Relationships between food groups, eating time slots and diabetes status in adults from the UK National Diet and Nutrition Survey (2008–2017)

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Short running head: Time of food consumption by diabetes status.

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**Abbreviations:**

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## ABSTRACT

**Background:** Time of eating has been shown to be associated with diabetes and obesity.

**Objective:** To identify potential relationships between foods and eating time, and see whether these associations may vary by diabetes status.

**Design:** The National Diet and Nutrition Survey (NDNS) included 6802 adults (age 19) collected 749026 food recordings by a 4-day-diary. The contingency table cross-classifying 60 foods with the pre-defined 7-time slots were analyzed by Correspondence Analysis (CA). Biplots displaying the associations were generated for all adults and separately by diabetes status (self-reported, pre-, undiagnosed-, and non-diabetics). Odds ratios (OR, 99%CIs) were derived of consuming unhealthy foods at evening/night (20:00 - 06:00) vs. earlier in the day, by logistic regression with generalized estimating equation.

**Results:** The biplots suggested positive associations between evening/night and spirits, beer, ice cream, chocolate, sugar-confectionery, biscuits, crisps, and sweetened beverages. The OR of consuming these foods at evening/night were respectively 11.13 (8.37-14.80), 7.19 (5.87-8.82), 2.38 (1.79-3.15), 3.19 (2.69-3.79), 1.92 (1.38-2.69), 1.91 (1.67-2.16), and 1.55 (1.27-1.88) vs. earlier time. Stratified biplots found that sweetened beverages, sugar-confectionery were more likely to be consumed at event/night among undiagnosed diabetics.

**Conclusions:** Foods consumed in the evening/night time tend to be highly processed, easily accessible, and rich in added sugar or saturated fat. Individuals with undiagnosed diabetes are more likely to consume unhealthy foods at night. Further longitudinal studies are required to explore the causality.

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## INTRODUCTION

The timing of energy intake has been shown to be associated with obesity and diabetes. (1)

We aimed to decribe the relationship between food groups and the time of day when they were consumed, and how such relationships may vary by status of type 2 diabetes.

## METHODS

6802 adults (2810 men and 3992 women) and 749026 food recordings collected by the UK National Diet and Nutrition Survey Rolling Programme (NDNS RP 2008-17) were analyzed in the current study (2). The sample was randomly drawn from a list of all addresses in the UK, clustered into postcode sectors. Details of the rationale, design and methods of the survey can be found in the previous published reports (3,4). Time of the day was categorized as 7 slots: 6-9 am, 9-12 noon, 12-2 pm, 2-5 pm, 5-8 pm, and 10 pm - 6 am. Foods recorded were classified into 60 standard food groups with 1 to 10 subgroups each: the details are given in Appendix R of the NDNS offical report (5). We focused on the 60 standard food groups in the current analysis. Diabetes statuses were defined as: 1) healthy if fasting glucose was lower than 6.10 (mmol/L), hemoglobin A1c (HbA1c) were less than 6.5 (%), and without self-reported diabetes or under treatment of diabetes (n = 2626); 2) pre-diabetic if fasting glucose was lower between 6.10 and 6.99 (inclusive) but without self-reported diabetes or under treatment of diabetes (n = 133); 3) undiagnosed diabetic if either fasting glucose was higher or equal to 7.00 (mmol/L) or HbA1c higher or equal to 6.5 (%) but without self-reported diabetes or under treatment of diabetes (n = 99); 4) diabetic if participant had self-reported diabetes or under treatment of diabetes (n = 227). Consequently, number of adults whose diabetes status could not be confirmed was 3717 (1519 men, 2198 women) and they were kept in the whole sample analyses. In addition, the National Statistics Socio-economic Classification (6) were applied in the survey and therefore accordingly, the socio-economic classification for the individuals’ household were defined with 8 categories.

