Erasmus University Rotterdam

Erasmus School of Economics

Master Thesis

Business Analytics & Quantitative Marketing

Comparison of Menu-Based Conjoint Methods for Different Questionnaire Designs

Ludo Pfaff (433964)

Supervisor: Prof. dr. Dennis Fok

Second Reader: Prof. dr. Richard Paap

External Supervisor: Remco Don

April 14, 2021

Abstract

This paper focuses on comparing different menu-based conjoint methods to make the best predictions for menu-based questionnaire designs. Three different methods are proposed: a serial cross-effect (SCE) method which estimates a probit model for every item on the menu, an exhaustive alternatives (EA) method that uses multinomial logit to predict the combination of items that is most likely to be chosen, and a multivariate choice (MVC) method which estimates a multivariate probit model for the separate items on the menu. For the EA method, two ways of composing the set of possible combinations of items are used with their own advantages and disadvantages. For the first way of composing the choice set, a fixed set containing the most frequently chosen combinations is used, which is an easy solution but does not give consistent estimates. For the second way, stratified importance sampling is used to construct a different choice set in every observation, which leads to a more accurate model but is also more difficult to perform than using a fixed choice set. Implementing the methods on two data sets obtained by two different menu-based questionnaire designs, the MVC method outperformed the other methods, based on predictive power, computation time and its ability to give insights into the correlations between choosing different items.

Contents

1 Introduction

It is commonly known that companies are interested in the wishes and needs of their customers. It can be seen that there is a gap between what customers want and what is sold to them. Otherwise, new products would not have such a high failure rate and the use of discounts and markdown sales would not be so frequent.

With the rise of mass customised products in the 1990s, companies were able to better satisfy the requirements of the customers. Mass customisation gives customers the opportunity to design a product to their own needs and wishes, themselves. For instance, mass customisation makes it possible to design your own personal computer by selecting the components and features you like the most. Magretta (1998) interviewed the founder of Dell computers, Michael Dell, who created a $12 billion company in 13 years by building computers directly in line of the customer's needs. By selling directly to the customers, Dell eliminated all costs and risks of storing large amounts of finished goods, as well as the reseller's markup costs. Another positive side effect Michael Dell mentions, is the creation of a relationship between the firm and the customers. So, besides the financial benefits for the companies and the satisfaction of the customer's needs, the relationship between the two becomes stronger due to mass customised products.

Wind and Mahajan (1997) were one of the first who recognised the importance of analysing mass customised products. They saw that companies are not interested anymore in designing the optimal product, but in offering the possibility to buy a self-customised product. Besides, they saw the additional benefit of mass customisation, which is, using mass customised products as information for designing products to supply to customers. Hence, according to Wind and Mahajan (1997), mass customisation cannot only be used to give customers the opportunity to build a product to their own needs, but also to make companies understand how to design products to supply to their customers. Wind and Mahajan (1997) propose to use conjoint analysis to get insights in the set of features and levels that need to be offered to customers, how customers want to customise products, and what price customers are willing to pay to customise their own products instead of buying a predesigned product. Using these insights, a company might be able to overcome the problem of designing a product.

Therefore, mass customisation is not only beneficial for customers by giving the opportunity to build a product to their own needs, but also for companies, by giving the opportunity to analyse the needs of the customers and come up with an optimal product corresponding to these needs.

Conjoint analysis is a statistical technique where the researcher uses questionnaires to find the value of the features of items, as well as a theoretical trade-off between these features. Using conjoint analysis, the optimal combination of features can be found, in order to create a product with the greatest chance of success on the market. Conjoint analysis can be roughly divided into two types; choice-based conjoint analysis (CBC) and menu-based conjoint analysis (MBC) (Cohen and Liechty, 2007). CBC is used to analyse and predict a customer's choice out of different alternatives, where the alternatives have different features and prices. Think of a choice between different TVs that differ in price, size, resolution, etc. On the other hand, MBC is used to understand and predict the customer's customisation of products and services, that is, which features are chosen from a menu of features if they all can be chosen separately and all can affect the total price. Think of a fast-food restaurant where consumers can create their own menu by combining different products, like a burger and fries, or can purchase a predesigned menu. Where the goal of CBC is mainly to find the most preferred items and features, MBC focuses more on finding which features need to be offered and at what price.

Nowadays, menus are found everywhere and customising your own product is possible in a lot of places. Whether you go to a restaurant, buy a new car or computer, or need a new mobile phone subscription, you can compose your own 'package' of features. Although, for every kind of product, the package is composed in another way. For instance, to compose your own computer, one alternative needs to be chosen for every computer part, where multiple options with different prices are possible. Alternatively, at some restaurants, it is possible to choose a predesigned value meal, as well as picking à-la-carte. For composing your own car, the brand and model of the car need to be selected first. Afterwards, one or multiple features can be added to the chosen car. These are a few examples of how a product can be composed. In this paper, these ways of offering mass customised products to a consumer are referred to as (menu-based questionnaire) designs. To date, multiple MBC methods have been proposed to analyse and predict filled-in menu-based questionnaires, among others, Ben-Akiva and Gershenfeld (1998); Liechty et al. (2001); Orme (2010). Although, not every one of these methods has been applied on every possible menu-based questionnaire design.

Altogether, the question arises which methods give the best forecasts for every menu-based questionnaire design, and if it is possible to extend or improve the already existing methods. To find an answer to this question, three methods are applied on two data sets gathered using different questionnaire designs. These methods are evaluated on their forecasting accuracy, as well as their computational time, to make sure that if another product with other prices is examined, the recommended methods still give the best results.

This paper will follow with an overview of relevant literature in Section 2. Afterwards, the data sets gathered using different menu-based questionnaire designs will be explained and analysed thoroughly in Section 3. Furthermore, the different methods and the gathered results will be described in Section 4 and Section 5, respectively. At last, the conclusion of this research, together with recommendations for future research will be stated in Section 6.

2 Literature Review

This section contains an overview of relevant literature of the different menu-based conjoint analysis methods and menu-based questionnaire designs.

Origin of Conjoint Analysis

The founding of conjoint analysis can be traced back to the 1960s, when behavioural sciences had a strong influence on market research methods (Green et al., 2001). The first conjoint algorithm, called Monanova (Kruskal, 1969), used ranked response data. During the 1980s, market researchers started to use CBC, among others, Mahajan et al. (1982). In CBC, the analyst assumes the presence of active competitors, contrary to traditional conjoint analysis where a stable, non-competitive market was assumed. Instead of rating various product profiles, the respondent picks one's most favourite profile out of a set of profile descriptions of two or more competitors fulfilling the assumption of active competitors in CBC.

Menu-Based Conjoint Analysis

Conjoint analysis kept evolving and in the late 1990s MBC was invented being a reaction to the rising interest in mass customised products. Wind and Mahajan (1997) state that organisations are searching for ways to allow customers to customise a product to their own wishes instead of searching for the optimal product. Therefore, the focus of conjoint analysis should not be on finding the best product, but on finding which features and levels should be considered, how consumers want to customise the products, and how much the consumers are willing to pay extra to buy their own-designed product (Wind and Mahajan, 1997). According to Ben-Akiva and Gershenfeld (1998), these mass customisation tasks can be seen as choosing from a menu, like in a restaurant. To find the required features and levels, the way consumers want to customise their products, and how much the consumers are willing to pay extra, Ben-Akiva and Gershenfeld (1998) propose a conjoint technique. Though, contrary to CBC where the most favourite profile is picked out of a set of profile descriptions, the respondents can pick one, multiple or even all options, which is like picking foods and drinks from a menu. This leads to a vector of zeroes and ones for every respondent in every menu scenario, which requires a way of modelling that is different from the single-choice analysis of CBC experiments.

Development of Menu-Based Conjoint Analysis

As one of the first analysts of menu-based conjoint experiments, Ben-Akiva and Gershenfeld (1998) propose a method, called the exhaustive alternatives model, where every possible combination of items is seen as an option considered by the respondent. If the number of items on the menu equals N, the number of possible combinations is therefore 2^N. By constructing the choice set this way, it can be modelled as choosing one favourite combination of items out of all possible combinations. Therefore, it can be modelled in the same way as in CBC, for instance, using a multinomial logit model (Louviere, 1994) or a multinomial probit model (Haaijer et al., 1998). Ben-Akiva and Gershenfeld (1998) applied this method on two different menu scenarios of calling features for residential telephone service, as shown in Figure 1. Firstly, they describe a simple menu where all different items are shown with the corresponding prices (see Figure 1a). The respondent can choose as many items as he/she wants. Secondly, they describe a more extended menu where next to the separate items, also packages containing some of the items with 50% discount are offered (see Figure 1b). The respondent can both choose a predesigned package and choose "à-la-carte" from the separate items. They used multinomial logit estimation to model the choices of the respondents, which can be used to predict demand and revenue for the calling features. A drawback of this approach is that if the total number of possible ways the respondents can complete the questionnaire is reasonably large, it will work inadequately in practice, as 2^N grows exponentially when N increases.

In 2001, Liechty et al. (2001) introduced a new method to model a consumer's portfolio of choices from a menu. For each item on the menu, they estimate a latent utility function depending on its characteristics, price and other attributes, e.g., multifeature discounts. Liechty et al. (2001) allowed for correlation between the utilities of the different items and added customer heterogeneity in the utility functions. They illustrated the predictive performance of this method in an application concerning a web-based information service in the simple menu form. They compared their approach with alternative approaches, including

Feature	Monthly Price
Call Waiting	$4.00
Call Forwarding	3.50
Speed Calling	3.75
Three Way Calling	4.00
Automatic Callback	4.50
Repeat Dial	3.00
Incoming Caller Identification	6.00
Preferred Call Forwarding	3.75
Preferred Call Waiting	4.25
Distinctive Ringing	4.50
Call Tracing	5.00
Selective Call Rejection	4.25

(a) Simple menu design

Discounted Packages (50% discount)	Price
Package A: Call Waiting, Call Forwarding Three-Way Calling, Speed Calling	$7.60
Package B: Call Waiting, Call Forwarding Automatic Callback	$6.00
Package C: Incoming Caller ID, Call Tracing, Distinctive Ringing	$7.75

Feature	Monthly Price
Call Waiting	$4.00
Call Forwarding	3.50
Speed Calling	3.75
Three Way Calling	4.00
Automatic Callback	4.50
Repeat Dial	3.00
Incoming Caller Identification	6.00
Preferred Call Forwarding	3.75
Preferred Call Waiting	4.25
Distinctive Ringing	4.50
Call Tracing	5.00
Selective Call Rejection	4.25

(b) Extended menu design

Figure 1: Simple menu and extended menu design by Ben-Akiva and Gershenfeld (1998)

the exhaustive alternatives method introduced by Ben-Akiva and Gershenfeld (1998), which they adjusted by using a multinomial probit model instead of a multinomial logit model (inspired by Haaijer et al. (1998), amongst others). By this adjustment, some of the limitations encountered by the model of Ben-Akiva and Gershenfeld (1998) are circumvented, for instance, the assumption that the customer's sensitivities towards the different items are homogeneous, which is a restricting assumption (Haaijer et al., 1998). The model of Liechty et al. (2001) outperformed the adjusted model of Ben-Akiva and Gershenfeld (1998). Where the adjusted model of Ben-Akiva and Gershenfeld (1998) predicted approximately 9 percent of the combinations of items correctly, the model of Liechty et al. (2001) predicted more than 40 percent correctly.

Furthermore, Cohen and Liechty (2007) compared the same methods as Liechty et al. (2001), but they also mentioned another method, namely, a method that converts the respondent's choices in a menu into a series of binary choice models. This model, called the serial cross-effects model, predicts whether each item is chosen, determined by the price effects of the item itself and the cross-price effects of the other items on the menu. Contrary to the method introduced by Liechty et al. (2001), the serial cross-effects model predicts the choices without taking into account the possibility that choosing an item is correlated with choosing other items. Not allowing for correlation between choosing the different items is considered a major drawback of this method. Therefore, it is not considered worthy to take along in the comparison by Cohen and Liechty (2007). Moreover, Orme (2010) mentions this method in his executive summary of menu-based choice research studies. He compares the method introduced by Ben-Akiva and Gershenfeld (1998) with the serial cross-effects model on a menu design where first one of three cars has to be chosen and afterwards multiple options can be added to the chosen car (see Figure 2). Using multinomial logit estimation in both methods, the exhaustive alternatives method outperforms the serial cross-effects method.

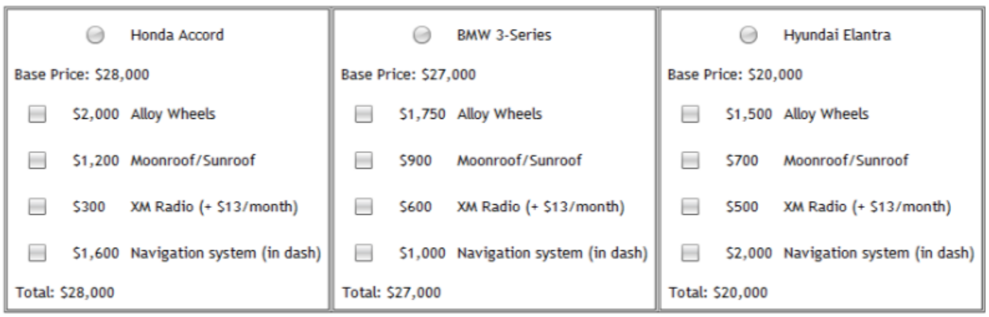
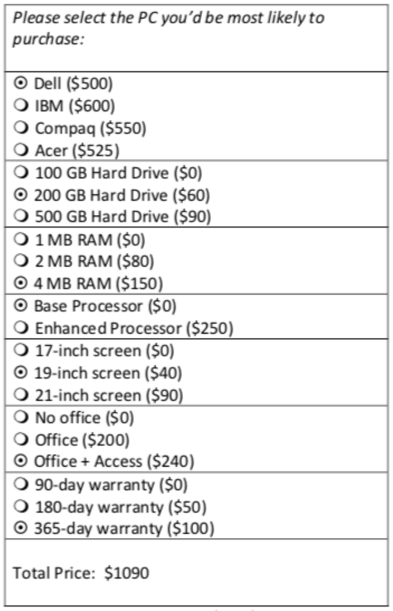


Figure 2: Menu design by Orme (2010)

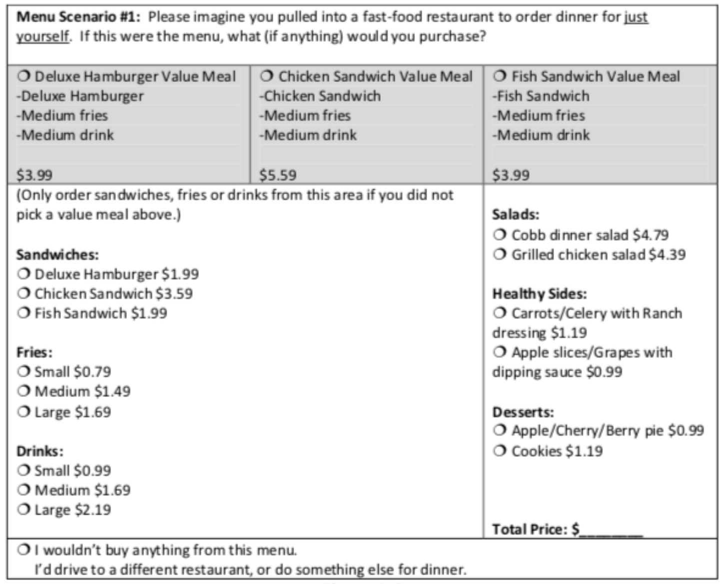
Nine years later, Orme (2019) wrote a manual for the menu-based conjoint analysis of Sawtooth Software. Apart from explaining how data files need to be prepared, how the data can be analysed and how the models need to be built, Orme (2019) shows four different menu-based questionnaire designs. Besides the simple menu design from Ben-Akiva and Gershenfeld (1998) and the design from Orme (2010), two other designs are shown. Firstly, a design is shown where the respondent builds his own personal computer by choosing all the different components that can all add extra costs to the total price (see Figure 3a). For almost every component, one of the options does not add any costs to the total price, which therefore can be seen as choosing “no component”. Furthermore, a menu design is explained where the respondent can choose a predesigned bundle of products or choose every product individually (see Figure 3b). This design resembles the extended menu design explained by Ben-Akiva and Gershenfeld (1998), but in the menu design of Orme (2019) it is not possible to choose both a bundle of products and individual products.



Please select the PC you'd be most likely to purchase:

⊙ Dell ($500) ❍ IBM ($600) ❍ Compaq ($550) ❍ Acer ($525)
❍ 100 GB Hard Drive ($0) ⊙ 200 GB Hard Drive ($60) ❍ 500 GB Hard Drive ($90)
❍ 1 MB RAM ($0) ❍ 2 MB RAM ($80) ⊙ 4 MB RAM ($150)
⊙ Base Processor ($0) ❍ Enhanced Processor ($250)
❍ 17-inch screen ($0) ⊙ 19-inch screen ($40) ❍ 21-inch screen ($90)
❍ No office ($0) ❍ Office ($200) ⊙ Office + Access ($240)
❍ 90-day warranty ($0) ❍ 180-day warranty ($50) ⊙ 365-day warranty ($100)
Total Price: $1090

(a) Menu for building own PC



Menu Scenario #1: Please imagine you pulled into a fast-food restaurant to order dinner for just yourself. If this were the menu, what (if anything) would you purchase?

❍ Deluxe Hamburger Value Meal	❍ Chicken Sandwich Value Meal	❍ Fish Sandwich Value Meal
-Deluxe Hamburger -Medium fries -Medium drink	-Chicken Sandwich -Medium fries -Medium drink	-Fish Sandwich -Medium fries -Medium drink
$3.99	$5.59	$3.99

(Only order sandwiches, fries or drinks from this area if you did not pick a value meal above.)

Sandwiches:
❍ Deluxe Hamburger $1.99
❍ Chicken Sandwich $3.59
❍ Fish Sandwich $1.99

Fries:
❍ Small $0.79
❍ Medium $1.49
❍ Large $1.69

Drinks:
❍ Small $0.99
❍ Medium $1.69
❍ Large $2.19

Salads:
❍ Cobb dinner salad $4.79
❍ Grilled chicken salad $4.39

Healthy Sides:
❍ Carrots/Celery with Ranch dressing $1.19
❍ Apple slices/Grapes with dipping sauce $0.99

Desserts:
❍ Apple/Cherry/Berry pie $0.99
❍ Cookies $1.19

Total Price: $_______

❍ I wouldn't buy anything from this menu.
I'd drive to a different restaurant, or do something else for dinner.

(b) Menu vs. à-la-carte

Figure 3: Menu designs by Orme (2019)

What stands out, is that the data sets used for the methods mentioned above have been gathered using surveys containing no more than 12 items. This raises the question if the conclusions drawn regarding these methods are also valid when the number of items in the menu scenarios is a lot higher. It may be possible that for example the method introduced by Liechty et al. (2001), which outperformed the exhaustive alternatives model, does not give such promising results or is not even computationally feasible when the menu scenarios contain a significant larger number of items than 12.

In summary, three different MBC methods and four different ways of designing a menu have been found in existing literature. Though, not every method has been applied on every menu-based questionnaire design and it can be questioned how the MBC methods perform when the menus contain a large number of items. In this paper, the serial cross-effects method and two variations of the exhaustive alternatives method will be considered, together with the method introduced by Liechty et al. (2001). These methods will be compared using two designs comparable to the extended menu design and the menu vs. à-la-carte design.

3 Data

For this research, two different data sets are used. One of the data sets is gathered using a menu design similar to the extended menu design, as shown in Figure 1b. This menu design will be referred to as the simple menu design and will be further explained in Section 3.1. The second data set consists of respondents' choices in a menu design similar to the menu vs. à-la-carte design, as shown in Figure 3b. In this design, the respondents can choose between predesigned bundles of products or individual products that may be contained in one of the predesigned bundles. It is not possible to choose both a bundle and the individual products contained in this bundle. This menu design will be referred to as the menu vs. à-la-carte design and will be further explained in Section 3.2.

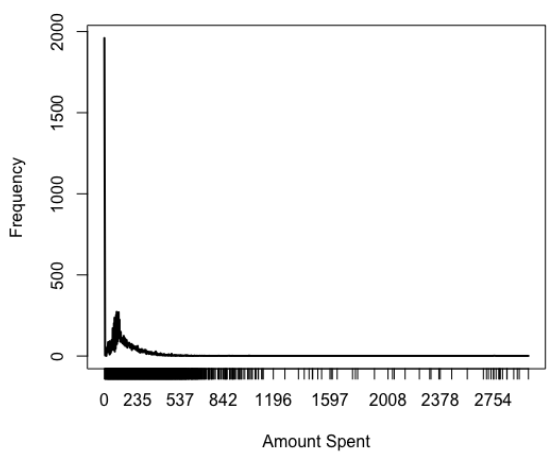
3.1 Simple Design

For the first data set, 2004 respondents filled in 12 menu scenarios for a restaurant in a simple design. In these menu scenarios, the respondent only orders for himself and can choose as many items as he/she wants. In every menu scenario, the respondent can choose from 57 different items, including 43 individual products and 14 meals containing some of the 43 products. It is possible to choose both a meal and an individual product contained in that meal. Besides, 10 of the 57 items can also be chosen two or three times, while it is not possible to choose the other items multiple times. These items are modelled as three different options in the used methods, leading to a total of 77 options. Obviously, it is not possible to choose a product both once and twice or three times, which should be taken into account in the estimation. The items that can be chosen multiple times are the more popular products such as a hamburger, desserts such as a piece of pie, or accompaniments such as sauce or topping. The items that cannot be ordered multiple times are products that are not expected to be chosen multiple times by one person, such as a big meal or a drink.

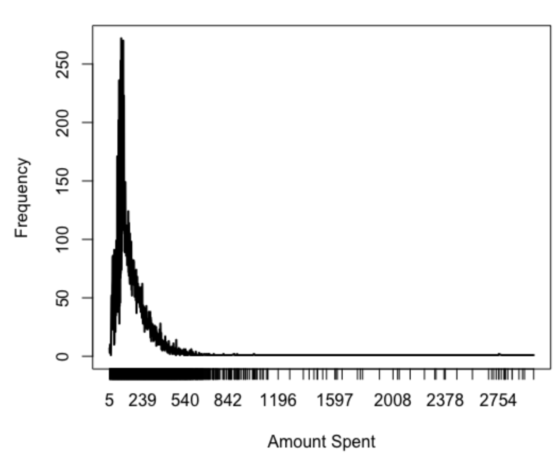
66 of the 77 options have five different price levels, while the remaining 11 items have four price levels. Additional to the different number of price levels, 10 of the items are not available in every menu scenario. The different price levels for every product are shown in Table 19 in the Appendix. It is also shown in this table which variables can be chosen

multiple times, as well as which variables are not available in every menu scenario.

The lowest amount of products chosen by a respondent is zero, while the highest amount is 52. The amounts spent lie between 0 and 3002. In Figure 4a, the frequency of every amount spent is shown. It can be seen that the figure shows a large peak at the amount spent equal to 0, which has been spent 1960 times. This implies that the respondents often do not choose any of the available items. To observe the amounts greater than zero more easily, the menu scenarios where no products are chosen, are left out in Figure 4b. Here, it can be seen that if a respondent chooses at least one item, the most frequently spent amount equals 87 (272 times) and that most respondents spent between 80 and 150.



(a) Frequency of every amount spent



(b) Frequency of every amount spent excluding the amounts where no products are chosen

Figure 4: Frequency of amounts spent in the simple design

In Table 1, the five most and least frequently chosen items are shown together with their frequency. It stands out that the least frequently chosen items and that also two of the most frequently chosen items are products that can be chosen multiple times.

Item	Frequency	Item	Frequency
PRODUCT16	3,226	PRODUCT35.2	96
PRODUCT34.1	2,885	PRODUCT37.2	39
PRODUCT24	2,836	PRODUCT41	37
PRODUCT36.1	2,692	PRODUCT37.3	24
MEAL10	2,496	PRODUCT38.3	23

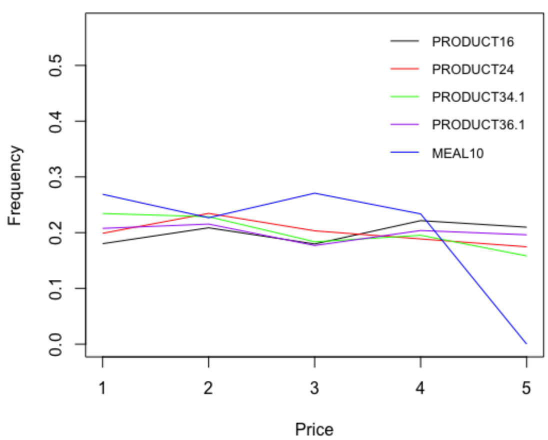
Table 1: Most and least frequently chosen items for the simple design

In Table 2, the frequencies of the most and least frequently chosen items are shown, but here, the frequencies of the items that can be chosen multiple times are the sum of the frequencies for choosing the relevant item once, two times and three times. This leads to higher frequencies for these items and therefore that three of the five most frequently items are items that can be chosen multiple times, namely, PRODUCT34, PRODUCT36 and PRODUCT1. Among the five least chosen items, no items are present that can be chosen multiple times. Furthermore, it can be seen that PRODUCT34 has been chosen in almost 20% of the menu scenarios and that the other four products have been chosen between 10 and 16 percent of the time. On the other hand, the five least chosen products have all been chosen less than one percent of the time.

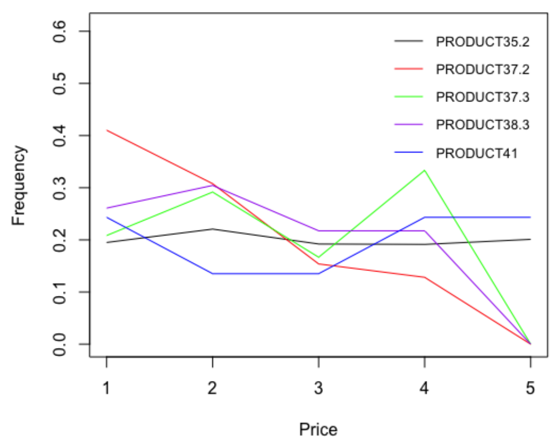
Item	Frequency	Item	Frequency
PRODUCT34	4,589*	PRODUCT39	177
PRODUCT36	3,832*	PRODUCT43	119
PRODUCT16	3,226	PRODUCT42	104
PRODUCT1	2,919*	PRODUCT40	101
PRODUCT24	2,836	PRODUCT41	37

Table 2: Most and least frequently chosen items for the simple design. *Frequency equals sum of frequencies of choosing this item once, two times and three times

Moreover, in Table 20 in the Appendix, the frequencies and relative frequencies for every price are shown for all items. The relative frequency per price equals the frequency per price level divided by the total frequency. In Figure 5a and 5b, the relative frequencies per price are shown for the five most and least frequently chosen items, respectively. In Figure 5a, it can be seen that the frequency of choosing the most frequently chosen products is almost constant for the five price levels, except for MEAL10, which only has four price levels. Looking at the relative frequency at its four price levels, the same can be stated as for the other most frequently chosen items, that is, that the frequency is almost constant for every price level. Where the relative frequency of PRODUCT16, PRODUCT24, PRODUCT34.1 and PRODUCT36.1 is constantly around 0.2, the relative frequency of MEAL10 does almost not differ from 0.25. Looking at Figure 5b, it can be stated that for some of the least frequently chosen items, the frequency is not as constant for every price level as for the most frequently chosen items. Except for PRODUCT35.2 and PRODUCT38.3, the frequency significantly fluctuates over the different price levels. Where the relative frequency of PRODUCT37.2 shows a negative relationship with the price, the relative frequency of PRODUCT37.3 and PRODUCT41 show a relationship with the price that makes less sense. Figure 5b shows that PRODUCT73.3 has been chosen most frequently at its highest price level and that PRODUCT41 has its highest frequency at its lowest and highest price levels.



(a) Relative frequency per price of the 5 most frequently chosen items



(b) Relative frequency per price of the 5 least frequently chosen items

Figure 5: Relative frequency per price for the simple design

So, it can be stated that the most frequently chosen items are certainly not price sensitive, while the frequency of choosing the least frequently chosen items fluctuate more over the different price levels. This higher sensitivity is mainly caused by the low frequency of these products. Namely, it can be seen in Table 20 that the absolute differences between the frequencies per price of the least chosen products are smaller than the absolute differences between the frequencies per price of the most frequently chosen items. However, because these frequencies per price level are divided by the total frequency, the relative frequencies differ more for the least frequently chosen items than for the most frequently chosen items.

