

A Bayesian Network Analysis of Family Closeness and Language on Family Happiness in Turkey

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Abstract

Understanding the factors that contribute to family happiness is critical for fostering social cohesion and individual well-being, especially within the unique cultural and relational dynamics of Turkey. Being at the crossroad between the East and the West, Turkey offers a heterogeneous environment for the analysis of family structure and happiness. As a large nationally representative dataset exists, we have a very rich source of information available to us. Utilizing the Turkish Family Structure Survey, conducted by the Turkish Statistical Institute in collaboration with the Ministry of Family and Social Services, this study uses the data from more than 35 thousand individuals to analyze various aspects of the family happiness and language consistency from a causal standpoint. Our analysis employs a Bayesian modeling framework to explore how family happiness interacts with key variables, including language consistency (the use of native language inside versus outside the home), as well as variables indicating family closeness, such as the frequency of meeting, giving gifts, living distance, and the frequency of arguments. To the best of our knowledge, no past studies have conducted such a comprehensive network analysis on distinct yet relevant aspects of family structure using Bayesian methods. The findings suggest a strong relationship between the family happiness, linguistic diversity, gift-giving, the living distance from family members, and the number of visits.

Keywords: Bayesian Networks, Family Structure, Happiness, Language

1. Introduction

Past studies in clinical and applied linguistics, psychology, education, and family studies have analyzed the relationship between the family well-being and language use (e.g. De Houwer, 2015, 2017; Lee, 2011; Tseng & Fuligni, 2000). Müller et al. (2020) analyze the effects of speaking multiple languages on the well-being and happiness of the family and children. They identify a positive link between minority language maintenance and child well-being. Wang (2013) also conducts a detailed analysis of some common issues that might hurt the happiness of multilingual families. Their focus is to suggest strategies to deal with those issues. They identified one of the main problems to come from the difference in the culture of the parents which results in various issues. Similarly, Hajdu and Hajdu (2015) examine the effects of culture on the well-being. Furthermore, Nayernia and Babayan (2019) demonstrate the effect of language proficiency on emotional exhaustion of teachers. But none of the past literature conduct a complete network analysis of relevant family closeness variables that might allow for better understanding of language use and family happiness. In addition, all above studies had limited access to small, experimental datasets of only 40 to 500 participants.

Another relevant line of study is done by Aknin et al. (2020). Building upon the past literatures on family satisfaction and gift giving (Dunn et al., 2008, 2014), they conduct further experiments on gift giving across different conditions. Their result supports the past work that gift giving does affect satisfaction. Although this amount might depend on the exact context of the gift, these results are also confirmed by the study of Hu et al. (2021). But this study is beyond the one-dimensional notion that gifts signal good friendships and they noted that higher amounts of gift giving increases the financial burden and might cause issues. Considering the given literature on this topic, it is crucial to conduct a detailed

analysis on the relationship of gift giving in the family happiness, in comparison to other relevant variables.

There is also significant research on other aspects of life happiness and satisfaction. Bjarnason and Haartsen (2023) build upon the past literature, analyzing one of the less explored sources of happiness in the literature, namely, the location of living. They demonstrate through a nationally representative dataset of Iceland that the proximity to family significantly influences residential satisfaction and the intention to remain in one's current residence. Hence, staying in a place close to family members highly increases the residential satisfaction and increases the likelihood of staying in the community. But this study does not go beyond the analysis of residential location and satisfaction.

Arimoto and Tadaka (2021) make an effort to identify various individual, community, and family-based factors relevant to loneliness among mothers raising children of young children. They build upon the past literature that mothers staying at home with young children are identified as a high-risk population for loneliness (Bates et al., 2016; Lee et al., 2019). Their work explains the importance of mothers to connect to organizations that focus on parenting concerns. Similarly, the study done by Luoma et al. (2017) mentions that the amount of loneliness among mothers is near 34 and 38%. Although many past works show the effect of having children on loneliness and satisfaction, none of them has covered a more comprehensive analysis.

Overall, it could be seen that although past literature has demonstrated a wide variety of elements that affect the life happiness of family members, there has been a lack of effort to bring these results together. Hereby, this study utilizes a network modeling approach to construct a comprehensive model of all these effects. Accordingly, we utilize Bayesian networks to analyze all these effects on the family satisfaction.