Correspondence analysis (CA) (7,8) was used as a tool for data mining, visualisation and hypotheses generation using half of the randomly selected NDNS diary entries data. Specifically, the contingency table generated by cross-tabulating foods and time of eating were analyzed by CA. Through CA, the 60 categories of standard food and the 7 time-slot were projected on two dimensions that could jointly contain large percentage of the deviation (or inertia) of the table. Biplots that graphically showing the association between time of day and food groups were derived for all adults and seprately according to their diabetes status. To account for the hierarchy of the data (food recorded by the same individuals who lived within the same sampling units) and to calculate population marginal odds ratios (OR), logistic regression models with generalized estimating equations (GEE) were used to test associations that were suggested from biplots generated by CA using the remaining half of the diary entries data. The marginal ORs and their 99% confidence intervals (CI) was derived of consuming unhealthy food groups selected by CA, later in ther day (8 pm - 6 am) compared to earlier in the day. CA and biplots were conducted and generated by the following packages under R environment (9): FactoMineR, factoextra, ggplot2, ggrepel (10–13). Logistic regression models with GEE were performed with SAS procedure GENMOD (14) adjusted for age, sex, and social economic levels.

## RESULTS

The dataset consisted of 2810 (41.3%) men and 3992 (58.7%) women aged older or equal to 19 years old with the mean age of 49.9 years (standard deviation, sd = 17.6). Among these individuals 22.6 % of them were current smokers, 24.3 % were past smokers. The average body mass index (BMI) was 27.7 kg/m (sd = 5.41). Among the food recordings collected, 56.9% were recorded during traditional breakfast (6 am - 9 am: 14.3%), lunch (12 noon - 2 pm: 18.5%), or dinner (5 pm - 8 pm: 24.1%) time slots. Table 1. shows the top 37 food groups that contributed to 90% of the total calories consumed by adults in NDNS RP. These food groups accounted for 478028 of the total diary entries (63.8 %). The random process splitted the data of food recordings into a hypothesis generating dataset of 374682 and a testing dataset of 374344.

