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Understanding Dietary Intake Behavior of Women in India: A Latent Class Approach

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Abstract

A recent development of the Indian National Family Health Survey is the collection of food consumption data from ever-married women aged 15-49 years. This study investigates the underlying complex dietary intake patterns among women using latent class models and examines its association with selected characteristics. Based on different combination of food intake frequency, a five component latent class solution was obtained which disaggregated the sample (N=90,180) into different groups representing very high mixed diet (26%), high and moderate (21% each), low and very low mixed diet (16% each). Demographic, spatial, socioeconomic and cultural dimensions of diet mixing behavior are further explored.

S^{3}RI Applications Working Paper A03/15

UNDERSTANDING DIETARY INTAKE BEHAVIOR OF WOMEN IN INDIA: A LATENT CLASS APPROACH

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The later half of the last century witnessed considerable shifts in the age specific mortality patterns signifying substantial improvements in human longevity. Concomitantly, many social scientists especially demographers began investigating issues related to the burden of morbidity, particularly nutrition and diet related non-communicable chronic diseases such as cancer, cardiovascular diseases, diabetes and other diseases due to nutritional disorders (Reddy 2002; Hu 2001; Vorster et al. 1999; Murray and Lopez 1997; Gopalan 1997; Chadha, Gopinath, and Shekawat 1997; Kant, Schatzkin and Ziegler 1995). The risk factors that explain these emerging and re-emerging diseases are mostly diet and life-style related, for example obesity caused by high fat foods consumption and lack of physical exercise or malnutrition caused by poor nutrient intakes.

Individuals experience different lifestyles and this complexity is reflected in their eating customs and dietary habits (1). The nutritional intake of individuals varies considerably by demographic and socioeconomic conditions within the household and sometimes even for the same individuals within the same household at different points in time (2-3). Recently, it has been observed that there is a transition in the food intake towards a modern diet (high saturated fat, sugar and refined foods and low fibre) even among the low

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income and rapidly urbanizing populations (4-5). Changing lifestyles, the growing inequalities in income and resources distribution and the widening gap between the rich and the poor are some of the important issues that concern the food intake analysis more complex and difficult to understand. This proposition holds universally true especially in a context like India, where the health, socio-economic and demographic inequalities are larger both among individuals and across regions. This study aims to investigate the complex dietary behavior of women in India using data from the most recent National Family Health Survey (NFHS-2).

Little research exists on diet and nutrition in India especially at the individual level. In the last few decades, the major source of diet information in India have had been the surveys conducted by the public health directorates of different states, the results of which were then published by the National Institute of Nutrition (6). Unfortunately, these surveys were of poor quality in terms of sample designs and were restrictive of regional or state comparisons. The National Nutrition Monitoring Board (NNMB) set up in 1972 as an integral part of the National Institute of Nutrition initiated efforts to periodically collect data on dietary intake and nutritional status based on representative multi-clustered samples from 10 selected states from different regions of India (7). These NNMB surveys covered households from rural villages to slums in the urban and metropolitan areas. The advantage of the NNMB surveys has been the possibilities to provide reasonable household and intra-familial estimates of food and nutrient intake and data comparison options across time. The disadvantages are mainly the methodological limitations of a three-day weighting and 24-hour oral recall methods that cannot be projected as truly valid estimates for longer period as well as the limited availability of data from selected states in different regions of India.

Until recently, the NNMB surveys were the only reliable source for diet and nutrition related information in India. Few other sources are the District Nutrition Profiles Surveys conducted in 15 states by the Food and Nutrition Board and the quinquennial consumer per-capita expenditure surveys of the National Sample Survey Organization (8). These studies have overtime stressed the need for further individual level research in understanding the complexities associated with dietary behavior and their influence on the higher incidence of non-communicable diseases and mortality (9-14). One of the main concerns in this regard is the availability of a nationally represented data on food intake together with a set of demographic and socio-economic variables. The second round of the NFHS conducted in India during 1998-1999 collected individual level information from women aged 15-49 years on their daily, weekly and occasional consumption of selected foods such as proteins, carbohydrates, fat, vitamins and legumes (15). A national level analysis of dietary consumption patterns holds considerable importance in India both from scientific and policy viewpoints. The scientific perspective lies in the better understanding of dietary practices and the risk factors (role of diet) related to chronic diseases at later life and the policy perspective in order to shape dietary guidance and evaluations for a comprehensive food policy to be integrated with the national population and reproductive health policies.

To our knowledge, the analysis of dietary behavior among women in India at the national level have neither received adequate attention nor been analyzed systematically. This research is intended to disentangle the underlying unobservable patterns of dietary intake among Indian women using Latent Class (LC) models. We aim to identify the complex patterns of diet mixing behavior based on a cluster of information related to the frequency of different food intake. By making use of the information on dietary intake of selected important foods appropriate for latent class modeling and considering other demographic and socioeconomic variables collected in the NFHS-2, we can answer the following questions:

- What are the general patterns of dietary intake among Indian women and how does it vary by different regions?
- How can we better explain the underlying complex patterns of dietary behavior using a LC analysis?

- Do certain clusters of women differ in their dietary behavior according to different demographic, socioeconomic and cultural backgrounds?

It has to be made clear that we do not intend to measure how much food do individuals consume or the average calorie intake but instead the diversity in dietary behavior with regard to important and commonly consumed foods. The analysis of this paper is based on limited survey information regarding some of the most commonly consumed foods. Through LC modeling, we seek to provide few policy clues that might bolster the existing recommendations to further enhance women's health, food supply and population sustainability.

MATERIALS AND METHODS

Data. NFHS-2 data used in this study was derived from a nationally represented cross-sectional survey conducted between November 1998 and March 1999. The survey was coordinated by the International Institute for Population Sciences in Mumbai, India and funded by the USAID through the ORC Macro, USA. NFHS-2 covered a representative sample of more than 90,000 eligible women aged between 15 and 49 years from 91,196 households in 25 states excluding Tripura, data of which was collected at later phase but was not included in the final all-India report (15). Throughout the states in India, the survey used uniform questionnaires, sample designs and field procedures to ensure data quality and comparability. Further details are available in IIPS (15). Although the principal objective of the NFHS was to provide information on demographic, health aspects including nutrition and health care, the survey also collected information on women's diet intake besides other information on living conditions and socio-economic characteristics. Information on dietary intake has been collected for the first time in India by the NFHS-2.