2. Materials and methods

a. Description of Data

In this study, we use the 2016 Türkiye Family Structure Survey. This data is gathered under the guidance of the Republic of Turkey Ministry of Family, Labour and Social Services, in collaboration with the Turkish Statistical Institute (TurkStat). Conducted in 2016 as part of the broader Official Statistics Program, the dataset is the third wave of a recurring survey that began in 2006. It is a nationally representative sample of Turkish households, employing stratified, multi-stage sampling to capture insights on diverse demographic, social, and cultural aspects of family life across all rural and urban regions in Turkey. Furthermore, the survey includes data from 17,239 households and 35,475 individuals aged 15 and older in the various aspects of household characteristics, marriage and fertility trends, intergenerational relationships, kinship dynamics, and evolving cultural values within Turkey.

b. Bayesian Modeling

This study applies Bayesian Networks to analyze the data, as they can model complex causal relationships using a Directed Acyclic Graph (DAG). Bayesian Network is a probabilistic graphical model that represents variables as nodes and causal dependencies as directed edges, enabling a structured representation of how variables influence one another (McElreath, 2018). In each variable, there is a conditional probability distribution considering dependence with the parent nodes in the DAG. This approach works best for a study that has established or hypothesized causal relationships among its variables-as are analyzed in this study with the variables Family's Happiness, Frequency of Visits to Relatives, and Language Consistency.

Bayesian Networks are a good fit for social science research as they are inherently natural in encoding network-like structures, thus allowing one to model explicitly the interdependencies and causal mechanisms of social systems. For example, in this study, Family's Happiness is influenced by variables such as Frequency of Visits and Family's Way of Dealing with Issues, while Living Distance from Relatives and Language Consistency shape Frequency of Visits. The formal framework presented supports effective probabilistic inference, as well as counterfactual and intervention analyses, allowing one to reason over observed and hypothetical social data in both realistic and hypothetical contexts. Our carefully defined DAG (based on the causal relationships mentioned in the past literature) is Figure 1.

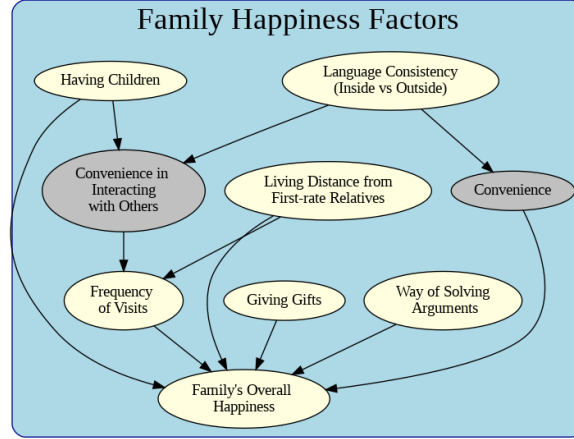


Figure 1. The graphical representation of family happiness factors fitted by our Bayesian network models.

Given the large scale of our dataset, we employed a two-stage inference process to estimate the parameters of the Bayesian Network, namely, we utilize a sequential combination of Variational Inference and No-U-Turn Sampler. Variational Inference (VI), as introduced by Hoffman et al. (2013), is a method for approximating complex posterior distributions in Bayesian inference by converting the problem into an optimization task. Instead of sampling (like MCMC), VI fits a simpler distribution $q(\theta)$ to the true posterior $p(\theta|\text{data})$ by minimizing their difference (KL divergence). VI is faster because it uses deterministic optimization techniques (e.g., gradient descent), scales well with large datasets via mini-batching, and allows for parallel computation. While it trades some accuracy for speed, VI is highly efficient for large-scale machine learning problems.