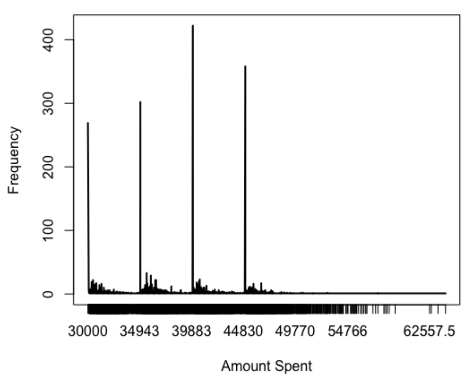
Besides examining the frequency of individual items, the frequency of the chosen combinations of items are investigated, where a combination of items contains the ordered products and meals of the respondent. The respondents have chosen a total of 10,761 different combinations of items, including 8,754 combinations that were only chosen once and 208 combinations of items that have a frequency higher than ten. In Table 3, the ten most frequently chosen combinations of items are shown. The most frequently chosen combination has been chosen approximately eight percent of the time, while the ten combinations in Table 3 have been chosen almost 17% in all observations in total. Looking at the table, a few things stand out. First of all, all ten most chosen combinations contain no more than one item. Secondly, the combination that has been chosen most frequently contains no items at all and its frequency is a lot higher than the frequencies of the other combinations, which is in line with the findings in Figure 4. The frequency of this "combination" is almost as high as the sum of the other nine combinations in Table 3. Lastly, it is remarkable that almost all ten combinations only exist of meals, while the most frequently chosen items mainly are no meal (see Table 1). This implies that respondents mostly choose nothing at all, only a meal, or a combination of different products.

"Combination"	Frequency	"Combination"	Frequency
	1,960	MEAL12	236
MEAL1	336	MEAL11	187
MEAL10	302	MEAL13	186
MEAL4	293	MEAL14	172
PRODUCT36.1	239	PRODUCT12	131

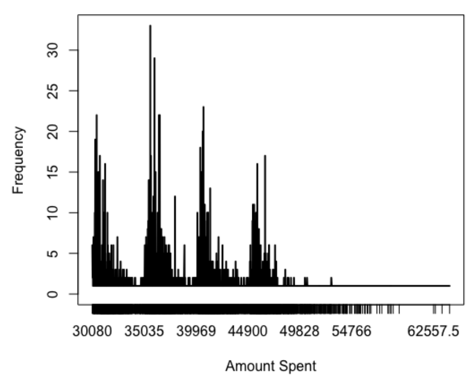
Table 3: Ten most frequently chosen combinations of items for the simple design

3.2 Menu vs. à-la-Carte Design

For the second data set, 625 respondents filled in 10 menu scenarios with a menu vs. à-la-carte design where they could customise their own car. In the menu scenarios, the respondents are shown a base product with its own price. The respondents have the possibility to add one or multiple products to this base product. They can choose between 32 different products, all having their own price. It is also possible to choose predesigned bundles containing one, two or three of the 32 products. These four bundles are referred to as PACK1, PACK2, PACK3 and PACK4, where PACK1 contains PRODUCT24 and PRODUCT25, PACK2 contains PRODUCT26, PRODUCT27 and PRODUCT28, PACK3 consists of PRODUCT29 and PRODUCT30, and only PRODUCT31 is contained in PACK4. Besides the mentioned products, additional items are contained in the four packs which are not individually available. The price of the bundles can be higher or lower than the cumulative prices of the products contained in the bundle. Furthermore, it is not possible for the respondents to choose both PRODUCT1 and PRODUCT2 or PRODUCT19 and PRODUCT20, as PRODUCT2 and PRODUCT20 are better versions of PRODUCT1 and PRODUCT19, respectively. The base product and the 32 products have four different price options, which are all shown in 1/4th of the menu scenarios. In Table 35 in the Appendix, the different price levels are shown for all products.



(a) Frequency of every amount spent



(b) Frequency of every amount spent excluding the amounts where no extra products are chosen

Figure 6: Frequency of amounts spent for the menu vs. à-la-carte design

In Figure 6a, the frequency of every amount spent is shown. The minimum amount spent is equal to the lowest price level of the base product, i.e., 30,000, and the maximum amount spent equals 64,081.50. The figure shows four enormous peaks at the four different price levels of the base product, namely, 30,000, 35,000, 40,000 and 45,000. The highest peak is at 40,000, which has been spent 422 times, while 30,000, 35,000 and 45,000 have been spent 269, 302 and 358 times, respectively. This finding implies that when the base price is higher, the respondents are less willing to choose extra products. Also in Figure 6b, the frequency of every amount spent is shown, but the amounts equal to the price levels of the base product are excluded. Therefore, the amounts in between these values can be observed more easily.

In this figure, it can be seen that the amounts 35,600, 36,000 and 40,660 have been spent most often, with frequencies equal to 33, 29 and 23, respectively. Besides, it can be observed that the four peaks in between the excluded amounts have similar shapes, where the peak between 35,000 and 40,000 is significantly higher and the peak after 45,000 is noticeably lower than the other peaks. This implies that for a base price of 35,000 the respondents are most willing to choose multiple products, while for the highest base price, the respondents are most reluctant to choose multiple products.

Additionally, the frequencies and the relative frequencies of the individual items are examined, which are shown in Table 36 in the Appendix. Here, the relative frequency per price equals the frequency per price divided by the total frequency. In Table 4, the frequencies of the five most and least frequently chosen items can be seen. The most frequently chosen item, PRODUCT1, is with its frequency of 1,472 a product that is selected more than 23 percent of the time. On the other hand, the five least chosen items are selected approximately 3.5% of the time, on average.

Product	Frequency	Product	Frequency
PRODUCT1	1,472	PRODUCT17	262
PRODUCT6	1,071	PRODUCT24	245
PACK1	946	PRODUCT14	219
PRODUCT10	920	PRODUCT16	190
PRODUCT7	914	PRODUCT28	182

Table 4: Most and least frequently chosen items for the menu vs. à-la-carte design

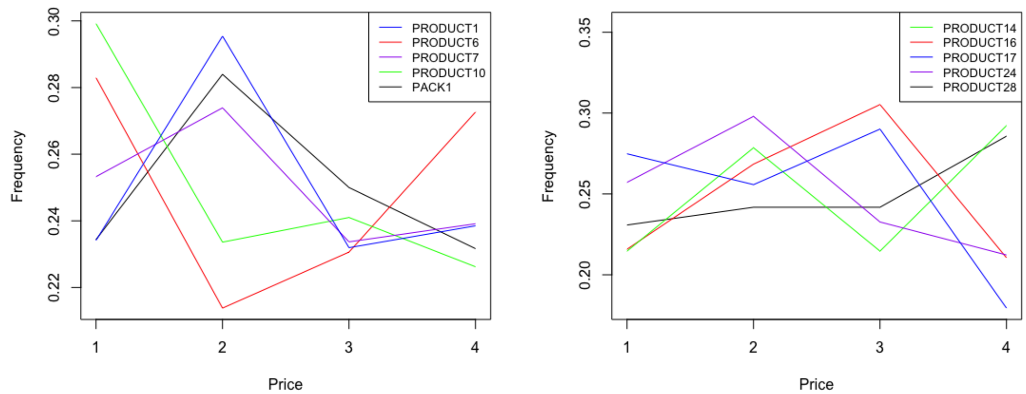
Moreover, in Table 5, the frequencies of the bundles of products are set against the frequencies of the products contained in these bundles. It can be seen that every product contained in one of the bundles has not been chosen more frequently than the corresponding pack. Besides, the frequency of PACK1, PACK3 and PACK4 are higher than the sum of the frequencies of the products contained in these packs. Therefore, it can be stated that when a respondent wants to choose one of the products contained in one of the bundles, it is likely that he or she picks the corresponding bundle instead.

Product	Frequency	Product	Frequency
PACK1	946	PRODUCT24	245
		PRODUCT25	579
PACK2	812	PRODUCT26	700
		PRODUCT27	587
		PRODUCT28	182
PACK3	797	PRODUCT29	447
		PRODUCT30	264
PACK4	735	PRODUCT31	492

Table 5: Frequency of packs vs. frequency of the products contained in the packs for the menu vs. à-la-carte design

Furthermore, the relative frequencies per price of the five most and least frequently chosen items are shown in Figure 7a and 7b, respectively. What stands out is that the most frequently chosen items have the highest relative frequency for one of the two lowest price levels, while the relative frequency of the least frequently chosen items is at it highest for one of the two highest price levels, except for PRODUCT24. This means that the respondents picked the most chosen items more frequently when the prices were low, contrary to the least chosen items.

After analysing the (relative) frequencies of the individual items, the frequencies of combinations of items are now examined. The respondents have chosen a total of 2,265 different combinations of items where 1,875 of the 2,265 combinations were only chosen once and only 51 combinations were chosen more than 10 times. In Table 6, the ten combinations of items with the highest frequency can be seen. In line with the findings in Figure 6a, the most



(a) Relative frequency per price of the five most frequently chosen items

(b) Relative frequency per price of the five least frequently chosen items

Figure 7: Relative frequencies per price for the menu vs. à-la-carte design

frequently chosen combination of items is the one where no item is chosen. No less than 26.4% of the time, this "combination" was chosen by the respondents. Moreover, almost all ten most frequently chosen combinations consist of only one item, which implies that the respondents often chose one or no items, namely, 2,410 of the 6,250 times.

Item 1	Item 2	Item 3	Frequency
			1,350
PRODUCT1	PRODUCT6	PRODUCT26	194
PRODUCT1			143
PACK1			82
PRODUCT5			81
PRODUCT25			72
PACK4			71
PRODUCT1	PRODUCT5	PACK1	68
PRODUCT2			55
PRODUCT6			52

Table 6: Most frequently chosen combinations of items for the menu vs. à-la-carte design

4 Methods

In this section, the different MBC methods will be thoroughly explained. Every method is applied to the two data sets introduced in Section 3. First, the serial cross-effects model will be discussed in Section 4.1, as well as the exhaustive alternatives model in Section 4.2. Additionally, in Section 4.2.1, the different ways of choosing the choice set for the exhaustive alternatives model are introduced. Afterwards, the multivariate choice model will be explained in Section 4.3. Lastly, in Section 4.4, the ways of measuring the performance of the different methods will be briefly explained.

4.1 Serial Cross-Effects Model

In this section, the serial cross-effects (SCE) model will be explained. The SCE model is one of the relatively easier models to implement. The basic idea of an SCE model is to build a separate binary choice model for every option in the menu. In every one of these models, a latent utility is predicted for all menu items in every menu scenario. When the latent utility is higher than a certain threshold, the relevant item is selected. The threshold is set to zero for identification purposes (Franses and Paap, 2001), leading to

$$Y_{ijs} = \begin{cases} 1, & \text{if } u_{ijs} > 0 \\ 0, & \text{if } u_{ijs} \leq 0, \end{cases}$$

where Y_{ijs} represents the choice of respondent $i = 1, \ldots, N$ whether item $j = 1, \ldots, J$ is selected in menu scenario $s = 1, \ldots, S$. The latent utility, u_{ijs}, depends on the intrinsic attraction of the menu item, as well as the price of both the relevant item and the other items on the menu, and therefore looks like

$$u_{ijs} = \beta_{0,ij} + \sum_{k=1}^{J} \beta_{1,ijk} p_{iks} + \varepsilon_{ijs}, \qquad \text{for } i = 1, \ldots, N, j = 1, \ldots, J, s = 1, \ldots, S, \tag{1}$$

where $\beta_{0,ij}$ is the intrinsic attraction of item j for respondent i, $\beta_{1,ijk}$ represents the influence of the price level of item k on the utility of item j experienced by respondent i, p_{iks} is the price level of item k in menu scenario s of individual i, and ε_{ijs} is the error term. Given this latent utility specification, two different model versions are considered. The first version is an aggregate model, where the parameters are equal for each individual. So,

$$\beta_{ij} = (\beta_{0,ij}, \beta_{1,ij1}, \ldots, \beta_{1,ijJ}) = (\beta_{0,j}, \beta_{1,j1}, \ldots, \beta_{1,jJ}) = \beta_j \quad \text{for } i = 1, \ldots, N, j = 1, \ldots, J. \tag{2}$$

The second version is a random effects model, leading to

$$\beta_{ij} = \bar{\beta}_j + \eta_{ij}, \quad \text{for } i = 1, \ldots, N, j = 1, \ldots, J \tag{3}$$

where $\eta_{ij} \sim \mathrm{N}(0, \Sigma_\beta)$ is a random term, making this model incorporating unobserved heterogeneity. The estimated individual-specific parameters are used in the prediction of the probabilities of choosing the different items.

To obtain the probability that individual i selects item j in menu scenario s, the probability that u_{ijs} is larger than zero is needed. This is achieved by

$$\begin{aligned}
\Pr(Y_{ijs} = 1|P_{is}) &= \Pr(u_{ijs} > 0|P_{is}) = \Pr(P_{is}\beta_{ij} + \varepsilon_{ijs} > 0|P_{is}) = \Pr(\varepsilon_{ijs} > -P_{is}\beta_{ij}|P_{is}) \quad (4)\\
&= \Pr(\varepsilon_{ijs} \leq P_{is}\beta_{ij}|P_{is}) = \mathrm{F}(P_{is}\beta_{ij}), \quad (5)\\
&\qquad \text{for } i = 1, \ldots, N, j = 1, \ldots, J, s = 1, \ldots, S,
\end{aligned}$$

where the independent variables are summarised in P_{is}, β_{ij} is a $(J+1) \times 1$ vector containing the parameters $\beta_{0,ij}$ to $\beta_{1,ijJ}$, and $\mathrm{F}(\cdot)$ represents the cumulative distribution function (CDF) of ε_{ijs}. It is assumed that ε_{ijs} follows a normal distribution, resulting in

$$\mathrm{F}(P_{is}\beta_{ij}) = \Phi(P_{is}\beta_{ij}) = \int_{-\infty}^{P_{is}\beta_{ij}} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) dz, \tag{6}$$

where $\Phi(\cdot)$ is used for standard normal distribution. The resulting model is called a probit model.

Due to the simplicity of this model, the choice-restrictions for the two data sets are not dealt with. This implies that it is possible that using the SCE method, two items are predicted to be chosen while it should not be possible, which is a big drawback of this method.

Variable Selection

It can be seen in the latent utility specification of this method, Equation 1, that if the number of items, J, is large, the amount of parameters is huge in every model. For instance, in the case of the simple design, 77 different SCE models are estimated containing 78 variables where most variables have four different levels. This leads to more than 200 parameters per model. An additional problem is that using all the variables may lead to overfitting of the model. Therefore, it can be stated that it is important to perform a variable selection before the probit models are implemented.

Dippold-Tausendpfund and Neuerburg (2018) show that for SCE models with cross-price effects, the χ^2-test performs well to select the right variables. A χ^2-test can be used to investigate whether two variables are related or not, where the null hypothesis of the χ^2-test is that the variables are independent. So, if the p-value of the test is significantly close to zero, it can be concluded that the two variables are related to one another. The price variables that have no significant influence on choosing an item are left out of the model. Before implementing the probit models, the χ^2-test is performed for every option in the menu and every price level of all items, for which the p-value is calculated. Afterwards, the variables with a p-value lower than 0.10 are included in the probit model.

4.2 Exhaustive Alternatives Model

This section focuses on the exhaustive alternatives (EA) model. The EA model is based on the method introduced by Ben-Akiva and Gershenfeld (1998), where not every individual menu item but every possible combination of items is considered. Therefore, the model assumes that the respondents approach a menu scenario by looking at all possible ways of selecting the items and choose the one most preferred way.

If a menu contains J items, the respondent has 2^J possible ways of completing a menu scenario. It can be imagined that if J is large, the amount of possible ways of completing the menu is enormous. Considering the simple design, the total number of possible combinations equals $2^{77} = 1.5 \times 10^{23}$. It is impossible that a respondent would take every one of these possible combinations into account if a choice has to be made. In this research, two ways of composing the considered set of combinations are used, which will be further explained in Section 4.2.1. The set of combinations being considered, is denoted as C.

Following the proposed method of Ben-Akiva and Gershenfeld (1998), the latent utility of every combination is a function of a set of categorical variables that indicate the price level of the items contained in the relevant combination. So, the latent utility $u_{c_{is}}$ of combination $c_{is} \in C$ for individual $i = 1, \ldots, N$ in menu scenario $s = 1, \ldots, S$ is equal to

$$u_{c_{is}} = \sum_{j \in c_{is}} \beta_{ij} p_{ijs} + \varepsilon_{c_{is}}, \quad \text{for } \forall c_{is} \in C, i = 1, \ldots, N, s = 1, \ldots, S, \tag{7}$$

where p_{ijs} equals the price level of item j in menu scenario s for individual i. The error term, $\varepsilon_{c_{is}}$, is assumed to follow an extreme value distribution.

To obtain the probability that combination $c_{is} \in C$ is chosen by individual $i = 1, \ldots, N$ in menu scenario $s = 1, \ldots, S$, the probability that the utility of combination c_{is} being the highest of all combinations needs to be found, that is,

$$\Pr(Y_{is} = c_{is} | P_{is}) = \Pr(u_{c_{is}} > u_c | P_{is}, \forall c \in C \backslash c_{is}) = \Pr(u_{c_{is}} - u_c > 0 | P_{is}, \forall c \in C \backslash c_{is}), \tag{8}$$
$$\text{for } \forall c_{is} \in C, i = 1, \ldots, N, s = 1, \ldots, S,$$

where Y_{is} is the random variable representing the choice of individual i in menu scenario s and P_{is} represents the price levels of all items in menu scenario s for individual i. Due to the error terms being assumed to follow an extreme value distribution, the logistic distribution arises when the difference of the utilities is considered, making it a multinomial logit (MNL) model. Now, the probability of combination $c_{is} \in C$ being chosen by individual $i = 1, \ldots, N$ in menu scenario $s = 1, \ldots, S$ is equal to

$$\Pr(Y_{is} = c_{is} | P_{is}) = \frac{\exp(u_{c_{is}})}{\sum_{c \in C} \exp(u_c)}, \quad \text{for } \forall c_{is} \in C, i = 1, \ldots, N, s = 1, \ldots, S. \tag{9}$$

Similarly to the SCE model, two different versions are considered, where the first version is an aggregate model,

$$\beta_i = (\beta_{i1}, \ldots, \beta_{iJ}) = (\beta_1, \ldots, \beta_J, \beta_P) = \beta, \quad \text{for } i = 1, \ldots, N, \tag{10}$$

and the second version is a random effects model,

$$\beta_i = \bar{\beta} + \eta_i, \quad \text{with } \eta_i \sim \mathrm{N}(0, \Sigma_\beta) \quad \text{for } i = 1, \ldots, N. \tag{11}$$

The estimated individual-specific parameters, $\hat{\beta}_i$, are used in making predictions of the probabilities of choosing the different items.

4.2.1 Composing C

As explained earlier, a major drawback of the exhaustive alternatives method is that if the number of items on a menu is large, the number of possible ways to choose a combination of items explodes. While a respondent can consider all possible combinations, it is not possible to take every possible combination of items into account in the analysis. Consequently, two ways of composing the considered set of combinations, C, are used.

Naive

An easy but also relatively poor way of choosing the considered set of possible combinations, C, is by looking at the most frequently chosen combinations in the data. When for example the researcher chooses to consider 40 combinations in every menu scenario, the 40 most frequently chosen combinations can be used. By using this naive way of choosing C, a lot of possible combinations of items are not considered in the analysis. As can be seen in Section 3.1, in the case of the simple design, $2^{77} - 40$ combinations are not looked at and $10,721$ combinations that have been chosen by the respondents are not taken into account by the researcher to estimate the EA model. While choosing the set of combinations this way solves the problem of having to consider every possible combination, a lot of information is thrown away. For the simple design, the 40 most frequently chosen combinations were chosen in 6,018 of the 24,048 menu scenarios. This means that approximately 75 percent of the observations cannot be used for the estimation of the EA model, due to the chosen combination not being contained in the considered set of combinations, C. A consequence of throwing away so much information about other combinations than the combinations in the fixed choice set, is that the estimations using this model are not consistent. If the extent of the thrown away information is not too large, the consequence of inconsistent estimations would less be of a problem. This is the case when the number of items, J, is not too large or when the respondents mostly choose a small number of different combinations.

In this research, the EA model using this way of choosing C is compared with an EA model where a sampling method is used to obtain the considered set of combinations in every menu scenario.

Stratified Importance Sampling

Besides the naive way of choosing C, a sampling method is used to compile a set of combinations containing the actually chosen combination. Similarly to the naive way, a subset of all chosen combinations is considered in every observation. However, contrary to the naive way, the considered set of possible combinations is different in every menu scenario for which a correction of the probabilities is necessary. The sampling method is based on the method introduced by Ben-Akiva and Lerman (1985), called stratified importance sampling (SIS).

Using this method, C_{is}, a subset of the full outcome space, is sampled in every menu scenario $s = 1, \ldots, S$ for every individual $i = 1, \ldots, N$. Following McFadden (1978), maximum likelihood estimation is consistent if the chosen combination is in C_{is}, in contrast to the estimations using a fixed C. Using Bayes' theorem, the probability of choosing c^*_{is} in menu scenario $s = 1, \ldots, S$ of individual $i = 1, \ldots, N$ can be written as

$$\Pr(Y_{is} = c^*_{is}|C_{is}, P_{is}) = \frac{\Pr(Y_{is} = c^*_{is}|P_{is}) \Pr(C_{is}|Y_{is} = c^*_{is}, P_{is})}{\sum_{c_{is} \in C_{is}} \Pr(Y_{is} = c_{is}|P_{is}) \Pr(C_{is}|Y_{is} = c_{is}, P_{is})} \tag{12}$$

$$= \frac{\exp(u_{c^*_{is}} + \log(\Pr(C_{is}|Y_{is} = c^*_{is}, P_{is})))}{\sum_{c_{is} \in C_{is}} \exp(u_{c_{is}} + \log(\Pr(C_{is}|Y_{is} = c_{is}, P_{is})))}, \tag{13}$$

$$\text{for } \forall c_{is} \in C_{is}, i = 1, \ldots, N, s = 1, \ldots, S,$$

where $\Pr(Y_{is} = c^*_{is}|P_{is})$ follows from Equation 8 and c_{is} represents a combination of items in subset C_{is}. It can be seen that a correction term is necessary in the estimation when a differing subset C_{is} is used instead of a fixed set in every observation, namely, $\log(\Pr(C_{is}|Y_{is} = c_{is}, P_{is}))$.

Following SIS, the full outcome space is split up into R disjoint strata with comparable alternatives. These strata are based on the number of items contained in the combination. So, the strata only consist of combinations of singles, pairs, triplets, et cetera. From every stratum r, a fixed number of alternatives, n_r, is randomly selected with equal probabilities. For every observation, it is made sure that the chosen combination c^*_{is} is contained in the selected subset of stratum $r(c^*_{is})$, where $r(c^*_{is})$ is the stratum containing c^*_{is}. The selection probabilities within every stratum is equal for all alternatives, namely, n_r/N_r where N_r is the number of alternatives contained in stratum r. This stratum-specific selection probability is denoted as q_r. According to Ben-Akiva and Lerman (1985), the undefined probability in Equation 12 is related to this stratum-specific selection probability, that is, $\Pr(C_{is}|Y_{is} = c^*_{is}, P_{is}) \propto 1/q_{r(c^*_{is})}$.

What follows, is that the correction term in Equation 13 equals minus the logarithm of q_r, leading to

$$\Pr(Y_{is} = c^*_{is}|C_{is}, P_{is}) = \frac{\exp(u_{c^*_{is}} - \log(q_{r(c^*_{is})}))}{\sum_{c_{is}\in C_{is}} \exp(u_{c_{is}} - \log(q_{r(c_{is})}))}, \quad \text{for } \forall c_{is} \in C_{is}, i = 1, \ldots, N, s = 1, \ldots, S. \tag{14}$$

Using SIS, it can be seen that instead of considering all 2^J combinations, only the alternatives contained in C_{is} needs to be taken into account in every menu scenario. This reduces the computational burden substantially, if the size of C_{is} is chosen considerably smaller than 2^J. The EA models following from the two ways of choosing C will be compared using the performance measures presented in Section 4.4.

4.3 Multivariate Choice Model

In this section, the multivariate choice (MVC) model will be described thoroughly. The MVC model is based on the method proposed by Liechty et al. (2001). This method resembles the SCE model in a way that the latent utility of every menu item is examined individually. The difference between the two methods is found in the way the different menu items are connected. The items in the SCE model are connected by using the price of every item as an explanatory variable in the latent utility function of all items. On the other hand, the explanatory variables of the utility function of an item in the MVC model only exist of the price of the relevant item:

$$u_{ijs} = \beta_{0,ij} + \beta_{1,ij} p_{ijs} + \varepsilon_{ijs}, \quad \text{for } i = 1, \ldots, N, j = 1, \ldots, J, s = 1, \ldots, S, \tag{15}$$

where $\varepsilon_{is} = (\varepsilon_{i1s}, \ldots, \varepsilon_{iJs}) \sim \mathrm{N}(0, \Sigma_\varepsilon)$. Liechty et al. (2001) considered a case where Σ_ε is a correlation matrix leading to the latent utility functions of the different items being able to be correlated, making it a multivariate probit (MVP) model.

For this model, only an aggregate version is considered due to the computational complexity of an MVP model. Here, the parameters follow

$$\beta_{ij} = (\beta_{0,ij}, \beta_{1,ij}) = (\beta_{0,j}, \beta_{1,j}) = \beta_j, \quad \text{for } i = 1, \ldots, N, j = 1, \ldots, J. \tag{16}$$

Multivariate Probit using Bivariate Probit

A drawback of the MVP model is that as the outcome dimensions rise, estimation can be difficult due to numerical computation constraints, as well as computational speed. Mullahy (2016) suggests to use a chain of bivariate probit (BVP) models to estimate the MVP model, where a BVP model is a specific version of an MVP model where the number of outcomes, J, equals two. He showed that when BVP models are used to estimate an MVP model in situations involving large numbers of outcomes (J) or large sample sizes, consistent estimators are provided and the reduction in computation time is significant. The savings in time arise because this way of estimation does not rely on simulation methods, contrary to an MVP model.

The main idea of this method is to estimate the J-outcome MVP model by estimating a BVP model for all $0.5J(J-1)$ possible outcome pairs, yielding $J-1$ estimates of each β_j and one estimate of the correlation between outcome p and q, ρ_{pq}, with $j, p, q = 1, \ldots, J$ and $p \neq q$. Using the single ρ_{pq} estimates, the correlation matrix Σ_ε can easily be constructed. To find single estimates of every β_j, $j = 1, \ldots, J$, the simple averages of the $J-1$ estimates are computed, that is, $\hat{\beta}_j = \frac{1}{J-1}\sum_{m=1, m\neq j}^{J} \hat{\beta}_{jm}$, where $\hat{\beta}_{jm}$ represents the parameters obtained from the BVP for outcome j and m relevant for outcome j, for $j, m = 1, \ldots, J$. These estimates $\hat{\beta}_j$, $j = 1, \ldots, J$, are consistent since the weighted average of consistent estimators is in general consistent (Chung and Zhong, 2001).

4.4 Performance Measures

To compare the different methods introduced in this section, the methods are judged on their predictive ability and computational time.

In order to measure the predictive power, the data sets are split up into a training part and a test part. After training the methods using the training data set, probabilities of choosing each item are predicted and compared with the actually chosen items for both the training and the test data.

To measure the predictive performance of the methods, both the root mean squared error (RMSE) and the root likelihood (RLH) are calculated for the estimated probabilities. The RMSE is defined by the root of the mean of the squared differences between the estimated probabilities and the choices in every observation, that is,

$$RMSE_j = \sqrt{\frac{\sum_{i=1}^{N}\sum_{s=1}^{S}(\hat{y}_{ijs} - y_{ijs})^2}{N \times S}}, \quad \text{for } j = 1, \ldots, J, \tag{17}$$

where $\hat{y}_{ijs}$ represents the probability that item j is chosen in menu scenario s by respondent i. Using this performance measure, an easily interpretable conclusion can be drawn of the predictive ability of the different methods.

Besides the RMSE, the RLH is used to measure the predictive performance, which is equivalent to computing the geometric mean of the probabilities of predicting correctly. The geometric mean is defined as the n-th root of the product of n values. Here, the geometric mean is taken over the values that represent the probabilities that the estimation is correct in every observation, that is,

$$RLH_j = \sqrt[N \times S]{\Pi_{i=1}^{N}\Pi_{s=1}^{S}(\hat{y}_{ijs}y_{ijs} + (1-\hat{y}_{ijs})(1-y_{ijs}))}, \quad \text{for } j = 1, \ldots, J. \tag{18}$$

When $N \times S$ is large, the product of the probabilities becomes zero. That is why the following transformation is necessary

$$RLH_j = \exp\left(\log\left(\sqrt[N \times S]{\Pi_{i=1}^{N}\Pi_{s=1}^{S}(\hat{y}_{ijs}y_{ijs} + (1-\hat{y}_{ijs})(1-y_{ijs}))}\right)\right) \tag{19}$$

$$= \exp\left(\frac{\sum_{i=1}^{N}\sum_{s=1}^{S}\log\left(\hat{y}_{ijs}y_{ijs} + (1-\hat{y}_{ijs})(1-y_{ijs})\right)}{N \times S}\right). \tag{20}$$

Because of the nature of the geometric mean, it is more affected by low values than the arithmetic mean. Therefore, the RLH is dragged lower by probabilities that are very different from the actual choice than an arithmetic mean would be. For example, suppose there are three binary choices and a model predicts probabilities equal to 0.95, 0.99 and 0.01 that it is actually chosen. If the model predicts the two first choices correctly, then the RLH would equal $\sqrt[3]{0.95 \times 0.99 \times 0.01} = 0.21108$, while taking the arithmetic mean would result in $(0.95 + 0.99 + 0.01)/3 = 0.65$. So, even though the model predicts two choices almost perfectly, the RLH is substantially affected by the fact that it predicts one choice completely wrong, in contrast to taking the arithmetic mean.