NFHS-2 asked women 'how often do you yourself consume the following items: daily, weekly, occasionally or never?' The survey probed women regarding the consumption of specific food items; milk or curd, pulses or beans, green leafy vegetables, other vegetables, fruits, eggs and chicken, meat or fish. Among these foods, meat, fish, eggs and milk, pulses and nuts are rich in protein, green leafy vegetables are rich source of iron, folic acid, vitamin C, carotene, riboflavin and calcium, whereas fruits contain especially vitamin C and vitamin A. The survey did not ask specifically about any cereal (wheat/rice/corn) intake, however, it is reasonably a well-known fact that wheat and rice consumption form a major ingredient in the daily food of Indian population. Although we have information of dietary consumption on daily or weekly basis, such information would be insufficient to understand women's total amount of calorie or energy intake. This is because the total amount of food consumed per day could vary substantially among individuals, even if we take into account the traditional concept of three meals a day (1). Nonetheless, the four category responses provided in NFHS-2 reflect the immediate past and current dietary habits of women. The survey does not provide information related to the quantity or level of food consumption over time and also such analysis is beyond the scope of this paper. The analysis is carried out for 26 Indian states, which represents more than 99% of India's total population. Including Tripura, we have a sample of 90,303 ever-married women of reproductive ages. Of these women, 90,180 cases provided complete responses and incomplete response cases (0.1%) were not considered in the analysis. The states included in the analysis have considerable demographic, social and cultural heterogeneities. The southern states are demographically advanced states with fertility rates below replacement levels. Furthermore, there are significant regional variations with regard to agricultural production; wheat is produced mainly in the northern regions whereas rice and other alternative crops such as pulses are mainly produced in eastern and southern states.

Methodology. The LC model suggested here reduces the dimensionality of different responses on the frequency of food intake into a meaningful set of latent grouping or classes representing different dietary intake patterns. In this approach, both the manifest and latent or class variables are categorical and the observed responses to the manifest variables are assumed to be mutually independent given that the latent class membership is taken into account (16). For understanding the underlying patterns of dietary intake, we identified different groups of the sample using the LC analysis based on the frequency of consumption of different foods, i.e. daily, weekly, occasionally and never. A LC analysis of dietary data of 1,028 US women was earlier attempted by Patterson, Dayton and Graubard (17). This particular study focused on vegetable consumption patterns using binary data. In our LC model, individuals are grouped with regard to certain underlying, unobservable variable based on the data from polytomous indicators thereby decomposing a sample into segments or clusters; these clusters form the categories of a categorical latent variable (18). The LC model can also be regarded as a factor analysis of categorical data with discrete latent variables (19). The model specifications are briefly summarized as follows.

Let $\mathbf{y}_i$ represent the dietary intake responses of woman i from a sample of size n and y_{ijl} be equal to 1, if woman i selected category l of variable j or 0 otherwise, with J categorical variables ($j = 1,..., J$) and with L_j the number of categories of variable j ($l = 1,..., L_j$). In the LC framework, the observation associated with woman i ($\mathbf{y}_i$) is assumed to be a realization of a random vector $\mathbf{Y}$ with probability density function $f(\mathbf{y}_i; \varphi)$, which corresponds to the probability of observing a specific sequence of categorical values (vector), defined by

$$f(\mathbf{y}_i; \varphi) = \sum_{s=1}^{S} \pi_s \prod_{j=1}^{J} \prod_{l=1}^{L_j} \theta_{sjl}^{\ y_{ijl}} \tag{1}$$

where φ is the set of all parameters. This model is defined by two different sets of parameters:

a) π_s ($s = 1,...,S$), the *a priori* probability that a given woman belongs to segment s, with $\pi_s > 0$ and $\sum_{s=1}^{S} \pi_s = 1$ and b) θ_{sjl} the probability of selecting category l of variable j conditional on belonging to segment s. This model is estimated using the EM algorithm (20). The model identification, a common problem to several finite mixture models, is evaluated using the Hessian matrix of the free parameters at the maximum value of the likelihood function (21).

We select the number of segments (S) that minimizes $C_S = -2\ell_S + dN_S$, where ℓ_S is the log-likelihood value for the maximum likelihood estimate, and N_S is the number of free parameters for the estimated model. For different values of *d*, we have the Akaike Information Criterion (AIC), $d = 2$; the Bayesian Information Criterion (BIC), $d = \log n$; and the Consistent Akaike Information Criterion (CAIC), $d = \log n + 1$ (22-24). For these criteria, smaller values indicate more parsimonious models. BIC and CAIC criteria have the advantage of being dimension consistent, *i.e.*, they point to the right model with probability one as the sample size increases.

Another important result from this statistical technique is the posterior probabilities that the woman i belongs to each group or cluster given data (α_{is}, $s = 1,...,S$, $i = 1,...,n$). Once the parameters are estimated, the posterior probabilities that woman i comes from group s can be calculated using the Bayes' rule:

$$\alpha_{is} = \frac{\hat{\pi}_s f_s(\mathbf{y}_i; \hat{\theta}_s)}{f(\mathbf{y}_i; \hat{\varphi})} = \frac{\hat{\pi}_s \prod_{j=1}^{J} \prod_{l=1}^{L_j} \hat{\theta}_{sjl}^{\ y_{ijl}}}{\sum_{h=1}^{S} \hat{\pi}_h \prod_{j=1}^{J} \prod_{l=1}^{L_j} \hat{\theta}_{hjl}^{\ y_{ijl}}}, \tag{2}$$

which enables to define allocation rules of the n women into the S groups.

Finally, we considered a multinomial logistic regression analysis to analyze several sets of characteristics that are associated with dietary behavior. The clusters, from the LC model, representing women's differential dietary intake patterns are regarded the dependent variable for the regression models. A note on sample weighting is worth mentioning. Weighting was not taken into account in our analyses. Wedel *et al.* (25) proposed a method based on the pseudo-maximum likelihood (PML) estimation of the latent class model taking into account weighting of the sample units. However, it is still not clear whether the weighted solution is better than the unweighted one (26). Because of the larger size of our sample – perhaps the largest sample ever used in LC estimation – we have decided for the unweighted solution. Nonetheless, we did compare the weighted and unweighted data after the estimations; the observed differences were in fact trivial.

RESULTS

Dietary intake patterns: an overview. The complex disparity of dietary behavior across different Indian regions is clearly manifested in the results (**Table 1**). More than 85% of women in India consume pulses or beans and green leafy vegetables at least once a week. Kerala is an exception where only 55% of women consume green leafy vegetables at least once in a week. Egg and meat products consumption is relatively low in many states, particularly in the North. Roughly 10% of women in the central states consume either eggs or meat/chicken/fish. Apparently, these states also fall below the national poverty line (27). Among different Indian states, Kerala and Goa which are located in the coastal area have the highest record of chicken/meat/fish consumption; fish consumption especially is particularly noteworthy in these states for a long time (28). Milk or curd consumption is around 90% among women in Haryana, Punjab and Himachal Pradesh and about 80% in Nagaland and

Gujarat. It is relatively much lower in Orissa, West Bengal, Madhya Pradesh, Kerala and few other northeastern states. The overall fruits consumption is also low in India noticeably in the Central and Eastern regions. Very few states, for example, Goa, Andhra Pradesh and Tamil Nadu show some consistency and balance in the consumption of different diets. According to the 1998 FAO report, the average Indian dietary intake remains largely deficient in the consumption of green leafy vegetables, milk and milk products, fish and meat (29).

--- Table 1 about here ---

Model estimation. We fitted a model consisting of 8 latent classes using several runs in order to avoid local maxima. It has to be noted that more than 8 classes would be difficult to accept because of the number of parameters involved in the model. The results suggested that the best solution has at least 8 classes ($S \geq 8$), corresponding to at least 175 free parameters (**Table 2**). However, when we observed the profile (elbow) of the C_S function (**Figure 1**), we figured out that a solution with more than 5 classes has a marginal effect for the given sample consistent criteria: i.e., BIC and CAIC. Therefore, we considered five latent classes or groups ($S = 5$) in the model corresponding to 109 independent parameters without loosing much information and for better interpretation reasons.