The No-U-Turn Sampler (NUTS), on the other hand, is an advanced algorithm for Bayesian inference, designed to efficiently sample from posterior distributions in high-dimensional spaces (Hoffman and Gelman, 2014). It builds on the Hamiltonian Monte Carlo (HMC) method by eliminating the need to manually tune the step size and the number of steps. NUTS automatically adjusts these parameters during sampling, ensuring efficient exploration of the parameter space. NUTS uses the gradient of the log-posterior distribution to propose new candidate points, which helps navigate the parameter space more effectively than random-walk methods. The algorithm prevents redundant computation by implementing a "No-U-Turn" criterion, which stops the sampling trajectory when it starts to loop back on itself. This ensures computational efficiency and improves convergence, which is the reason we selected NUTS as our main sampling approach.

In this study, variational inference was initially employed for 15,000 steps to efficiently approximate posterior distributions. Following this, the No-U-Turn Sampler (NUTS) was used for precise sampling. For the first model, 1,000 learning steps were performed, followed by 1,000 sampling steps per

chain for the initial model, while the extended model used 2,000 sampling steps per chain, with a total of four sampling chains. This combination of variational inference for computational efficiency and NUTS for accuracy ensures robust and scalable Bayesian Networks, making them well-suited for analyzing causal structures in such large datasets.

In total, we developed 2 main models to analyze the data. The first model is a simple classification model of using overall visits to predict the family happiness. As below parameters.

$$\alpha=[\alpha_1, \alpha_2, \dots, \alpha_5], \alpha_k \sim N(0, 1000), k=1, 2, 3, 4$$

$$\beta=[\beta_1, \beta_2, \dots, \beta_5], \beta_k \sim N(0, 1000), k=1, 2, 3, 4$$

$$\text{logit}_k = \alpha_k + \beta_k \cdot \text{overall_visit}, k=1, 2, 3, 4$$

where the probabilities are calculated by the SoftMax function

$$\text{probs}_k = \frac{e^{\text{logit}_k}}{\sum_{j=1}^5 e^{\text{logit}_j}}$$

This model assumes a wide normal distribution for the priors. This choice is based on the fact that the logit function is continuous over the range $-\infty$ to $+\infty$. Using a uniform prior would be illogical as it leads to a non-informative prior issue, while selecting a non-normal continuous distribution introduces asymmetry and imposes a prior assumption about the tails. To address these concerns, a wide normal distribution is chosen as the most suitable option for this case. After analyzing this model, we defined a second extended version of the above classification model by adding the effects of living distance and family arguments to the model.

$$\alpha=[\alpha_1, \alpha_2, \dots, \alpha_5], \alpha_k \sim N(0, 1000), k=1, 2, 3, 4$$

$$\beta_{k1}=[\beta_{11}, \beta_{21}, \dots, \beta_{51}],$$

$$\beta_{k2}=[\beta_{12}, \beta_{22}, \dots, \beta_{52}],$$

$$\beta_{k3}=[\beta_{13}, \beta_{23}, \dots, \beta_{53}],$$

$$\text{where } \beta_{ki} \sim N(0, 1000), k=1, 2, 3, 4, i=1, 2, 3$$

$$\text{logit}_k = \alpha_k + \beta_{k1} \cdot \text{overall_visit} + \beta_{k2} \cdot \text{weighted_distance} + \beta_{k3} \cdot \text{argument } k=1, 2, 3, 4$$

$$\text{Family_Happiness} \sim \text{Categorical}(\text{probs}), \text{ where } \text{probs}=[\text{probs}_1, \dots, \text{probs}_4]$$

It should be noted that the family happiness variable has five labels in total. However, in the models above, we defined $k=1, 2, 3, 4$. This is because our model automatically assumes that the fifth label (family being "very happy") always has a zero logit, and the logits for the remaining labels are fitted relative to this fifth label.

c. Sampling Diagnosis

As ensuring the sampling quality of Bayesian Models is critical, we use the following approaches to ensure our model has converged, and the sample space is well-explored. For the further description of the following methods, check the studies by Brooks and Gelman (1998), Efron et al. (2004), and Gelman and Rubin (1992).

Highest Density Interval (HDI): The HDI is calculated by finding the interval where the density (probability) is the highest while ensuring the total probability within the interval sums to the specified percentage. This is typically done by sorting samples by their probability density and then determining the narrowest range that satisfies the desired coverage. HDI is useful for understanding the range of credible values for a parameter.