Both performance measures lie between zero and one, where the RMSE is considered better when it is low and the RLH vice versa.

5 Results

In this section, the obtained results from the methods explained in Section 4 will be discussed. There are seven models that have been implemented, namely, an aggregate and a random effects SCE model, an aggregate and a random effects EA model with a naive choice of C, an aggregate and a random effects EA model using SIS, and an MVC model. For comparison, a model is included which predicts a probability equal to the average of choosing the specific item in the data. What follows, is a brief summary of the implementation of all methods for both data sets in Section 5.1. Then, the computational time of the different models are compared in Section 5.2, after which the RMSE and RLH of the predicted probabilities are presented and discussed in Section 5.3 and 5.4, respectively. This section finishes with a small conclusion on the results and findings in Section 5.5.

5.1 Summary

All models have been implemented in R 1.3.1073 (R Core Team, 2020) on a dual-core Intel Core 2.30Ghz i5 processor with 8GB RAM. The two data sets are split up in a training and test part, where the training data set contains 75% of the menu scenarios of every individual for the simple design and 80% for the menu vs. à-la-carte design.

Serial Cross Effects Model

The SCE methods have been implemented using the packages stats (R Core Team, 2021) and Rchoice (Sarrias, 2016) for the aggregate and the random effects models, respectively. First, a variable selection has been performed as explained in Section 4.1. So, for every item on the menu, a χ^2-test is performed on every possible cross-price effect. The variables, i.e., the price levels of every product on the menu, that have a p-value lower than 0.10 are included in the model. For the simple design, the resulting number of variables per model lies between 2 and 43 and can be found in Table 21 in the Appendix. The number of selected variables for the SCE models in the menu vs. à-la-carte design is shown in Table 37. For multiple items, the SCE model has less than ten significant variables, implying that for many variables the choice whether it is chosen or not, is not influenced by the price of many other variables.

Exhaustive Alternatives Model

For the estimation of the aggregate and random effects versions of the naive exhaustive alternatives model, the mlogit package (Croissant, 2020) and the ChoiceModelR package (Sermas, 2012) are used, respectively. However, for the random effects version of the EA method using SIS, the Rchoice package (Sarrias, 2016) is used, while the mlogit package (Croissant, 2020) is also used for the aggregate version.

For the EA models with the naive choice of the choice set, C, the 40 most frequently chosen combinations in the training data are considered as the choice set, see Table 22 and 38 in the Appendix for the considered choice sets. For the simple design, all combinations do not contain more than two items, while the maximum number of items per combination for the menu vs. à-la-carte design is three. Consequently, many of the items are not even contained in one of the 40 combinations. Specifically, 41 of the 77 items and 14 of the 36 items are not present in C for the simple and menu vs. à-la-carte design, respectively.

A consequence of choosing such a small choice set is that in 75 percent of the observations in the training data for the simple design and 50 percent for the menu vs. à-la-carte design, a combination of items is chosen that does not correspond with a combination in C. Therefore, these observations cannot be taken into account for the estimation of the model, leaving an inconsistent EA model. For this reason, a lot of information is thrown away and a lot of individuals are not present in the training data anymore, namely, only 1,173 of the 2,004 individuals for the simple design and 476 of the 625 individuals for the menu vs. à-la-carte design are present.

For the random effects version of the EA, a unique set of parameters is drawn for every individual in the training data used for estimation. To still be able to make predictions for the individuals absent in the used training data, the mean of the estimated coefficients for the individuals present in the training data are used. Moreover, the chosen combination of items is included in the choice set for the prediction of choices. This way, for all observations in the training and test data, probabilities of choosing the items in C can be predicted. For the items absent in C, probabilities equal to zero have been predicted, due to the absence of information about these items.

For the EA models using SIS, eight strata of item combinations are created based on the number of items present in the combination. In Table 7, all relevant information of every stratum is shown for both designs. n_r is based on the frequency of stratum r. So, the higher the frequency, the higher n_r. If all n_r are added up, it becomes clear that for both designs the choice set for every observation consists of 39 combinations of items including the chosen combination. Contrary to the EA models using the naive way of choosing C, all observations and variables are maintained for the model estimation resulting in a consistent model. This is expected to be an advantage over the naive EA models.

Design	Number of items	0 items	1 item	2 items	3 items	4 items	5 items	6 items	≥7 items
Simple	Frequency	1,464	3,418	3,818	3,147	2,259	1,464	931	1,535
	n_r	1	8	9	7	5	3	2	4
	N_r	1	70	986	2,078	1,906	1,266	793	1,405
	q_r	1.0000	0.1143	0.0091	0.0034	0.0026	0.0024	0.0025	0.0029
Menu vs.	Frequency	1,075	848	725	847	306	242	179	778
à-la-carte	n_r	1	8	7	8	3	2	2	8
	N_r	1	35	231	333	231	203	152	702
	q_r	1.0000	0.2286	0.0303	0.0240	0.0130	0.0099	0.0132	0.0114

Table 7: Information about the strata for the simple and menu vs. à-la-carte design

Multivariate Choice Model

For the estimation of the MVC model, the GJRM package (Marra and Radice, 2017) is used. Using the MVC method, a correlation matrix is estimated containing the correlations between the choices of the different items. The resulting correlation matrix for the simple design is shown in Table 23 through 28 in the Appendix. In Table 39, 40 and 41 in the Appendix, the resulting correlation matrix for the menu vs. à-la-carte design is displayed. That such correlation matrices are estimated, may be an advantage over the other prediction methods, where only the intrinsic attraction and price influences of the different items are estimated. The estimated correlation matrices are not positive definite, though. This is a result of estimating the MVP model using many BVP models. As a consequence, it may occur that the resulting correlation values are intransitive. Transitivity implies that if choosing item A and B is sufficiently positively correlated and choosing item B and C is sufficiently positively correlated, choosing items A and C should also be positively correlated. However, due to the design of the MVC method, choosing item A and C may be negatively correlated, leading to a correlation matrix which is not positive definite. Before predictions can be made using the estimated parameters, the correlation matrices are made positive definite using the corpcor package (Schafer et al., 2017). This package uses the algorithm of Higham (1988) to compute the nearest positive definite matrix of a real symmetric matrix.

Using the correlation matrix, statements concerning the relations between the items on the menu can be made. In Table 8, 9 and 10, three snippets of the resulting correlation matrix for the simple design are shown together with the standard errors of the included correlation estimates.

$$\begin{vmatrix} 1 & \underset{(0.111)}{-0.86} & \underset{(0.141)}{-0.83} \\ \underset{(0.111)}{-0.86} & 1 & \underset{(0.136)}{-0.79} \\ \underset{(0.141)}{-0.83} & \underset{(0.136)}{-0.79} & 1 \end{vmatrix}$$

Table 8: Correlation between choosing PRODUCT1 once, twice or three times

$$\begin{vmatrix} 1 & \underset{(0.101)}{-0.89} & \underset{(0.928)}{0.99} \\ \underset{(0.101)}{-0.89} & 1 & \underset{(0.073)}{-0.92} \\ \underset{(0.928)}{0.99} & \underset{(0.073)}{-0.92} & 1 \end{vmatrix}$$

Table 9: Correlation between choosing PRODUCT38 once, twice or three times

$$\begin{vmatrix} \underset{(0.000)}{0.31} & \underset{(0.000)}{0.07} & \underset{(0.000)}{-0.01} \\ \underset{(0.000)}{0.00} & \underset{(0.000)}{0.42} & \underset{(0.000)}{0.17} \\ \underset{(0.000)}{0.08} & \underset{(0.000)}{0.28} & \underset{(0.000)}{0.51} \end{vmatrix}$$

Table 10: Correlation between choosing PRODUCT1 and PRODUCT34 once, twice or three times

Some findings are very intuitive, such as that for a product that can be chosen multiple times, choosing this product once is significantly negatively correlated with choosing the product twice or three times. For example, in Table 8 can be seen that the correlation between choosing PRODUCT1 once, twice or three times is very close to minus one, making it unlikely that these items are predicted to be chosen simultaneously in the same observation by the MVC model.

On the other hand, it also occurs that the correlation between choosing a product once or multiple times is counterintuitive. For example, in Table 9, the correlations between choosing PRODUCT38 once, twice or three times are shown. Similar to the findings for PRODUCT1, the correlation between choosing PRODUCT38 once and choosing PRODUCT38 twice is close to minus one, which also applies for choosing PRODUCT38 twice and three times. However, it is surprising that the correlation between choosing PRODUCT38 once or three times is as good as equal to one. That would mean that if PRODUCT38 is chosen once, it would also be chosen three times, which is not possible. An explanation of this result can be found in the standard error of this estimation. Observing that the standard error of the correlation estimate between choosing PRODUCT38 once and three times equals 0.928, it can be stated that this estimation is not accurate. This high standard error can possibly be explained by the fact that PRODUCT38 has almost never been chosen three times, see Table 1. Therefore, almost no information is available about choosing this item. It particularly is the case that for the items that are rarely chosen, the correlations with choosing other items make less sense.

Moreover, it is interesting to see that if the correlation is considered between two products that can be chosen multiple times, for example PRODUCT1 and PRODUCT34, the correlation between choosing both items the same amount of times is significantly larger than choosing them a different amount of times, see Table 10. This implies that PRODUCT1 and PRODUCT34 are rather complementary products than substitutes, such as, fries and ketchup.

Furthermore, in Table 11, 12 and 13, snippets of the resulting correlation matrix for the menu vs. à-la-carte design are shown including the standard errors of the correlation estimations.

1	0.43 (0.001)	−0.60 (0.001)
0.43 (0.001)	1	−0.47 (0.001)
−0.60 (0.001)	−0.47 (0.001)	1

Table 11: Correlation between choosing the products in PACK3 and PACK3

1	0.69 (0.000)	0.63 (0.000)	0.48 (0.000)
0.69 (0.000)	1	0.64 (0.000)	0.54 (0.000)
0.63 (0.000)	0.64 (0.000)	1	0.65 (0.000)
0.48 (0.000)	0.54 (0.000)	0.65 (0.000)	1

Table 12: Correlation between choosing PACK1, PACK2, PACK3 and PACK4

1	0.19 (0.000)	0.60 (0.000)	0.27 (0.001)
0.19 (0.000)	1	0.01 (0.001)	0.19 (0.001)
0.60 (0.000)	0.01 (0.001)	1	0.17 (0.001)
0.27 (0.001)	0.19 (0.001)	0.17 (0.001)	1

Table 13: Correlation between choosing PRODUCT6, PRODUCT7, PRODUCT26 and PRODUCT27

What stands out, is that the choices of the products that cannot be chosen simultaneously are significantly negatively correlated. That is, the correlation between choosing PRODUCT1 and PRODUCT2 equals -0.67 and for PRODUCT19 and PRODUCT20 the correlation equals -0.90. Moreover, the correlations between choosing the packs and the products contained in those packs are negative. For example, in Table 39, the correlations between PACK3 and the products contained in PACK3, i.e., PRODUCT29 and PRODUCT30, are shown. It can be seen that the choice of PACK3 is negatively correlated with choosing PRODUCT29 or PRODUCT30, while the choices of PRODUCT29 and PRODUCT30 are positively correlated, which is in line of expectations. The same findings can be seen for PACK1, PACK2 and PACK4, in Table 41 in the Appendix.

Furthermore, in Table 12, the correlations between choosing the different packs are shown. It can be seen that the choices of the different packs are strongly positively correlated. This corresponds with the choice set shown in Table 38, where it can be seen that in a couple of the 40 most frequently chosen combinations, multiple packs are chosen.

On the other hand, it can also be seen in the choice set in Table 38 that PRODUCT6, PRODUCT7, PRODUCT26 and PRODUCT27 are chosen simultaneously in many observations. Consequently, it is expected that the correlations between choosing these four products are high. However, the resulting correlation matrix is not in line with these expectations. In Table 13, the correlations of the choices of these products are shown. Only between the choices of PRODUCT6 and PRODUCT26, the correlation is strong, but the other values are not higher than 0.27.

These findings show that the MVC model has an advantage over the other methods, since it can be used to make statements concerning the relations between choosing different items, if the information on these items is sufficient.

5.2 Computation Time

The computation time of the different methods using the simple design and the menu vs. à-la-carte design data sets is presented in Table 14. What immediately stands out, is the enormous amount of computation time of the random effects SCE model. For the simple design, this model had to run more than five days before it was finished, while for the menu vs. à-la-carte design, the computation time was at least 2.5 times higher than for the other methods. This is clearly a big drawback of this method.

Furthermore, almost the same conclusions can be drawn for both data sets. Namely, it is in line of expectations that for all methods the aggregate models are computationally less heavy than their random effects alternatives. Besides, it is expected that the EA methods using SIS need more computation time than the naive versions of EA, because the used training data set is substantially larger and the number of included variables is also considerably higher when SIS is used instead of the naive way of choosing C. Although these findings are similar for both data sets, the conclusion regarding the MVC method is totally different. Where for the simple design, the MVC method is one of the most time consuming methods with a total computation time of more than 10 hours, the MVC method is one of the fastest methods for the menu vs. à-la-carte design. This enormous difference may be a result of the big difference in the number of observations and especially in the number of items on the menu for both designs, leading to a correlation matrix that is substantially larger for the simple design. It can be concluded that if the number of items on the menu is not too high, computation time does not cause a problem for using the MVC method.

Model	Simple	Menu vs. à-la-Carte
aggregate SCE	2	0.2
random effects SCE	7763	387
aggregate naive EA	4	0.3
random effects naive EA	92	35
aggregate EA with SIS	73	1.2
random effects EA with SIS	610	147
MVC	411	9

Table 14: Computation time (in minutes) of the different methods for the two data sets

5.3 RMSE

Besides examining the computation time of the methods explained in Section 4, the different models are judged on their predictive power. The resulting RMSE values per item for every method can be seen in Table 29 and 30 in the Appendix, for the training data and the test data in the simple design, respectively. For the menu vs. à-la-carte design, the resulting in-sample and out-of-sample RMSE values can be found in Table 42 and 43 in the Appendix, respectively.

For the simple design, the means of the RMSE values are shown in Table 15 for all introduced methods, as well as for the method where only probabilities equal to the frequency of choosing the item are predicted. It stands out that the two most time consuming methods, namely, the random effects SCE and random effects EA using SIS, have the worst RMSE scores, with approximately five and three percent points higher than the other methods, respectively. The remaining methods perform similarly regarding the RMSE values, where all values are approximately 18% for both in-sample and out-of-sample. It can be seen in Table 15 that the aggregate EA method using SIS performs best, where the aggregate SCE and MVC methods follow up closely with roughly 0.1 percent points difference.

Model	in-sample	out-of-sample
aggregate SCE	0.18022	0.18072
random effects SCE	0.23669	0.23565
aggregate naive EA	0.18174	0.18171
random effects naive EA	0.18152	0.18190
aggregate EA with SIS	**0.17935**	**0.17950**
random effects EA with SIS	0.21767	0.20399
MVC	0.18067	0.18072
average y	0.18715	0.18722

Table 15: RMSE of the different methods for the simple design

For the menu vs. à-la-carte design, the means of the RMSE values are shown in Table 16 for all methods. Compared to the resulting RMSEs for the simple design, these RMSE values lie closer to each other. Similarly to the results for the simple design, the worst performing methods are the random effects SCE method and the random effects EA using SIS, while the best performing method is the aggregate EA method using SIS.

Model	in-sample	out-of-sample
aggregate SCE	0.27691	0.27858
random effects SCE	0.28934	0.29008
aggregate naive EA	0.28435	0.28496
random effects naive EA	0.27631	0.27732
aggregate EA with SIS	**0.27563**	**0.27663**
random effects EA with SIS	0.30681	0.29761
MVC	0.27745	0.27808
average y	0.28440	0.28570

Table 16: RMSE of the different methods for the menu vs. à-la-carte design

In summary, regarding the RMSE values for both data sets, it can be stated that the most time consuming methods are also the worst performing methods, namely, the random effects SCE method and the random effects EA using SIS. Moreover, the other methods, including the 'average y' method, perform quite similarly, for which the RMSE values have a range of approximately one percent point for both data sets. Although the remaining methods perform so similarly, the best performing method for both data sets is the aggregate EA method using SIS, considering the RMSE score. In combination with its relatively low computation time, the aggregate EA method using SIS seems like a useful method for predicting menu-based choices.

5.4 Root Likelihood

Furthermore, the RLH values for the estimated probabilities are calculated following Equation 20. The resulting RLH values per item for every method in the training and test data for the simple design can be seen in Table 31 and 32 in the Appendix, respectively. For the menu vs. à-la-carte design, the RLH values per item can be seen in Table 44 and 45 in the Appendix for the training and test data set, respectively.

In Table 17, the means of the RLH values are displayed for the simple design. If the RLH values are analysed, it is noticed that the best performing methods for the simple design are also the methods with the best RMSE scores, that is, the aggregate SCE method, the aggregate EA method using SIS and the MVC method. Moreover, the random effects naive EA and 'average y' methods follow closely behind these three models, while the difference with the random effects SCE model, aggregate naive EA model and random effects EA model using SIS is considerably larger.

Model	in-sample	out-of-sample
aggregate SCE	**0.85912**	0.85676
random effects SCE	0.81762	0.81452
aggregate naive EA	0.78408	0.78553
random effects naive EA	0.84589	0.84306
aggregate EA with SIS	0.85877	**0.85808**
random effects EA with SIS	0.81210	0.83767
MVC	0.85706	0.85691
average y	0.83297	0.83286

Table 17: RLH of the different methods for the simple design

For the menu vs. à-la-carte design, the average RLH values for every method can be seen in Table 18. The findings are quite similar to the conclusions of the RLH values for the simple design. Namely, the aggregate SCE model obtains a surprisingly high RLH value. Moreover, the aggregate EA model using SIS and the MVC model are one of the best performing models according to the RLH measure, where the random effects SCE and the aggregate naive EA models perform poorly. Additionally, what stands out is that for the SCE model and EA model using SIS, the random effects versions perform less accurate than their aggregate alternatives according to the RLH measure.

Model	in-sample	out-of-sample
aggregate SCE	0.75106	0.74666
random effects SCE	0.62492	0.61981
aggregate naive EA	0.66964	0.66561
random effects naive EA	0.74853	0.74175
aggregate EA with SIS	**0.75388**	**0.75229**
random effects EA with SIS	0.70321	0.72953
MVC	0.74957	0.74822
average y	0.73296	0.73066

Table 18: RLH of the different methods for the menu vs. à-la-carte design

It is surprising that the random effects EA model using SIS, as one of the most complex methods, performs so poorly according to both the RMSE and RLH measures. A reason for this can be found in the height of the estimated probabilities. Namely, the probabilities for the random effects EA model using SIS are on average twice as high as the estimated probabilities using the best performing methods, see Table 33, 34, 46 and 47 in the Appendix. This would give better RMSE and RLH values if the estimated probabilities are accurate, but apparently this is not the case, leading to even worse performance measures. Moreover, it is observed that the average probabilities of the best performing methods are nearly the same as the average y values. This could explain the similar RMSE and RLH values of the best performing methods and the 'average y' method.

5.5 Small Conclusion

Following both the RMSE and the RLH, the best performing methods are the aggregate SCE method, the aggregate EA method using SIS and the MVC method. While it is in line of expectations that an EA model using SIS and the MVC model would perform well, it comes as a surprise that the least complex method, i.e., aggregate SCE, gives such good predictions. In combination with its computation time, it is considered a useful method. However, the MVC method has an additional advantage over the other methods by providing a correlation matrix of choosing the different items. Besides, if the menu does not contain too many items, the MVC method is computationally one of the lighter methods to perform, certainly making it a useful method for analysing and predicting menu-based choices. Lastly, the aggregate EA using SIS performs best according to both the RMSE and RLH for both the simple and menu vs. à-la-carte design. Together with its relatively low computation time, it can be stated that using SIS makes the EA method much more accurate while the increase in computation time is trivial.

Obviously, computation time and forecasting accuracy are not the only aspects to base a conclusion on regarding which method to use. Namely, the SCE method can be used to find out which cross-price effects are significant and which product prices influence the choice of an item. Moreover, the EA method can help to understand which combinations of items are more likely to be chosen, making it clear if a certain combination of products should maybe be offered as one item. If a combination of products is frequently chosen, it suggests that it may yield more clientele and consequent sales if these products are offered as one. Lastly, as mentioned earlier, the MVC method can help to better understand the underlying relationships between choosing the different items, leading to a better comprehension of possible complementary and substitute goods. If it is known that a certain product A is complementary to another product B and a retailer wishes more sales of product A, it is also possible to lower the price or make a deal for product B. If this leads to more sales of product B, it should also lead to an increase of demand for product A. On the other hand, if product A and B are substitutes of one another, it is possible to boost the sales of product A by lowering the demand of product B, for example, by increasing the price of product B. These are simple examples of how the MVC method can be used to increase the demand of certain products.

To conclude, the different methods cannot only be used to predict menu-based choices, but also to analyse these choices and use this analysis for knowing which items should be offered and at what price. Furthermore, because the respondents mainly choose no products or only one product in the two data sets, relations between the different items cannot easily be obtained by just analysing the data. Therefore, these methods are necessary to obtain any idea about the relationships between the different items and to come up with an appropriate strategy in a menu-based environment.

6 Conclusion

This research focuses on comparing several menu-based conjoint (MBC) methods to find the best predictive model for choices on a menu. Besides, several ways of constructing a menu are encountered for which not every MBC method has been applied before. Therefore, the question arises which MBC method performs best for different menu designs. For this research, two data sets containing choices on a menu of a restaurant and a menu to customise a car, are considered to compare the different methods, where these menus are set up in different ways. Three different methods are compared, namely, a serial cross-effect (SCE), an exhaustive alternatives (EA) and a multivariate choice (MVC) method. For these methods, the computation time and predictive power are examined.

For the SCE method, a probit model is constructed for every choice on the menu. The variables for these probit models are the prices of all items on the menu that are significant according to a preceding χ^2-test. For the SCE method, both an aggregate and random effects approach is examined. Where for the aggregate version a single parameter for all individuals is estimated, the random effects SCE model obtains unique parameters for every individual.

Furthermore, instead of considering every menu item individually, the EA method considers possible combinations of items. Because the number of possible ways of choosing from a menu grows exponentially with the number of menu items, a selection of the possible combinations of items is taken to make the EA method feasible. Considering the selection of combinations of items as the different alternatives, a multinomial logit model is implemented to obtain probabilities of choosing the different alternatives. Similarly to the SCE method, an aggregate and a random effects version are considered. Moreover, to obtain a choice set containing the different combinations of items, two approaches are used. Where for the first way a fixed choice set is constructed containing the most frequently chosen combinations, for the second way, a sampling method (stratified importance sampling (SIS)) is used to construct a different choice set in every observation.

Lastly, the MVC method also analyses the menu items individually. Similarly to the SCE method, a probit model is constructed for every choice on the menu. However, the separate models are correlated with each other, making it a multivariate probit model. Contrary to the SCE and EA methods, only an aggregate version of the MVC method is implemented.

Following the predictive performance of the different methods, the aggregate SCE model, the aggregate EA model using SIS and the MVC model are the most accurate for both data sets. It is surprising that the least complex method, namely, the aggregate SCE model, performs so well. Together with its low computational burden, the aggregate SCE model can be seen as the best working method. However, especially for a menu containing not too many items, the MVC model is more informative than the SCE model, while the difference in computation time is negligible. Furthermore, the EA models and MVC model better take into account the items that are not able to be chosen together than the SCE model. Lastly, it is observed that using SIS in combination with an EA method helps improving the accuracy significantly, while the increase of computation time is insignificant if the menu does not contain too many items.

In conclusion, the relatively simple SCE model performs best for different menu designs when both computation time and predictive ability are taken into account, but the MVC model can be seen as a more informative method which is equally accurate and has a quite similar computational burden when the number of menu items is not too large.

6.1 Recommendations for future research

Of course, this research also has his limitations. Firstly, the possibility of a random effects version of the MVC model has not been examined. It may be possible that especially for data sets that are not too extensive, a random effects MVC model performs better than its aggregate alternative. Taking into account that the random effects SCE model had a surprisingly high computational time and that for a large data set the aggregate version of the MVC model already was relatively computationally expensive, it is expected that a random effect MVC model could also have a heavy computational burden.

Secondly, in this research two different menu designs have been analysed, while in existing literature and actual practice obviously more different menu designs can be found. It is possible that for other menu designs, alternative conclusions may be drawn.

Lastly, for the SCE and MVC method, no additional programming has been implemented for the items that can be chosen together. Although the conclusions are quite similar for the simple and menu vs à-la-carte design, it may be possible that the SCE and MVC models give better results when in programming it is taken into account that some items cannot be chosen simultaneously.

References

Ben-Akiva, M. and Gershenfeld, S. (1998). Multi-featured products and services: analysing pricing and bundling strategies. *Journal of Forecasting*, 17(3-4):175–196.

Ben-Akiva, M. and Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand.* Cambridge: The MIT Press.

Chung, K. L. and Zhong, K. (2001). *A course in probability theory.* Academic press.

Cohen, S. H. and Liechty, J. C. (2007). Have it your way. *Marketing Research*, 19(3).

Croissant, Y. (2020). *mlogit: Multinomial Logit Models.* R package version 1.1-0.

Dippold-Tausendpfund, K. and Neuerburg, C. (2018). Variable selection for mbc cross-price effects. In *Sawtooth Software Conference Proceedings, Orlando, FL.*

Franses, P. H. and Paap, R. (2001). *Quantitative models in marketing research.* Cambridge University Press.

Green, P. E., Krieger, A. M., and Wind, Y. (2001). Thirty years of conjoint analysis: Reflections and prospects. *Interfaces*, 31(3):S56–S73.

Haaijer, R., Wedel, M., Vriens, M., and Wansbeek, T. (1998). Utility covariances and context effects in conjoint mnp models. *Marketing Science*, 17(3):236–252.

Higham, N. J. (1988). Computing a nearest symmetric positive semidefinite matrix. *Linear algebra and its applications*, 103:103–118.

Kruskal, J. B. (1969). Monanova: Monotone analysis of variance, a fortran iv program for nonmetric analysis of factorial experiments. *Journal of Marketing Research*, 6(4):497–497.

Liechty, J., Ramaswamy, V., and Cohen, S. H. (2001). Choice menus for mass customization: An experimental approach for analyzing customer demand with an application to a web-based information service. *Journal of Marketing research*, 38(2):183–196.

Louviere, J. (1994). " conjoint analysis" in. *Advanced methods of marketing research*, pages 223–259.

Magretta, J. (1998). The power of virtual integration: An interview with dell computer's michael dell.

Mahajan, V., Green, P. E., and Goldberg, S. M. (1982). A conjoint model for measuring self-and cross-price/demand relationships. *Journal of Marketing Research*, 19(3):334–342.

Marra, G. and Radice, R. (2017). Bivariate copula additive models for location, scale and shape. *Computational Statistics and Data Analysis.*

McFadden, D. (1978). Modeling the choice of residential location. *Transportation Research Record*, (673).

Mullahy, J. (2016). Estimation of multivariate probit models via bivariate probit. *The Stata Journal*, 16(1):37–51.

Orme, B. K. (2010). Menu-based choice modeling using traditional tools. In *Sawtooth Software Conference Proceedings, Sequim, WA*.

Orme, B. K. (2019). Menu-based choice (mbc) for multi-check choice experiments.

R Core Team (2020). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

R Core Team (2021). *The R Stats Package*. R Foundation for Statistical Computing. R package version 4.1.0.

Sarrias, M. (2016). Discrete choice models with random parameters in R: The Rchoice package. *Journal of Statistical Software*, 74(10):1–31.

Schafer, J., Opgen-Rhein, R., Zuber, V., Ahdesmaki, M., Silva, A. P. D., and Strimmer, K. (2017). *corpcor: Efficient Estimation of Covariance and (Partial) Correlation*. R package version 1.6.9.

Sermas, R. (2012). *ChoiceModelR: Choice Modeling in R*. R package version 1.2.

Wind, J. and Mahajan, V. (1997). Issues and opportunities in new product development: An introduction to the special issue.