--- Table 2 and Figure 1 about here ---

The observed frequency at the aggregate level for each category of the variable that corresponds to the aggregate sample proportions under the homogeneity hypothesis is shown in **Table 3**. The definitions are based on the frequency and combinations of dietary intake on a daily, weekly, occasionally or never basis ($\hat{\theta}_{sjl}$). Comparing these proportions with those within each class, we obtain a description of each class that enables one to label it. Based on the estimation of the prior probability or size of each class ($\hat{\pi}_s$), it became clear that these five classes are quite balanced, ranging from 16.2% to 25.5% of the entire sample. A graphical representation of the patterns of food intake within these classes is shown in **Figure 2(a-f)**. After ordering the identified classes, we defined the class corresponding to 25.5% of the sample as women having a very high mixed diet, 21.4% representing a high mixed diet, 20.6% representing a moderate consumption of mixed diet, and roughly 16% each representing a low and a very low mixed diet respectively. The interpretations although little complex reveal interesting diet intake patterns.

Women who favor a high mixed diet consume mostly vegetables other than green and leafy ones, and pulses or beans on a daily basis, whereas eggs, chicken, meat or fish are consumed on a weekly basis (Table 3). On the other extreme, women who consume low or very low mixed diet seem to have completely avoided non-vegetarian diet. For example, among women in the low mixed diet cluster, more than three-fifth consume milk/curd, pulses/beans and other vegetables on a daily basis whereas only negligible proportions seem to have consumed eggs, meat/chicken/fish. This clearly pinpoints the distinctiveness of the low mixed diet cluster. About 99% of women in this cluster consume important vegetarian foods; more than 60% of them tend to consume vegetarian foods on a daily basis (Figure 2e). Frequent fruit consumption on a daily basis is also relatively high in this cluster. We presume that most of the respondents in the low mixed diet cluster might be belonging to the affluent class. About 98% in the low mixed diet cluster appear to have never included chicken/meat/fish in their diet, which probably indicates the segregation of a vegetarian group in the sample. Although about one half of those belonging to very high mixed diet cluster consumes milk/curd, pulses/beans and vegetables on a daily basis, the relative intake of eggs and chicken/meat/fish is only close to 10%. The consumption of fruits on a daily/weekly basis is dismally low for the very low mixed diet groups.

--- Table 3 and Figure 2 about here ---

After estimating the LC model and obtaining five latent patterns of food intake, a profile of each segment is needed. Each woman was allocated to the segments according to the posterior probability based on optimal Bayesian classification (**Table 4**). The allocation of clusters using a hard partition explains small differences between results for all India figures in Table 4 and segment sizes (prior probabilities) in Table 3, which are based on a fuzzy-like partition. This means that each woman was classified into the segment, as shown in Table 4, with the highest posterior probability. The analysis of response profiles provide vital information about the nature of the class assignment yielded from the LC analysis. Inter-state variations with regard to dietary practices are also highly pronounced (Table 4). The aggregate (mean) posterior probabilities (α_{is}) of dietary intake by states indicate that the average probability of belonging to group with very high mixed diet in the southern states of Tamil Nadu and Andhra Pradesh and Assam in the northeastern part is larger than 50%. A low mixed diet representation is mostly observed in Punjab (64%) and Haryana (76.3%) respectively. A moderate mixed diet is observed in Kerala, Orissa, West Bengal and few northeastern states. The central states and Rajasthan and Punjab in the North showed poorer intake of very high mixed diet whereas these states appear to have demonstrated either low or very low composition of mixed diet in their food intake.

--- Table 4 about here ---

Characterizing dietary intake patterns. The spatial and socioeconomic profiles of respondents differed considerably among different diet composition patterns (**Table 5**). Regarding demographic characteristics, various compositions of dietary intake do not significantly diverge; the differences seem to be trivial with respect to aggregate figures. Both very high and low mixed diet clusters were predominantly urban respondents whereas a significant proportion of rural respondents belong to either moderate or very low mixed diet cluster. Regional variations indicate that considerable proportions of respondents from the southern regions fall in the very high mixed diet cluster whereas those from the northern regions fall in the low mixed diet cluster. Living standards differentials indicate that the affluent respondents tend to fall towards either low or very high mixed diet. Respondents without any schooling experiences are more likely to fall in the very low mixed diet cluster whereas those who had completed high school and above are more likely to fall in the low mixed diet cluster. A significant proportion of Muslim respondents fall in the very high mixed cluster and a very high proportion of Hindus in the low and very low mixed diet clusters respectively. A major proportion of women do not have a defined ethnicity and they seem to represent the low mixed diet cluster. Scheduled caste and scheduled tribe respondents represent mostly high and moderate mixed diet clusters. Non-working women are more likely to belong to the low mixed diet group and those engaged in agricultural activities fall mostly in the very low mixed diet cluster. We examined few other variables that were either less important or did not show any significant associations, for example respondent’s current pregnancy status, total number of household members, head of the household and respondent’s current marital status (not shown in Table 5).

--- Table 5 about here ---

Multinomial results. The relative effects of selected characteristics on different dietary clustering were examined using multinomial logistic regression models (**Table 6**). The direction and statistical significance of characteristics were more important than the magnitude of the effects. The reference category of the dependent variable, in the regression model, was respondents representing the very low mixed diet cluster. The model examined the spatial, socioeconomic and cultural influences on women’s dietary behavior with a statistical control of selected demographic characteristics. The estimated coefficients for the place of residence are generally positive and significantly larger especially for very high mixed diet groups suggesting that rural respondents are relatively more likely than their urban counterparts to fall in the very high mixed diet cluster. In comparison with very low mixed diet group, respondents in most of the regions except southern and northeastern regions are less likely to represent the very high mixed diet cluster (*p*<0.001). The poorer women are significantly more likely to represent moderate or high mixed diet cluster when compared with their affluent counterparts; the affluent groups seem to be found mostly in the low mixed diet cluster. The effects although similar are not strong for those living in average conditions. On the other hand, the results purport that women living in better conditions are almost equally likely to consume either a very high or a low mixed diet. This indicates a differential behavior pattern of dietary intake among people living in better conditions, which could be ascribed to two possible reasons; either non-accessibility of very high mixed diet options such as fish or meat or vegetables in various regions (non-coastal/semi-arid) or a strong attitude towards a low mixed diet (vegetarian). Better levels of education are found less likely to belong in the very low mixed diet cluster. The odds to be in the low mixed diet category are significantly likely for Muslim respondents than their Hindu counterparts and also for respondents without any predefined ethnicity. Other ethnic groups are likely to fall in the very high mixed diet cluster. When compared with women who were not working at the time of survey, those engaged in professional and services sector are significantly less likely to be in the very low mixed diet cluster.

In a separate model, we tested the interaction effect between place of residence and standard of living on dietary behavior after adjusting for the potential confounding effects of demographic and other socioeconomic and cultural variables (**Table 7**). The results revealed that urban affluent women are likely to be either in the very high or low mixed diet cluster; the effects are positive and statistically significant. Furthermore, rural women who live in better or moderate conditions are likely to be in either a very high or low mixed diet when compared to the poorer counterparts (*p*<0.001). Most of the control variables in this model were found significant.