Effective Sample Size for Bulk Distribution (ESS_{Bulk}): This measures the effective number of independent samples in the "bulk" (main body) of the posterior distribution. A higher ESS_{Bulk} indicates less autocorrelation and more reliable sampling. The effective sample size is calculated by taking the total number of samples and reducing it to account for the degree of autocorrelation. If the samples are highly correlated, the effective sample size will be much smaller than the total number of samples. For example, as our initial model has a total of 1000 samples per chain across 4 chains, resulting in a total of 4000 samples, an ESS_{Bulk} close to 4000 would indicate that the samples taken from all four randomly initialized chains are effectively independent and provide similar information about the posterior distribution. This suggests that the chains are exploring similar regions of the parameter space and producing consistent results, which is typically a key indication that the model has converged.

Effective Sample Size for the Tails of the Distribution (ESS_{Tail}): This measure works very similar to ESS_{Bulk} , with the only difference being the fact that ESS_{Tail} measures the effective number of independent samples specifically in the tails of the posterior distribution rather than the bulk. It ensures that rare or extreme values are adequately captured by the sampling process.

Potential Scale Reduction Factor (r_{hat}): This is a convergence diagnostic that checks whether multiple chains have mixed well and converged to the same distribution. A r_{hat} value close to 1 indicates convergence, while values significantly greater than 1 suggest that the chains have not mixed well. This is computed by comparing the variance of the samples within each chain to the variance of the samples between all chains. If the randomly initialized chains have not converged, the differences between the variance of samples taken inside each chain from the variance of samples taken in different chains will be large, resulting in a r_{hat} different from 1.

d. Data Preparation

Our data has the following variables:

- Family's Happiness: This variable has five levels, where '1' indicates low happiness and '5' represents high happiness.
- Language Consistency (Using or Not Using Native Language Inside vs. Outside Home): This variable categorizes the use of a family's native language in four levels: speaking the native language both inside and outside the home, speaking it only outside the home, speaking it only inside the home, and not speaking the native language in either setting.
- Frequency of Visits to First-Rate Family Members: This continuous variable ranges from 1 to 5 and is calculated as the average of nine discrete variables (e.g., visits for holidays, visiting a patient, attending a housewarming, etc.). Each discrete variable is scored on a scale from '1' ("Never Visits") to '5' ("Always Visits"). To generate this variable, the average of these 9 discrete variables was taken.

- Family's Way of Dealing with Issues: This is a continuous variable ranging from 1 to 5, generated by averaging over 30 discrete variables (e.g., scolding, sulking, insulting, etc.), each rated from '1' ("Never") to '5' ("Always").
- Giving Gifts to Relatives: This is a continuous variable between 1 to 2. Generated by taking the average of 14 categorical variables (e.g, giving gifts for holidays, birthdays, weddings, etc.) with '1' and '2' representing 'Yes' and 'No' answers, respectively.
- Living Distance from First-Rate Relatives: This continuous variable ranges from 1 to 7 and is calculated as the weighted average of 20 discrete variables. A value of '1' represents "In the Same House," while '7' represents "Abroad." The calculation weights immediate family variables by 3, close extended family variables by 2, and extended family variables by 1. These weighted variables are summed and averaged for each data row.
- Having Children: This is a simple categorical variable with two levels: '1' ("No") and '2' ("Yes").

