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Biclustering Swiss In-home Food Consumption Across Consumer Groups and Foods

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Abstract

This study is the first to apply biclustering to households' home consumption of food and finds patterns of households and foods that may account for factors of consumption in Switzerland. Leveraging biclustering theory and rich data from the Swiss Federal Statistical Office, we apply the FABIA algorithm to define and label five overlapping biclusters - basic, vegan processed, old & poor, vegan raw, and sweet-toothed - which are distinguished mainly by age and household size. Our results may help to target food and nutrition policy and marketing activities in the future by using clearer behavioural information about consumers. Vegan behaviour can also be stimulated using evidence that their nutrition and lifestyle are sustainable.

Categories: Consumer Behavior, Social systems (economies, governments, industry), Sustainable Marketing
Keywords: biclustering, consumer behavior, consumption, switzerland, food
JEL Classifications: Q11, Q13, Q18, D12

Introduction

Traditional clustering is used in market research to divide a market into smaller groups of buyers with distinct needs, characteristics, or behaviours who might require separate products or marketing mixes (Lamb et al., 2003) and (Kotler and Armstong, 2005). In travel marketing research, clustering techniques have been used in combination with factor analysis (Dolnicar, 2008) to enable studying the features of consumers. Although food consumption may be explained by the socioeconomic characteristics of the consumer (Aepli and Finger, 2013), (Sahakian et al., 2020), and (Götze and Brunner, 2021), the mere clustering of consumers in terms of their consumption patterns has limitations. For example, a certain group of consumers with a higher consumption of bread than average consumers may indicate only part of a more general pattern, such as a preference for vegan food or for low-priced items. Scholars in the mentioned fields have not yet adequately addressed this kind of pattern. Addressing this research gap is difficult because it does not require only consumers clustering or foods clustering, but rather clustering in both consumers and foods dimensions. Thus, for a systematic analysis of such general patterns in the consumption structure of socioeconomic groups, biclustering, which has mostly been used in genetical research to simultaneously cluster gene expressions and gene conditions (Madeira and Oliveira, 2004), is a yet untested but promising methodological option.

A research objective of ex-post food market segmentation across consumers with different socioeconomic characteristics is not new and has been previously performed using regression and cluster analysis (Schäufele-Elbers and Janssen, 2023) and (Gazdecki et al., 2021). However, none of the previous studies on the food sector have highlighted a research question on the potential of biclustering to switch the scope of the studies from single foods to food sets and from single consumers to consumer groups. Currently, biclustering has not been employed as a tool for studying food sets, consumers, or any other socioeconomic research aspects in Switzerland. This paper attempts to fill these gaps and identify the link between consumer groups and food sets in Switzerland, promoting an additional area where biclustering can be applied for advanced socioeconomic analysis of society. We use household data from Switzerland issued from the Swiss Federal Statistical Office and R-Package 'fabia' by Hochreiter et al. (Hochreiter et al., 2010) and (R-Package FABIA, 2020) for biclustering the log normalised food consumptions of the households, clustering both food items and households.

The novelty and a key challenge of our study is that it uses biclustering as a helpful method for ex-post socioeconomic analysis of foods, consumers, and the socioeconomic state of society in general. As a result of our research, we discover five overlapping biclusters - basic, vegan processed, old & poor, vegan raw and sweet-toothed - which are distinguished mainly by age and household size. The application of these results lies in the area of targeted food policies and food and health education and promotion, as well as in the specific food-related topics of psychology, behaviour, socioeconomics, and marketing. This research also contributes to debates on the use of biclustering for socioeconomic policy making. The key consumer and food groups will help to build more accurate and sane long-term policies and improve strategies that align with environmental objectives and foster socio-economic development at country and global levels.

Literature analysis

To check the novelty of our approach, two different literature analyses were carried out. First, we explored the available knowledge about consumer clusters in other countries of the Global North with respect to food consumption patterns. In this respect, existing review papers that collected the insights of several studies turned out to contribute most comprehending the state of the art. Verain et al. (Verain et al, 2012), for example, distinguished between clustering personality characteristics with respect to food consumption, food-related lifestyles and food choices. Ten years later, a review by Ballco and Gracia (Ballco and Gracia, 2022) re-emphasized the importance of consumer characteristics like nutritional knowledge and motivation having a strong impact on food choices. However, it seems that the potential of mere cluster analysis in identifying consumer groups has largely been exploited.