Appendix

Simple Design

Item	price1	price2	price3	price4	price5
PRODUCT1.1	28	29	30	32	33
PRODUCT1.2	28	29	30	32	33
PRODUCT1.3	28	29	30	32	33
PRODUCT2.1	24	25	26	28	29
PRODUCT2.2	24	25	26	28	29
PRODUCT2.3	24	25	26	28	29
PRODUCT3	56	59	62	65	68
PRODUCT4	49	52	55	57	60
PRODUCT5	47	49	51	54	56
PRODUCT6	48	51	54	56	59
PRODUCT7	49	52	55	57	60
PRODUCT8	86	91	96	100	105
PRODUCT9	88	93	98	102	107
PRODUCT10	62	65	68	72	75
PRODUCT11	59	62	65	68	71
PRODUCT12	62	65	68	72	75
MEAL1	96	101	106	111	116
MEAL2	90	95	100	105	109
MEAL3	86	91	96	100	105
MEAL4	87	92	97	101	106
MEAL5	90	95	100	105	109
MEAL6	128	135	142	149	155
MEAL7	130	137	144	151	158
MEAL8	102	107	112	118	123
MEAL9	99	104	109	114	120
PRODUCT13	19	21	22	24	26
PRODUCT14	24	26	28	30	32
PRODUCT15	27	29	31	33	35
PRODUCT16	31	33	35	36	38
PRODUCT17	25	26	27	29	30
PRODUCT18	24	25	26	28	29
PRODUCT19	18	19	20	21	22
PRODUCT20	23	24	25	26	28
PRODUCT21	30	32	34	36	38
PRODUCT22	29	31	33	35	37
PRODUCT23	23	25	26	28	30
PRODUCT24	27	29	30	32	34
PRODUCT25	32	34	36	38	40

PRODUCT26	37	39	41	43	45
PRODUCT27	31	33	35	36	38
PRODUCT28	47	49	51	54	56
PRODUCT29	36	38	40	42	44
PRODUCT30.1	41	43	45	47	49
PRODUCT30.2	41	43	45	47	49
PRODUCT30.3	41	43	45	47	49
PRODUCT31.1	23	24	25	26	28
PRODUCT31.2	23	24	25	26	28
PRODUCT31.3	23	24	25	26	28
PRODUCT32.1	18	19	20	21	22
PRODUCT32.2	18	19	20	21	22
PRODUCT32.3	18	19	20	21	22
PRODUCT33	28	29	30	32	33
PRODUCT34.1	8	9	10	11	12
PRODUCT34.2	8	9	10	11	12
PRODUCT34.3	8	9	10	11	12
PRODUCT35.1	5	6	7	8	9
PRODUCT35.2	5	6	7	8	9
PRODUCT35.3	5	6	7	8	9
PRODUCT36.1	72	75	79	83	87
PRODUCT36.2	72	75	79	83	87
PRODUCT36.3	72	75	79	83	87
PRODUCT37.1	3	5	7	9	
PRODUCT37.2	3	5	7	9	
PRODUCT37.3	3	5	7	9	
PRODUCT38.1	3	5	7	9	
PRODUCT38.2	3	5	7	9	
PRODUCT38.3	3	5	7	9	
MEAL10*	68	72	77	83	
MEAL11*	81	85	91	98	
MEAL12*	71	75	81	86	
MEAL13*	83	87	94	100	
MEAL14*	52	55	59	63	
PRODUCT39*	30	32	34	36	38
PRODUCT40*	29	31	33	35	37
PRODUCT41*	18	19	20	21	22
PRODUCT42*	47	49	51	54	56
PRODUCT43*	47	49	51	54	56

Table 19: Prices for every item for the simple design. *Items that are not available in every menu scenario.

Item	Price1	Price2	Price3	Price4	Price5	Total	Price1	Price2	Price3	Price4	Price5
PRODUCT1.1	337	374	374	319	364	1768	0.191	0.212	0.212	0.180	0.206
PRODUCT1.2	162	171	155	142	164	794	0.204	0.215	0.195	0.179	0.207
PRODUCT1.3	80	76	68	63	70	357	0.224	0.213	0.190	0.176	0.196
PRODUCT2.1	256	295	258	246	184	1239	0.207	0.238	0.208	0.199	0.149
PRODUCT2.2	101	107	84	92	83	467	0.216	0.229	0.180	0.197	0.178
PRODUCT2.3	70	56	62	53	53	294	0.238	0.190	0.211	0.180	0.180
PRODUCT3	260	345	273	270	302	1450	0.179	0.238	0.188	0.186	0.208
PRODUCT4	144	175	157	164	149	789	0.183	0.222	0.199	0.208	0.189
PRODUCT5	234	266	258	252	256	1266	0.185	0.210	0.204	0.199	0.202
PRODUCT6	201	249	222	225	227	1124	0.179	0.222	0.198	0.200	0.202
PRODUCT7	139	129	123	105	116	612	0.227	0.211	0.201	0.172	0.190
PRODUCT8	126	130	137	116	125	634	0.199	0.205	0.216	0.183	0.197
PRODUCT9	150	162	134	149	125	720	0.208	0.225	0.186	0.207	0.174
PRODUCT10	103	128	112	111	119	573	0.180	0.223	0.195	0.194	0.208
PRODUCT11	138	135	143	138	136	690	0.200	0.196	0.207	0.200	0.197
PRODUCT12	391	404	359	370	349	1873	0.209	0.216	0.192	0.198	0.186
MEAL1	480	516	478	434	397	2305	0.208	0.224	0.207	0.188	0.172
MEAL2	128	147	118	128	123	644	0.199	0.228	0.183	0.199	0.191
MEAL3	176	173	164	130	145	788	0.223	0.220	0.208	0.165	0.184
MEAL4	356	334	301	285	235	1511	0.236	0.221	0.199	0.189	0.156
MEAL5	123	112	115	101	102	553	0.222	0.203	0.208	0.183	0.184
MEAL6	192	162	150	160	166	830	0.231	0.195	0.181	0.193	0.200
MEAL7	216	254	195	176	179	1020	0.212	0.249	0.191	0.173	0.175
MEAL8	148	101	108	118	109	584	0.253	0.173	0.185	0.202	0.187
MEAL9	129	123	131	122	132	637	0.203	0.193	0.206	0.192	0.207
PRODUCT13	229	229	202	244	205	1109	0.206	0.206	0.182	0.220	0.185
PRODUCT14	277	314	268	236	218	1313	0.211	0.239	0.204	0.180	0.166
PRODUCT15	307	275	272	242	235	1331	0.231	0.207	0.204	0.182	0.177
PRODUCT16	576	649	681	622	698	3226	0.179	0.201	0.211	0.193	0.216
PRODUCT17	336	389	335	413	391	1864	0.180	0.209	0.180	0.222	0.210
PRODUCT18	303	297	271	255	227	1353	0.224	0.220	0.200	0.188	0.168
PRODUCT19	338	342	305	295	271	1551	0.218	0.221	0.197	0.190	0.175
PRODUCT20	276	276	275	243	240	1310	0.211	0.211	0.210	0.185	0.183
PRODUCT21	318	330	389	373	309	1719	0.185	0.192	0.226	0.217	0.180
PRODUCT22	161	172	169	143	193	838	0.192	0.205	0.202	0.171	0.230
PRODUCT23	351	403	416	370	316	1856	0.189	0.217	0.224	0.199	0.170
PRODUCT24	540	615	565	558	558	2836	0.190	0.217	0.199	0.197	0.197
PRODUCT25	451	532	461	428	396	2268	0.199	0.235	0.203	0.189	0.175
PRODUCT26	256	291	270	235	252	1304	0.196	0.223	0.207	0.180	0.193
PRODUCT27	326	337	328	301	315	1607	0.203	0.210	0.204	0.187	0.196
PRODUCT28	262	261	212	201	225	1161	0.226	0.225	0.183	0.173	0.194
PRODUCT29	277	297	299	298	247	1418	0.195	0.209	0.211	0.210	0.174
PRODUCT30.1	217	288	247	243	213	1208	0.180	0.238	0.204	0.201	0.176

PRODUCT30.2	68	68	77	64	67	344	0.198	0.198	0.224	0.186	0.195
PRODUCT30.3	44	54	49	44	42	233	0.189	0.232	0.210	0.189	0.180
PRODUCT31.1	244	279	212	288	251	1274	0.192	0.219	0.166	0.226	0.197
PRODUCT31.2	68	61	76	61	57	323	0.211	0.189	0.235	0.189	0.176
PRODUCT31.3	40	44	41	27	39	191	0.209	0.230	0.215	0.141	0.204
PRODUCT32.1	210	251	182	189	208	1040	0.202	0.241	0.175	0.182	0.200
PRODUCT32.2	112	105	72	77	87	453	0.247	0.232	0.159	0.170	0.192
PRODUCT32.3	64	64	57	49	52	286	0.224	0.224	0.199	0.171	0.182
PRODUCT33	176	219	223	206	203	1027	0.171	0.213	0.217	0.201	0.198
PRODUCT34.1	554	692	577	575	487	2885	0.192	0.240	0.200	0.199	0.169
PRODUCT34.2	218	269	255	239	211	1192	0.183	0.226	0.214	0.201	0.177
PRODUCT34.3	120	117	94	100	81	512	0.234	0.229	0.184	0.195	0.158
PRODUCT35.1	56	75	55	63	58	307	0.182	0.244	0.179	0.205	0.189
PRODUCT35.2	14	26	21	19	16	96	0.146	0.271	0.219	0.198	0.167
PRODUCT35.3	29	20	24	25	24	122	0.238	0.164	0.197	0.205	0.197
PRODUCT36.1	525	594	517	515	541	2692	0.195	0.221	0.192	0.191	0.201
PRODUCT36.2	178	203	164	153	182	880	0.202	0.231	0.186	0.174	0.207
PRODUCT36.3	54	56	46	53	51	260	0.208	0.215	0.177	0.204	0.196
PRODUCT37.1	145	142	114	117		518	0.280	0.274	0.220	0.226	
PRODUCT37.2	16	12	6	5		39	0.410	0.308	0.154	0.128	
PRODUCT37.3	5	7	4	8		24	0.208	0.292	0.167	0.333	
PRODUCT38.1	178	231	172	124		705	0.252	0.328	0.244	0.176	
PRODUCT38.2	40	28	22	22		112	0.357	0.250	0.196	0.196	
PRODUCT38.3	6	7	5	5		23	0.261	0.304	0.217	0.217	
MEAL10	671	566	676	583		2496	0.269	0.227	0.271	0.234	
MEAL11	399	330	386	377		1492	0.267	0.221	0.259	0.253	
MEAL12	321	247	273	270		1111	0.289	0.222	0.246	0.243	
MEAL13	251	201	231	217		900	0.279	0.223	0.257	0.241	
MEAL14	295	239	264	205		1003	0.294	0.238	0.263	0.204	
PRODUCT39	40	37	35	39	26	177	0.226	0.209	0.198	0.220	0.147
PRODUCT40	22	15	21	22	21	101	0.218	0.149	0.208	0.218	0.208
PRODUCT41	9	5	5	9	9	37	0.243	0.135	0.135	0.243	0.243
PRODUCT42	26	18	27	23	10	104	0.250	0.173	0.260	0.221	0.096
PRODUCT43	31	16	22	17	33	119	0.261	0.134	0.185	0.143	0.277

Table 20: Frequency and relative frequency per price for every item for the simple design

Item	Number of variables
PRODUCT1.1	20
PRODUCT1.2	20
PRODUCT1.3	8
PRODUCT2.1	29
PRODUCT2.2	20
PRODUCT2.3	2
PRODUCT3	43
PRODUCT4	23
PRODUCT5	9
PRODUCT6	25
PRODUCT7	18
PRODUCT8	23
PRODUCT9	20
PRODUCT10	39
PRODUCT11	10
PRODUCT12	28
MEAL1	40
MEAL2	33
MEAL3	11
MEAL4	35
MEAL5	11
MEAL6	14
MEAL7	21
MEAL8	12
MEAL9	19
PRODUCT13	15
PRODUCT14	13
PRODUCT15	10
PRODUCT16	11
PRODUCT17	29
PRODUCT18	43
PRODUCT19	13
PRODUCT20	13
PRODUCT21	13
PRODUCT22	7
PRODUCT23	8
PRODUCT24	43
PRODUCT25	43
PRODUCT26	29

Product	Number of variables
PRODUCT27	39
PRODUCT28	43
PRODUCT29	15
PRODUCT30.1	43
PRODUCT30.2	9
PRODUCT30.3	8
PRODUCT31.1	43
PRODUCT31.2	4
PRODUCT31.3	16
PRODUCT32.1	26
PRODUCT32.2	5
PRODUCT32.3	19
PRODUCT33	43
PRODUCT34.1	43
PRODUCT34.2	22
PRODUCT34.3	11
PRODUCT35.1	24
PRODUCT35.2	10
PRODUCT35.3	12
PRODUCT36.1	13
PRODUCT36.2	6
PRODUCT36.3	2
PRODUCT37.1	40
PRODUCT37.2	15
PRODUCT37.3	12
PRODUCT38.1	43
PRODUCT38.2	7
PRODUCT38.3	5
MEAL10	43
MEAL11	43
MEAL12	43
MEAL13	43
MEAL14	43
PRODUCT39	8
PRODUCT40	5
PRODUCT41	4
PRODUCT42	12
PRODUCT43	31

Table 21: Number of variables in SCE models for simple design

Item 1	Item 2
MEAL1	
MEAL10	
MEAL4	
PRODUCT36.1	
MEAL12	
MEAL11	
MEAL13	
MEAL14	
PRODUCT12	
MEAL6	
PRODUCT27	
MEAL7	
PRODUCT30.1	
PRODUCT16	
MEAL9	
PRODUCT6	
PRODUCT3	
PRODUCT23.1	
PRODUCT1.1	
PRODUCT29	
MEAL4	PRODUCT34.1
PRODUCT36.2	
MEAL2	
PRODUCT19	
MEAL8	
PRODUCT36.3	
PRODUCT2.1	
PRODUCT23	
PRODUCT31.1	
MEAL10	PRODUCT17
MEAL10	PRODUCT19
PRODUCT28	
PRODUCT11	
MEAL3	
PRODUCT9	
MEAL1	
MEAL1	PRODUCT34.1
PRODUCT4	
PRODUCT24	
MEAL10	MEAL11

Table 22: Choice set for the EA models in the simple design

	P1.1	P1.2	P1.3	P2.1	P2.2	P2.3	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	M1	M2	M3	M4	M5	M6	M7	M8	M9	P13
P1.1	1																									
P1.2	-0.86	1																								
P1.3	-0.83	-0.79	1																							
P2.1	0.46	-0.09	0.08	1																						
P2.2	-0.07	0.43	0.02	-0.81	1																					
P2.3	-0.15	0.06	0.67	-0.82	-0.77	1																				
P3	-0.01	-0.12	0.18	0.02	-0.03	0.19	1																			
P4	-0.07	-0.08	0.28	0.05	-0.09	0.28	0.34	1																		
P5	0.03	0.25	0.26	0.06	-0.07	0.22	0.32	0.38	1																	
P6	-0.02	-0.14	0.16	0.03	-0.17	0.20	0.37	0.32	0.31	1																
P7	-0.13	0.05	0.28	-0.12	-0.16	0.28	0.23	0.39	0.37	0.39	1															
P8	-0.08	0.03	0.26	-0.04	-0.23	0.26	0.27	0.31	0.37	0.32	0.40	1														
P9	-0.13	-0.32	0.29	-0.16	-0.05	0.28	0.26	0.27	0.23	0.29	0.31	0.33	1													
P10	-0.12	-0.12	0.29	-0.04	-0.06	0.29	0.24	0.34	0.21	0.26	0.46	0.30	0.46	1												
P11	-0.09	0.04	0.22	-0.02	-0.07	0.25	0.16	0.39	0.32	0.25	0.36	0.29	0.37	0.50	1											
P12	0.07	0.15	0.27	0.01	0.02	0.21	0.06	0.14	0.24	0.08	0.16	0.10	0.14	0.16	0.12	1										
M1	-0.21	-0.12	0.18	-0.19	-0.09	0.14	-0.03	-0.04	-0.06	-0.07	-0.03	-0.02	0.02	-0.08	-0.10	-0.03	1									
M2	-0.15	-0.23	0.30	-0.04	-0.01	0.35	0.06	0.23	0.15	0.12	0.22	0.15	0.15	0.16	0.15	0.12	0.33	1								
M3	-0.15	-0.07	0.32	-0.08	0.11	0.34	0.07	0.17	0.10	0.08	0.19	0.15	0.16	0.15	0.16	0.09	0.34	0.47	1							
M4	-0.13	-0.02	0.19	-0.21	-0.09	0.21	-0.17	0.00	-0.05	-0.02	0.03	0.00	-0.04	0.02	-0.02	-0.06	0.34	0.23	0.30	1						
M5	-0.16	-0.11	0.32	-0.07	-0.06	0.38	0.07	0.17	0.16	0.14	0.28	0.20	0.18	0.22	0.17	0.13	0.19	0.48	0.40	0.39	1					
M6	-0.15	-0.01	0.23	-0.10	-0.18	0.29	-0.04	0.09	0.09	0.09	0.16	0.27	0.11	0.13	0.12	0.16	0.25	0.28	0.36	0.24	0.40	1				
M7	-0.16	-0.26	0.18	-0.29	-0.18	0.26	-0.10	-0.01	-0.04	-0.02	0.10	0.08	0.13	0.10	0.06	0.01	0.29	0.23	0.30	0.25	0.29	0.29	1			
M8	-0.17	-0.28	0.25	-0.12	-0.10	0.32	-0.01	0.11	0.06	0.04	0.23	0.14	0.17	0.24	0.16	0.04	0.16	0.32	0.35	0.29	0.49	0.26	0.48	1		
M9	-0.12	-0.13	0.22	-0.09	-0.01	0.30	0.00	0.14	0.08	0.05	0.19	0.14	0.12	0.18	0.22	0.00	0.15	0.31	0.33	0.19	0.38	0.31	0.44	0.53	1	
P13	0.10	0.09	0.28	0.25	0.02	0.25	0.22	0.23	0.25	0.24	0.32	0.33	0.24	0.29	0.18	0.12	-0.10	0.13	0.13	-0.01	0.16	0.05	-0.03	0.09	0.06	1

Table 23: Correlation matrix part 1

	P1.1	P1.2	P1.3	P2.1	P2.2	P2.3	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	M1	M2	M3	M4	M5	M6	M7	M8	M9	P13
P14	0.16	0.15	0.24	0.19	0.18	0.27	0.26	0.19	0.22	0.21	0.26	0.28	0.24	0.26	0.21	0.13	0.04	0.12	0.12	-0.01	0.15	0.18	-0.06	0.10	0.09	0.24
P15	-0.08	0.30	0.29	-0.04	0.18	0.29	0.21	0.10	0.19	0.18	0.22	0.19	0.12	0.15	0.14	0.20	0.21	0.28	0.30	0,19	0,20	0,28	0,30	0.23	0.17	0.11
P16	0.06	0.11	0.21	0.08	0.11	0.25	0.19	0.31	0.25	0.17	0.25	0.21	0.22	0.21	0.23	0.21	-0.03	0.15	0.15	-0.02	0.26	0.08	0.11	0.11	0.13	0.12
P17	0.12	0.19	0.20	0.07	0.14	0.17	0.30	0.24	0.29	0.20	0.29	0.14	0.18	0.17	0.21	0.15	-0.12	0.08	0.06	-0.09	0.02	-0.06	-0.08	0.00	0.01	0.10
P18	0.10	0.21	0.33	0.15	0.23	0.27	0.29	0.28	0.23	0.21	0.39	0.09	0.19	0.29	0.21	0.11	-0.04	0.11	0.11	-0.03	0.10	-0.04	-0.05	0.05	0.04	0.18
P19	0.02	0.07	0.22	0.14	0.19	0.30	0.19	0.27	0.16	0.20	0.29	0.18	0.21	0.29	0.22	0.12	-0.08	0.12	0.13	-0.07	0.10	0.03	0.03	0.11	0.14	0.17
P20	0.12	0.02	0.19	0.07	0.18	0.30	0.07	0.24	0.18	0.15	0.22	0.16	0.21	0.17	0.26	0.21	-0.03	0.09	0.17	-0.03	0.10	0.00	0.05	0.06	0.14	0.12
P21	0.05	0.15	0.24	-0.06	0.01	0.20	0.12	0.10	0.14	0.13	0.12	0.10	0.12	0.07	0.14	0.19	0.17	0.19	0.23	0.00	0.16	0.14	0.17	0.08	0.12	-0.09
P22	-0.01	0.13	0.24	-0.01	0.13	0.28	0.10	0.21	0.08	0.14	0.26	0.18	0.18	0.20	0.21	0.22	0.15	0.27	0.28	0.11	0.31	0.20	0.29	0.29	0.27	0.05
P23	0.29	0.14	0.32	0.30	0.12	0.22	0.19	0.25	0.24	0.22	0.22	0.25	0.23	0.23	0.11	0.19	-0.11	0.01	0.03	-0.06	0.05	-0.05	-0.08	0.02	-0.02	0.39
P24	0.29	0.32	0.32	0.22	0.30	0.27	0.31	0.24	0.25	0.29	0.23	0.20	0.12	0.20	0.13	0.18	-0.11	0.02	-0.01	-0.11	0.05	-0.01	-0.08	0.00	-0.06	0.20
P25	0.16	0.41	0.43	0.14	0.25	0.28	0.23	0.25	0.30	0.19	0.18	0.22	0.14	0.17	0.17	0.19	0.10	0.13	0.26	0.07	0.18	0.11	0.19	0.15	0.17	0.12
P26	0.06	0.13	0.34	0.12	0.10	0.41	0.16	0.24	0.26	0.22	0.28	0.22	0.21	0.30	0.24	0.29	0.00	0.19	0.24	0.05	0.25	0.20	0.20	0.27	0.21	0.15
P27	-0.05	0.06	0.21	0.05	0.07	0.23	0.12	0.17	0.16	0.12	0.25	0.16	0.21	0.16	0.22	0.07	0.03	0.18	0.15	0.02	0.21	0.06	0.14	0.13	0.15	0.19
P28	-0.05	-0.05	0.26	-0.03	0.03	0.25	0.12	0.17	0.19	0.15	0.27	0.20	0.25	0.23	0.27	0.17	-0.04	0.19	0.18	0.03	0.22	0.14	0.20	0.20	0.23	0.16
P29	0.09	-0.02	0.22	-0.02	0.01	0.26	0.04	0.16	0.14	0.11	0.26	0.12	0.23	0.23	0.19	0.20	0.11	0.22	0.19	0.11	0.22	0.11	0.22	0.26	0.24	0.07
P30.1	0.13	0.01	0.06	0.02	-0.07	-0.02	0.00	0.03	0.04	0.01	0.09	-0.02	0.11	-0.05	0.04	0.05	0.14	0.14	0.03	-0.05	0.07	-0.04	0.00	0.02	0.06	-0.02
P30.2	-0.15	0.28	0.15	-0.19	0.22	0.04	-0.02	-0.04	0.02	0.06	-0.08	0.10	0.06	0.02	0.03	0.15	0.13	0.10	0.16	0.10	0.07	0.22	0.19	0.24	0.22	-0.02
P30.3	-0.09	0.06	0.50	-0.10	-0.17	0.52	0.33	0.32	0.30	0.35	0.35	0.37	0.38	0.38	0.37	0.20	0.20	0.34	0.46	0.27	0.45	0.39	0.40	0.43	0.35	0.29
P31.1	0.19	-0.02	-0.08	0.11	-0.10	-0.17	-0.09	0.06	0.10	0.13	0.05	0.04	0.01	0.04	0.03	0.05	-0.10	0.04	-0.06	-0.08	0.08	-0.05	-0.01	0.04	0.03	-0.01
P31.2	-0.19	0.28	0.00	-0.16	0.25	0.07	-0.14	-0.21	0.12	0.07	0.04	-0.09	0.00	0.02	0.02	0.05	0.08	0.11	0.01	0.15	0.07	0.09	0.13	0.10	0.07	-0.05
P31.3	-0.32	0.05	0.54	-0.14	-0.13	0.51	0.30	0.34	0.30	0.29	0.42	0.36	0.38	0.38	0.34	0.30	0.34	0.42	0.49	0.39	0.53	0.41	0.40	0.53	0.47	0.31
P32.1	0.09	0.07	-0.05	0.15	0.01	0.10	-0.03	-0.04	0.10	0.03	0.04	-0.01	0.02	0.05	0.00	0.02	-0.08	0.00	0.03	-0.06	0.02	0.01	-0.06	0.03	0.08	0.08
P32.2	-0.04	0.31	0.10	-0.02	0.22	0.14	-0.04	0.00	0.08	0.09	0.10	-0.10	0.02	-0.15	0.13	-0.05	0.08	0.11	0.21	0.00	0.04	0.04	0.18	0.13	0.28	0.03
P32.3	-0.10	0.25	0.56	-0.08	-0.05	0.60	0.27	0.31	0.23	0.28	0.36	0.30	0.33	0.37	0.33	0.24	0.22	0.35	0.35	0.23	0.32	0.27	0.32	0.32	0.36	0.27
P33	0.05	0.00	0.22	0.12	-0.08	0.30	0.08	0.23	0.14	0.12	0.25	0.17	0.21	0.29	0.20	0.11	-0.05	0.21	0.13	0.06	0.20	0.09	0.15	0.15	0.22	0.17

Table 24: Correlation matrix part 2

	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26	P27	P28	P29	P30.1	P30.2	P30.3	P31.1	P31.2	P31.3	P32.1	P32.2	P32.3	P33
P14	1																									
P15	0.26	1																								
P16	0.06	0.17	1																							
P17	0.01	-0.06	0.09	1																						
P18	0.13	-0.01	0.15	0.35	1																					
P19	0.11	0.00	0.20	0.13	0.24	1																				
P20	-0.02	0.01	0.24	0.08	0.10	0.24	1																			
P21	-0.01	0.15	0.07	-0.01	-0.08	0.00	0.08	1																		
P22	0.11	0.27	0.23	-0.04	0.17	0.16	0.16	0.38	1																	
P23	0.11	-0.04	0.21	0.29	0.20	0.19	0.19	-0.05	0.05	1																
P24	0.39	0.16	0.20	0.18	0.34	0.18	0.14	0.12	0.25	0.14	1															
P25	0.23	0.47	0.27	0.15	0.10	0.14	0.17	0.28	0.36	-0.03	0.03	1														
P26	0.13	0.35	0.22	0.09	0.15	0.20	0.14	0.17	0.25	0.02	-0.02	0.30	1													
P27	0.04	0.13	0.21	0.18	0.15	0.15	0.11	0.08	0.18	0.16	0.13	0.17	0.15	1												
P28	0.10	0.17	0.31	0.22	0.21	0.22	0.33	0.23	0.28	0.10	0.10	0.14	0.26	0.33	1											
P29	0.05	0.16	0.19	0.06	0.12	0.05	0.11	0.10	0.23	0.13	0.03	0.22	0.26	0.35	0.35	1										
P30.1	0.02	0.03	0.13	0.02	0.06	-0.11	0.08	0.09	0.13	0.03	0.05	0.04	0.07	0.19	0.11	0.18	1									
P30.2	0.17	0.32	0.13	-0.06	-0.02	-0.06	0.13	0.20	0.17	-0.06	-0.02	0.25	0.22	0.20	0.16	0.13	-0.81	1								
P30.3	0.26	0.32	0.22	0.18	0.25	0.31	0.27	0.28	0.35	0.20	0.17	0.39	0.29	0.32	0.32	0.31	-0.81	-0.74	1							
P31.1	0.04	-0.01	0.14	0.09	0.07	0.04	0.24	0.17	0.08	0.00	0.08	0.08	0.04	0.07	0.16	0.20	0.30	-0.03	-0.14	1						
P31.2	-0.06	0.15	0.22	0.01	-0.02	0.04	0.25	0.23	0.23	-0.01	-0.05	0.15	0.09	0.08	0.18	0.08	0.02	0.51	-0.13	-0.81	1					
P31.3	0.29	0.33	0.34	0.29	0.33	0.32	0.28	0.33	0.34	0.21	0.16	0.34	0.30	0.33	0.41	0.32	-0.06	0.11	0.75	-0.78	-0.75	1				
P32.1	0.10	-0.01	0.08	0.08	-0.03	0.11	0.02	0.02	0.08	0.07	0.02	0.05	0.09	0.07	0.00	0.06	0.28	0.04	0.05	0.29	0.03	-0.04	1			
P32.2	0.02	0.25	0.21	0.11	-0.01	0.14	0.09	0.12	0.30	0.03	0.10	0.23	0.15	0.13	0.03	0.14	0.00	0.44	0.20	-0.02	0.44	0.07	-0.81	1		
P32.3	0.23	0.30	0.28	0.22	0.27	0.34	0.24	0.20	0.34	0.23	0.26	0.33	0.26	0.22	0.25	0.29	-0.10	-0.01	0.58	-0.11	0.04	0.58	-0.81	-0.77	1	
P33	0.07	0.13	0.25	0.25	0.21	0.23	0.37	0.18	0.28	0.18	0.09	0.11	0.15	0.29	0.40	0.37	0.05	0.08	0.32	0.14	0.08	0.37	0.15	0.18	0.36	1