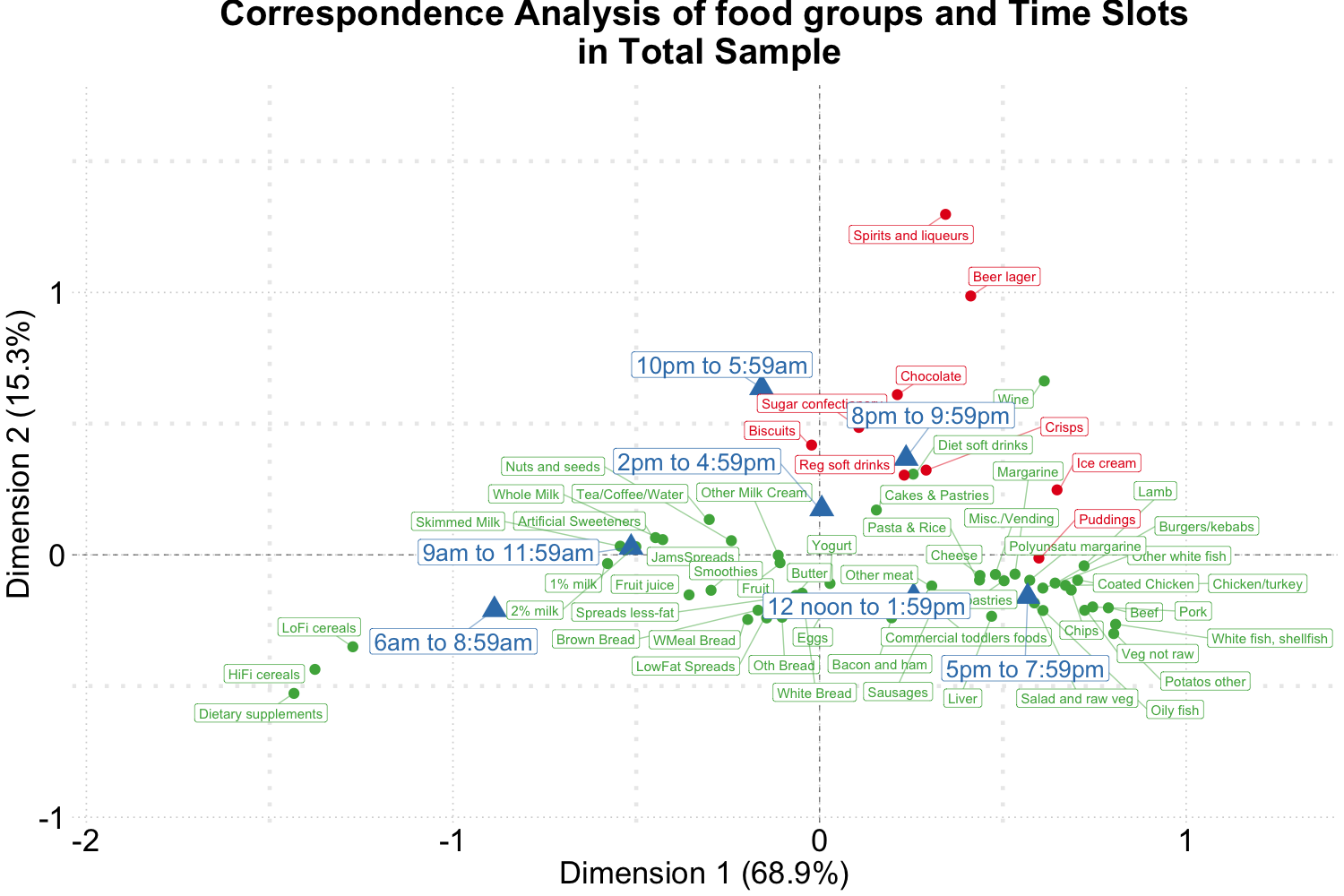


Figure 1. Biplot of food groups and eating time slots among total sample of NDNS RP.

Figure 1-5 are CA biplots that summarise the associations between 60 food groups and the time of their consumption in total sample and stratified by their diabetes status. In **Figure 1**, the horizontal axis explains 68.9 % the correlation between food and time while the verticle axis reflects 15.3 % of the same relationship. Therefore, a total of 84.2 % of the inertia between food and time were captured in this figure which shows a visual summary of how the two variables are related. Specifically, time slots later than 8 pm are shown in the upper side of the figure closer to foods contained alcohol (beers and spirits) or condensed energy (sugar, chocolates, biscuits, soft drinks, ice cream, etc.); time earlier than the noon time are shown in the left hand side together with breakfast foods (cereals, milk, bread, etc.).