We then performed a more methodological step through a search in Scopus on January 30, 2024, with the only restriction on the term “biclustering” in titles, keywords and abstracts. We obtained only 1,634 works: 1,158 (71%) studies contained either the word “gene” or “DNA” in their abstract, which mainly signals the bioinformatical and statistical content of the papers; 733 (45%) studies were medical, computer, neuroscience conference papers; 11 (0.6%) studies contained the word “food”, but the usage of “food” was either in the names of organisations (e.g. “Food and Drug Administration” in (Chen et al., 2013) and (Harpaz et al., 2011), on the nutritional context (e.g. “food nutrition” in (Lee et al., 2010), in general terms (e.g. “food security” in (Bo et al., 2013)), in genetics and biology (Venkatasubramanian et al., 2017), (Zinati, 2017), and (García-Casarrubias et al., 2019), or related to birds (Liu and Chen, 2010), (Liu, Hu, et al., 2009), (Liu et al., 2011), and (Liu et al., 2012). Thus, the food market is scarcely represented in these studies.

Only a few investigations in fields beyond bioinformatics and web-scrapping after 2009 can be found in previous literature. As biclustering allows for remixing the rows and columns, it neglects the important features of the time series. However, there are studies that apply biclustering to time scales. (Huang and Lu, 2009), for example, explored currencies and exchange rates over time. A similar work was done with bank non-performing loans (Liu et al., 2019). The other works contributed to marketing studies (Liu, Chen, et al., 2009) and (Fang et al., 2020) and attempted to match consumers and products (smartphones and cosmetics) in China. Among 161 works in 2022 and 2023, only two applied biclustering in economics: (Haedo and Mouchart, 2022) studied the relative sectorial specialisation of regions (the matrix, therefore, contained sectors and regions as the rows and columns), while (Garbuio and Gheno, 2023) studied the match between consumers and product characteristics in the field of the Internet of Things devices. Since 2020, most of the studies have been published in medical and statistical journals, with minor contributions to socioeconomic studies. The high potential of the biclustering method has also been harnessed in pioneering fields, for example, for workers and firms (Mann, 2024). This way, our paper is the first to apply biclustering as a tool for studying food sets, consumers and socioeconomic aspects in Switzerland.

Research Method

Data

We used data from a randomised observational survey of households in Switzerland who reported their household characteristics and food purchasing diaries, specifically a list and the amount (in kilograms or litres) of food they bought over a one-month period. These data are collected by the Swiss Federal Statistical Office, and the size and reliability of the dataset that we used has previously encouraged a number of studies in Switzerland (Household Budget Survey, 2024), (Mann and Loginova, 2023), and (Mann and Loginova, 2024). In 2017, the data held the responses from 3,217 random households in Switzerland. Our analysis included 7,01,964 observations representing the consumption volumes per person of 97 foods (Loginova and Mann, 2024) and (Loginova and Mann, 2025). We briefly describe the data used in this study in Table *1*.

Method

Biclustering was born and used mainly in bioinformatics studies, most often for linking genes and various experimental conditions (Kluger et al., 2003), (Dharan and Nair, 2008), and (Srivastava et al., 2019). The most commonly used biclustering algorithms were developed in the early 2000s (Table *2*). Madeira and Oliveira (Madeira and Oliveira, 2004) developed nine classes of biclustering results, according to which biclusters can overlap, have a hierarchical structure, and cover only a small portion of observations. Thus, using biclustering may potentially help to find the linkages between households and food sets and analyse the potential features of consumers in the resulting biclusters.

Biclustering algorithms simultaneously cluster rows and columns of a data matrix. The resulting sets of linked rows and columns are called “biclusters”. Unlike simple clustering, which groups objects in one dimension, biclustering does this simultaneously across two dimensions, while multi-clustering encompasses many dimensions. Thus, the objects do not have a fixed order and may be remixed to reach the best match and grouping between them.