--- Tables 6 and 7 about here ---

DISCUSSION

Three research questions were addressed in this study using the data from NFHS-2. First, we sought to examine the patterns of dietary intake among women in India. Second, we asked how a LC analysis provides better insights to understand the complex patterns of dietary intake behavior. Third, we questioned whether certain clusters of women differ in their dietary intake according to different demographic, socioeconomic and cultural characteristics. NFHS-2 showed that overall consumption of green, leafy and other vegetables and pulses or beans were high in the sample. Fruit or egg consumption at least once a week was very low in the central states whereas milk or curd consumption was found below the national average in the eastern and few other northeastern regions. Few states such as Goa, Kerala and West Bengal recorded a high consumption of chicken, meat or fish; presumably more fish than other meat products. These states are also geographically located in the coastal areas.

The information on the frequency of diet intake was further pooled and then disaggregated into five classes or clusters using the LC models. This five component solution provided a good compromise between capturing unobserved heterogeneity and disentangling the model complexity. These segments were ordered based on the degree of diet mixing and were labeled as: very high, high, moderate, low and very low mixed diets. About 26% of the sample constituted very high and roughly 15% were very low mixed diet clusters. The states Andhra Pradesh, Tamil Nadu, Kerala, Goa and few northeastern states showed a very high or high mixed diet clustering and in contrast, the larger and poorer states such as Rajasthan, Uttar Pradesh and Madhya Pradesh fall in either low or very low mixed diet cluster.

The LC analysis employed in this study provided some useful results which is probably difficult to establish otherwise. Amongst women in the very high mixed diet cluster, quite large proportions consume non-green and non-leafy vegetables on a daily basis, and fruits and other non-vegetarian diet on a weekly basis. This suggests three different possible scenarios. First, only few households could afford to buy non-vegetarian foods on a daily basis. Second, although there is an income provision to afford non-vegetarian foods on a daily basis, sometimes it may be difficult to access such foods due to either a lack of production in certain regions (geographical constraints) or due to certain intra-household decisions on food consumption. Finally, it may be because of either a lack of awareness about balanced nutrition intake or because of general aversion to certain foods. The result that low mixed diet cluster consume more than three fifth of the major vegetarian diet ingredients vis-à-vis milk/curd, pulses/beans and vegetables on a daily basis is highly convincing. This particular group seems to be segregated in the northern region especially in Punjab and Haryana.

The concentration of very high mixed diet cluster is observed predominantly in rural areas and those residing in the southern areas. More than 50% of women who belong to low diet cluster were living in affluent conditions. Most of the spatial and socioeconomic and cultural characteristics showed stronger associations with dietary behavior than the selected demographic characteristics. Among other important results, one noteworthy result is women who lived in better conditions are equally likely to be in either a very high or a low mixed diet cluster. They are, however, less likely to be in the very low mixed diet cluster. This result could be interpreted as follows. In the case of vegetarians, women might tend to include all possible mixed diets except meat, chicken or fish and therefore a low mixed diet composition. In the case of non-vegetarians, they seem to have a well-balanced diet in their food consumption. These results are only possible indications and might not reflect the actual diet mixing attitudes.

Quite unfortunately, we could not differentiate between vegetarians and non-vegetarians from the NFHS sample although we partly succeeded in differentiating various diet compositions; the information of which would have yielded better insights of dietary practices and poverty. Our results showed that the urban affluent groups are highly likely to have followed a very high or low mixed diet and their poorer counterparts are likely to have had a high or moderate mixed diet in their food intake. The discrepancy is found much larger for the poor living in rural areas. The lack of appropriate food supply networks and instable political conditions especially in the poorer central and eastern Indian states could explain the vulnerability of certain groups to access the required food (27, 30). Nonetheless, the poorer households seem to allocate more than 70% of the household income on food alone; yet the nutritional needs are largely unmet and many of these poor continue to starve (31-32). The results from an Engel curve analysis of food consumption in Maharashtra reported that in many larger households size the budget share of coarse cereals, pulses, fruits and vegetables including rice tend to decrease whereas wheat consumption tend to increase significantly irrespective of any demographic or economic influences (33). Apart from poverty reasons, there are also cultural factors such as religious restrictions to diet intake. Religion and ethnicity are two other major characteristics that distinguish people's food consumption habits especially in the some southern and northern regions in India; for example, traditional orthodox Hindu Brahmin communities consume mostly vegetarian foods unlike other religious groups. These interlinked factors highlight not only socio-economic, cultural and demographic disparities related to dietary practices but also the heterogeneity within different type of food that people consume.

An important data limitation of our study is the self-reported information available only for women. In the Indian context if a woman is particularly not working (more than 60% of our sample was not working at the time of survey) she is likely to bear the full household burden including cooking and upbringing children. Apparently, she is likely to position herself as the last priority after taking care of other household members, especially in joint families. Furthermore, the self-reported information on the frequency of food intake was gathered at one point in time, i.e., cross-sectional and not longitudinal. The nature of cross-sectional data impedes our analysis to capture the historical and prospective time effects.

Besides, we could not consider many other important nutrient related foods including cereals in the model due to lack of information. Therefore, the results presented in this study should be deemed with caution. Finally, to the best of our knowledge, this is probably one of the first attempts to model complex food intake patterns. Further extensions of the model for different populations and more refinements of data collection methodology are suggested for a deeper understanding of dietary behavior.

Finally, our findings recommend the need for a comprehensive and effective food policy in India to be integrated along with the national population and health policy. Although, the country succeeded in controlling population growth to a certain extent, the nutritional health of people especially women and children remain a distant goal especially in the light of emerging coexistence of both obesity and undernutrition (34-36). The available statistics show that there is no dearth of food resources in order to maintain population sustainability especially in these regions, but to the fact whether food supply reaches each population segment and whether dietary intake is well-balanced in different compositions are the important concerns to be addressed. The importance of an optimal or balanced diet mixing is reflected in the fact that the nutritional quality of the diet does improve with the consumption of greater diet diversity (37-39). The conclusion of this study points out the need for a detailed demographic investigation of dietary intake between the vegetarians and the non-vegetarians both at the individual and population levels. Whilst, there exist few interventions from the state and national government to enhance better health through mid-day meal programs in the schools and nutrition supply for pregnant mothers, the question is what proportion of the population gets a balanced diet and whether food is accessible, available and affordable to everyone.