3. Results

a. Descriptive Statistics

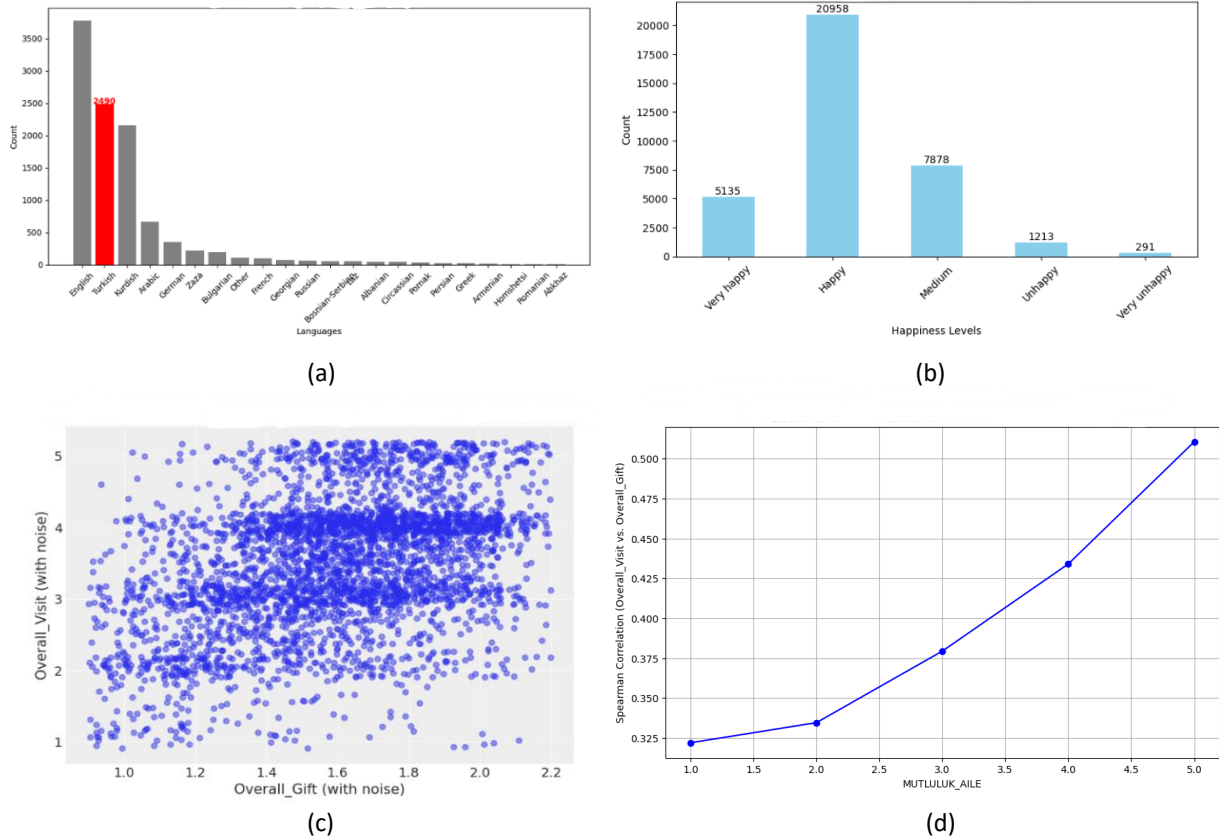


Figure 2. (a) Bar plot representing the count of participants by their non-native language. (b) Bar plot showing the distribution of participants' happiness levels. (c) Scatter plot of gifts versus overall visits, with 10% added noise for variability. (d) Correlation plot of gifts versus visits, stratified by different levels of family happiness.

We first examine the number of participants who listed Turkish as their non-native language. Figure 2(a) presents a bar plot illustrating the distribution of participants based on their use of a non-

native language. In addition to the figure, it is notable that out of the 2,500 participants who listed Turkish as their non-native language, approximately 900 reported speaking it only at home, around 700 reported using it exclusively outside their home, and the remaining participants reported using it both inside and outside their home. This ensure that we have enough participants available from each category, so we can get reliable results from our models.

Regarding overall happiness levels, Figure 2(b) reveals that very few participants selected "very unhappy," while the majority reported being relatively happy. Additionally, Figure 2(c) demonstrates a positive relationship between the number of gifts given by family members and the number of visits they have with close family members.

To further analyze the relationship between these two variables and overall happiness, we plotted the correlation of gifts and visits, stratified by happiness levels, as shown in Figure 2(d). The plot shows that as happiness levels increase, the correlation between gifts and visits also increases. This suggests an interesting pattern: the happier a family is, the more likely they are to exchange gifts as they tend to visit their family members more frequently.