Table 25: Correlation matrix part 3

	P1.1	P1.2	P1.3	P2.1	P2.2	P2.3	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	M1	M2	M3	M4	M5	M6	M7	M8	M9	P13
P34.1	0.31	0.07	-0.01	0.30	0.11	-0.07	0.01	-0.05	0.11	0.06	-0.05	-0.04	-0.02	-0.04	-0.06	0.06	0.05	0.03	0.03	0.01	-0.09	-0.01	-0.01	-0.02	-0.05	0.03
P34.2	0.00	0.42	0.17	-0.01	0.38	0.18	0.12	0.00	0.31	0.03	0.02	0.14	0.07	0.12	-0.05	0.13	0.12	0.02	0.21	0.06	0.05	0.18	0.19	0.14	0.12	0.04
P34.3	0.08	0.28	0.51	0.01	0.13	0.50	0.20	0.29	0.32	0.32	0.39	0.31	0.29	0.30	0.33	0.25	0.26	0.30	0.37	0.25	0.36	0.24	0.40	0.36	0.36	0.21
P35.1	0.22	0.08	0.12	0.27	0.01	0.01	0.01	0.09	0.01	0.05	0.14	0.08	0.06	0.03	0.10	0.16	-0.21	0.08	0.01	-0.15	0.07	-0.02	-0.03	0.08	0.11	0.10
P35.2	0.06	0.30	0.21	0.15	0.33	0.11	0.06	-0.03	-0.18	-0.01	-0.08	-0.10	-0.01	0.14	0.00	0.28	-0.10	0.11	0.04	-0.07	0.09	-0.12	0.15	0.18	0.08	-0.01
P35.3	-0.26	0.15	0.69	0.15	0.13	0.72	0.34	0.47	0.36	0.42	0.50	0.45	0.45	0.47	0.43	0.25	0.24	0.48	0.44	0.30	0.48	0.40	0.38	0.48	0.46	0.42
P36.1	0.12	0.19	-0.06	0.14	0.08	-0.15	-0.09	-0.05	-0.01	-0.01	-0.10	-0.08	-0.08	-0.06	-0.06	0.09	0.07	0.00	0.01	0.03	0.06	0.00	0.10	0.00	0.05	-0.02
P36.2	0.02	0.21	0.19	-0.03	0.17	0.05	0.06	-0.10	-0.10	-0.05	-0.05	-0.11	0.05	-0.02	-0.11	0.08	0.22	0.06	0.12	0.00	0.10	-0.03	0.06	-0.03	0.03	0.03
P36.3	0.01	0.23	0.50	-0.10	-0.17	0.52	0.27	0.32	0.20	0.23	0.35	0.34	0.35	0.37	0.31	0.23	0.21	0.35	0.32	0.28	0.40	0.34	0.27	0.38	0.32	0.30
P37.1	-0.04	-0.22	0.03	-0.20	-0.07	-0.07	-0.21	-0.19	-0.10	0.00	-0.08	-0.19	-0.17	-0.08	-0.09	-0.05	0.33	0.36	0.36	0.35	0.30	0.18	0.35	0.38	0.29	-0.14
P37.2	-0.10	-0.71	-0.69	-0.05	-0.69	0.15	-0.75	-0.72	-0.05	-0.03	-0.72	-0.72	-0.72	-0.69	0.04	0.00	0.43	0.42	0.26	0.25	0.32	0.12	0.36	0.31	0.43	-0.73
P37.3	-0.72	-0.71	0.74	-0.71	-0.66	0.75	0.57	0.64	0.62	0.61	0.68	0.64	0.69	0.68	0.68	0.50	0.56	0.72	0.77	0.56	0.72	0.76	0.79	0.74	0.73	0.54
P38.1	-0.02	-0.20	-0.05	-0.14	-0.01	-0.08	-0.20	-0.19	-0.22	0.00	-0.16	-0.36	-0.19	-0.19	-0.26	-0.06	0.42	0.34	0.31	0.34	0.26	0.09	0.29	0.32	0.30	-0.29
P38.2	-0.16	-0.77	-0.02	-0.05	-0.07	0.11	-0.22	-0.04	-0.11	-0.09	0.00	-0.11	-0.12	-0.09	0.03	-0.03	0.49	0.28	0.25	0.54	0.25	0.10	0.42	0.42	0.41	-0.19
P38.3	-0.74	-0.69	0.81	-0.71	-0.65	0.82	0.66	0.73	0.68	0.66	0.72	0.71	0.78	0.76	0.74	0.59	0.65	0.83	0.82	0.61	0.77	0.77	0.75	0.80	0.79	0.61
M10	-0.21	-0.11	0.02	-0.16	-0.12	0.04	0.01	0.02	0.00	-0.06	0.03	-0.04	-0.04	-0.11	-0.02	-0.09	-0.14	0.01	-0.03	-0.04	0.01	-0.08	-0.02	-0.05	-0.02	0.11
M11	-0.21	-0.25	0.08	-0.04	-0.24	0.22	-0.01	0.09	0.02	-0.06	0.11	0.13	0.06	0.04	0.06	0.02	-0.11	0.12	0.10	-0.12	0.12	0.01	0.07	0.11	0.05	0.12
M12	-0.21	-0.27	0.08	-0.15	-0.13	0.15	-0.08	0.11	-0.03	0.07	0.16	0.08	0.12	0.12	0.05	-0.03	-0.11	0.10	0.09	0.03	0.15	0.09	0.05	0.12	0.10	0.08
M13	-0.19	-0.28	0.14	-0.14	-0.10	0.20	-0.04	0.06	-0.03	-0.01	0.23	0.14	0.04	0.10	0.08	0.01	-0.13	0.15	0.15	0.00	0.28	0.11	0.03	0.19	0.12	0.10
M14	-0.13	-0.07	0.14	-0.05	-0.13	0.18	0.11	0.22	0.07	0.10	0.20	0.15	0.18	0.14	0.19	0.06	-0.09	0.14	0.14	-0.03	0.23	0.14	0.05	0.12	0.13	0.08
P39	0.12	-0.01	0.06	0.15	-0.73	-0.72	-0.11	0.06	-0.02	-0.07	-0.07	0.09	0.10	0.04	-0.04	0.09	-0.04	-0.02	-0.19	-0.08	-0.15	-0.02	-0.05	-0.07	-0.16	0.07
P40	-0.06	-0.13	-0.02	-0.10	0.04	0.00	-0.02	-0.04	0.04	-0.17	0.07	0.05	0.09	0.08	0.04	0.06	-0.11	0.05	-0.04	-0.22	0.20	0.02	-0.01	0.12	0.06	-0.03
P41	0.00	-0.72	-0.70	0.14	0.08	0.14	0.04	0.25	0.06	-0.03	0.05	0.04	0.03	0.17	0.32	0.06	-0.78	-0.72	-0.71	-0.07	0.18	0.02	0.00	-0.72	-0.72	-0.75
P42	-0.06	-0.77	-0.71	-0.09	-0.72	-0.73	-0.13	0.03	-0.05	-0.17	-0.74	0.06	0.14	-0.08	-0.02	0.09	-0.10	0.00	-0.12	-0.12	0.15	-0.04	0.04	0.02	0.01	-0.02
P43	-0.03	-0.04	-0.03	0.19	-0.72	0.00	-0.08	0.02	-0.05	-0.04	-0.11	0.04	0.18	0.06	0.12	0.02	-0.21	-0.12	-0.77	-0.05	0.01	-0.14	-0.17	0.10	-0.01	0.05

Table 26: Correlation matrix part 4

	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26	P27	P28	P29	P30.1	P30.2	P30.3	P31.1	P31.2	P31.3	P32.1	P32.2	P32.3	P33
P34.1	0.15	0.10	0.06	0.02	-0.02	0.01	0.11	0.04	-0.09	0.21	0.30	0.27	0.25	-0.08	0.06	0.01	0.11	-0.12	-0.21	0.18	-0.04	-0.12	0.15	-0.01	0.02	-0.05
P34.2	0.20	0.17	0.22	0.02	0.12	0.11	0.15	0.16	0.14	0.19	0.33	0.45	0.32	0.11	0.07	0.07	0.07	0.34	0.09	0.05	0.25	0.00	0.12	0.24	0.12	0.01
P34.3	0.36	0.40	0.24	0.20	0.27	0.21	0.20	0.25	0.33	0.25	0.37	0.48	0.46	0.20	0.22	0.29	-0.03	0.11	0.54	0.01	-0.09	0.61	-0.02	0.17	0.48	0.23
P35.1	0.06	0.02	0.14	0.07	0.18	0.14	0.18	0.23	0.13	-0.01	0.06	-0.02	0.13	0.04	0.16	0.11	0.35	-0.02	-0.02	0.28	0.03	-0.08	0.36	0.21	0.09	0.17
P35.2	0.30	0.28	0.17	0.14	0.07	0.15	0.26	0.23	0.21	-0.06	0.34	0.23	0.08	0.08	0.19	0.15	-0.02	0.36	-0.71	0.21	0.26	0.18	-0.01	0.47	0.12	0.29
P35.3	0.50	0.36	0.40	0.37	0.41	0.35	0.42	0.39	0.43	0.32	0.30	0.38	0.38	0.37	0.45	0.39	-0.07	0.13	0.64	-0.03	0.13	0.69	0.08	0.22	0.66	0.46
P36.1	0.13	0.08	0.11	0.05	-0.05	0.00	0.08	0.11	0.08	0.02	0.05	0.11	0.07	-0.01	-0.02	-0.02	0.14	0.08	-0.06	0.12	-0.04	-0.11	0.19	0.13	0.14	-0.09
P36.2	0.05	0.22	0.10	0.04	0.04	0.01	0.02	0.16	0.16	0.01	0.05	0.16	0.02	0.04	0.00	0.14	0.00	0.41	0.30	-0.04	0.31	0.12	-0.21	0.35	0.20	0.01
P36.3	0.21	0.26	0.14	0.23	0.22	0.26	0.25	0.18	0.36	0.24	0.20	0.33	0.29	0.23	0.28	0.27	-0.04	0.10	0.62	-0.06	-0.04	0.61	-0.15	0.02	0.66	0.26
P37.1	-0.10	-0.01	0.04	-0.20	-0.10	-0.17	-0.06	-0.06	0.07	-0.22	-0.18	-0.02	0.10	0.03	-0.07	0.05	0.18	0.16	0.21	0.11	0.09	0.38	0.06	0.00	0.07	-0.09
P37.2	-0.06	0.06	-0.79	-0.11	0.11	-0.75	-0.06	0.03	0.20	-0.11	-0.07	-0.05	0.13	0.01	-0.74	-0.07	-0.04	0.27	0.19	-0.74	0.13	0.21	-0.02	0.21	0.35	-0.02
P37.3	0.55	0.58	0.44	0.50	0.51	0.52	0.52	0.51	0.61	0.50	0.42	0.51	0.56	0.52	0.53	0.54	-0.71	0.18	0.85	-0.70	-0.66	0.82	0.02	-0.66	0.74	0.58
P38.1	-0.18	-0.08	-0.11	-0.23	-0.09	-0.21	-0.11	-0.12	0.01	-0.28	-0.15	0.02	0.00	-0.05	-0.08	0.12	0.18	0.08	-0.14	0.08	-0.01	0.19	0.06	0.09	0.02	-0.08
P38.2	-0.21	-0.02	-0.11	-0.17	-0.02	-0.15	-0.06	-0.06	0.22	-0.17	-0.15	-0.02	0.06	0.02	-0.19	-0.02	0.07	0.27	0.03	-0.05	-0.02	-0.70	-0.02	0.29	0.22	-0.02
P38.3	0.59	0.59	0.46	0.55	0.58	0.57	0.59	0.55	0.65	0.54	0.48	0.57	0.63	0.56	0.61	0.58	-0.71	-0.64	0.84	-0.71	-0.64	0.83	-0.71	-0.66	0.80	0.62
M10	0.16	0.22	0.14	0.13	0.12	0.16	0.13	0.09	0.14	-0.15	-0.16	-0.03	-0.06	0.10	0.10	0.10	-0.06	0.14	0.23	0.00	0.07	0.10	0.01	0.10	0.14	0.02
M11	0.21	0.19	0.20	0.08	0.15	0.17	0.20	0.14	0.21	-0.07	-0.10	-0.04	0.12	0.10	0.13	0.21	-0.04	0.09	0.29	-0.05	0.08	0.24	0.03	0.10	0.19	0.16
M12	0.01	-0.01	0.06	-0.04	0.00	-0.02	0.08	-0.12	0.09	-0.02	-0.07	0.00	0.09	0.15	0.14	0.11	0.01	0.07	0.27	0.04	0.11	0.28	0.02	0.09	0.22	0.14
M13	0.08	0.07	0.07	-0.09	0.01	0.02	0.01	-0.07	0.12	-0.04	-0.06	0.00	0.17	0.11	0.19	0.20	-0.07	0.07	0.32	-0.07	0.10	0.31	-0.06	0.13	0.27	0.19
M14	0.02	-0.04	0.09	0.07	0.04	0.05	0.11	-0.08	0.12	0.04	0.00	0.00	0.03	0.09	0.20	0.12	0.04	0.07	0.23	0.01	-0.06	0.34	0.00	0.08	0.30	0.21
P39	-0.09	-0.09	0.02	0.04	-0.20	-0.21	0.02	0.01	-0.77	0.08	-0.03	0.02	0.05	0.23	0.10	0.03	0.14	-0.08	-0.71	0.15	0.16	0.00	0.07	-0.11	-0.71	0.01
P40	0.03	-0.20	-0.03	-0.25	0.02	-0.22	-0.01	-0.16	0.02	-0.03	-0.03	0.04	0.09	0.11	0.32	-0.02	0.12	0.09	-0.72	0.10	0.16	0.07	0.03	0.11	-0.71	0.03
P41	-0.06	-0.76	0.11	-0.77	0.04	-0.08	0.11	-0.77	-0.74	0.06	-0.01	0.04	0.12	-0.09	0.14	0.04	0.08	-0.69	-0.67	-0.05	0.13	-0.66	0.08	-0.71	-0.67	0.17
P42	-0.20	0.00	0.02	0.16	0.06	0.00	0.17	0.13	0.07	0.04	-0.24	-0.10	-0.11	0.12	0.05	0.16	0.20	-0.74	0.13	0.01	0.09	0.17	0.00	0.18	-0.72	0.11
P43	0.08	0.08	0.10	0.13	0.05	-0.09	0.14	0.12	0.05	0.22	-0.15	0.01	0.05	0.21	0.17	0.09	0.10	-0.71	0.12	-0.06	-0.03	0.23	0.09	0.11	0.00	0.15

Table 27: Correlation matrix part 5

	P34.1	P34.2	P34.3	P35.1	P35.2	P35.3	P36.1	P36.2	P36.3	P37.1	P37.2	P37.3	P38.1	P38.2	P38.3	M10	M11	M12	M13	M14	P39	P40	P41	P42	P43
P34.1	1																								
P34.2	-0.90	1																							
P34.3	-0.87	-0.82	1																						
P35.1	0.24	0.19	0.06	1																					
P35.2	-0.06	0.51	0.27	-0.71	1																				
P35.3	-0.08	0.15	0.66	-0.70	-0.99	1																			
P36.1	0.21	0.15	0.02	0.24	0.16	-0.07	1																		
P36.2	-0.06	0.24	0.15	0.05	0.34	0.23	-0.88	1																	
P36.3	-0.32	-0.05	0.54	-0.03	-0.71	0.64	-0.82	-0.79	1																
P37.1	0.14	0.13	0.16	0.17	0.04	0.01	-0.03	-0.06	0.04	1															
P37.2	-0.78	0.29	0.33	0.14	-0.66	-0.62	0.35	-0.73	-0.67	-0.68	1														
P37.3	-0.14	-0.70	0.71	-0.68	-0.62	0.82	-0.12	-0.69	0.78	-0.67	-0.58	1													
P38.1	0.15	0.18	0.06	0.08	-0.01	-0.13	0.10	0.11	0.07	0.82	0.27	-0.69	1												
P38.2	-0.82	0.41	0.24	0.21	-0.65	-0.67	0.11	-0.06	0.02	0.13	0.81	-0.61	-0.88	1											
P38.3	-0.10	-0.71	0.71	-0.63	-0.57	0.87	-0.76	-0.70	0.84	-0.64	-0.53	1.00	0.99	-0.92	1										
M10	-0.04	0.02	0.15	-0.11	0.03	0.23	0.04	0.02	0.19	-0.10	-0.13	0.43	-0.17	-0.14	0.49	1									
M11	-0.12	0.06	0.24	-0.05	0.21	0.37	0.01	-0.01	0.21	-0.09	-0.77	0.54	-0.14	-0.15	0.58	0.32	1								
M12	-0.17	-0.11	0.14	0.01	0.01	0.32	0.01	0.01	0.33	-0.04	-0.74	0.57	-0.01	-0.19	0.59	0.20	0.13	1							
M13	-0.22	-0.07	0.16	0.02	-0.02	0.39	-0.07	-0.03	0.30	0.01	0.13	0.54	-0.03	-0.01	0.60	0.10	0.30	0.49	1						
M14	-0.18	-0.13	0.11	0.10	0.10	0.37	0.05	-0.04	0.31	-0.06	-0.74	0.50	-0.13	-0.08	0.61	0.14	0.21	0.26	0.29	1					
P39	-0.23	-0.08	-0.13	0.02	-0.70	-0.68	0.07	0.01	-0.03	-0.14	-0.64	-0.62	0.05	-0.69	-0.61	0.08	-0.03	-0.06	-0.22	-0.25	1				
P40	-0.02	0.08	-0.07	0.00	-0.66	-0.67	0.05	0.13	0.03	-0.74	-0.62	-0.57	-0.01	-0.67	-0.57	-0.01	0.07	-0.03	0.01	-0.17	0.61	1			
P41	0.04	-0.75	-0.69	-0.69	-0.62	-0.63	0.21	-0.73	-0.61	-0.68	-0.59	-0.57	-0.69	-0.64	-0.57	0.08	0.16	-0.06	-0.74	-0.74	0.55	0.67	1		
P42	-0.18	-0.03	-0.06	0.10	-0.66	-0.66	-0.18	-0.04	0.15	-0.06	-0.65	-0.62	0.05	-0.65	-0.58	-0.03	-0.07	0.10	0.08	0.04	0.68	0.68	0.63	1	
P43	-0.20	-0.11	0.02	0.10	-0.66	-0.67	0.03	0.00	0.20	-0.08	-0.61	-0.62	-0.12	-0.67	-0.57	-0.04	-0.05	0.04	0.06	-0.08	0.77	0.65	0.45	0.78	1

Table 28: Correlation matrix part 6

Item	SCE	RE SCE	naive EA	naive RE EA	EA SIS	RE EA SIS	MVC	avg y
PRODUCT1.1	0.25793	0.26416	0.26496	0.26060	0.25565	0.28319	0.25850	0.26184
PRODUCT1.2	0.17709	0.18007	0.17412	0.17740	0.17685	0.19661	0.17766	0.17987
PRODUCT1.3	0.12156	0.12253	0.11801	0.12046	0.12121	0.16459	0.12203	0.12823
PRODUCT2.1	0.21841	0.22294	0.22217	0.21825	0.21674	0.24478	0.21873	0.22168
PRODUCT2.2	0.13864	0.14012	0.13509	0.13828	0.13838	0.15270	0.13927	0.14387
PRODUCT2.3	0.11073	0.11142	0.10688	0.10936	0.11070	0.15469	0.11110	0.11784
PRODUCT3	0.23700	0.24342	0.24151	0.23857	0.23569	0.27973	0.23755	0.24060
PRODUCT4	0.18054	0.18295	0.18254	0.17892	0.18030	0.22426	0.18099	0.18358
PRODUCT5	0.22286	0.22687	0.22503	0.22544	0.22181	0.26767	0.22313	0.22539
PRODUCT6	0.21025	0.21411	0.21276	0.21300	0.20905	0.24926	0.21063	0.21300
PRODUCT7	0.15725	0.15885	0.15483	0.15666	0.15674	0.20362	0.15774	0.16114
PRODUCT8	0.16344	0.16524	0.16006	0.16315	0.16299	0.20469	0.16398	0.16689
PRODUCT9	0.17162	0.17343	0.17315	0.17010	0.17074	0.21366	0.17202	0.17504
PRODUCT10	0.15355	0.15536	0.15076	0.15322	0.15299	0.19435	0.15422	0.15792
PRODUCT11	0.17149	0.17291	0.17293	0.17227	0.17035	0.21231	0.17188	0.17445
PRODUCT12	0.26610	0.49195	0.27086	0.26961	0.26499	0.31394	0.26634	0.27057
PACK1	0.29450	0.50331	0.29513	0.29844	0.29238	0.32895	0.29503	0.30181
PACK2	0.16374	0.46177	0.16471	0.16385	0.16377	0.21078	0.16428	0.16742
PACK3	0.17730	0.17939	0.17905	0.17644	0.17673	0.22342	0.17768	0.18002
PACK4	0.24266	0.48187	0.24170	0.24189	0.24057	0.27830	0.24304	0.24602
PACK5	0.15203	0.15345	0.14934	0.15133	0.15147	0.20001	0.15248	0.15606
PACK6	0.18088	0.18346	0.18130	0.18672	0.18047	0.21994	0.18126	0.18398
PACK7	0.19811	0.20178	0.19955	0.19930	0.19749	0.23907	0.19849	0.20025
PACK8	0.15575	0.15713	0.15659	0.15452	0.15525	0.19746	0.15621	0.15975
PACK9	0.15942	0.16098	0.15987	0.15796	0.15934	0.20282	0.15992	0.16348
PRODUCT13	0.21046	0.21417	0.21090	0.21221	0.20898	0.25206	0.21084	0.21321
PRODUCT14	0.22726	0.23241	0.23041	0.22985	0.22624	0.26755	0.22756	0.22973
PRODUCT15	0.22702	0.23269	0.22825	0.22973	0.22603	0.27588	0.22730	0.22938
PRODUCT16	0.33962	0.35086	0.35959	0.35515	0.33736	0.40876	0.33983	0.35344
PRODUCT17	0.26622	0.27465	0.27411	0.26946	0.26368	0.30736	0.26655	0.27046
PRODUCT18	0.23139	0.23778	0.23436	0.23476	0.23022	0.27193	0.23191	0.23443
PRODUCT19	0.24426	0.25103	0.24846	0.24483	0.24249	0.28646	0.24460	0.24734
PRODUCT20	0.22845	0.23363	0.23000	0.23129	0.22721	0.27289	0.22881	0.23111
PRODUCT21	0.25785	0.26584	0.26214	0.26306	0.25575	0.29704	0.25807	0.26183
PRODUCT22	0.18323	0.18611	0.18331	0.18286	0.18250	0.23105	0.18354	0.18566
PRODUCT23	0.26663	0.27095	0.27528	0.26977	0.26468	0.30651	0.26688	0.27102
PRODUCT24	0.32236	0.33639	0.34148	0.33487	0.31996	0.36839	0.32327	0.33377
PRODUCT25	0.29036	0.30180	0.29952	0.30024	0.28886	0.35157	0.29062	0.29708
PRODUCT26	0.22531	0.22977	0.22628	0.22812	0.22375	0.27984	0.22568	0.22822
PRODUCT27	0.24850	0.25372	0.25345	0.25070	0.24804	0.30234	0.24892	0.25169
PRODUCT28	0.21439	0.47234	0.21840	0.21438	0.21376	0.26872	0.21495	0.21726
PRODUCT29	0.23400	0.23789	0.23877	0.23503	0.23250	0.28721	0.23453	0.23686

PRODUCT30.1	0.21722	0.47146	0.22000	0.21681	0.21599	0.24883	0.21774	0.22003
PRODUCT30.2	0.11862	0.11955	0.11638	0.11763	0.11853	0.14234	0.11910	0.12566
PRODUCT30.3	0.09879	0.09934	0.09628	0.09735	0.09951	0.14613	0.09924	0.10812
PRODUCT31.1	0.22368	0.47596	0.22819	0.22456	0.22274	0.25531	0.22418	0.22632
PRODUCT31.2	0.11823	0.11910	0.11574	0.11752	0.11746	0.13758	0.11866	0.12465
PRODUCT31.3	0.08824	0.08873	0.08823	0.08684	0.08869	0.13863	0.08877	0.09930
PRODUCT32.1	0.20360	0.47146	0.20604	0.20354	0.20222	0.23071	0.20404	0.20621
PRODUCT32.2	0.13418	0.13539	0.13165	0.13334	0.13400	0.16090	0.13455	0.13926
PRODUCT32.3	0.10813	0.10892	0.10656	0.10690	0.10801	0.15217	0.10863	0.11641
PRODUCT33	0.20217	0.20598	0.20156	0.20374	0.20107	0.25277	0.20270	0.20476
PRODUCT34.1	0.32203	0.33395	0.33649	0.32968	0.31963	0.35484	0.32294	0.33377
PRODUCT34.2	0.21756	0.22314	0.22080	0.21970	0.21639	0.24696	0.21799	0.22025
PRODUCT34.3	0.14270	0.14438	0.14248	0.14172	0.14378	0.19194	0.14320	0.14750
PRODUCT35.1	0.11307	0.11381	0.11131	0.11187	0.11292	0.13274	0.11353	0.12035
PRODUCT35.2	0.06215	0.06229	0.06076	0.06115	0.06195	0.07872	0.06253	0.07895
PRODUCT35.3	0.07040	0.44978	0.06930	0.06888	0.07079	0.12199	0.07085	0.08470
PRODUCT36.1	0.31720	0.33392	0.32437	0.32542	0.31461	0.35046	0.31757	0.32723
PRODUCT36.2	0.18672	0.19026	0.18825	0.18636	0.18511	0.20551	0.18700	0.18938
PRODUCT36.3	0.10100	0.10155	0.10099	0.10128	0.10143	0.14427	0.10140	0.10985
PRODUCT37.1	0.14446	0.14624	0.14472	0.14365	0.14301	0.16143	0.14504	0.14945
PRODUCT37.2	0.03787	0.44594	0.03791	0.03739	0.03773	0.04538	0.03822	0.06289
PRODUCT37.3	0.03322	0.03359	0.03330	0.03169	0.03458	0.07536	0.03356	0.06019
PRODUCT38.1	0.16941	0.46105	0.17007	0.16891	0.16722	0.18508	0.16992	0.17280
PRODUCT38.2	0.06641	0.06660	0.06638	0.06558	0.06458	0.07449	0.06682	0.08199
PRODUCT38.3	0.02976	0.03009	0.02978	0.02800	0.03120	0.07184	0.03004	0.05839
PACK10	0.29630	0.52461	0.29735	0.30513	0.29416	0.35769	0.29718	0.31146
PACK11	0.23798	0.49816	0.24011	0.24385	0.23685	0.30100	0.23872	0.24512
PACK12	0.20748	0.48376	0.20731	0.20866	0.20626	0.25648	0.20805	0.21229
PACK13	0.19010	0.19385	0.18975	0.19073	0.18918	0.23775	0.19053	0.19486
PACK14	0.19882	0.48054	0.19915	0.20253	0.19773	0.24379	0.19934	0.20335
PRODUCT39	0.08385	0.08423	0.08045	0.08279	0.08365	0.09174	0.08433	0.09505
PRODUCT40	0.06515	0.06533	0.06262	0.06423	0.06494	0.07504	0.06558	0.08094
PRODUCT41	0.03864	0.03869	0.03714	0.03811	0.03861	0.04415	0.03896	0.06321
PRODUCT42	0.06379	0.06404	0.06073	0.06321	0.06358	0.07216	0.06428	0.08016
PRODUCT43	0.06754	0.06784	0.06444	0.06641	0.06738	0.07792	0.06804	0.08242
Mean	0.18022	0.23669	0.18174	0.18152	0.17935	0.21767	0.18067	0.18715