Data	Levels	Roles in the study
Household ID	Individual ID for each household in 2017	The raw of the matrix
Food	97 foods	The column of the matrix
Household consumption	Numeric variable, in grams	The content of the matrix
Household population (size)	Numeric variable, number of persons	The features of the consumers (households)
Gross household income (monthly)	Less than 3,999 CHF; 4,000–7,000 CHF; 7,000–10,000 CHF; More than 10,000 CHF	
Age	Age for each member of a household	
Gender	The number of female respondents relative to the household size	
Education	Dummy on presence of expenditures on university and equivalent education	

TABLE 1: Data description

Source: Author.

#	Name	Abbreviation	Information	Authors
1	Cheng and Church's algorithm	CC	Based on a mean squared residue score	(Cheng and Church, 2000)
2	Iterative Signature Algorithm	ISA	Searches for submatrices representing fix points	(Ihmels et al., 2004)
3	Order-Preserving Submatrix Algorithm	OPSM	Tries to identify large submatrices for which the induced linear order of the columns is identical for all rows	(Ben-Dor et al., 2004)
4	xMotifs algorithm	xMotifs	(ETH BicAT Manual): an iterative search method which seeks biclusters with quasi-constant expression values; (BCXmotifs {biclust}): searches for a submatrix where each row has a similar motif through all columns	(Murali and Kasif, 2003)
5	Bimax	Bimax	A divide-and-conquer strategy that is capable of finding all maximal bicliques in a corresponding graph-based matrix representation	(Prelic et al., 2006)
6	The Plaid Model bicluster algorithm	BCPlaid	Models data matrices to a sum of layers; the model is fitted to data through minimisation of error.	(Lazzeroni and Owen, 2002) and (Turner et al., 2005)
7	Questmotif bicluster algorithm	BCQuest	Searches subgroups of questionnaires with the same or similar answers to some questions	(Murali and Kasif, 2003)
8	The Spectral bicluster algorithm	BCSpectral	Supposes that normalised microarray data matrices have a checkerboard structure that can be discovered by the use of SVD decomposition in eigenvectors, applied to genes (rows) and conditions (columns)	(Kluger et al., 2003)
9	Biclustering via a sparse singular value decomposition	sv4d	A bicluster structure forces the row and column singular vectors to be very sparse. This structure is achieved by interpreting the singular vectors as regression coefficients.	(Lee et al., 2010)
10	Biclustering by Factor Analysis for Bicluster Acquisition	FABIA	A multiplicative model that extracts linear dependencies between samples and feature patterns	(Hochreiter et al., 2010)

TABLE 2: Applied biclustering algorithms

Source: Author.

1–5 from (BicAT Manual, 2018); 6–8 from (Kaiser, 2023); 9 from (Kaiser, 2011).

Various studies have tested and overviewed the performance of these methods (Xie et al., 2019), (José-García et al., 2023), and (Madeira and Oliveira, 2004).

Design

Our study promotes the application of the biclustering method in the argi-food sector. The two dimensions - the household IDs and the food IDs - shaped the rows and the column names for a matrix filled with corresponding consumptions. We performed range normalisation for the log consumption to the maximum and minimum log consumptions within the foods. The range normalised log consumption was employed in all the calculations of this study. Therefore, the values in the matrix for different foods and households are comparable. We used the function “fabia” from R-Package ‘fabia’ by (Hochreiter et al., 2010) and (R-Package FABIA, 2020) for biclustering normalised log consumptions and analysing the linkages between households and foods. This method does both factor analysis and biclustering in R; therefore, it was chosen after reviewing the alternatives presented in the guide by (De Troyer, 2022). We consider and the number of cycles is 1,000, as by default for this method.

FABIA algorithms allow only the number of clusters to be equal to the number of hidden factors. Based on the data we had, we were able to assess a maximum of five overlapping biclusters. The features of these biclusters are presented in Figure *1*.