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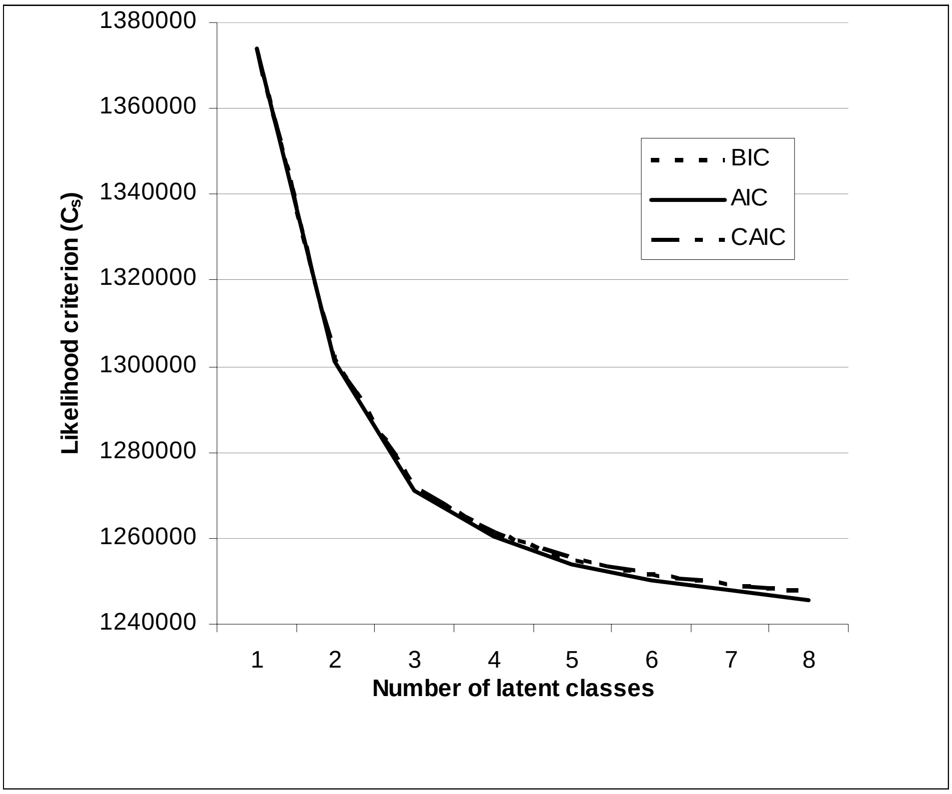

FIGURE 1 Plot of likelihood criteria by the number of latent classes

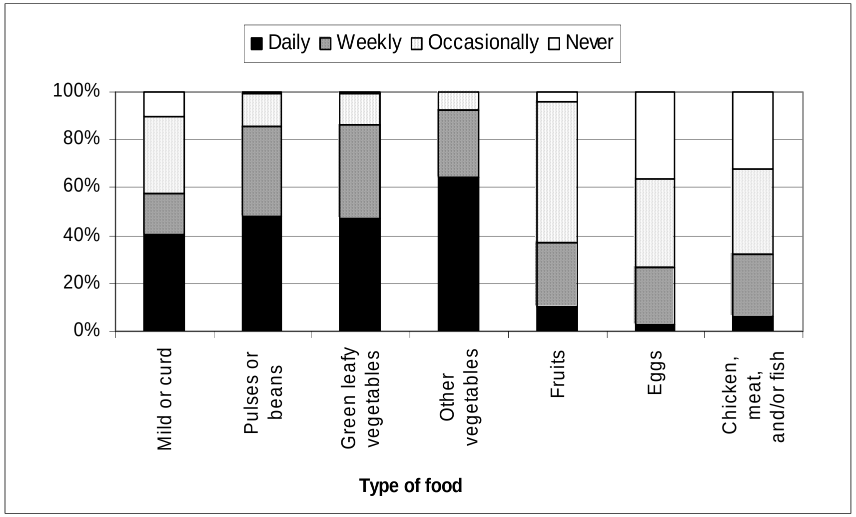

FIGURE 2a Aggregate Model

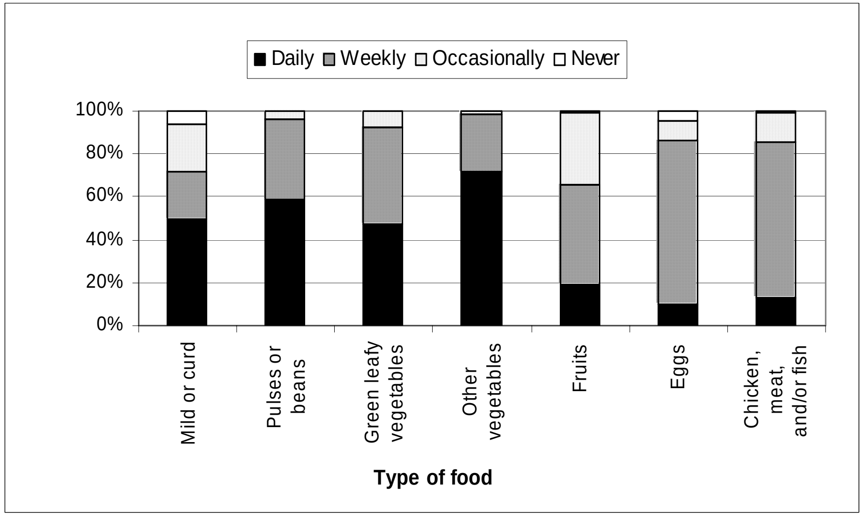

FIGURE 2b Very high mixed diet cluster

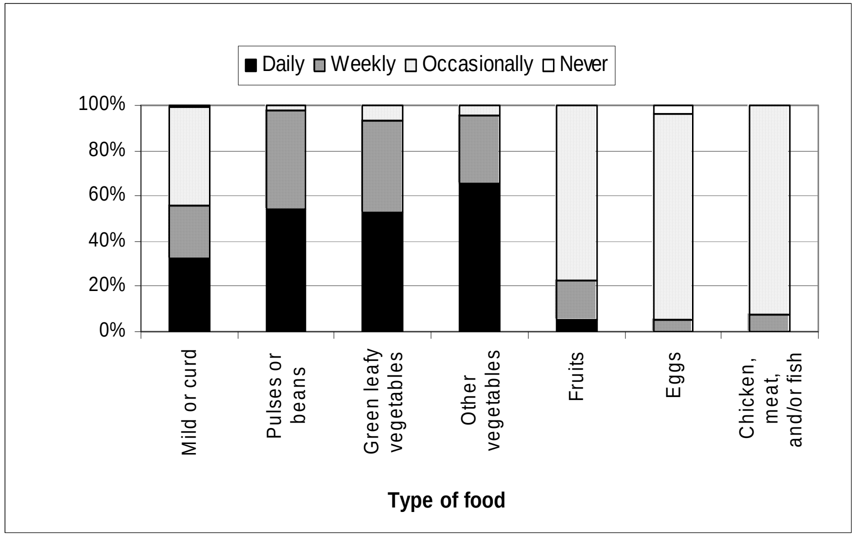

FIGURE 2c High mixed diet cluster

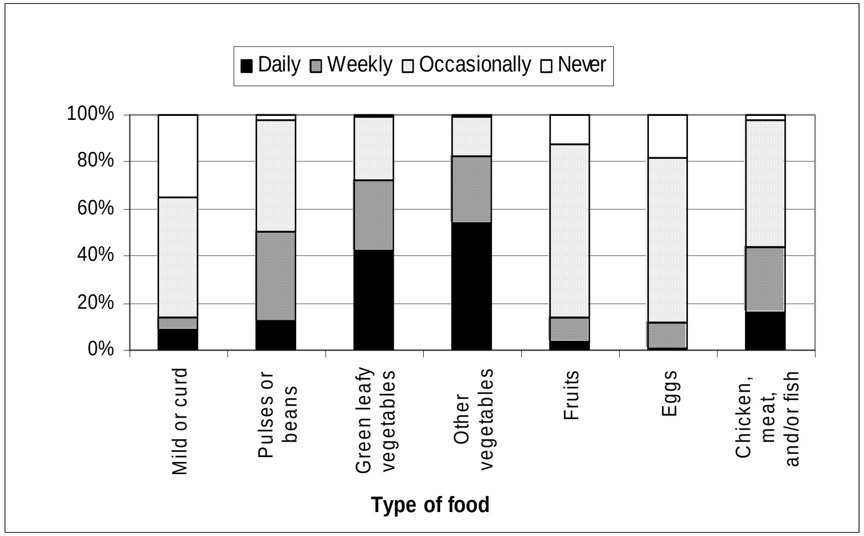

FIGURE 2d Moderate mixed diet cluster

Contd.

