note:

The five-factor solution derived from maximum likelihood estimation with oblimin rotation confirmed the theoretical structure of the barrier constructs. Each factor displayed strong and clean loadings (>0.50) on its intended items with minimal cross-loadings, and the solution explained 61% of the total variance, which indicates a well-defined latent structure. The Environmental barrier factor (ML1) accounted for the largest proportion of variance (17%), followed by Political (15%), Socio-Cultural (12%), Economic (10%), and Technological (8%) barriers. Inter-factor correlations ranged between 0.29 and 0.65, suggesting that while these constructs are distinct, they are moderately related, consistent with theoretical expectations that institutional, financial, and regulatory constraints co-occur in innovation processes. The low RMSR (0.04) and high off-diagonal fit (0.99) indicate an excellent model fit for EFA results.

Table A3.13: Factor Adequacy Summary

Factor	Items	h² Range	Mean h²	Factor Score Correlation	Interpretation
ML1 – Environmental	10	0.60–0.84	0.74	0.98	Strong, well-defined factor
ML4 – Political	12	0.37–0.79	0.63	0.98	Strong reliability
ML3 – Socio-cultural	11	0.49–0.84	0.65	0.98	Excellent internal structure
ML2 – Economic	10	0.27–0.72	0.52	0.96	Moderate-to-strong loadings
ML5 – Technological	11	0.40–0.74	0.54	0.95	Stable but weaker secondary loadings

Note: The exploratory factor analysis (EFA) produced five interpretable factors corresponding to the hypothesized dimensions of innovation barriers: environmental, political, socio-cultural, economic, and technological. Communalities (h^2) ranged from 0.27 to 0.84 across items, with mean values between 0.52 and 0.74, indicating that each factor explained a substantial portion of variance in its items. The environmental and socio-cultural dimensions displayed particularly high communalities (mean $h^2 = 0.74$ and 0.65, respectively), signifying well-defined and internally consistent constructs. Factor score correlations ranged from 0.95 to 0.98, demonstrating excellent stability and measurement reliability. Overall, the five-factor solution is psychometrically robust, with all dimensions showing adequate to strong internal coherence and distinct construct identities consistent with the theoretical framework.

Table A3.14 Model Fit Indices for the Five-Factor CFA Model

Fit Index	Value	Acceptable Threshold	Interpretation
χ^2 (df = 1367)	3537.60 ($p < .001$)	—	Large sample, significant χ^2 is common
CFI	0.921	≥ 0.90 (good), ≥ 0.95 (excellent)	Good fit
TLI	0.917	≥ 0.90 (good), ≥ 0.95 (excellent)	Good fit
RMSEA	0.065 (90% CI = 0.063 – 0.068)	≤ 0.08 (good), ≤ 0.05 (excellent)	Acceptable fit
SRMR	0.064	≤ 0.08	Good fit
Estimator	DWLS (robust WLSMV)	—	Appropriate for ordinal data
Observations	374	—	—

Note:
The CFA model fits the data well, with all indices within recommended thresholds (CFI = 0.92, TLI = 0.92, RMSEA = 0.065, SRMR = 0.064). These results confirm that the five-factor structure identified through EFA (economic, technological, political, socio-cultural, environmental barriers) adequately represents the observed data.

Table A3.15: Standardized Factor Loadings for Latent Constructs

Construct	Range of Standardized Loadings	Interpretation
Economic Barriers	0.45 – 0.78	Moderate to strong loadings
Technological Barriers	0.64 – 0.84	Strong loadings, reliable factor
Political Barriers	0.64 – 0.86	Excellent loadings, cohesive factor
Socio-Cultural Barriers	0.68 – 0.90	Very strong internal consistency
Environmental Barriers	0.81 – 0.91	Exceptionally strong loadings, highly reliable

Note: All standardized loadings are positive and significant ($p < 0.001$), exceeding the recommended 0.50 threshold. This indicates that each observed variable contributes substantially to its intended latent construct, supporting convergent validity.

Table A3.16. Latent Variable Correlations

Latent Variables	Economic	Technological	Political	Socio-Cultural	Environmental
Economic	1.00	0.67	0.59	0.49	0.41
Technological	—	1.00	0.75	0.67	0.58
Political	—	—	1.00	0.70	0.69
Socio-Cultural	—	—	—	1.00	0.66
Environmental	—	—	—	—	1.00

Note: Inter-factor correlations range from 0.41 – 0.75, suggesting moderate relationships among constructs. Since no correlations exceed 0.85, the factors demonstrate discriminant validity, confirming that each barrier dimension is conceptually distinct yet meaningfully related.

summary:

The confirmatory factor analysis confirmed the five-factor measurement model's validity and reliability. The model fit indices (CFI = 0.921, TLI = 0.917, RMSEA = 0.065, SRMR = 0.064) indicate a well-fitting model for the ordinal data. All items loaded significantly ($p < 0.001$) on their hypothesized factors, supporting convergent validity. Reliability estimates were high (α = 0.88–0.95; ω = 0.89–0.96), and average variance extracted values (AVE = 0.49–0.75) exceeded recommended cutoffs, confirming construct validity. Correlations among latent factors (r = 0.41–0.75) demonstrate adequate discriminant validity. Overall, the results validate the theoretical five-barrier framework—economic, technological, political, socio-cultural, and environmental—as robust and psychometrically sound.