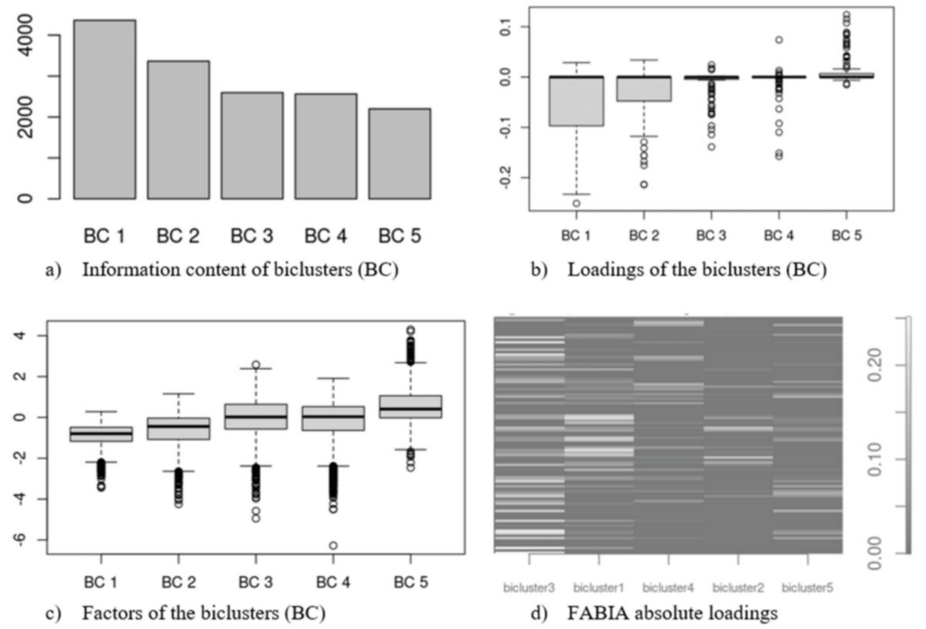

FIGURE 1: The features of biclusters

Notes. BC stands for "bicluster".

a) Information content of biclusters (BC), no unit. Source: Author. b) Loadings of the biclusters (BC), no unit. Source: Author. c) Factors of the biclusters (BC), no unit. Source: Author. d) FABIA absolute loadings, no unit. Source: Author.

The information content of the samples (households) ranges between 3.47 and 5.15. The information content of biclusters is high and ranges from 2,197 (for Bicluster 5) to 4,363 (for Bicluster 1). The loadings of the biclusters and the factors of the biclusters differ from bicluster to bicluster.

As factor analysis may be integrated into biclustering only at the cost of a number of methodological problems as compared to simpler algorithms (Kaiser, 2011) [p. 81], we avoided intervention to FABIA algorithms and used bicluster-wise violin plots and descriptive statistics of features of the households in attempts to identify patterns that could help distinguish biclusters with the use of real factors that we observe for the households. Thus, we collected information from the household data that could not have been achieved with any other simpler method. For example, regression analyses, decision trees, and simple clustering algorithms are usually applied to numeric data and mainly to one type of object, while we have various food names and household IDs in the applied setting.

Results

Our main result is that we biclustered food items and households in Switzerland in 2017, with five biclusters emerging and labelled as basic, vegan processed, poor & old, vegan raw, and sweet-toothed. The five biclusters of households and foods overlapped and covered 34 of 97 food items studied and 2,993 of 3,217 surveyed households. We described biclusters by food in the text, initially with a focus on food items and then on households, and by household features, as shown in Figure *2* and Table *3*.