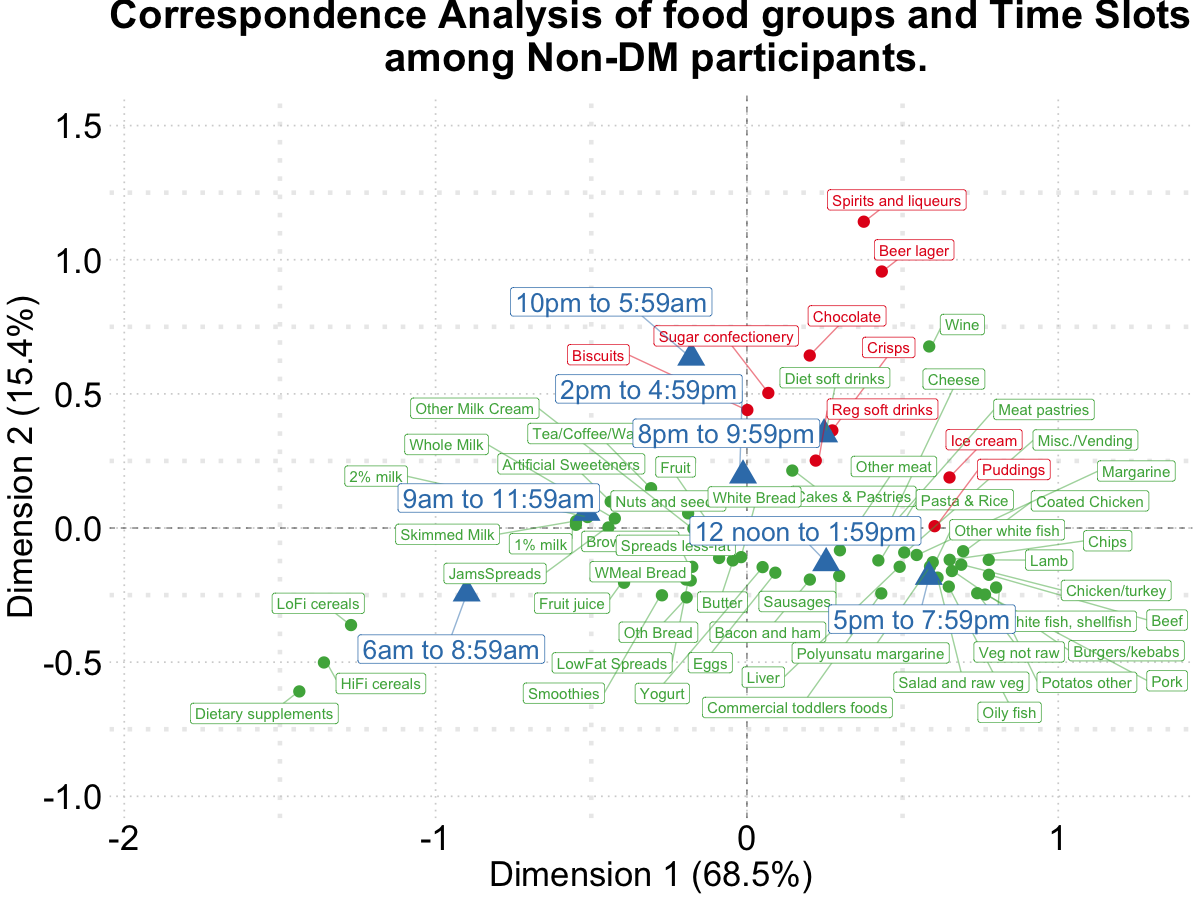


Figure 2. Biplot of food groups and eating time slots among **non-diabetics**.