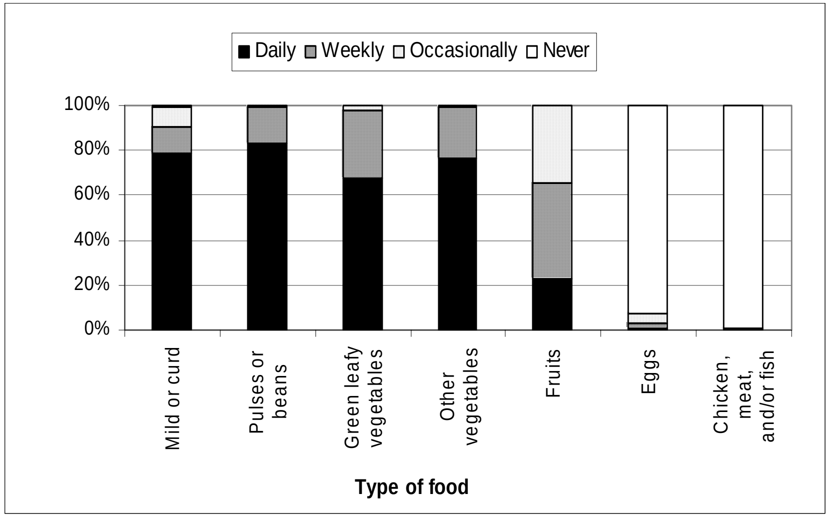

FIGURE 2e Low mixed diet cluster

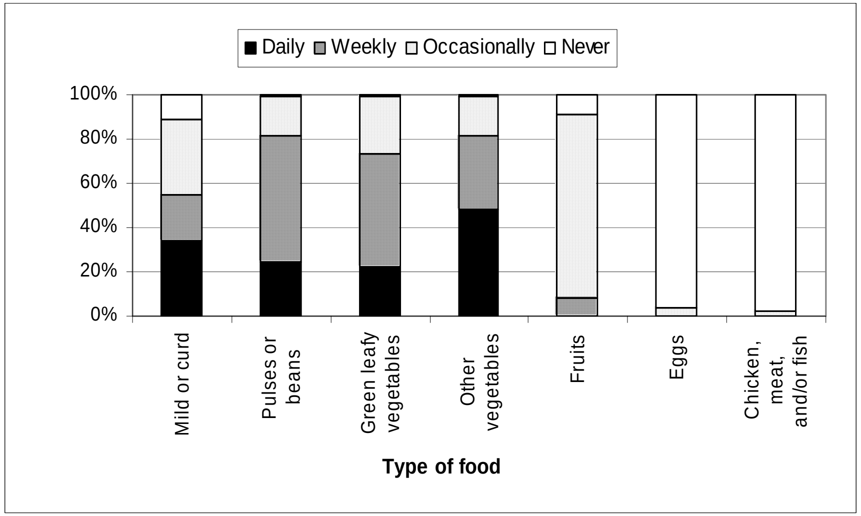

FIGURE 2f Very low mixed diet cluster

FIGURE 2 Dietary intake profiles for the five latent classes and the aggregate model (%)

TABLE 1

Percent distribution of ever-married women classified by dietary intake at least once in week, India and states, 1998-99

State	Type of food							Number of women
	Milk or curd	Pulses or beans	Green, leafy vegetables	Other vegetables	Fruits	Eggs	Chicken, meat, or fish	
India	55.0	87.8	85.2	93.1	33.0	27.8	31.9	90303
North								
Delhi	73.3	91.2	86.8	92.8	57.8	21.2	15.1	2477
Haryana	93.2	99.3	99.2	99.2	54.8	7.7	3.8	2908
Himachal Pradesh	87.0	99.1	94.3	98.8	71.7	14.7	6.2	3012
Jammu & Kashmir[1]	72.1	68.5	85.5	88.3	44.0	14.2	31.1	2744
Punjab	91.1	99.2	99.1	99.5	50.7	10.8	3.6	2796
Rajasthan	70.7	81.4	77.8	78.9	20.5	6.1	7.8	6813
Central								
Madhya Pradesh	32.5	79.9	80.9	86.1	22.7	11.7	11.2	6941
Uttar Pradesh	57.2	88.0	90.0	90.7	19.0	9.9	8.7	9292
East								
Bihar	46.7	88.7	96.0	96.1	18.3	22.1	21.5	7024
Orissa	20.7	80.7	90.9	95.8	14.4	15.6	28.2	4425
West Bengal	25.0	76.3	91.4	98.7	15.0	43.5	69.0	4408
Northeast								
Arunachal Pradesh	19.9	51.2	95.6	72.7	28.9	33.5	57.4	1117
Assam	41.7	85.3	87.6	94.9	33.3	58.4	57.7	3441
Manipur	15.3	37.3	96.9	93.2	34.3	14.8	47.4	1435
Meghalaya	23.7	61.5	88.9	91.8	40.3	32.6	61.8	945
Mizoram	22.9	64.5	99.2	87.1	61.6	42.5	59.3	1048
Nagaland	82.7	59.6	96.3	80.6	40.9	30.2	72.3	818
Sikkim	72.4	82.9	94.9	87.5	28.8	26.8	57.1	1107
Tripura[2]	51.0	86.1	91.2	91.5	39.9	56.3	65.2	1104
West								
Goa	65.0	76.5	74.6	82.5	65.8	36.6	89.0	1246
Gujarat	80.0	97.0	74.1	99.2	44.4	14.0	12.4	3845
Maharashtra	47.3	94.5	87.9	91.1	44.7	34.4	38.2	5391
South								
Andhra Pradesh	72.0	92.3	72.7	95.7	47.6	59.7	56.7	4032
Karnataka	75.5	98.6	93.3	91.8	53.7	39.9	33.9	4374
Kerala	45.3	69.8	54.8	90.9	56.5	27.3	82.8	2884
Tamil Nadu	66.5	94.6	77.6	98.7	46.2	52.7	52.6	4676

Note : weighted data, source: IIPS (2000, p. 244).

[1]Jammu region of Jammu & Kashmir.

Less than 0.1 cases were missing for all India and states.