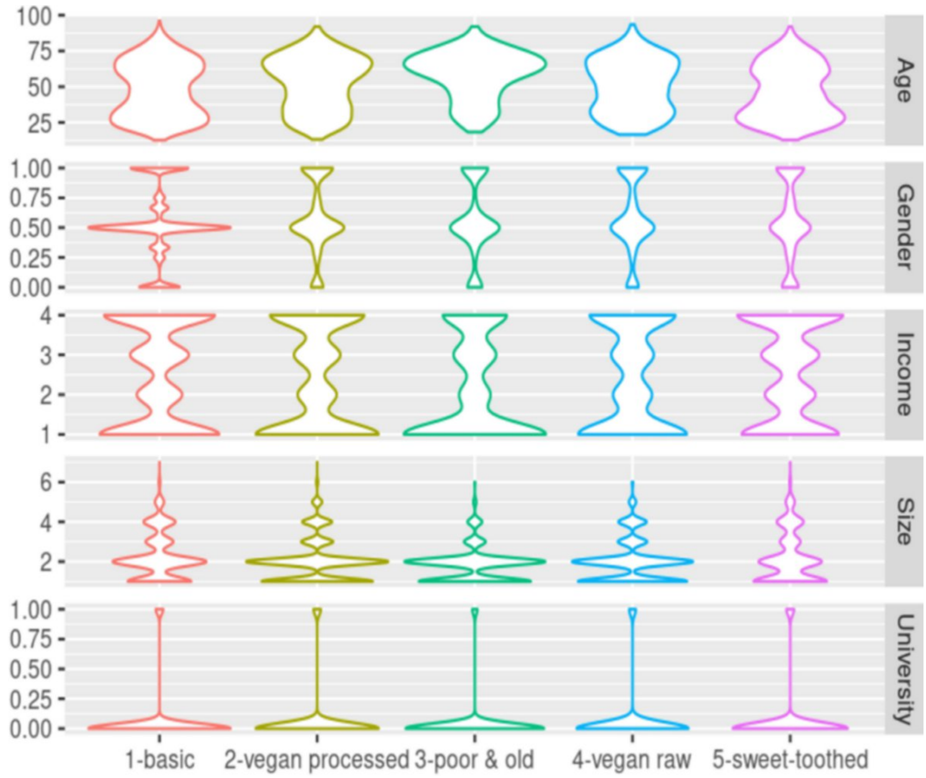

FIGURE 2: Presentation of the factors of biclusters by means of violin plots

Axes: As defined in Table 1.

Source: Author.

The resulting biclusters are as follows:

Bicluster 1 - “basic” - contains 74% of households and 20 foods: beef, pork, poultry, edible meat products (incl. offal), whole milk, yoghurt, pears and quinces, kitchen herbs, fruiting vegetables, canned vegetables and mushrooms, potatoes, confectionery, sauces, flavour essences, baby food, mineral water, syrups for drinks, non-alcoholic wines, wines, and beer.

Bicluster 2 - “vegan processed” - contains 47% of households and 10 foods: edible vegetable oils and animal fats, lemons, bananas, melons and watermelons, exotic fruits, canned fruit, green salads and other leafy vegetables, stem vegetables, kitchen herbs, and garlic.

Bicluster 3 - “poor & old” - contains 27% of households and 2 foods: bread, milk drink, and skimmed milk.

Bicluster 4 - “vegan raw” - contains 28% of households and 3 foods: pears and quinces, cabbage vegetables, beans, and peas.

Bicluster 5 - “sweet-toothed” - contains 46% of households and 3 foods: yoghurt, chocolate, and flavour essences.

The biggest bicluster 1 is “basic”, as it captures 74% of households in population and key foods. It also contains parts of other biclusters. This bicluster is a simplification of the rule in the dimension of foods for the total population, albeit the households in this bicluster have slightly higher incomes than a populational average and by far the lowest share of single households. The second bicluster is shaped by older households that consume mostly crop-based food, often in a processed state, thus the label is “vegan processed”. The households in the third bicluster, which we call “poor & old”, have the lowest incomes and are older than the households in any other bicluster. They also have the lowest share of members with a university education. These households consume more bread and milk drinks, which can all be considered staple food. The fourth bicluster is labelled “vegan raw”. These households can be at any age and consume more pears and quinces, cabbage vegetables, beans, and peas. Finally, the fifth bicluster captures the “sweet-toothed” households that consume more yoghurt, chocolate, and flavour essences compared to others. These households are younger, on average, and have a high share of men and large households.

Bicluster		1	2	3	4	5
Bicluster name		Basic	Vegan processed	Poor & old	Vegan raw	Sweet-toothed
Households		2,362	1,513	868	912	1,464
Foods		20	10	2	3	3
Age	Most frequent	22	70	70	70	28
	Average	48	52.5	58	50.5	46
Income, monthly, CHF	Less than 3,999	844 (36)	615 (41)	442 (51)	360 (39)	457 (31)
	4,000–7,000	321 (14)	195 (13)	96 (11)	128 (14)	238 (16)
	7,000–10,000	415 (18)	232 (15)	132 (15)	140 (15)	272 (19)
	Over 10,000	782 (33)	471 (31)	198 (23)	284 (31)	497 (34)
Gender	Male	306 (13)	156 (10)	126 (15)	107 (12)	223 (15)
	Female	438 (19)	406 (27)	228 (26)	265 (29)	374 (26)
	Mixed	1,618 (69)	951 (63)	514 (59)	540 (59)	867 (59)
Education	University	118 (5)	84 (6)	31 (4)	50 (5)	91 (6)
	Not university	2,244 (95)	1,429 (94)	837 (96)	862 (95)	1,373 (94)
Size	1	658 (28)	514 (34)	332 (38)	336 (37)	552 (38)
	2	973 (41)	658 (43)	418 (48)	373 (41)	476 (33)
	3	287 (12)	147 (10)	64 (7)	90 (10)	154 (11)
	4	331 (14)	138 (9)	43 (5)	87 (10)	202 (14)
	5	95 (4)	46 (3)	9 (1)	22 (2)	68 (5)
	6 or more	18 (1)	10 (1)	2 (0)	4 (0)	12 (1)