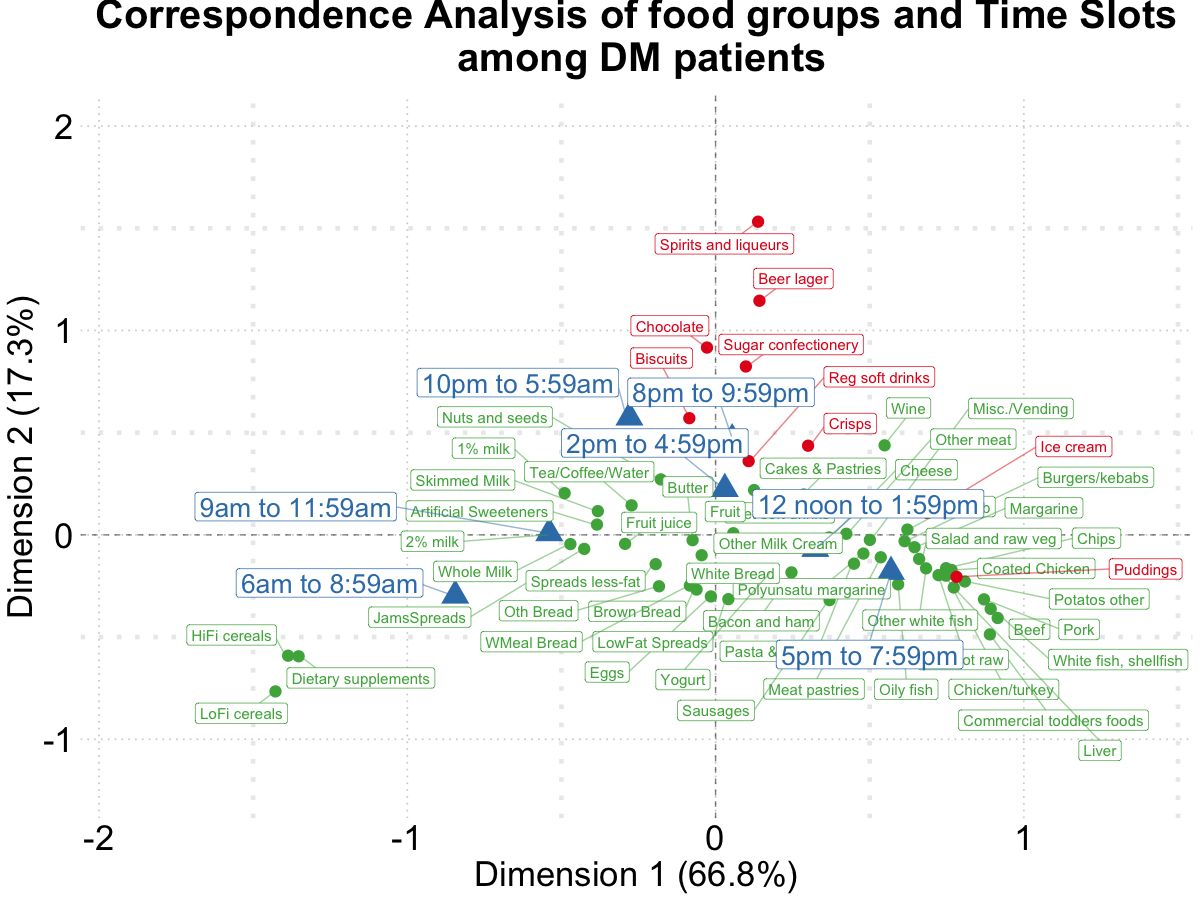


Figure 3. Biplot of food groups and eating time slots among **diabetics**.

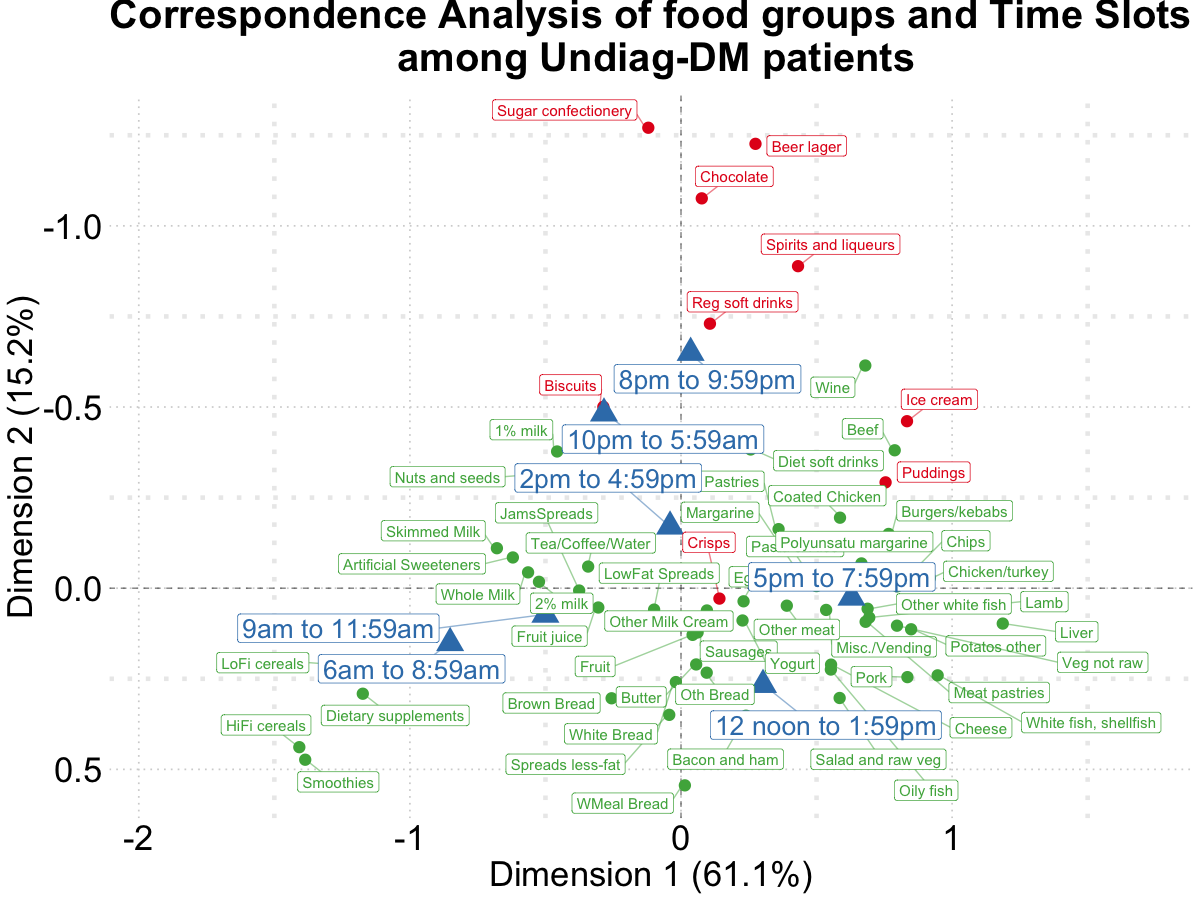


Figure 4. Biplot of food groups and eating time slots among **undiagnosed diabetics**.