[2]At the time when the NFHS-2 report was published, the state Tripura was not included because the fieldwork was not completed. We included Tripura in the analysis.

TABLE 2

Number of latent classes and the corresponding information criteria for the dietary intake patterns

No. of components	Log-likelihood	No. of parameters	Information Criteria		
			BIC	AIC	CAIC
1	-686850	21	1373940	1373743	1373961
2	-650662	43	1301814	1301410	1301857
3	-635575	65	1271892	1271280	1271957
4	-630190	87	1261373	1260555	1261460
5	-626884	109	1255011	1253985	1255120
6	-624971	131	1251437	1250205	1251568
7	-623692	153	1249130	1247691	1249283
8	-622683	175	1247364	1245717	1247539

BIC: Bayesian Information Criterion

AIC: Akaike Information Criterion

CAIC: Consistent Akaike Information Criterion

TABLE 3

Estimation of model parameters for the five latent classes representing different dietary intake behavior, India, 1998-99

Variables		Latent classes[1] Very high mixed diet	High mixed diet	Moderate mixed diet	Low mixed diet	Very low mixed diet	Aggregate
Mild or curd							
	Daily	0.492	0.312	0.125	0.767	0.365	0.402
	Weekly	0.222	0.221	0.074	0.131	0.192	0.172
	Occasionally	0.218	0.435	0.503	0.084	0.338	0.321
	Never	0.068	0.033	0.299	0.019	0.105	0.106
Pulses or beans							
	Daily	0.585	0.524	0.174	0.795	0.303	0.476
	Weekly	0.374	0.417	0.398	0.196	0.521	0.383
	Occasionally	0.038	0.059	0.405	0.009	0.171	0.135
	Never	0.004	0.000	0.023	0.000	0.005	0.007
Green leafy vegetables							
	Daily	0.477	0.514	0.433	0.656	0.270	0.472
	Weekly	0.447	0.401	0.316	0.307	0.491	0.394
	Occasionally	0.073	0.085	0.242	0.036	0.234	0.131
	Never	0.002	0.000	0.009	0.001	0.006	0.004
Other vegetables							
	Daily	0.712	0.650	0.555	0.761	0.504	0.641
	Weekly	0.266	0.302	0.287	0.225	0.332	0.282
	Occasionally	0.021	0.047	0.152	0.014	0.161	0.075
	Never	0.001	0.001	0.006	0.000	0.004	0.002
Fruits							
	Daily	0.188	0.053	0.040	0.229	0.004	0.106
	Weekly	0.452	0.193	0.115	0.419	0.106	0.266
	Occasionally	0.350	0.753	0.735	0.352	0.805	0.590
	Never	0.010	0.001	0.109	0.000	0.085	0.039
Eggs							
	Daily	0.099	0.000	0.011	0.005	0.000	0.028
	Weekly	0.735	0.078	0.139	0.020	0.004	0.236
	Occasionally	0.124	0.882	0.695	0.044	0.029	0.375
	Never	0.043	0.041	0.156	0.931	0.968	0.361
Chicken, meat, and/or fish							
	Daily	0.123	0.011	0.149	0.003	0.000	0.065
	Weekly	0.710	0.104	0.259	0.003	0.008	0.258
	Occasionally	0.159	0.880	0.569	0.014	0.043	0.355
	Never	0.009	0.005	0.023	0.981	0.949	0.323
Component prior probability		0.255	0.214	0.206	0.164	0.162	

[1]The asymptotic standard errors for the parameter estimates ranged between 0.0007 and 0.0068.

TABLE 4

Profiling of latent class probabilities representing different dietary intake patterns by region and states, India, 1998-99

State	Very high mixed diet	High mixed diet	Moderate mixed diet	Low mixed diet	Very low mixed diet	Total
	Latent classes					
India	0.258	0.224	0.194	0.171	0.153	1.000
North						
Delhi	0.183	0.228	0.086	0.349	0.154	1.000
Haryana	0.062	0.105	0.005	0.763	0.065	1.000
Himachal Pradesh	0.166	0.319	0.007	0.450	0.058	1.000
Jammu & Kashmir	0.218	0.268	0.263	0.135	0.116	1.000
Punjab	0.101	0.172	0.007	0.643	0.077	1.000
Rajasthan	0.054	0.087	0.100	0.167	0.592	1.000
Central						
Madhya Pradesh	0.081	0.188	0.207	0.185	0.339	1.000
Uttar Pradesh	0.088	0.322	0.104	0.184	0.302	1.000
East						
Bihar	0.202	0.466	0.198	0.075	0.059	1.000
Orissa	0.187	0.379	0.364	0.026	0.044	1.000
West Bengal	0.453	0.116	0.403	0.021	0.007	1.000
Northeast						
Arunachal Pradesh	0.256	0.160	0.574	0.007	0.003	1.000
Assam	0.520	0.220	0.236	0.018	0.006	1.000
Manipur	0.119	0.120	0.748	0.006	0.007	1.000
Meghalaya	0.321	0.126	0.537	0.005	0.011	1.000
Mizoram	0.450	0.090	0.450	0.000	0.010	1.000
Nagaland	0.395	0.258	0.346	0.000	0.001	1.000
Sikkim	0.363	0.313	0.212	0.064	0.048	1.000
Tripura	0.551	0.174	0.248	0.009	0.018	1.000
West						
Goa	0.517	0.068	0.361	0.035	0.019	1.000
Gujarat	0.140	0.106	0.041	0.361	0.352	1.000
Maharashtra	0.408	0.164	0.134	0.170	0.124	1.000
South						
Andhra Pradesh	0.565	0.186	0.160	0.059	0.030	1.000
Karnataka	0.372	0.283	0.062	0.219	0.064	1.000
Kerala	0.357	0.063	0.543	0.017	0.020	1.000
Tamil Nadu	0.565	0.256	0.125	0.038	0.016	1.000

TABLE 5

Profiling of latent class probabilities representing dietary intake patterns by demographic, spatial, socio-economic and cultural characteristics, India, 1998-99

Characteristics	Latent classes					
	Very high mixed diet (N=23,290)	High mixed diet (N=20,189)	Moderate mixed diet (N=17,523)	Low mixed diet (N=15,391)	Very low mixed diet (N=13,787)	Aggregate (N=90,180)
Demographic						
Current age (in years)						
<24	0.247	0.249	0.274	0.229	0.276	0.255
25-34	0.390	0.373	0.379	0.372	0.358	0.376
35+	0.363	0.378	0.347	0.399	0.366	0.369
Children below 5 years[1]						
2+	0.232	0.280	0.303	0.248	0.325	0.274
1	0.278	0.292	0.275	0.254	0.260	0.273
None	0.490	0.428	0.422	0.498	0.415	0.453
Spatial						
Place of residence						
Urban	0.469	0.231	0.208	0.405	0.186	0.311
Rural	0.531	0.769	0.792	0.595	0.814	0.689
Region						
South	0.325	0.167	0.175	0.093	0.039	0.177
West	0.145	0.068	0.076	0.153	0.148	0.116
Northeast	0.186	0.102	0.245	0.011	0.008	0.122
East	0.182	0.270	0.273	0.048	0.046	0.176
Central	0.060	0.212	0.137	0.194	0.373	0.180
North	0.102	0.180	0.095	0.503	0.385	0.230
Socio-economic & cultural						
Standard of living						
Low	0.208	0.476	0.378	0.090	0.287	0.290
Medium	0.494	0.441	0.486	0.400	0.549	0.475
High	0.298	0.083	0.136	0.510	0.164	0.235
Education						
High school+	0.138	0.049	0.034	0.200	0.036	0.093
Secondary	0.343	0.180	0.178	0.315	0.139	0.238
Primary	0.185	0.160	0.188	0.155	0.156	0.171
None	0.334	0.611	0.600	0.330	0.669	0.498
Religion						
Others	0.027	0.016	0.049	0.020	0.009	0.025
Sikh	0.010	0.018	0.002	0.084	0.013	0.023
Christian	0.089	0.032	0.127	0.001	0.002	0.056
Muslim	0.189	0.141	0.178	0.010	0.015	0.119
Hindu	0.685	0.793	0.644	0.885	0.961	0.777

contd.