Table 29: RMSE of simple design training data

Item	SCE	RE SCE	naive EA	naive RE EA	EA SIS	RE EA SIS	MVC	avg y
PRODUCT1.1	0.26906	0.27471	0.27582	0.27175	0.26503	0.27811	0.26823	0.27188
PRODUCT1.2	0.18256	0.18522	0.17691	0.18288	0.18093	0.18781	0.18248	0.18498
PRODUCT1.3	0.11889	0.11955	0.11383	0.11819	0.11803	0.14112	0.11916	0.12537
PRODUCT2.1	0.22831	0.23302	0.23233	0.22878	0.22603	0.24041	0.22802	0.23036
PRODUCT2.2	0.13548	0.13629	0.13187	0.13422	0.13412	0.14300	0.13559	0.14051
PRODUCT2.3	0.10730	0.10788	0.10367	0.10631	0.10716	0.13229	0.10777	0.11533
PRODUCT3	0.23962	0.24588	0.24391	0.24144	0.23799	0.26440	0.23980	0.24182
PRODUCT4	0.17017	0.17165	0.17125	0.16864	0.16980	0.20340	0.17043	0.17401
PRODUCT5	0.22422	0.22804	0.22533	0.22702	0.22244	0.24934	0.22432	0.22635
PRODUCT6	0.21297	0.21667	0.21515	0.21651	0.21165	0.23919	0.21305	0.21527
PRODUCT7	0.15763	0.15885	0.15590	0.15702	0.15634	0.18987	0.15781	0.16083
PRODUCT8	0.14937	0.15026	0.14499	0.14870	0.14983	0.17850	0.14993	0.15408
PRODUCT9	0.16628	0.16766	0.16739	0.16616	0.16599	0.19810	0.16665	0.16960
PRODUCT10	0.14832	0.14937	0.14625	0.14745	0.14811	0.17551	0.14856	0.15251
PRODUCT11	0.15221	0.15251	0.15252	0.15324	0.15250	0.18524	0.15272	0.15574
PRODUCT12	0.27311	0.49364	0.27793	0.27703	0.27168	0.29635	0.27288	0.27812
PACK1	0.29312	0.49363	0.29258	0.29613	0.29094	0.31108	0.29255	0.29928
PACK2	0.15388	0.45469	0.15396	0.15429	0.15426	0.18209	0.15397	0.15741
PACK3	0.17992	0.18183	0.18144	0.17925	0.17874	0.21094	0.17989	0.18280
PACK4	0.24178	0.48118	0.24007	0.24036	0.23852	0.26073	0.24150	0.24451
PACK5	0.14297	0.14364	0.14051	0.14194	0.14266	0.17831	0.14321	0.14801
PACK6	0.18701	0.18967	0.18726	0.19269	0.18554	0.20953	0.18702	0.18929
PACK7	0.21112	0.21497	0.21241	0.21209	0.20900	0.23241	0.21068	0.21290
PACK8	0.14808	0.14852	0.14792	0.14636	0.14800	0.17522	0.14813	0.15237
PACK9	0.16374	0.16477	0.16379	0.16254	0.16345	0.18825	0.16365	0.16662
PRODUCT13	0.20712	0.20989	0.20713	0.20786	0.20554	0.23167	0.20699	0.20898
PRODUCT14	0.22674	0.23133	0.22925	0.22918	0.22485	0.25450	0.22671	0.22868
PRODUCT15	0.23339	0.23885	0.23499	0.23626	0.23122	0.25851	0.23299	0.23481
PRODUCT16	0.34373	0.35524	0.36417	0.35866	0.34196	0.38461	0.34392	0.35821
PRODUCT17	0.27012	0.27855	0.27765	0.27404	0.26657	0.29253	0.26999	0.27439
PRODUCT18	0.22675	0.23147	0.22756	0.22902	0.22406	0.25584	0.22642	0.22832
PRODUCT19	0.24934	0.25587	0.25325	0.24909	0.24696	0.27282	0.24911	0.25198
PRODUCT20	0.22210	0.22581	0.22178	0.22425	0.21984	0.25229	0.22175	0.22405
PRODUCT21	0.25637	0.26388	0.26002	0.26132	0.25381	0.28089	0.25632	0.26055
PRODUCT22	0.18372	0.18639	0.18317	0.18371	0.18250	0.21218	0.18379	0.18608
PRODUCT23	0.26716	0.27096	0.27534	0.27080	0.26492	0.28954	0.26700	0.27109
PRODUCT24	0.32109	0.33335	0.33838	0.33190	0.31718	0.34589	0.32055	0.33017
PRODUCT25	0.29694	0.30888	0.30596	0.30757	0.29555	0.32348	0.29652	0.30382
PRODUCT26	0.22950	0.23357	0.22974	0.23158	0.22876	0.26094	0.22926	0.23114
PRODUCT27	0.25263	0.25710	0.25695	0.25421	0.25056	0.28343	0.25217	0.25547
PRODUCT28	0.21307	0.46429	0.21627	0.21305	0.21174	0.24581	0.21308	0.21540
PRODUCT29	0.23962	0.24284	0.24396	0.24031	0.23792	0.27470	0.23914	0.24178

PRODUCT30.1	0.22100	0.47210	0.22327	0.21946	0.21904	0.23933	0.22073	0.22273
PRODUCT30.2	0.11883	0.11955	0.11673	0.11781	0.11850	0.13603	0.11912	0.12599
PRODUCT30.3	0.09531	0.09565	0.09277	0.09448	0.09622	0.12551	0.09572	0.10514
PRODUCT31.1	0.22375	0.46874	0.22749	0.22395	0.22205	0.24583	0.22362	0.22563
PRODUCT31.2	0.10507	0.10553	0.10286	0.10408	0.10490	0.11989	0.10568	0.11343
PRODUCT31.3	0.09015	0.09028	0.08733	0.08899	0.08944	0.11824	0.09026	0.09995
PRODUCT32.1	0.20238	0.46429	0.20396	0.20163	0.20148	0.21773	0.20219	0.20491
PRODUCT32.2	0.14098	0.14236	0.13934	0.14017	0.13958	0.15767	0.14116	0.14601
PRODUCT32.3	0.10909	0.10943	0.10625	0.10814	0.10880	0.13680	0.10921	0.11725
PRODUCT33	0.20147	0.20443	0.19881	0.20230	0.20088	0.23202	0.20138	0.20315
PRODUCT34.1	0.33055	0.34276	0.34560	0.33873	0.32809	0.34415	0.33081	0.34232
PRODUCT34.2	0.21508	0.21963	0.21669	0.21647	0.21347	0.23510	0.21488	0.21668
PRODUCT34.3	0.14913	0.15039	0.14794	0.14827	0.15012	0.18115	0.14890	0.15350
PRODUCT35.1	0.10954	0.11011	0.10854	0.10831	0.10863	0.12818	0.10998	0.11751
PRODUCT35.2	0.06569	0.06575	0.06553	0.06483	0.06535	0.07632	0.06599	0.08152
PRODUCT35.3	0.07287	0.44151	0.07161	0.07174	0.07286	0.10473	0.07311	0.08723
PRODUCT36.1	0.30892	0.32300	0.31403	0.31546	0.30794	0.32847	0.30875	0.31616
PRODUCT36.2	0.19075	0.19430	0.19224	0.18974	0.18938	0.19984	0.19069	0.19393
PRODUCT36.3	0.11034	0.11094	0.11032	0.11106	0.11043	0.13690	0.11049	0.11849
PRODUCT37.1	0.14681	0.14813	0.14660	0.14545	0.14504	0.15464	0.14688	0.15117
PRODUCT37.2	0.04655	0.44019	0.04645	0.04573	0.04656	0.05045	0.04668	0.06804
PRODUCT37.3	0.02585	0.02622	0.02579	0.02560	0.02797	0.05967	0.02624	0.05730
PRODUCT38.1	0.16615	0.45960	0.16645	0.16521	0.16344	0.17829	0.16614	0.16967
PRODUCT38.2	0.07282	0.07296	0.07277	0.07173	0.07106	0.07394	0.07303	0.08677
PRODUCT38.3	0.03412	0.03434	0.03412	0.03388	0.03464	0.06117	0.03431	0.06142
PACK10	0.30348	0.51957	0.30292	0.31101	0.29702	0.34699	0.30247	0.31677
PACK11	0.23542	0.48923	0.23685	0.24149	0.23373	0.28569	0.23571	0.24136
PACK12	0.20770	0.47369	0.20729	0.20912	0.20684	0.24513	0.20783	0.21192
PACK13	0.18149	0.18432	0.18079	0.18157	0.18105	0.21677	0.18178	0.18592
PACK14	0.19557	0.47122	0.19493	0.19980	0.19391	0.23055	0.19545	0.19889
PRODUCT39	0.09001	0.09026	0.08631	0.08900	0.09007	0.09601	0.09018	0.10051
PRODUCT40	0.06307	0.06317	0.06071	0.06232	0.06289	0.07119	0.06348	0.07977
PRODUCT41	0.04077	0.04078	0.03876	0.03966	0.04053	0.04451	0.04103	0.06453
PRODUCT42	0.07057	0.07062	0.06443	0.06928	0.07045	0.07545	0.07074	0.08485
PRODUCT43	0.07731	0.07738	0.07444	0.07616	0.07643	0.08222	0.07742	0.09044
Mean	0.18072	0.23565	0.18171	0.18190	0.17950	0.20399	0.18072	0.18722

Table 30: RMSE of simple design test data

Item	SCE	RE SCE	naive EA	naive RE EA	EA SIS	RE EA SIS	MVC	avg y
PRODUCT1.1	0.77365	0.74398	0.72054	0.74588	0.77921	0.72733	0.77203	0.74264
PRODUCT1.2	0.86785	0.80781	0.77470	0.85824	0.87062	0.83929	0.86550	0.85626
PRODUCT1.3	0.92560	0.88655	0.83273	0.93125	0.91911	0.88752	0.92296	0.90771
PRODUCT2.1	0.82006	0.76550	0.78485	0.80695	0.82382	0.77939	0.81890	0.79626
PRODUCT2.2	0.90915	0.87428	0.85607	0.91105	0.91275	0.89230	0.90596	0.89274
PRODUCT2.3	0.93555	0.90243	0.85993	0.94411	0.92714	0.89847	0.93337	0.91979
PRODUCT3	0.79857	0.74186	0.76496	0.77866	0.79586	0.73132	0.79671	0.77251
PRODUCT4	0.86368	0.83790	0.84207	0.86720	0.85745	0.80593	0.86172	0.84846
PRODUCT5	0.81467	0.78213	0.57319	0.78243	0.81487	0.75372	0.81371	0.79551
PRODUCT6	0.82954	0.79222	0.81012	0.82135	0.82752	0.77744	0.82814	0.81065
PRODUCT7	0.88951	0.87234	0.74238	0.89062	0.88876	0.83679	0.88707	0.87603
PRODUCT8	0.88289	0.85281	0.75295	0.87730	0.87989	0.83067	0.88025	0.87053
PRODUCT9	0.87344	0.85109	0.85600	0.87595	0.87276	0.82000	0.87164	0.85791
PRODUCT10	0.89410	0.87399	0.76326	0.89249	0.89340	0.84505	0.89069	0.87901
PRODUCT11	0.87353	0.86019	0.85665	0.87374	0.87360	0.82398	0.87176	0.86183
PRODUCT12	0.76332	0.74026	0.73791	0.72222	0.76485	0.69340	0.76262	0.72722
MEAL1	0.72960	0.64257	0.72719	0.69683	0.73150	0.66497	0.72827	0.67806
MEAL2	0.88258	0.84812	0.87336	0.88254	0.87390	0.82280	0.88002	0.86685
MEAL3	0.86706	0.84063	0.84839	0.86976	0.86519	0.81024	0.86541	0.85295
MEAL4	0.79154	0.70418	0.79409	0.78498	0.79429	0.72714	0.79038	0.76426
MEAL5	0.89485	0.87767	0.76093	0.89555	0.88736	0.84464	0.89258	0.88074
MEAL6	0.86313	0.82274	0.86041	0.85901	0.86026	0.80896	0.86147	0.84650
MEAL7	0.84377	0.79551	0.83361	0.83900	0.84288	0.78502	0.84219	0.83118
MEAL8	0.89122	0.87360	0.88259	0.89276	0.88906	0.84366	0.88877	0.87734
MEAL9	0.88706	0.87205	0.88382	0.89091	0.88156	0.83538	0.88464	0.87365
PRODUCT13	0.82938	0.79933	0.62430	0.80268	0.83577	0.77167	0.82796	0.80923
PRODUCT14	0.80942	0.74822	0.57574	0.78018	0.81228	0.75203	0.80844	0.78985
PRODUCT15	0.80980	0.73935	0.58443	0.77370	0.81004	0.74394	0.80881	0.79129
PRODUCT16	0.67584	0.64075	0.56597	0.59203	0.67949	0.58497	0.67543	0.59547
PRODUCT17	0.76325	0.68801	0.62321	0.73400	0.76743	0.70061	0.76235	0.72939
PRODUCT18	0.80519	0.73461	0.55908	0.76708	0.80541	0.74659	0.80341	0.78077
PRODUCT19	0.78946	0.72571	0.76244	0.77771	0.79315	0.72847	0.78838	0.76396
PRODUCT20	0.80829	0.76035	0.56670	0.77645	0.80781	0.74565	0.80704	0.78763
PRODUCT21	0.77311	0.70042	0.52911	0.72115	0.77508	0.71474	0.77248	0.74133
PRODUCT22	0.86019	0.81696	0.67842	0.85455	0.85724	0.80315	0.85887	0.84742
PRODUCT23	0.76273	0.74109	0.68908	0.72642	0.76657	0.70303	0.76197	0.72771
PRODUCT24	0.69673	0.63407	0.55200	0.62089	0.70075	0.62980	0.69478	0.62815
PRODUCT25	0.73446	0.65833	0.39937	0.65277	0.73666	0.65200	0.73377	0.68498
PRODUCT26	0.81202	0.76624	0.57117	0.77714	0.81337	0.73861	0.81070	0.78935
PRODUCT27	0.78471	0.75658	0.75188	0.75496	0.78528	0.70688	0.78340	0.75937
PRODUCT28	0.82534	0.78919	0.78750	0.81174	0.81928	0.75148	0.82325	0.80642
PRODUCT29	0.80186	0.77909	0.76437	0.78744	0.80362	0.72997	0.80012	0.77819

PRODUCT30.1	0.82208	0.79483	0.80080	0.81300	0.82447	0.77371	0.82024	0.80117
PRODUCT30.2	0.92868	0.89351	0.87200	0.93526	0.93097	0.90818	0.92582	0.90994
PRODUCT30.3	0.94666	0.90122	0.86068	0.95645	0.93462	0.90848	0.94378	0.92558
PRODUCT31.1	0.81437	0.77845	0.77416	0.79803	0.81607	0.76469	0.81261	0.79373
PRODUCT31.2	0.92864	0.89369	0.88758	0.93232	0.93508	0.91285	0.92622	0.91336
PRODUCT31.3	0.95641	0.90977	0.87745	0.96514	0.94222	0.92137	0.95259	0.93212
PRODUCT32.1	0.83751	0.80542	0.81786	0.83244	0.84163	0.79866	0.83581	0.82199
PRODUCT32.2	0.91280	0.87649	0.83517	0.91582	0.91572	0.88945	0.91085	0.89871
PRODUCT32.3	0.93874	0.89504	0.84255	0.94615	0.92902	0.90156	0.93563	0.91757
PRODUCT33	0.83926	0.79681	0.62781	0.81595	0.83683	0.77367	0.83729	0.82305
PRODUCT34.1	0.69719	0.64894	0.62176	0.65225	0.70294	0.64381	0.69530	0.62611
PRODUCT34.2	0.82118	0.72063	0.61109	0.79887	0.82484	0.78341	0.81960	0.80296
PRODUCT34.3	0.90464	0.82056	0.74659	0.90783	0.89522	0.85371	0.90208	0.89098
PRODUCT35.1	0.93395	0.90465	0.86816	0.93751	0.93413	0.91739	0.93099	0.91507
PRODUCT35.2	0.97551	0.96573	0.95549	0.98014	0.97886	0.96963	0.97235	0.94462
PRODUCT35.3	0.96979	0.93358	0.90720	0.97796	0.95500	0.93891	0.96631	0.94251
PRODUCT36.1	0.70235	0.58898	0.67578	0.64056	0.70740	0.64860	0.70156	0.63841
PRODUCT36.2	0.85619	0.69791	0.84249	0.85167	0.86339	0.83067	0.85506	0.84235
PRODUCT36.3	0.94438	0.89561	0.94424	0.94398	0.92887	0.90839	0.94192	0.92435
PRODUCT37.1	0.90331	0.81842	0.83276	0.90779	0.91000	0.88540	0.90019	0.88657
PRODUCT37.2	0.99054	0.98823	0.98656	0.99370	0.99268	0.99008	0.98712	0.95359
PRODUCT37.3	0.99262	0.99132	0.96121	0.99518	0.98109	0.97718	0.98897	0.95462
PRODUCT38.1	0.87627	0.78819	0.78279	0.87487	0.88674	0.85183	0.87387	0.86111
PRODUCT38.2	0.97260	0.93891	0.96097	0.98100	0.98001	0.97371	0.96928	0.94315
PRODUCT38.3	0.99351	0.99183	0.96562	0.99653	0.98256	0.97967	0.99045	0.95600
MEAL10	0.74511	0.71689	0.74290	0.70301	0.74620	0.64277	0.74352	0.66218
MEAL11	0.81115	0.77291	0.80441	0.77480	0.81056	0.71095	0.80948	0.76704
MEAL12	0.84381	0.81659	0.84436	0.82611	0.84262	0.76346	0.84221	0.81411
MEAL13	0.86271	0.83269	0.86374	0.84607	0.86011	0.78749	0.86128	0.83402
MEAL14	0.85261	0.82770	0.85139	0.83402	0.85298	0.78165	0.85096	0.82318
PRODUCT39	0.95972	0.93905	0.94422	0.96647	0.96376	0.95448	0.95621	0.93633
PRODUCT40	0.97339	0.96652	0.96760	0.97960	0.97658	0.96884	0.97004	0.94344
PRODUCT41	0.98924	0.98557	0.98715	0.99324	0.99125	0.98904	0.98627	0.95336
PRODUCT42	0.97519	0.96700	0.97073	0.97942	0.97839	0.97148	0.97121	0.94433
PRODUCT43	0.97250	0.95241	0.96151	0.97853	0.97548	0.96773	0.96854	0.94416
Mean	0.85912	0.81762	0.78408	0.84589	0.85877	0.81210	0.85706	0.83297

Table 31: RLH of simple design training data

Item	SCE	RE SCE	naive EA	naive RE EA	EA SIS	RE EA SIS	MVC	avg y
PRODUCT1.1	0.75770	0.72272	0.69998	0.71767	0.76978	0.74582	0.76028	0.72678
PRODUCT1.2	0.85976	0.79517	0.78476	0.84649	0.86648	0.86001	0.86028	0.84792
PRODUCT1.3	0.92691	0.89005	0.85052	0.93086	0.91955	0.92035	0.92553	0.91099
PRODUCT2.1	0.80717	0.74629	0.76853	0.77986	0.81692	0.79701	0.80832	0.78990
PRODUCT2.2	0.90989	0.87714	0.86916	0.91406	0.91870	0.91184	0.90965	0.89686
PRODUCT2.3	0.93835	0.90766	0.87292	0.94569	0.92903	0.92846	0.93582	0.92012
PRODUCT3	0.79450	0.73530	0.76109	0.76841	0.79781	0.76579	0.79406	0.77350
PRODUCT4	0.87372	0.85360	0.85937	0.87800	0.87353	0.84592	0.87275	0.85728
PRODUCT5	0.81237	0.77927	0.59090	0.77911	0.81897	0.78809	0.81212	0.79383
PRODUCT6	0.82543	0.78651	0.80785	0.81299	0.82645	0.79471	0.82522	0.80968
PRODUCT7	0.88738	0.87029	0.74114	0.88889	0.88894	0.86113	0.88675	0.87702
PRODUCT8	0.89645	0.87461	0.78903	0.89892	0.88458	0.87481	0.89401	0.88116
PRODUCT9	0.87836	0.85785	0.86430	0.87069	0.87031	0.84837	0.87698	0.86563
PRODUCT10	0.89714	0.87871	0.76569	0.90054	0.89683	0.87552	0.89630	0.88553
PRODUCT11	0.89272	0.88650	0.88488	0.89899	0.89436	0.86632	0.89069	0.88213
PRODUCT12	0.75404	0.72839	0.72772	0.70709	0.74593	0.72808	0.75476	0.71367
MEAL1	0.73015	0.64437	0.73073	0.69722	0.73569	0.70275	0.73159	0.68382
MEAL2	0.89041	0.86257	0.88600	0.89019	0.88361	0.87555	0.89019	0.87996
MEAL3	0.86296	0.83548	0.84516	0.86475	0.86089	0.83926	0.86322	0.84867
MEAL4	0.79134	0.70573	0.79616	0.78851	0.79150	0.76206	0.79226	0.76557
MEAL5	0.90235	0.88942	0.76305	0.90893	0.89126	0.87853	0.90144	0.88706
MEAL6	0.85518	0.80985	0.85309	0.85119	0.85248	0.83384	0.85534	0.84347
MEAL7	0.82618	0.76734	0.81618	0.82185	0.82398	0.80564	0.82853	0.81401
MEAL8	0.89649	0.88206	0.89466	0.90312	0.88737	0.87867	0.89643	0.88358
MEAL9	0.87974	0.86341	0.87837	0.88339	0.86715	0.85605	0.88062	0.86916
PRODUCT13	0.83157	0.80381	0.64028	0.81015	0.83518	0.81370	0.83214	0.81696
PRODUCT14	0.80889	0.74774	0.58156	0.77951	0.81511	0.78121	0.80916	0.78930
PRODUCT15	0.80053	0.72461	0.55616	0.76342	0.79957	0.77970	0.80207	0.78369
PRODUCT16	0.67064	0.63364	0.55829	0.58523	0.67111	0.62301	0.67029	0.58340
PRODUCT17	0.75793	0.67938	0.61095	0.71835	0.76498	0.73253	0.75832	0.72247
PRODUCT18	0.80839	0.74241	0.58741	0.76794	0.81751	0.78130	0.80947	0.79058
PRODUCT19	0.78191	0.71440	0.75458	0.77054	0.78647	0.75641	0.78283	0.75583
PRODUCT20	0.81373	0.77108	0.60431	0.77794	0.82231	0.78381	0.81495	0.79561
PRODUCT21	0.77438	0.70302	0.52821	0.72200	0.78101	0.74771	0.77456	0.74218
PRODUCT22	0.85895	0.81548	0.68286	0.84695	0.85985	0.83582	0.85868	0.84658
PRODUCT23	0.76116	0.73954	0.68763	0.72100	0.76640	0.73620	0.76165	0.72703
PRODUCT24	0.69692	0.63604	0.55557	0.62206	0.70457	0.66827	0.69807	0.63665
PRODUCT25	0.72583	0.64383	0.38331	0.63541	0.72596	0.69683	0.72701	0.68041
PRODUCT26	0.80518	0.75554	0.55291	0.76424	0.79917	0.77425	0.80629	0.79056
PRODUCT27	0.77779	0.74783	0.74588	0.74714	0.78158	0.74532	0.77938	0.74848
PRODUCT28	0.82508	0.78871	0.79086	0.81438	0.81990	0.79416	0.82518	0.80863
PRODUCT29	0.79315	0.76823	0.75530	0.77333	0.79642	0.75728	0.79492	0.77215

PRODUCT30.1	0.81494	0.78667	0.79214	0.80789	0.81854	0.79827	0.81616	0.80148
PRODUCT30.2	0.92716	0.89223	0.87291	0.93610	0.92738	0.92305	0.92571	0.90969
PRODUCT30.3	0.94843	0.90619	0.87695	0.95556	0.94137	0.93788	0.94625	0.92812
PRODUCT31.1	0.81250	0.77633	0.77536	0.79873	0.81909	0.78769	0.81307	0.79607
PRODUCT31.2	0.94002	0.91473	0.90430	0.94839	0.94410	0.93731	0.93692	0.92100
PRODUCT31.3	0.95065	0.90185	0.89366	0.96246	0.94195	0.94384	0.95153	0.93336
PRODUCT32.1	0.83676	0.80517	0.82071	0.83118	0.84169	0.82721	0.83764	0.82110
PRODUCT32.2	0.90569	0.86444	0.82826	0.90964	0.91207	0.90034	0.90476	0.89014
PRODUCT32.3	0.93379	0.88810	0.84772	0.93878	0.92596	0.92399	0.93476	0.91903
PRODUCT33	0.83800	0.79691	0.63628	0.81905	0.82942	0.81122	0.83866	0.82836
PRODUCT34.1	0.68614	0.63156	0.60698	0.63239	0.69183	0.66804	0.68574	0.61350
PRODUCT34.2	0.82209	0.72399	0.63197	0.80127	0.82984	0.80174	0.82295	0.80455
PRODUCT34.3	0.89469	0.80174	0.72767	0.89922	0.88488	0.87651	0.89659	0.87980
PRODUCT35.1	0.93601	0.90836	0.87540	0.94178	0.94161	0.92823	0.93390	0.91609
PRODUCT35.2	0.97067	0.95885	0.94449	0.97907	0.97723	0.97442	0.96987	0.94435
PRODUCT35.3	0.96547	0.92674	0.90628	0.97063	0.94962	0.95867	0.96487	0.93870
PRODUCT36.1	0.71141	0.60718	0.69070	0.65650	0.71442	0.68553	0.71174	0.66075
PRODUCT36.2	0.85082	0.68576	0.83655	0.84373	0.85822	0.84421	0.85119	0.83371
PRODUCT36.3	0.93493	0.87592	0.93505	0.93326	0.92705	0.91936	0.93441	0.91698
PRODUCT37.1	0.89769	0.80934	0.82526	0.89755	0.90919	0.90007	0.89823	0.88556
PRODUCT37.2	0.98026	0.95845	0.97520	0.99072	0.98763	0.98835	0.98277	0.95137
PRODUCT37.3	0.98978	0.98899	0.97400	0.99630	0.98884	0.98667	0.99113	0.95626
PRODUCT38.1	0.87717	0.79194	0.78064	0.86652	0.88942	0.87194	0.87767	0.86260
PRODUCT38.2	0.96622	0.92475	0.95212	0.97815	0.97581	0.97534	0.96532	0.94149
PRODUCT38.3	0.98162	0.98429	0.96625	0.99358	0.98684	0.98625	0.98896	0.95389
MEAL10	0.73422	0.70462	0.73471	0.69394	0.74430	0.66455	0.73613	0.65341
MEAL11	0.81312	0.77778	0.80820	0.77695	0.81448	0.74325	0.81251	0.77161
MEAL12	0.84233	0.81232	0.84363	0.81870	0.84171	0.78989	0.84198	0.81287
MEAL13	0.87077	0.84668	0.87269	0.85576	0.87170	0.82451	0.86972	0.84536
MEAL14	0.85496	0.83115	0.85689	0.83385	0.85888	0.81035	0.85530	0.83169
PRODUCT39	0.95256	0.92739	0.93856	0.96052	0.95751	0.95627	0.95200	0.93157
PRODUCT40	0.97415	0.96816	0.96715	0.97987	0.97630	0.97476	0.97127	0.94372
PRODUCT41	0.98729	0.98340	0.98802	0.99332	0.98999	0.98851	0.98538	0.95241
PRODUCT42	0.96771	0.95887	0.97143	0.97812	0.97267	0.97192	0.96707	0.94322
PRODUCT43	0.96151	0.93179	0.95026	0.96932	0.97111	0.96829	0.96217	0.93821
Mean	0.85676	0.81452	0.78553	0.84306	0.85808	0.83766	0.85691	0.83285