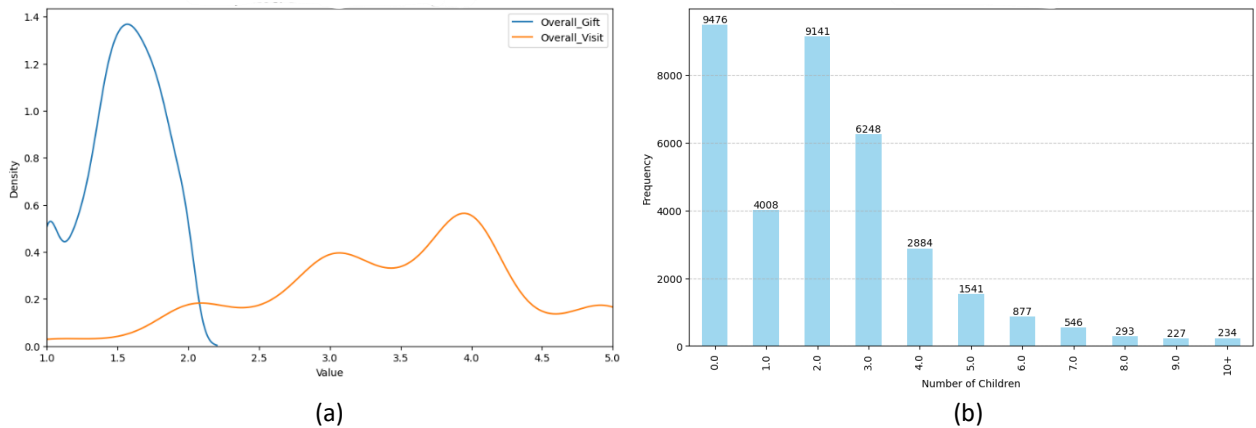


Figure 3. (a) represents the density plots of overall gifts and overall visits. (b) shows the Bar plot of the total number of children in each family.

We also check the individual densities of these 2 variables in Figure 3(a). As demonstrated, the distribution is relatively normal for the overall gift variable, while the overall visits are more biased towards the higher values. In addition, Figure 3(b) shows that families with 0 or 2 children are in the majority between the participants.

In Table 1, we observe the overall data summary.

Variable	Min	Mean	Max	SD
Family Happiness	1.000	2.184	5.000	0.750
Weighted Distance	1.000	4.603	9.000	0.967
Visiting Relatives	1.000	3.449	5.000	0.894
Giving Gifts	1.000	1.454	2.000	0.273
Total Number of Children	0.000	2.152	18.00	2.001
Disagreement Average	1.000	1.267	4.667	0.312

Table 1. Data Summary.

b. Bayesian Statistical Analysis

Now, we analyze our 2 main models.

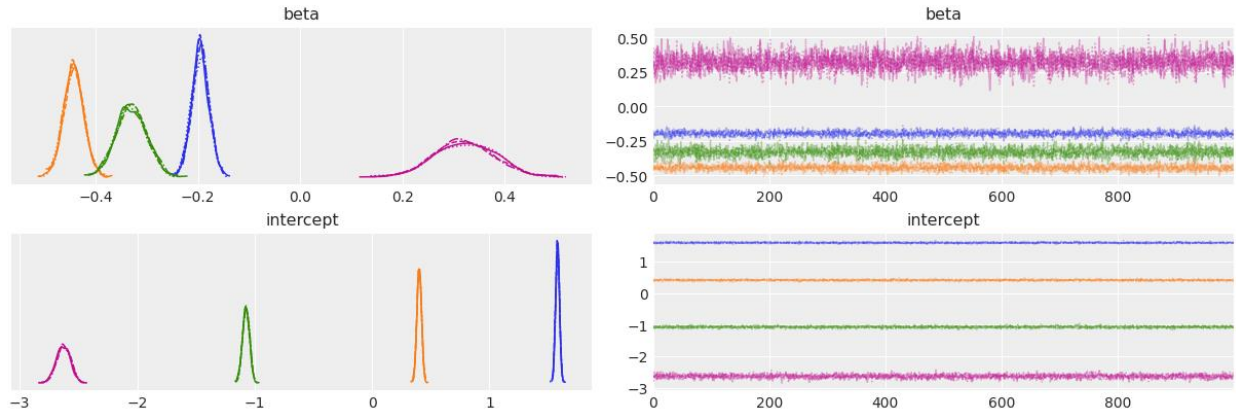


Figure 4. Left plots show the resulting posteriors for our 4 main parameters, and the right plots demonstrate the average trace plots of our chains for the duration of sampling stage. In these plots, K=1 is shown by blue, K=2 is shown by blue orange, K=3 is green, and K=4 is demonstrated by purple.