TABLE 5 (contd.)

Profiling of latent class probabilities representing dietary intake patterns by demographic, spatial, socio-economic and cultural characteristics, India, 1998-99

	Latent classes					
Characteristics	Very high mixed diet (N=23,290)	High mixed diet (N=20,189)	Moderate mixed diet (N=17,523)	Low mixed diet (N=15,391)	Very low mixed diet (N=13,787)	Aggregate (N=90,180)
Ethnicity						
Scheduled caste	0.155	0.223	0.185	0.107	0.160	0.169
Scheduled tribe	0.104	0.113	0.252	0.025	0.100	0.121
Other backward class	0.307	0.332	0.233	0.232	0.329	0.288
None	0.434	0.332	0.330	0.636	0.411	0.422
Type of employment						
Professional	0.039	0.018	0.014	0.043	0.009	0.026
Services	0.044	0.023	0.035	0.026	0.013	0.030
Agriculture	0.145	0.250	0.303	0.121	0.348	0.226
Skilled manual	0.050	0.043	0.061	0.030	0.034	0.045
Unskilled manual	0.039	0.046	0.065	0.013	0.036	0.041
Non working	0.683	0.620	0.522	0.767	0.560	0.632

[1]children currently living at home.

TABLE 6

Multinomial logistic model of dietary intake patterns[a] (N=90,157)

	Latent classes							
Characteristic	Very high mixed diet		High mixed diet		Moderate mixed diet		Low mixed diet	
Spatial								
Place of residence (Ref.=Urban)								
Rural	0.914***	(0.03)	0.292	(0.03)	0.327***	(0.04)	0.103**	(0.03)
Region (Ref.=South)								
West	-2.560***	(0.06)	-2.342***	(0.06)	-2.441***	(0.06)	-1.165***	(0.06)
Northeast	0.548***	(0.10)	0.685***	(0.10)	1.017***	(0.10)	-1.022***	(0.06)
East	-0.664***	(0.06)	0.252***	(0.06)	0.218**	(0.07)	-1.032***	(0.08)
Central	-3.984***	(0.05)	-2.074***	(0.05)	-2.573***	(0.06)	-1.599***	(0.13)
North	-3.997***	(0.06)	-2.515***	(0.06)	-3.249***	(0.06)	-1.173***	(0.06)
Socioeconomic & cultural								
Standard of living (Ref.=High)								
Low	-0.612***	(0.05)	0.175***	(0.04)	0.769***	(0.05)	-1.292***	(0.04)
Medium	-0.403***	(0.04)	0.025	(0.04)	0.320***	(0.04)	-0.739***	(0.03)
Education (Ref.=None)								
Primary	0.429***	(0.04)	0.105**	(0.03)	0.247***	(0.04)	0.286***	(0.04)
Secondary	0.816***	(0.04)	0.305***	(0.04)	0.375***	(0.04)	0.719***	(0.04)
High school+	1.138***	(0.06)	0.459***	(0.07)	0.429***	(0.08)	1.230***	(0.06)
Religion (Ref.=Hindu)								
Muslim	-3.633***	(0.07)	-3.066***	(0.07)	-3.700***	(0.07)	0.315**	(0.10)
Christian	-0.751**	(0.24)	-0.573*	(0.23)	-0.288	(0.23)	-0.549*	(0.32)
Others	-2.789***	(0.10)	-2.246***	(0.10)	-2.502***	(0.10)	1.303***	(0.12)
Ethnicity (Ref.=None)								
Other backward class	0.047	(0.03)	0.198***	(0.03)	-0.133***	(0.03)	-0.340***	(0.03)
Scheduled tribe	0.541***	(0.05)	0.619***	(0.05)	1.024***	(0.04)	-0.691***	(0.06)
Scheduled caste	0.916***	(0.04)	0.939***	(0.04)	0.822***	(0.04)	-0.230***	(0.04)
Type of employment (Ref.=Non-working)								
Unskilled manual	0.052	(0.07)	0.158*	(0.06)	0.564***	(0.06)	-0.760***	(0.09)
Skilled manual	-0.206**	(0.06)	-0.194**	(0.06)	0.294***	(0.06)	-0.442***	(0.07)
Agriculture	-0.448***	(0.03)	-0.233***	(0.03)	0.035	(0.03)	-0.746***	(0.03)
Services	0.354***	(0.09)	0.275**	(0.10)	0.576***	(0.10)	-0.023	(0.10)
Professional	0.313**	(0.11)	0.407***	(0.11)	0.176	(0.12)	0.120	(0.10)
Intercept	5.686***	(0.09)	4.282***	(0.09)	4.306***	(0.10)	1.645***	(0.13)

Note: estimates of b coefficients are presented and standard errors are shown in parantheses.

-2log-likelihood of the final model was 92,229.

[a]Controlled for current age, children aged below 5 years and respondent's current pregnancy status.

**p* <0.05; ***p* <0.01; ****p* <0.001.

TABLE 7

Multinomial logistic model of dietary intake patterns[a]: Adjusted interaction effects (N=90,157)

Characteristic	Latent classes: Very high mixed diet	High mixed diet	Moderate mixed diet	Low mixed diet
Living standards*residence (Ref.=Low*rural)				
High*urban	1.497*** (0.05)	0.134* (0.06)	-0.520*** (0.07)	1.423*** (0.06)
Medium*urban	1.179*** (0.05)	0.144** (0.05)	-0.053 (0.05)	0.589*** (0.06)
Low*urban	1.009*** (0.08)	0.289*** (0.06)	0.240** (0.08)	0.111 (0.09)
High*rural	0.728*** (0.05)	-0.181*** (0.05)	-0.696*** (0.06)	1.264*** (0.05)
Medium*rural	0.215*** (0.04)	-0.151*** (0.03)	-0.487*** (0.03)	0.567*** (0.05)
Intercept	5.051*** (0.10)	4.457*** (0.10)	5.079*** (0.11)	0.359*** (0.13)

Note: estimates of b coefficients are presented and standard errors are shown in parantheses.
-2log-likelihood of the final model was 92,168.
[a]Controlled for demographic, other spatial, socioeconomic and cultural characteristics.
**p* <0.05; ***p* <0.01; ****p* <0.001.