Table 32: RLH of simple design test data

Item	SCE	RE SCE	naive EA	naive RE EA	EA SIS	RE EA SIS	MVC	avg y
PRODUCT1.1	0.07202	0.01840	0.01240	0.01460	0.07202	0.09746	0.07691	0.07202
PRODUCT1.2	0.03254	0.00197	0.00125	0.00056	0.03255	0.05264	0.04156	0.03255
PRODUCT1.3	0.01502	0.00040	0.00062	0.00027	0.01503	0.03773	0.02436	0.01503
PRODUCT2.1	0.05034	0.00737	0.00954	0.01490	0.05034	0.08154	0.05769	0.05034
PRODUCT2.2	0.01968	0.00146	0.00080	0.00029	0.01968	0.03349	0.02917	0.01968
PRODUCT2.3	0.01242	0.00019	0.00056	0.00024	0.01242	0.03363	0.02147	0.01242
PRODUCT3	0.05999	0.00710	0.01360	0.01440	0.05999	0.10300	0.06629	0.05999
PRODUCT4	0.03382	0.00594	0.00748	0.01350	0.03382	0.07413	0.04270	0.03382
PRODUCT5	0.05251	0.01120	0.00103	0.00086	0.05251	0.10316	0.05967	0.05251
PRODUCT6	0.04646	0.00776	0.01340	0.01910	0.04646	0.08630	0.05421	0.04646
PRODUCT7	0.02545	0.00467	0.00083	0.00047	0.02545	0.06178	0.03482	0.02545
PRODUCT8	0.02756	0.00557	0.00108	0.00049	0.02756	0.05619	0.03683	0.02756
PRODUCT9	0.03044	0.00708	0.00754	0.01520	0.03044	0.06386	0.03958	0.03044
PRODUCT10	0.02428	0.00422	0.00088	0.00042	0.02429	0.05294	0.03372	0.02429
PRODUCT11	0.03038	0.00988	0.00791	0.01790	0.03038	0.06237	0.03953	0.03038
PRODUCT12	0.07685	0.19900	0.02330	0.01430	0.07685	0.13649	0.08117	0.07685
MEAL1	0.09625	0.19900	0.06210	0.02870	0.09625	0.12772	0.09828	0.09625
MEAL2	0.02767	0.19900	0.01020	0.02180	0.02767	0.06030	0.03694	0.02767
MEAL3	0.03255	0.00621	0.00773	0.01380	0.03255	0.07233	0.04154	0.03255
MEAL4	0.06304	0.19900	0.05940	0.03820	0.06304	0.08854	0.06897	0.06304
MEAL5	0.02373	0.00429	0.00079	0.00043	0.02373	0.05974	0.03316	0.02373
MEAL6	0.03393	0.00426	0.01970	0.02250	0.03393	0.06058	0.04283	0.03393
MEAL7	0.04103	0.00419	0.01590	0.01900	0.04103	0.07663	0.04936	0.04103
MEAL8	0.02495	0.00617	0.00993	0.01450	0.02495	0.05443	0.03432	0.02495
MEAL9	0.02617	0.00581	0.01380	0.01430	0.02617	0.05496	0.03554	0.02617
PRODUCT13	0.04657	0.00866	0.00116	0.00079	0.04657	0.08982	0.05437	0.04657
PRODUCT14	0.05472	0.00700	0.00089	0.00098	0.05472	0.10208	0.06162	0.05472
PRODUCT15	0.05461	0.00453	0.00139	0.00095	0.05461	0.11169	0.06155	0.05461
PRODUCT16	0.13329	0.04650	0.01480	0.02300	0.13329	0.25388	0.13126	0.13329
PRODUCT17	0.07696	0.01100	0.00861	0.01450	0.07696	0.12638	0.08125	0.07696
PRODUCT18	0.05700	0.00454	0.00114	0.00097	0.05700	0.10393	0.06365	0.05700
PRODUCT19	0.06387	0.00723	0.01790	0.02890	0.06387	0.11633	0.06971	0.06387
PRODUCT20	0.05539	0.00783	0.00138	0.00097	0.05539	0.10746	0.06222	0.05539
PRODUCT21	0.07175	0.00812	0.00166	0.00133	0.07175	0.12417	0.07669	0.07175
PRODUCT22	0.03482	0.00287	0.00067	0.00073	0.03482	0.08183	0.04364	0.03482
PRODUCT23	0.07718	0.03030	0.00886	0.01490	0.07718	0.13129	0.08144	0.07718
PRODUCT24	0.11848	0.02600	0.00739	0.01550	0.11849	0.19193	0.11810	0.11849
PRODUCT25	0.09320	0.01240	0.00193	0.00159	0.09320	0.18720	0.09551	0.09320
PRODUCT26	0.05378	0.01030	0.00143	0.00089	0.05378	0.12049	0.06074	0.05378
PRODUCT27	0.06637	0.01790	0.01680	0.01360	0.06637	0.13182	0.07190	0.06637
PRODUCT28	0.04851	0.19900	0.00815	0.01360	0.04851	0.10512	0.05607	0.04851
PRODUCT29	0.05833	0.01830	0.01150	0.01490	0.05833	0.12013	0.06479	0.05833

PRODUCT30.1	0.04990	0.19900	0.01540	0.01550	0.04990	0.08459	0.05731	0.04990
PRODUCT30.2	0.01430	0.00043	0.00043	0.00024	0.01431	0.03215	0.02356	0.01431
PRODUCT30.3	0.00987	0.00003	0.00034	0.00021	0.00987	0.03154	0.01857	0.00987
PRODUCT31.1	0.05306	0.19900	0.00887	0.01340	0.05306	0.08954	0.06011	0.05306
PRODUCT31.2	0.01419	0.00032	0.00044	0.00019	0.01419	0.02902	0.02343	0.01419
PRODUCT31.3	0.00787	0.00001	0.00005	0.00018	0.00787	0.02929	0.01615	0.00787
PRODUCT32.1	0.04347	0.19900	0.01240	0.01460	0.04347	0.07372	0.05153	0.04347
PRODUCT32.2	0.01835	0.00066	0.00057	0.00030	0.01835	0.04158	0.02780	0.01835
PRODUCT32.3	0.01186	0.00006	0.00029	0.00023	0.01187	0.03504	0.02085	0.01187
PRODUCT33	0.04286	0.00572	0.00124	0.00069	0.04286	0.09223	0.05100	0.04286
PRODUCT34.1	0.11832	0.03670	0.01930	0.03610	0.11832	0.16664	0.11782	0.11832
PRODUCT34.2	0.04996	0.00176	0.00067	0.00087	0.04996	0.09334	0.05742	0.04996
PRODUCT34.3	0.02085	0.00008	0.00031	0.00040	0.02085	0.06007	0.03033	0.02085
PRODUCT35.1	0.01298	0.00089	0.00033	0.00024	0.01297	0.02765	0.02211	0.01297
PRODUCT35.2	0.00388	0.00021	0.00011	0.00008	0.00388	0.00936	0.01057	0.00388
PRODUCT35.3	0.00499	0.19900	0.00011	0.00013	0.00499	0.02210	0.01232	0.00499
PRODUCT36.1	0.11377	0.01050	0.04240	0.02190	0.11377	0.16710	0.11373	0.11377
PRODUCT36.2	0.03621	0.00007	0.01090	0.01450	0.03621	0.05948	0.04495	0.03621
PRODUCT36.3	0.01031	0.00002	0.00939	0.01520	0.01031	0.02800	0.01912	0.01031
PRODUCT37.1	0.02140	0.00038	0.00024	0.00040	0.02140	0.03406	0.03087	0.02140
PRODUCT37.2	0.00144	0.19900	0.00000	0.00002	0.00144	0.00363	0.00585	0.00144
PRODUCT37.3	0.00111	0.00442	0.00000	0.00006	0.00111	0.00764	0.00538	0.00111
PRODUCT38.1	0.02966	0.19900	0.00039	0.00059	0.02966	0.04215	0.03887	0.02966
PRODUCT38.2	0.00444	0.00000	0.00002	0.00007	0.00444	0.00756	0.01148	0.00444
PRODUCT38.3	0.00089	0.00474	0.00000	0.00006	0.00089	0.00665	0.00489	0.00089
MEAL10	0.10285	0.19900	0.06860	0.05100	0.10285	0.17694	0.10083	0.10285
MEAL11	0.06249	0.19900	0.03280	0.02310	0.06249	0.12911	0.06456	0.06249
MEAL12	0.04624	0.19900	0.03760	0.01440	0.04624	0.08826	0.05040	0.04624
MEAL13	0.03837	0.01370	0.03050	0.01300	0.03837	0.07706	0.04331	0.03837
MEAL14	0.04214	0.19900	0.02850	0.01960	0.04214	0.07989	0.04694	0.04214
PRODUCT39	0.00710	0.00021	0.00035	0.00013	0.00710	0.01244	0.01512	0.00710
PRODUCT40	0.00427	0.00023	0.00020	0.00007	0.00427	0.00915	0.01123	0.00427
PRODUCT41	0.00150	0.00007	0.00007	0.00002	0.00150	0.00331	0.00629	0.00150
PRODUCT42	0.00410	0.00030	0.00023	0.00005	0.00410	0.00857	0.01086	0.00410
PRODUCT43	0.00460	0.00001	0.00025	0.00010	0.00460	0.00890	0.01163	0.00460
Mean	0.04096	0.04434	0.00949	0.00917	0.04096	0.07617	0.04769	0.04096

Table 33: Average probabilities for simple design train data

Item	SCE	RE SCE	naive EA	naive RE EA	EA SIS	RE EA SIS	MVC	avg y
PRODUCT1.1	0.07176	0.01840	0.01240	0.01460	0.07267	0.09621	0.07675	0.07801
PRODUCT1.2	0.03262	0.00196	0.00176	0.00050	0.03257	0.05016	0.04159	0.03443
PRODUCT1.3	0.01507	0.00040	0.00077	0.00017	0.01486	0.03220	0.02432	0.01431
PRODUCT2.1	0.05054	0.00738	0.00955	0.01470	0.05099	0.07924	0.05768	0.05506
PRODUCT2.2	0.01975	0.00146	0.00069	0.00033	0.01991	0.03140	0.02919	0.01863
PRODUCT2.3	0.01234	0.00019	0.00051	0.00017	0.01200	0.02931	0.02143	0.01164
PRODUCT3	0.05994	0.00709	0.01360	0.01400	0.06043	0.09884	0.06624	0.06121
PRODUCT4	0.03358	0.00597	0.00741	0.01310	0.03327	0.07002	0.04263	0.02977
PRODUCT5	0.05243	0.01120	0.00126	0.00077	0.05250	0.09688	0.05965	0.05306
PRODUCT6	0.04632	0.00778	0.01340	0.01960	0.04664	0.08048	0.05410	0.04757
PRODUCT7	0.02545	0.00470	0.00064	0.00040	0.02547	0.05566	0.03481	0.02545
PRODUCT8	0.02761	0.00554	0.00099	0.00034	0.02688	0.05162	0.03683	0.02279
PRODUCT9	0.03053	0.00705	0.00754	0.01500	0.03034	0.06238	0.03956	0.02844
PRODUCT10	0.02429	0.00421	0.00060	0.00036	0.02441	0.04702	0.03371	0.02246
PRODUCT11	0.03022	0.00990	0.00794	0.01830	0.03011	0.05611	0.03949	0.02362
PRODUCT12	0.07681	0.19200	0.02340	0.01430	0.07628	0.12735	0.08111	0.08101
MEAL1	0.09623	0.19200	0.06170	0.02820	0.09707	0.12464	0.09817	0.09464
MEAL2	0.02768	0.19200	0.01010	0.02120	0.02765	0.05538	0.03693	0.02412
MEAL3	0.03270	0.00621	0.00769	0.01350	0.03224	0.06874	0.04156	0.03343
MEAL4	0.06300	0.19200	0.05930	0.03810	0.06268	0.08586	0.06899	0.06221
MEAL5	0.02399	0.00430	0.00058	0.00033	0.02350	0.05342	0.03317	0.02079
MEAL6	0.03379	0.00425	0.01960	0.02330	0.03459	0.05646	0.04283	0.03626
MEAL7	0.04095	0.00418	0.01590	0.01910	0.04139	0.07347	0.04936	0.04657
MEAL8	0.02505	0.00616	0.00987	0.01400	0.02438	0.04924	0.03425	0.02229
MEAL9	0.02594	0.00579	0.01380	0.01390	0.02624	0.05061	0.03550	0.02745
PRODUCT13	0.04656	0.00868	0.00102	0.00081	0.04723	0.08566	0.05448	0.04474
PRODUCT14	0.05471	0.00701	0.00092	0.00086	0.05378	0.09771	0.06152	0.05423
PRODUCT15	0.05478	0.00453	0.00129	0.00088	0.05338	0.10593	0.06159	0.05755
PRODUCT16	0.13345	0.04650	0.01480	0.02310	0.13405	0.23672	0.13115	0.13673
PRODUCT17	0.07704	0.01100	0.00886	0.01480	0.07778	0.12439	0.08131	0.07918
PRODUCT18	0.05723	0.00452	0.00125	0.00082	0.05740	0.10002	0.06349	0.05406
PRODUCT19	0.06392	0.00721	0.01780	0.02830	0.06446	0.10911	0.06959	0.06637
PRODUCT20	0.05551	0.00784	0.00141	0.00073	0.05589	0.10248	0.06216	0.05173
PRODUCT21	0.07182	0.00808	0.00170	0.00123	0.07192	0.12123	0.07662	0.07069
PRODUCT22	0.03473	0.00287	0.00076	0.00060	0.03485	0.07503	0.04358	0.03493
PRODUCT23	0.07669	0.03030	0.00875	0.01480	0.07724	0.12661	0.08143	0.07718
PRODUCT24	0.11849	0.02600	0.00733	0.01530	0.11814	0.18533	0.11800	0.11627
PRODUCT25	0.09310	0.01250	0.00224	0.00155	0.09309	0.17474	0.09532	0.09764
PRODUCT26	0.05385	0.01030	0.00155	0.00099	0.05358	0.11177	0.06065	0.05556
PRODUCT27	0.06634	0.01800	0.01680	0.01370	0.06619	0.12477	0.07191	0.06820
PRODUCT28	0.04856	0.19200	0.00808	0.01350	0.04851	0.09602	0.05603	0.04757
PRODUCT29	0.05803	0.01830	0.01140	0.01510	0.05772	0.11248	0.06471	0.06088

PRODUCT30.1	0.04987	0.19200	0.01540	0.01560	0.05031	0.08061	0.05727	0.05123
PRODUCT30.2	0.01441	0.00043	0.00038	0.00022	0.01485	0.03192	0.02355	0.01431
PRODUCT30.3	0.00984	0.00003	0.00031	0.00011	0.01024	0.02689	0.01856	0.00915
PRODUCT31.1	0.05330	0.19200	0.00890	0.01330	0.05270	0.08643	0.06017	0.05273
PRODUCT31.2	0.01418	0.00032	0.00032	0.00016	0.01410	0.02775	0.02340	0.01114
PRODUCT31.3	0.00793	0.00001	0.00029	0.00012	0.00782	0.02384	0.01611	0.00815
PRODUCT32.1	0.04339	0.19200	0.01240	0.01500	0.04427	0.06937	0.05146	0.04258
PRODUCT32.2	0.01841	0.00066	0.00049	0.00033	0.01818	0.03966	0.02779	0.02029
PRODUCT32.3	0.01196	0.00006	0.00039	0.00014	0.01189	0.03072	0.02082	0.01198
PRODUCT33	0.04300	0.00576	0.00152	0.00068	0.04268	0.08553	0.05098	0.04225
PRODUCT34.1	0.11891	0.03670	0.01920	0.03540	0.11951	0.16669	0.11763	0.12492
PRODUCT34.2	0.04993	0.00176	0.00080	0.00080	0.04988	0.09034	0.05738	0.04840
PRODUCT34.3	0.02096	0.00008	0.00041	0.00032	0.02101	0.05594	0.03036	0.02262
PRODUCT35.1	0.01295	0.00089	0.00020	0.00022	0.01271	0.02704	0.02208	0.01214
PRODUCT35.2	0.00384	0.00022	0.00002	0.00006	0.00405	0.00872	0.01053	0.00433
PRODUCT35.3	0.00502	0.19200	0.00011	0.00009	0.00465	0.01839	0.01231	0.00532
PRODUCT36.1	0.11402	0.01050	0.04230	0.02130	0.11344	0.15887	0.11373	0.10645
PRODUCT36.2	0.03610	0.00007	0.01100	0.01470	0.03649	0.05787	0.04496	0.03776
PRODUCT36.3	0.01037	0.00002	0.00938	0.01520	0.00975	0.02483	0.01911	0.01231
PRODUCT37.1	0.02123	0.00038	0.00024	0.00042	0.02095	0.03242	0.03085	0.02196
PRODUCT37.2	0.00139	0.19200	0.00000	0.00004	0.00141	0.00346	0.00584	0.00216
PRODUCT37.3	0.00108	0.00449	0.00000	0.00001	0.00098	0.00596	0.00537	0.00067
PRODUCT38.1	0.02976	0.19200	0.00030	0.00051	0.02954	0.04174	0.03885	0.02828
PRODUCT38.2	0.00438	0.00000	0.00001	0.00009	0.00438	0.00692	0.01149	0.00532
PRODUCT38.3	0.00089	0.00473	0.00000	0.00001	0.00080	0.00529	0.00489	0.00116
MEAL10	0.10580	0.19200	0.07030	0.05260	0.10428	0.17438	0.10331	0.10662
MEAL11	0.06282	0.19200	0.03300	0.02350	0.06135	0.12396	0.06498	0.06071
MEAL12	0.04656	0.19200	0.03790	0.01440	0.04759	0.08528	0.05098	0.04608
MEAL13	0.03866	0.01370	0.03070	0.01250	0.03813	0.07180	0.04354	0.03460
MEAL14	0.04166	0.19200	0.02820	0.01980	0.04121	0.07642	0.04656	0.04042
PRODUCT39	0.00709	0.00021	0.00040	0.00012	0.00701	0.01470	0.01510	0.00815
PRODUCT40	0.00427	0.00023	0.00017	0.00005	0.00419	0.00954	0.01122	0.00399
PRODUCT41	0.00153	0.00007	0.00009	0.00005	0.00142	0.00353	0.00631	0.00166
PRODUCT42	0.00402	0.00030	0.00048	0.00010	0.00406	0.00878	0.01084	0.00499
PRODUCT43	0.00467	0.00001	0.00025	0.00010	0.00456	0.00961	0.01166	0.00599
Mean	0.04101	0.04298	0.00952	0.00913	0.04097	0.07218	0.04771	0.04103

Table 34: Average probabilities for simple design test data

Menu vs. à-la-Carte Design

Item	Price1	Price2	Price3	Price4
PRODUCT1	480	600	660	780
PRODUCT2	1200	1500	1650	1950
PRODUCT3	960	1200	1320	1560
PRODUCT4	240	300	330	390
PRODUCT5	360	450	495	585
PRODUCT6	80	100	110	130
PRODUCT7	160	200	220	260
PRODUCT8	320	400	440	520
PRODUCT9	480	600	660	780
PRODUCT10	320	400	440	520
PRODUCT11	260	325	357.50	422.50
PRODUCT12	680	850	935	1105
PRODUCT13	960	1200	1320	1560
PRODUCT14	120	150	165	195
PRODUCT15	280	350	385	455
PRODUCT16	760	950	1045	1235
PRODUCT17	480	600	660	780
PRODUCT18	148	185	203.50	240.50
PRODUCT19	480	600	660	780
PRODUCT20	720	900	990	1170
PRODUCT21	320	400	440	520
PRODUCT22	192	240	264	312
PRODUCT23	320	400	440	520
PRODUCT24	720	900	990	1170
PRODUCT25	360	450	495	585
PACK1	1520	1900	2090	2470
PRODUCT26	576	720	792	936
PRODUCT27	120	150	165	195
PRODUCT28	240	300	330	390
PACK2	800	1000	1100	1300
PRODUCT29	320	400	440	520
PRODUCT30	400	500	550	650
PACK3	728	910	1001	1183
PRODUCT31	360	450	495	585
PACK4	800	1000	1100	1300
PRODUCT32	400	500	550	650
BASE	30000	35000	40000	45000

Table 35: Prices for every item for the menu vs. à-la-carte design

Item	Price1	Price2	Price3	Price4	Total	Price1	Price2	Price3	Price4
PRODUCT1	345	418	368	341	1472	0.234	0.284	0.250	0.232
PRODUCT2	200	177	164	174	715	0.280	0.248	0.229	0.243
PRODUCT3	131	110	110	98	449	0.292	0.245	0.245	0.218
PRODUCT4	85	95	96	82	358	0.237	0.265	0.268	0.229
PRODUCT5	205	203	216	207	831	0.247	0.244	0.260	0.249
PRODUCT6	303	229	247	292	1071	0.283	0.214	0.231	0.273
PRODUCT7	214	270	212	218	914	0.234	0.295	0.232	0.239
PRODUCT8	142	148	164	153	607	0.234	0.244	0.270	0.252
PRODUCT9	91	144	103	96	434	0.210	0.332	0.237	0.221
PRODUCT10	233	252	215	220	920	0.253	0.274	0.234	0.239
PRODUCT11	145	163	154	150	612	0.237	0.266	0.252	0.245
PRODUCT12	161	159	149	130	599	0.269	0.265	0.249	0.217
PRODUCT13	128	145	124	131	528	0.242	0.275	0.235	0.248
PRODUCT14	47	61	47	64	219	0.215	0.279	0.215	0.292
PRODUCT15	113	126	103	104	446	0.253	0.283	0.231	0.233
PRODUCT16	41	51	58	40	190	0.216	0.268	0.305	0.211
PRODUCT17	72	67	76	47	262	0.275	0.256	0.290	0.179
PRODUCT18	95	129	86	79	389	0.244	0.332	0.221	0.203
PRODUCT19	111	114	127	113	465	0.239	0.245	0.273	0.243
PRODUCT20	91	115	112	92	410	0.222	0.280	0.273	0.224
PRODUCT21	88	112	78	79	357	0.246	0.314	0.218	0.221
PRODUCT22	98	111	103	99	411	0.238	0.270	0.251	0.241
PRODUCT23	89	111	89	94	383	0.232	0.290	0.232	0.245
PRODUCT24	63	73	57	52	245	0.257	0.298	0.233	0.212
PRODUCT25	140	140	153	146	579	0.242	0.242	0.264	0.252
PACK1	283	221	228	214	946	0.299	0.234	0.241	0.226
PRODUCT26	183	190	154	173	700	0.261	0.271	0.220	0.247
PRODUCT27	147	165	117	158	587	0.250	0.281	0.199	0.269
PRODUCT28	42	44	44	52	182	0.231	0.242	0.242	0.286
PACK2	208	200	204	200	812	0.256	0.246	0.251	0.246
PRODUCT29	119	111	120	97	447	0.266	0.248	0.268	0.217
PRODUCT30	64	69	65	66	264	0.242	0.261	0.246	0.250
PACK3	191	197	208	201	797	0.240	0.247	0.261	0.252
PRODUCT31	123	136	114	119	492	0.250	0.276	0.232	0.242
PACK4	208	181	167	179	735	0.283	0.246	0.227	0.244
PRODUCT32	149	177	154	143	623	0.239	0.284	0.247	0.230

Table 36: Frequency and relative frequency per price for every item for the menu vs. à-la-carte design

Item	Number of variables
PRODUCT1	43
PRODUCT2	9
PRODUCT3	10
PRODUCT4	2
PRODUCT5	6
PRODUCT6	2
PRODUCT7	4
PRODUCT8	9
PRODUCT9	41
PRODUCT10	23
PRODUCT11	5
PRODUCT12	13
PRODUCT13	28
PRODUCT14	9
PRODUCT15	6
PRODUCT16	4
PRODUCT17	9
PRODUCT18	43
PRODUCT19	2
PRODUCT20	2
PRODUCT21	14
PRODUCT22	22
PRODUCT23	25
PRODUCT24	9
PRODUCT25	4
PACK1	10
PRODUCT26	4
PRODUCT27	4
PRODUCT28	5
PACK2	6
PRODUCT29	10
PRODUCT30	7
PACK3	4
PRODUCT31	29
PACK4	10
PRODUCT32	43

Table 37: Number of variables in SCE models for menu vs. à-la-carte design

Item 1	Item 2	Item 3	Item 4
PRODUCT1	PRODUCT6	PRODUCT27	
PRODUCT1			
PRODUCT5			
PACK1			
PRODUCT25			
PRODUCT1	PRODUCT5	PACK1	
PACK4			
PRODUCT2			
PRODUCT6	PRODUCT26		
PRODUCT7			
PRODUCT6			
PRODUCT6	PRODUCT27		
PRODUCT26			
PACK2			
PRODUCT1	PRODUCT5	PRODUCT25	
PRODUCT31			
PACK3			
PRODUCT27			
PRODUCT2	PRODUCT6	PRODUCT26	
PRODUCT7	PRODUCT27		
PRODUCT29			
PRODUCT17			
PRODUCT8			
PRODUCT32			
PRODUCT8	PRODUCT28		
PACK1	PACK2	PACK3	PACK4
PACK1	PACK2		
PRODUCT1	PRODUCT7		
PRODUCT7	PRODUCT28		
PRODUCT1	PRODUCT32		
PRODUCT20			
PRODUCT1	PRODUCT5	PRODUCT26	
PRODUCT1	PRODUCT6	PRODUCT27	
PRODUCT19			
PRODUCT23	PRODUCT29	PRODUCT31	PRODUCT32
PACK1	PACK2	PACK3	
PRODUCT18			
PRODUCT2	PRODUCT26	PRODUCT27	
PRODUCT1	PACK2		

Table 38: Choice set for the naive EA models in the menu vs. à-la-carte design

	PR1	PR2	PR3	PR4	PR5	PR6	PR7	PR8	PR9	PR10	PR11	PR12	PR13	PR14	PR15	PR16	PR17	PR18
PR1	1																	
PR2	-0.67	1																
PR3	0.02	0.46	1															
PR4	0.00	0.51	0.57	1														
PR5	0.33	0.31	0.23	0.35	1													
PR6	0.30	0.36	0.19	0.28	0.23	1												
PR7	0.17	0.17	0.31	0.32	0.22	0.19	1											
PR8	-0.03	0.41	0.34	0.37	0.35	0.24	0.36	1										
PR9	0.22	0.22	0.30	0.35	0.35	0.35	0.56	0.47	1									
PR10	0.27	0.32	0.34	0.39	0.33	0.28	0.42	0.43	0.50	1								
PR11	0.16	0.34	0.46	0.36	0.17	0.23	0.43	0.33	0.39	0.55	1							
PR12	0.14	0.36	0.43	0.52	0.36	0.30	0.38	0.45	0.43	0.62	0.56	1						
PR13	0.02	0.42	0.45	0.55	0.24	0.18	0.33	0.46	0.27	0.55	0.56	0.59	1					
PR14	-0.06	0.53	0.41	0.56	0.33	0.21	0.26	0.47	0.29	0.54	0.50	0.64	0.98	1				
PR15	-0.03	0.51	0.45	0.56	0.39	0.30	0.19	0.44	0.27	0.34	0.40	0.45	0.43	0.48	1			
PR16	0.00	0.45	0.45	0.55	0.33	0.28	0.22	0.36	0.25	0.56	0.45	0.52	0.55	0.59	0.49	1		
PR17	-0.12	0.24	0.33	0.43	0.30	0.16	0.16	0.27	0.23	0.33	0.22	0.39	0.36	0.45	0.43	0.40	1	
PR18	-0.02	0.27	0.37	0.45	0.22	0.11	0.41	0.38	0.38	0.37	0.38	0.43	0.43	0.41	0.36	0.37	0.37	1

Table 39: Correlation matrix for menu vs. à-la-carte design part 1

	PR1	PR2	PR3	PR4	PR5	PR6	PR7	PR8	PR9	PR10	PR11	PR12	PR13	PR14	PR15	PR16	PR17	PR18
PR19	0.01	0.38	0.24	0.38	0.27	0.20	0.26	0.30	0.38	0.47	0.35	0.36	0.35	0.39	0.32	0.35	0.20	0.16
PR20	-0.04	0.39	0.47	0.43	0.34	0.23	0.35	0.41	0.29	0.36	0.35	0.50	0.51	0.48	0.40	0.47	0.43	0.31
PR21	0.00	0.31	0.43	0.42	0.23	0.23	0.40	0.30	0.37	0.39	0.40	0.48	0.60	0.55	0.28	0.45	0.41	0.43
PR22	-0.02	0.28	0.28	0.40	0.29	0.16	0.28	0.25	0.30	0.30	0.32	0.41	0.47	0.46	0.29	0.44	0.41	0.45
PR23	0.06	0.34	0.30	0.40	0.31	0.19	0.29	0.43	0.42	0.46	0.26	0.51	0.47	0.57	0.36	0.47	0.42	0.39
PR24	0.24	0.16	0.24	0.10	0.30	0.17	0.24	0.02	0.16	0.32	0.20	0.32	0.10	0.04	0.08	0.28	0.07	0.14
PR25	0.08	0.28	0.14	0.26	0.28	0.07	0.09	0.07	0.07	0.24	0.13	0.28	0.17	0.10	0.19	0.11	0.08	0.09
P1	0.10	0.37	0.38	0.36	0.43	0.12	0.15	0.29	0.12	0.30	0.38	0.36	0.46	0.50	0.38	0.41	0.30	0.31
PR26	0.31	0.14	0.06	0.08	0.09	0.60	0.01	-0.04	0.07	0.07	0.00	0.15	-0.02	-0.05	0.05	-0.03	0.15	0.01
PR27	-0.09	0.14	0.16	0.23	-0.01	0.27	0.19	0.13	0.14	0.14	0.11	0.21	0.15	0.10	0.25	-0.02	0.16	0.24
PR28	-0.20	0.12	0.15	0.11	-0.04	0.06	0.16	0.27	0.14	-0.01	0.05	0.25	0.08	0.12	0.12	-0.24	0.13	-0.06
P2	-0.02	0.37	0.42	0.46	0.28	0.14	0.16	0.36	0.20	0.35	0.42	0.43	0.45	0.52	0.44	0.42	0.32	0.31
PR29	-0.02	0.17	0.32	0.21	0.05	-0.02	0.18	0.21	0.24	0.19	0.26	0.18	0.23	0.18	0.13	0.15	0.12	0.28
PR30	0.04	0.18	0.20	0.26	0.22	0.10	0.16	0.25	0.23	0.22	0.20	0.34	0.31	0.24	0.17	0.19	0.19	0.13
P3	0.02	0.34	0.40	0.39	0.25	0.20	0.27	0.29	0.29	0.45	0.50	0.48	0.52	0.50	0.45	0.39	0.33	0.35
PR31	0.13	0.07	0.21	0.17	0.10	0.07	0.30	0.17	0.20	0.37	0.35	0.24	0.17	0.18	0.11	0.33	0.05	0.20
P4	0.02	0.33	0.30	0.37	0.09	0.12	0.22	0.28	0.31	0.40	0.40	0.46	0.45	0.53	0.29	0.40	0.22	0.26
PR32	0.21	0.25	0.26	0.35	0.21	0.14	0.30	0.32	0.47	0.51	0.30	0.43	0.45	0.45	0.24	0.57	0.26	0.33