TABLE 3: Biclustered households and their features

Note: Values in brackets are the shares of the households in the number of households in the bicluster.

Source: Author.

Discussion

Interpretation

Leveraging biclustering theory and rich data from the Swiss Federal Statistical Office, we describe food-household groups in Switzerland in 2017 as basic, vegan processed, old & poor, vegan raw, and sweet-toothed, following the overlapping biclusters we obtained. Our results show that the key factors that differ among these biclusters are age, gender, and household size, while incomes and university payments play a role in exceptional cases. This confirms previous research that emphasizes the role of age (Desbouys et al., 2019), gender (Ekebas-Turedi et al., 2020), and household size (Kwon, 2022) found in other studies. Our categories extend the previous one-dimensional groupings of consumers by various, mainly behavioural, consumer characteristics (Drive Research, 2022), meat versus sustainable consumption (Schäufele-Elbers and Janssen, 2023), and energy-driven consumption (Gazdecki et al, 2021) towards socioeconomic pairing between consumer groups and food sets.

Limitations

The main limitation of this study is that there are other significant factors that correlate with consumption but were not included in this study because of the lower level of details in the data and method. For example, (Kearney, 2010) defined drivers of food consumption at a global level: urbanisation, trade liberalisation, international corporations and retail spread, marketing, and attitudes. We could not define these factors in the household-level data. The other factors correlated with the factors included in the research. For example, in (Inanir et al., 2021), the smoking status of the household's residents was significant, among other factors, for dairy consumption among the Swiss population. However, the smoking status of households correlates with the level of education in many countries (Pampel et al., 2015) and (Corsi et al., 2014). By including educational factors, we approximated many other factors. Education level was significant for poultry and fish consumption trends in the USA (Daniel et al., 2011) and for many meats in Switzerland (Loginova and Mann, 2025). Education is also a recognised factor in "healthy" consumption (CEDAR, 2014), (Kirbiš et al., 2021), (Miller et al., 2022), and (Schneid Schuh et al., 2018).

Conclusions

We found that food-household groups in Switzerland in 2017 can be described as basic, vegan processed, old & poor, vegan raw, and sweet-toothed, following the overlapping biclusters we obtained. The key factors that differ among these biclusters are age, gender, and household size. Future research on the socioeconomics of food may consider that consumers tend to choose food mixes, as shown in our results. Future statistical research may find it intriguing to develop biclustering and biclustering in food socioeconomic studies towards versions that include more factors in a more accurate and controlled way.

The targeted nutritional and food policies, education, promotion, and marketing may be addressed to specific consumer biclusters. The chocolate and confectionary industries will find the "sweet-toothed" bicluster for advertising innovations, whereas public authorities will use this bicluster to promote healthy diets with social and educational programs. Vegan behaviour can also be stimulated using evidence that their nutrition and lifestyle are sustainable. In our opinion, our approach offers options for similar research in other sectors. Real estate transactions, energy consumption behaviour, or the car market offers similar potentials for biclustering that are so far unexplored. It promises additional insights of a simultaneous grouping of population segments with market segments.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Daria Loginova, Stefan Mann

Acquisition, analysis, or interpretation of data: Daria Loginova, Stefan Mann

Drafting of the manuscript: Daria Loginova

Critical review of the manuscript for important intellectual content: Daria Loginova, Stefan Mann

Supervision: Stefan Mann

Disclosures

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