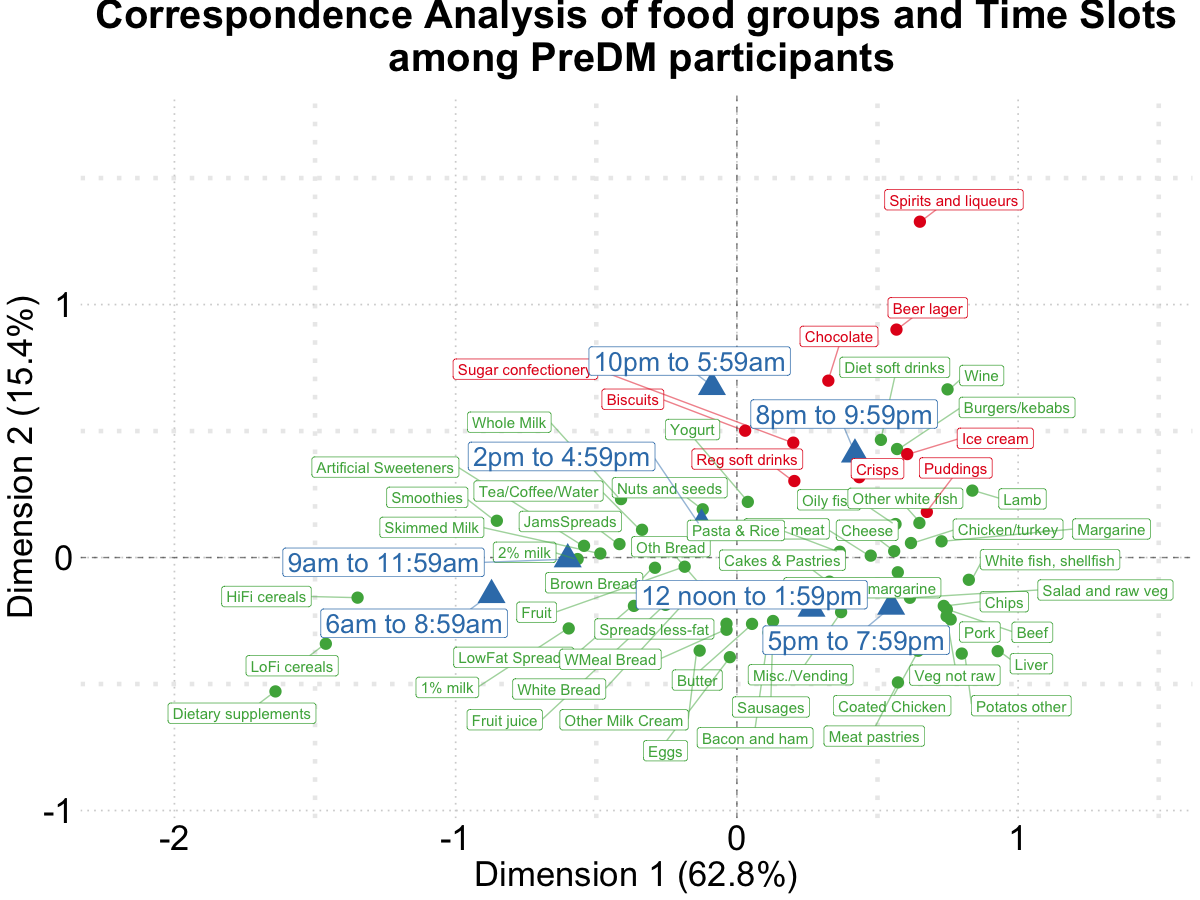


Figure 5. Biplot of food groups and eating time slots among **pre-diabetics**.

## DISCUSSION

### Conclusions

## ACKNOWLEDGEMENT

## CONFLIT OF INTEREST (COI) STATEMENT

The authors declared no conflicts of interest.

## AUTHOR’S CONTRIBUTIONS

CW, SA, and LP: designed research and had primary responsibility for final content; CW and LP performed statistical analysis; and all authors: wrote the manuscript, read and approved the final manuscript.

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