Variables	Mean	SD	3% HDI	97% HDI	ESS Bulk	ESS Tail	\hat{R}
beta[1]	-0.196	0.017	-0.228	-0.164	2199	2620	1.00
beta[2]	-0.443	0.02	-0.48	-0.406	2284	2756	1.00
beta[3]	-0.33	0.03	-0.384	-0.274	2441	2976	1.00
beta[4]	0.323	0.06	0.215	0.437	2761	2791	1.00
intercept[1]	1.58	0.016	1.548	1.609	2669	2602	1.00
intercept[2]	0.402	0.02	0.365	0.438	2842	2641	1.00
intercept[3]	-1.073	0.029	-1.126	-1.016	2936	2795	1.00
intercept[4]	-2.627	0.059	-2.736	-2.517	3002	2568	1.00

Table 2. Sampling diagnosis and model summary for the first model (using overall visit to predict the family happiness). In this table, hdi represents the highest density interval, ess_bulk and ess_tail represent the effective sample size for posterior bulk and tail, respectively, and r_hat represents the Potential Scale Reduction Factor. As observed, the trace plots from the sampling stage indicate consistency and randomness. Additionally, the r_{hat} values are all 1.00, and the effective sample sizes derived from our chains

are close to 3000. This demonstrates that the sampling steps were performed consistently and within the same parameter space, indicating that our model has converged sufficiently for credible analysis. Furthermore, the HDI intervals are narrow, signifying high confidence in the estimated mean values.

The results for the initial models are presented in Table 2 and Figure 4. The findings show that as overall visits increase, the logit—and consequently the probability—of label 4 (“relatively happy”) exhibits the largest increase compared to label 5 (“very happy”). Conversely, the probabilities of the other three labels, which represent lower levels of happiness, decrease relative to the probability of being “very happy” (label 5) as visits increase. This result is both logical and well-supported by previous literature, as discussed in the introduction, demonstrating that families are more likely to be “very happy” or “relatively happy” when they visit their relatives more frequently.

In addition, the intercept values show us an interesting information: when the overall visit value is zero, the logits of family being relatively happy is very low, meaning that the probability of the family being relatively happy is low when the family does not visit their relatives at all. Now, we train and observe the results for the extended version of this model.