Table: A3.17 Variance Inflation Factor for Different models

VIF for barreirs and with different outcomes

avg_econbar	avg_techbar	avg_polbar	avg_scbar
1.625980	2.560668	2.477752	2.022830

VIF with dummy

avg_econbar	avg_envbar	avg_techbar	avg_polbar	avg_scbar
1.626650	1.892448	2.569001	2.782748	2.198031

VIF with Effort and openness

avg_econbar	avg_envbar	avg_techbar	avg_polbar	avg_scbar	Effort	Openness
1.654645	2.025315	2.581860	2.795641	2.223381	1.333954	1.334641

VIF with with Binary outomes

avg_econbar	avg_envbar	avg_techbar	avg_polbar	avg_scbar	outcome_2B	outcome_1B
1.654645	2.025315	2.581860	2.795641	2.223381	1.333954	1.334641

VIF with Ordered outcomes

outcome_1	outcome_2	outcome_3
2.185594	1.994417	1.612221

VIF with Barriers

avg_econbar	avg_envbar	avg_techbar	avg_polbar	avg_scbar	outcome_1	outcome_2	outcome_3
1.674827	2.046313	2.592254	2.828657	2.224501	2.233347	2.099162	1.645450

Table A3.18 Alternative dependent variable ordering / outcome recoding

Variable	Estimate	p-value	Interpretation
avg_envbar	+0.189	0.134	Positive, similar magnitude as before but less precise — the effect remains when industry heterogeneity is controlled.
avg_envbar × size_cat	All ns	>0.15	The slope differences across size categories are not significant; pattern consistent with base model.
Industry dummies	Mostly ns	—	As expected; a few industries (e.g., Natural Resources) trend positive, indicating higher innovation propensity, but not dominant.

Note: To mitigate potential reverse causality—where more innovative industries might both perceive greater environmental constraints and report higher innovation—we re-estimated the ordered probit model including industry fixed effects. The coefficient on environmental barriers remained positive ($\beta = 0.19$, $p = 0.13$), similar in magnitude to the baseline specification, while the interaction with firm size was unchanged. This suggests that the observed positive association is not an artifact of cross-industry differences in regulation or innovation intensity, supporting a directional interpretation from environmental constraint → adaptive innovation.

Model	**Key variable**	**β**	**p-value**	**Interpretation**
Baseline	avg_envbar	0.213	0.084	Positive, marginally sig.
+ Industry FE	avg_envbar	0.189	0.134	Similar sign & size → robust to heterogeneity

Note: The positive environmental-barrier effect persists within industries, mitigating concerns about reverse causality or omitted-industry bias.

Reverse Causality for three outcomes

Table A3.19 : Ordered Probit Models with Industry Fixed Effects (Reverse-Causality Check)

Variable	Outcome 1 (Openness)	Outcome 2 (Effort)	Outcome 3 (Success)
Environmental barriers (avg_envbar)	0.189 (0.126) [0.134]	0.328 (0.124) [0.008 **]	0.125 (0.123) [0.311]
× Small firm	0.173 (0.151)	0.007 (0.148)	–0.105 (0.148)
× Medium firm	0.215 (0.154)	0.137 (0.150)	0.360 (0.150 *)
× Large firm	0.025 (0.159)	–0.006 (0.157)	0.155 (0.156)
Controls (Econ, Tech, Pol, Soc)	Included	Included	Included
Industry FE	Yes	Yes	Yes
N	374	374	374
Link	Probit	Probit	Probit

Note: The coefficient on environmental barriers remained positive and of comparable magnitude across all three outcomes (Openness β = 0.19, p = 0.13; Effort β = 0.33, p = 0.008; Success β = 0.13, p = 0.31). The size interactions were stable, with the strongest inducement effect for medium-sized firms. These results indicate that the observed pattern is not driven by innovative industries self-reporting higher environmental barriers, but rather reflects a genuine mechanism of constraint-induced innovation consistent with problemistic search and adaptive resource reallocation under pressure.

Table A3.20. Comparison of Triple-Hurdle Probit Estimates Using Conventional and Cluster-Robust Standard Errors

Variable	Openness (Original)	Openness (Clustered)	Effort (Original)	Effort (Clustered)	Success (Original)	Success (Clustered)
Economic barriers	-0.168 (0.123)	-0.168 (0.123)	-0.282** (0.112)	-0.282** (0.106)	0.192† (0.112)	0.192† (0.111)
Environmental barriers	0.403*** (0.096)	0.403*** (0.105)	0.342*** (0.086)	0.342*** (0.088)	0.165† (0.086)	0.165† (0.091)
Technological barriers	-0.155 (0.135)	-0.155 (0.134)	-0.111 (0.125)	-0.111 (0.119)	-0.170 (0.127)	-0.170 (0.130)
Policy barriers	0.123 (0.127)	0.123 (0.138)	0.138 (0.117)	0.138 (0.113)	-0.065 (0.119)	-0.065 (0.118)
Socio-cultural barriers	-0.239* (0.114)	-0.239* (0.118)	-0.110 (0.104)	-0.110 (0.105)	-0.094 (0.107)	-0.094 (0.111)

Notes: Entries are probit coefficients with standard errors in parentheses. Clustered estimates use cluster-robust standard errors. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.