Table 40: Correlation matrix for menu vs. à-la-carte design part 2

	PR19	PR20	PR21	PR22	PR23	PR24	PR25	P1	PR26	PR27	PR28	P2	PR29	PR30	P3	PR31	P4	PR32
PR19	1																	
PR20	-0.90	1																
PR21	0.34	0.40	1															
PR22	0.30	0.39	0.49	1														
PR23	0.44	0.38	0.43	0.36	1													
PR24	0.06	0.28	0.12	0.13	0.06	1												
PR25	0.16	0.29	0.09	0.27	0.12	0.47	1											
P1	0.19	0.35	0.24	0.31	0.27	-0.44	-0.55	1										
PR26	0.00	-0.06	0.02	-0.02	0.14	0.18	0.01	-0.19	1									
PR27	0.29	0.10	0.14	-0.01	0.17	0.10	0.16	0.02	0.17	1								
PR28	0.13	0.10	0.04	0.00	-0.07	0.13	0.11	-0.11	0.09	0.24	1							
P2	0.27	0.34	0.19	0.28	0.32	0.09	0.05	0.69	-0.67	-0.60	-0.39	1						
PR29	0.22	0.24	0.26	0.25	0.26	0.36	0.17	-0.03	-0.03	0.06	0.13	0.04	1					
PR30	0.22	0.21	0.22	0.24	0.30	0.33	0.36	0.01	0.09	0.22	0.13	0.15	0.43	1				
P3	0.35	0.33	0.30	0.38	0.37	0.02	0.13	0.63	-0.03	0.06	-0.05	0.64	-0.60	-0.47	1			
PR31	0.22	0.07	0.19	0.18	0.32	0.36	0.22	0.04	-0.03	0.01	0.07	0.07	0.57	0.29	0.09	1		
P4	0.23	0.34	0.37	0.24	0.35	0.10	0.08	0.48	-0.08	0.02	-0.19	0.54	-0.07	0.06	0.65	-0.92	1	
PR32	0.42	0.26	0.54	0.42	0.62	0.10	0.08	0.15	-0.06	0.00	-0.18	0.18	0.21	0.25	0.30	0.41	0.40	1

Table 41: Correlation matrix for menu vs. à-la-carte design part 3

Item	SCE	SCE HB	naive EA	naive EA HB	EA SIS	EA SIS HB	MVC	avg y
PRODUCT1	0.42110	0.47470	0.42332	0.41416	0.41583	0.45349	0.42242	0.44910
PRODUCT2	0.31624	0.33366	0.32575	0.31337	0.31532	0.34665	0.31746	0.32327
PRODUCT3	0.25802	0.26720	0.26699	0.26247	0.25821	0.29534	0.25866	0.26410
PRODUCT4	0.23277	0.23809	0.23870	0.23351	0.23237	0.26385	0.23300	0.23973
PRODUCT5	0.33544	0.35099	0.33971	0.32983	0.33286	0.36161	0.33587	0.34036
PRODUCT6	0.37466	0.39459	0.37447	0.36471	0.36963	0.40321	0.37490	0.38543
PRODUCT7	0.35342	0.36965	0.36826	0.34951	0.35069	0.39012	0.35336	0.35986
PRODUCT8	0.29394	0.30283	0.30454	0.29136	0.29388	0.32532	0.29457	0.29806
PRODUCT9	0.25089	0.26115	0.25897	0.25416	0.25004	0.27543	0.25160	0.25682
PRODUCT10	0.35071	0.37815	0.37723	0.37070	0.34991	0.39577	0.35128	0.35876
PRODUCT11	0.29819	0.31364	0.31246	0.30663	0.29693	0.33563	0.29832	0.30266
PRODUCT12	0.29334	0.30692	0.30723	0.30143	0.29407	0.33173	0.29382	0.29666
PRODUCT13	0.27752	0.29071	0.28915	0.28305	0.27758	0.31269	0.27819	0.28160
PRODUCT14	0.18632	0.18977	0.18946	0.18544	0.18656	0.20551	0.18694	0.19832
PRODUCT15	0.25499	0.26201	0.26329	0.25861	0.25383	0.28862	0.25523	0.25795
PRODUCT16	0.17418	0.17695	0.17646	0.17265	0.17445	0.19139	0.17448	0.18960
PRODUCT17	0.19591	0.19890	0.19848	0.19235	0.19568	0.22696	0.19647	0.20782
PRODUCT18	0.24234	0.25219	0.25035	0.24141	0.24229	0.27245	0.24359	0.24899
PRODUCT19	0.26449	0.27098	0.27353	0.26301	0.26281	0.29802	0.26459	0.26876
PRODUCT20	0.24597	0.25162	0.25273	0.24346	0.24555	0.27608	0.24611	0.25183
PRODUCT21	0.23326	0.24081	0.23951	0.23412	0.23276	0.26065	0.23406	0.24048
PRODUCT22	0.24541	0.25384	0.25245	0.24649	0.24433	0.27452	0.24576	0.25174
PRODUCT23	0.23843	0.24666	0.24040	0.23593	0.23815	0.26929	0.23891	0.24515
PRODUCT24	0.19382	0.19760	0.19620	0.19384	0.19331	0.21388	0.19412	0.20533
PRODUCT25	0.29527	0.30394	0.29923	0.29377	0.29528	0.32463	0.29558	0.29787
PACK1	0.35581	0.38132	0.36361	0.35137	0.35312	0.38397	0.35640	0.36400
PRODUCT26	0.31703	0.32868	0.31618	0.30993	0.30981	0.33316	0.31749	0.32248
PRODUCT27	0.29065	0.29748	0.29284	0.28806	0.28826	0.32053	0.29093	0.29398
PRODUCT28	0.16701	0.16862	0.16682	0.16631	0.16576	0.18405	0.16750	0.18411
PACK2	0.33191	0.35205	0.34596	0.32805	0.32958	0.36315	0.33238	0.33832
PRODUCT29	0.25902	0.26757	0.26558	0.25462	0.25827	0.29353	0.25965	0.26359
PRODUCT30	0.20352	0.20738	0.20709	0.20342	0.20240	0.22831	0.20442	0.21346
PACK3	0.33272	0.35089	0.34722	0.33090	0.32977	0.36815	0.33300	0.33771
PRODUCT31	0.26649	0.27851	0.27265	0.26307	0.26545	0.29810	0.26743	0.27144
PACK4	0.32040	0.33997	0.33034	0.32205	0.32009	0.35156	0.32086	0.32722
PRODUCT32	0.29773	0.31622	0.30947	0.29349	0.29795	0.32786	0.29889	0.30201
Mean	0.27691	0.28934	0.28435	0.27631	0.27563	0.30681	0.27745	0.28440

Table 42: RMSE of menu vs. à-la-carte design training data

Item	SCE	RE SCE	naive EA	naive RE EA	EA SIS	RE EA SIS	MVC	avg y
PRODUCT1	0.42865	0.48349	0.43050	0.42112	0.41927	0.41565	0.42852	0.45495
PRODUCT2	0.32324	0.33833	0.33005	0.31663	0.32012	0.34186	0.32168	0.32491
PRODUCT3	0.25718	0.26409	0.26314	0.25825	0.25631	0.28114	0.25584	0.26083
PRODUCT4	0.23067	0.23487	0.23556	0.23023	0.22961	0.25656	0.23003	0.23694
PRODUCT5	0.35470	0.37216	0.35926	0.34964	0.34978	0.35639	0.35357	0.36161
PRODUCT6	0.38437	0.40704	0.38461	0.38053	0.37839	0.39616	0.38490	0.39631
PRODUCT7	0.35152	0.36653	0.36485	0.34820	0.34993	0.36847	0.35081	0.35878
PRODUCT8	0.30202	0.31176	0.31367	0.30143	0.30099	0.31542	0.30210	0.30786
PRODUCT9	0.26315	0.27276	0.27058	0.26507	0.25981	0.27484	0.26210	0.26604
PRODUCT10	0.36397	0.39357	0.39224	0.38639	0.36269	0.38791	0.36409	0.37112
PRODUCT11	0.29067	0.30495	0.30361	0.29836	0.29001	0.32357	0.29135	0.29558
PRODUCT12	0.29562	0.30886	0.30963	0.30289	0.29702	0.33679	0.29589	0.29893
PRODUCT13	0.27853	0.28968	0.28868	0.28246	0.27961	0.30636	0.27722	0.28356
PRODUCT14	0.17224	0.17399	0.17368	0.16925	0.17348	0.20019	0.17236	0.18844
PRODUCT15	0.26674	0.27299	0.27378	0.26854	0.26203	0.28628	0.26579	0.26848
PRODUCT16	0.16068	0.16228	0.16176	0.15858	0.16095	0.17273	0.16107	0.17746
PRODUCT17	0.21700	0.21948	0.21882	0.21217	0.21591	0.22524	0.21552	0.22487
PRODUCT18	0.23247	0.23833	0.23673	0.22788	0.23020	0.25519	0.23166	0.24072
PRODUCT19	0.25375	0.25839	0.26033	0.25099	0.25278	0.28745	0.25368	0.25878
PRODUCT20	0.25346	0.25936	0.26039	0.25066	0.25193	0.28201	0.25315	0.26000
PRODUCT21	0.22413	0.22943	0.22792	0.22386	0.22278	0.25247	0.22357	0.23134
PRODUCT22	0.25659	0.26501	0.26395	0.25727	0.25532	0.26222	0.25617	0.26198
PRODUCT23	0.24129	0.24948	0.24340	0.23856	0.23996	0.26675	0.24138	0.24850
PRODUCT24	0.19429	0.19765	0.19661	0.19324	0.19335	0.21685	0.19454	0.20281
PRODUCT25	0.26671	0.26995	0.26578	0.26127	0.26404	0.29241	0.26581	0.26973
PACK1	0.36525	0.39051	0.37279	0.36117	0.36318	0.37413	0.36430	0.37240
PRODUCT26	0.30658	0.31590	0.30526	0.30370	0.29661	0.31388	0.30688	0.31182
PRODUCT27	0.29467	0.30179	0.29727	0.29050	0.29107	0.31549	0.29502	0.29938
PRODUCT28	0.17195	0.17344	0.17159	0.17144	0.16936	0.17816	0.17190	0.18776
PACK2	0.35198	0.37462	0.36807	0.34968	0.34974	0.36055	0.35133	0.35884
PRODUCT29	0.25079	0.25582	0.25349	0.24423	0.24570	0.27763	0.24899	0.25491
PRODUCT30	0.18959	0.19080	0.19054	0.18648	0.18876	0.21438	0.18889	0.20188
PACK3	0.33436	0.35192	0.34818	0.33266	0.33249	0.36692	0.33426	0.33849
PRODUCT31	0.27731	0.28840	0.28250	0.27135	0.27551	0.28586	0.27594	0.28034
PACK4	0.32453	0.34171	0.33198	0.32600	0.32306	0.34893	0.32380	0.32834
PRODUCT32	0.29809	0.31368	0.30724	0.29272	0.29609	0.31728	0.29674	0.30044
Mean	0.27858	0.29008	0.28496	0.27732	0.27633	0.29761	0.27808	0.28570

Table 43: RMSE of menu vs. à-la-carte design test data

Item	SCE	RE SCE	naive EA	naive RE EA	EA SIS	RE EA SIS	MVC	avg y
PRODUCT1	0.58338	0.36797	0.58029	0.58870	0.59039	0.51508	0.58166	0.51467
PRODUCT2	0.70450	0.58937	0.66874	0.71019	0.70637	0.65888	0.70188	0.68436
PRODUCT3	0.77405	0.68017	0.61016	0.75158	0.77328	0.71911	0.77208	0.75974
PRODUCT4	0.80303	0.75383	0.65627	0.79901	0.80341	0.76244	0.80224	0.78946
PRODUCT5	0.68104	0.61305	0.66969	0.69200	0.68588	0.63498	0.68019	0.66461
PRODUCT6	0.63514	0.57070	0.63537	0.65086	0.64412	0.57608	0.63470	0.60335
PRODUCT7	0.65985	0.60004	0.60642	0.66418	0.66494	0.59795	0.65993	0.63973
PRODUCT8	0.73049	0.68503	0.66899	0.73685	0.73136	0.67864	0.72895	0.71876
PRODUCT9	0.78302	0.29006	0.62645	0.77094	0.78642	0.74028	0.78111	0.76943
PRODUCT10	0.66354	0.46841	0.38856	0.57138	0.66490	0.59003	0.66245	0.63926
PRODUCT11	0.72520	0.56146	0.51724	0.68183	0.72796	0.66290	0.72483	0.71275
PRODUCT12	0.73129	0.61675	0.51451	0.69217	0.73023	0.67513	0.73012	0.72175
PRODUCT13	0.75044	0.51930	0.54854	0.71983	0.74955	0.69296	0.74867	0.74006
PRODUCT14	0.85811	0.79749	0.75425	0.86875	0.85597	0.83157	0.85540	0.83422
PRODUCT15	0.77700	0.72378	0.61404	0.75732	0.77943	0.72882	0.77631	0.77142
PRODUCT16	0.87081	0.81096	0.78672	0.88407	0.86888	0.84540	0.86936	0.84112
PRODUCT17	0.84687	0.81840	0.82251	0.85988	0.84697	0.80071	0.84469	0.82305
PRODUCT18	0.79426	0.41443	0.71701	0.80121	0.79316	0.74750	0.79059	0.77918
PRODUCT19	0.76515	0.72385	0.67550	0.77141	0.76883	0.71718	0.76485	0.75627
PRODUCT20	0.78734	0.74424	0.71781	0.79469	0.78810	0.74625	0.78692	0.77513
PRODUCT21	0.80376	0.68312	0.66435	0.80340	0.80644	0.76058	0.80116	0.78866
PRODUCT22	0.78830	0.64447	0.64497	0.78425	0.79268	0.74339	0.78723	0.77428
PRODUCT23	0.79802	0.65248	0.76255	0.81033	0.79705	0.75048	0.79615	0.78317
PRODUCT24	0.84869	0.78053	0.79149	0.85074	0.85117	0.81559	0.84741	0.82648
PRODUCT25	0.72860	0.68585	0.71362	0.73037	0.72863	0.67558	0.72787	0.72091
PACK1	0.65765	0.52615	0.63718	0.66096	0.66206	0.61185	0.65643	0.63373
PRODUCT26	0.70275	0.64887	0.70430	0.71679	0.71939	0.66219	0.70177	0.68618
PRODUCT27	0.73399	0.70259	0.72618	0.73743	0.74026	0.68514	0.73336	0.72568
PRODUCT28	0.87866	0.85780	0.87974	0.88190	0.88588	0.85987	0.87654	0.84594
PACK2	0.68515	0.55619	0.62502	0.68930	0.69040	0.63636	0.68424	0.66584
PRODUCT29	0.77311	0.69877	0.73035	0.78276	0.77564	0.72366	0.77093	0.76242
PRODUCT30	0.83863	0.79886	0.76741	0.84198	0.84470	0.80962	0.83516	0.81819
PACK3	0.68433	0.58880	0.62005	0.68387	0.69012	0.62970	0.68374	0.66900
PRODUCT31	0.76414	0.49711	0.73053	0.77314	0.76679	0.71066	0.76150	0.75199
PACK4	0.69987	0.55521	0.66123	0.69320	0.70071	0.64736	0.69878	0.68000
PRODUCT32	0.72793	0.27090	0.66907	0.73972	0.72760	0.67155	0.72519	0.71559
Mean	0.75106	0.62492	0.66964	0.74853	0.75388	0.70321	0.74957	0.73296

Table 44: RLH of menu vs. à-la-carte design training data

Item	SCE	RE SCE	naive EA	naive RE EA	EA SIS	RE EA SIS	MVC	avg y
PRODUCT1	0.57421	0.35497	0.57160	0.57969	0.58892	0.58817	0.57462	0.50905
PRODUCT2	0.69266	0.57600	0.66148	0.70172	0.70067	0.67855	0.69615	0.68499
PRODUCT3	0.77026	0.67577	0.62405	0.76536	0.77476	0.75172	0.77510	0.76387
PRODUCT4	0.80349	0.75733	0.65825	0.80199	0.80754	0.77760	0.80554	0.79264
PRODUCT5	0.65611	0.57500	0.64257	0.65928	0.66661	0.66015	0.65851	0.63321
PRODUCT6	0.62383	0.55127	0.62322	0.61919	0.63420	0.61267	0.62287	0.59006
PRODUCT7	0.66141	0.60321	0.61196	0.66412	0.66356	0.64895	0.66274	0.63869
PRODUCT8	0.72012	0.66874	0.64923	0.71105	0.72150	0.70625	0.71995	0.70505
PRODUCT9	0.76417	0.24891	0.61232	0.74623	0.77132	0.76253	0.76841	0.76079
PRODUCT10	0.64676	0.43743	0.34766	0.53126	0.64774	0.62183	0.64668	0.62374
PRODUCT11	0.73403	0.57921	0.52619	0.68784	0.73630	0.69954	0.73276	0.72034
PRODUCT12	0.72716	0.61071	0.50082	0.68326	0.72308	0.68016	0.72716	0.71852
PRODUCT13	0.74606	0.51774	0.51883	0.71829	0.74488	0.71800	0.75000	0.73533
PRODUCT14	0.87067	0.81962	0.77634	0.89010	0.86436	0.84841	0.87029	0.84207
PRODUCT15	0.75865	0.69827	0.60113	0.73144	0.77302	0.73919	0.76181	0.75831
PRODUCT16	0.88332	0.83585	0.81151	0.89515	0.88658	0.87508	0.88224	0.85449
PRODUCT17	0.81548	0.77770	0.78757	0.82718	0.81702	0.81243	0.82274	0.80586
PRODUCT18	0.80025	0.45456	0.73989	0.81403	0.81076	0.78043	0.80360	0.78705
PRODUCT19	0.77674	0.74275	0.70311	0.78054	0.77984	0.74029	0.77703	0.76757
PRODUCT20	0.77737	0.72945	0.70534	0.78324	0.78054	0.74646	0.77826	0.76430
PRODUCT21	0.81175	0.70252	0.68470	0.80870	0.81656	0.78601	0.81348	0.79878
PRODUCT22	0.77268	0.61697	0.59839	0.75733	0.77628	0.77141	0.77415	0.76139
PRODUCT23	0.79409	0.64579	0.75581	0.80081	0.79523	0.77153	0.79337	0.77970
PRODUCT24	0.84573	0.77544	0.77455	0.85358	0.84999	0.82854	0.84579	0.83100
PRODUCT25	0.76044	0.73682	0.76028	0.76540	0.76743	0.73461	0.76226	0.75419
PACK1	0.64463	0.50306	0.62229	0.64135	0.64716	0.63605	0.64629	0.61964
PRODUCT26	0.71452	0.66725	0.71705	0.71925	0.73718	0.70675	0.71370	0.69815
PRODUCT27	0.72872	0.69477	0.71875	0.73115	0.73891	0.70375	0.72781	0.71763
PRODUCT28	0.87138	0.84542	0.87207	0.87862	0.88682	0.87602	0.87181	0.84284
PACK2	0.65951	0.51171	0.58832	0.65268	0.66257	0.65285	0.66092	0.63546
PRODUCT29	0.77861	0.71354	0.75093	0.79569	0.79256	0.75376	0.78337	0.77153
PRODUCT30	0.85007	0.82043	0.78569	0.86455	0.85302	0.83122	0.85194	0.82934
PACK3	0.68154	0.58506	0.61786	0.67440	0.68564	0.64486	0.68171	0.66814
PRODUCT31	0.74716	0.46239	0.71402	0.76616	0.75282	0.74125	0.75160	0.74131
PACK4	0.69194	0.54385	0.65659	0.67156	0.69677	0.66862	0.69361	0.67942
PRODUCT32	0.72419	0.27371	0.67142	0.73065	0.73013	0.70747	0.72759	0.71915
Mean	0.74666	0.61981	0.66561	0.74175	0.75229	0.72953	0.74822	0.73066

Table 45: RLH of menu vs. à-la-carte design test data

Item	SCE	RE SCE	naive EA	naive RE EA	EA SIS	RE EA SIS	MVC	avg y
PRODUCT1	0.23382	0.01800	0.17871	0.18445	0.23380	0.21332	0.22536	0.23380
PRODUCT2	0.11380	0.01050	0.03693	0.07139	0.11380	0.15179	0.11387	0.11380
PRODUCT3	0.07220	0.00503	0.00046	0.00168	0.07220	0.11890	0.07703	0.07220
PRODUCT4	0.05760	0.00833	0.00032	0.00159	0.05760	0.09729	0.06416	0.05760
PRODUCT5	0.12980	0.02800	0.07153	0.08710	0.12980	0.14116	0.12817	0.12980
PRODUCT6	0.16920	0.04540	0.13916	0.16365	0.16920	0.15873	0.16400	0.16920
PRODUCT7	0.14680	0.03910	0.04089	0.08890	0.14680	0.18962	0.14365	0.14680
PRODUCT8	0.09600	0.02420	0.01586	0.04858	0.09600	0.13646	0.09805	0.09600
PRODUCT9	0.06820	0.00000	0.00058	0.00186	0.06820	0.09687	0.07355	0.06820
PRODUCT10	0.14480	0.00584	0.00128	0.00377	0.14480	0.21374	0.14180	0.14480
PRODUCT11	0.09900	0.00306	0.00070	0.00254	0.09900	0.14806	0.10077	0.09900
PRODUCT12	0.09560	0.00701	0.00062	0.00242	0.09560	0.15041	0.09768	0.09560
PRODUCT13	0.08460	0.00050	0.00051	0.00231	0.08460	0.13334	0.08788	0.08460
PRODUCT14	0.03620	0.00218	0.00015	0.00092	0.03620	0.05198	0.04482	0.03620
PRODUCT15	0.07020	0.01140	0.00045	0.00169	0.07020	0.11599	0.07531	0.07020
PRODUCT16	0.03140	0.00128	0.00013	0.00081	0.03140	0.04684	0.04042	0.03140
PRODUCT17	0.04020	0.00803	0.00811	0.02200	0.04020	0.07041	0.04853	0.04020
PRODUCT18	0.06360	0.00001	0.00525	0.02345	0.06360	0.10088	0.06945	0.06360
PRODUCT19	0.07580	0.01740	0.00522	0.02265	0.07580	0.12492	0.08031	0.07580
PRODUCT20	0.06480	0.01230	0.00567	0.02470	0.06480	0.10521	0.07054	0.06480
PRODUCT21	0.05820	0.00150	0.00042	0.00176	0.05820	0.08793	0.06465	0.05820
PRODUCT22	0.06460	0.00128	0.00044	0.00200	0.06460	0.09827	0.07032	0.06460
PRODUCT23	0.06100	0.00109	0.00654	0.02633	0.06100	0.09526	0.06712	0.06100
PRODUCT24	0.03920	0.00189	0.00036	0.00082	0.03920	0.06108	0.04758	0.03920
PRODUCT25	0.09680	0.02560	0.03993	0.04488	0.09680	0.12672	0.09859	0.09680
PACK1	0.15000	0.01520	0.06995	0.10957	0.15000	0.18005	0.14669	0.15000
PRODUCT26	0.11380	0.02760	0.11713	0.11364	0.11380	0.09861	0.11376	0.11380
PRODUCT27	0.09340	0.03060	0.05117	0.11907	0.09340	0.11937	0.09569	0.09340
PRODUCT28	0.02880	0.00634	0.01409	0.04820	0.02880	0.03741	0.03798	0.02880
PACK2	0.12660	0.01050	0.03274	0.08927	0.12660	0.16994	0.12544	0.12660
PRODUCT29	0.07280	0.00813	0.01468	0.05040	0.07280	0.11693	0.07761	0.07280
PRODUCT30	0.04360	0.00636	0.00036	0.00115	0.04360	0.07221	0.05169	0.04360
PACK3	0.12740	0.01740	0.02507	0.06715	0.12740	0.18075	0.12602	0.12740
PRODUCT31	0.07760	0.00018	0.01950	0.04753	0.07760	0.10502	0.08187	0.07760
PACK4	0.11740	0.00706	0.03193	0.04465	0.11740	0.15439	0.11728	0.11740
PRODUCT32	0.10000	0.00001	0.01918	0.07267	0.10000	0.13242	0.10171	0.10000
Mean	0.09069	0.01134	0.02656	0.04432	0.09069	0.12229	0.09359	0.09069

Table 46: Average probabilities of menu vs. à-la-carte design train data

Item	SCE	RE SCE	naive EA	naive RE EA	EA SIS	RE EA SIS	MVC	avg y
PRODUCT1	0.23253	0.01790	0.17916	0.18597	0.23499	0.25567	0.22497	0.24240
PRODUCT2	0.11378	0.01060	0.03702	0.07067	0.11344	0.19756	0.11379	0.11680
PRODUCT3	0.07137	0.00493	0.00059	0.00189	0.07197	0.15912	0.07690	0.07040
PRODUCT4	0.05753	0.00835	0.00026	0.00154	0.05719	0.13504	0.06435	0.05600
PRODUCT5	0.12940	0.02780	0.07150	0.08601	0.13036	0.19474	0.12815	0.14560
PRODUCT6	0.16843	0.04500	0.13976	0.15754	0.17162	0.22865	0.16393	0.18000
PRODUCT7	0.14637	0.03890	0.04067	0.08868	0.15075	0.25568	0.14351	0.14400
PRODUCT8	0.09527	0.02390	0.01568	0.04796	0.09544	0.18017	0.09830	0.10160
PRODUCT9	0.06802	0.00000	0.00060	0.00213	0.06753	0.14229	0.07368	0.07440
PRODUCT10	0.14446	0.00595	0.00153	0.00385	0.14433	0.28913	0.14179	0.15680
PRODUCT11	0.09877	0.00304	0.00072	0.00233	0.09588	0.20716	0.10053	0.09360
PRODUCT12	0.09587	0.00713	0.00047	0.00259	0.09471	0.22651	0.09779	0.09680
PRODUCT13	0.08519	0.00050	0.00033	0.00215	0.08671	0.18899	0.08826	0.08400
PRODUCT14	0.03622	0.00217	0.00012	0.00090	0.03645	0.08484	0.04493	0.03040
PRODUCT15	0.07085	0.01150	0.00053	0.00199	0.07127	0.14592	0.07538	0.07600
PRODUCT16	0.03136	0.00128	0.00012	0.00064	0.03168	0.06673	0.04080	0.02640
PRODUCT17	0.03987	0.00801	0.00796	0.02172	0.04095	0.08764	0.04819	0.04880
PRODUCT18	0.06358	0.00001	0.00525	0.02342	0.06377	0.13857	0.06972	0.05680
PRODUCT19	0.07579	0.01740	0.00524	0.02197	0.07534	0.15886	0.08026	0.06880
PRODUCT20	0.06409	0.01220	0.00561	0.02405	0.06352	0.14566	0.07050	0.06880
PRODUCT21	0.05770	0.00148	0.00044	0.00137	0.05856	0.12437	0.06485	0.05280
PRODUCT22	0.06427	0.00129	0.00037	0.00217	0.06482	0.12616	0.07028	0.07040
PRODUCT23	0.06095	0.00108	0.00651	0.02536	0.06006	0.13143	0.06710	0.06240
PRODUCT24	0.03915	0.00189	0.00028	0.00095	0.03904	0.08166	0.04769	0.03920
PRODUCT25	0.09707	0.02570	0.03967	0.04343	0.09675	0.15457	0.09864	0.07600
PACK1	0.14904	0.01510	0.06934	0.10652	0.14831	0.23950	0.14586	0.15680
PRODUCT26	0.11346	0.02730	0.11729	0.10673	0.11465	0.13016	0.11399	0.10480
PRODUCT27	0.09329	0.03060	0.05124	0.11709	0.09257	0.15516	0.09555	0.09600
PRODUCT28	0.02860	0.00616	0.01397	0.04803	0.02891	0.04208	0.03807	0.03040
PACK2	0.12548	0.01040	0.03289	0.09399	0.12885	0.21439	0.12508	0.14320
PRODUCT29	0.07355	0.00810	0.01461	0.04840	0.07380	0.13922	0.07776	0.06640
PRODUCT30	0.04387	0.00644	0.00025	0.00104	0.04200	0.08670	0.05161	0.03680
PACK3	0.12602	0.01710	0.02524	0.06513	0.12679	0.23836	0.12584	0.12800
PRODUCT31	0.07829	0.00018	0.01934	0.04667	0.07512	0.13400	0.08168	0.08320
PACK4	0.11698	0.00715	0.03206	0.04369	0.11650	0.20433	0.11712	0.11840
PRODUCT32	0.09926	0.00001	0.01920	0.07108	0.09786	0.18724	0.10193	0.09840
Mean	0.09044	0.01129	0.02655	0.04360	0.09062	0.16328	0.09358	0.09171

Table 47: Average probabilities of menu vs. à-la-carte design test data