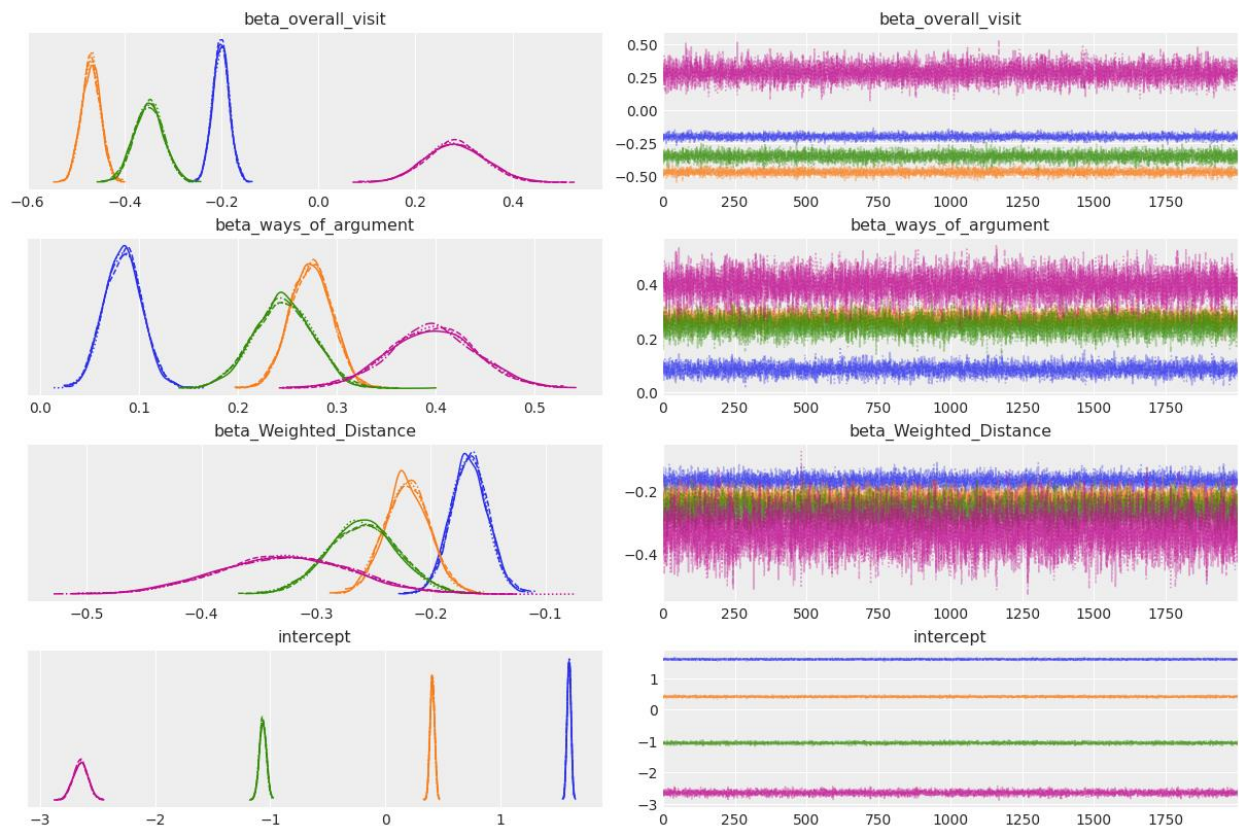


Figure 5. Left plots show the resulting posteriors for our 4 main parameters, and the right plots demonstrate the average trace plots of our chains for the duration of sampling stage. In these plots, K=1 is shown by blue, K=2 is shown by blue orange, K=3 is green, and K=4 is demonstrated by purple.

The results for the advanced model are presented in Table 3 and Figure 5. As observed, our model demonstrates robust sampling diagnostic results, similar to the previous model. This indicates that the model has converged sufficiently to allow for credible analysis. Consistent with prior findings, the results show that families tend to have a higher probability of happiness when they visit their relatives more

frequently. Additionally, the results indicate that the greater the living distance between families and their relatives, the lower the probability of happiness. These findings align well with existing literature.

However, a surprising observation is that families who argue appear to have a slightly higher probability of happiness, though the difference in logit is very small. This result is inconsistent with past research and may be attributed to the unaccounted effects of other variables not included in our model. Further modeling and analysis are required to better understand this variable and its influence on family happiness, to enable a more comprehensive interpretation of the results.

Variables	Mean	SD	3% HDI	97% HDI	ESS Bulk	ESS Tail	\hat{R}
beta_visit[1]	-0.201	0.017	-0.236	-0.17	5517	6080	1.00
beta_visit[2]	-0.469	0.02	-0.506	-0.433	6228	5810	1.00
beta_visit[3]	-0.35	0.03	-0.407	-0.296	7289	6071	1.00
beta_visit[4]	0.283	0.06	0.172	0.399	7729	6434	1.00
beta_argument[1]	0.084	0.019	0.049	0.120	5148	5548	1.00
beta_argument[2]	0.274	0.021	0.236	0.314	5299	5892	1.00
beta_argument[3]	0.246	0.03	0.188	0.300	6764	6033	1.00
beta_argument[4]	0.397	0.044	0.314	0.482	8372	6146	1.00
beta_distance[1]	-0.166	0.016	-0.197	-0.136	5601	5895	1.00
beta_distance[2]	-0.221	0.02	-0.259	-0.185	5989	5759	1.00
beta_distance[3]	-0.259	0.031	-0.318	-0.202	8445	6345	1.00
beta_distance[4]	-0.327	0.058	-0.436	-0.221	9184	6613	1.00
intercept[1]	1.597	0.017	1.565	1.627	5684	6384	1.00
intercept[2]	0.409	0.02	0.372	0.446	6518	6587	1.00
intercept[3]	-1.063	0.03	-1.122	-1.008	7160	5631	1.00
intercept[4]	-2.647	0.063	-2.766	-2.533	7865	6161	1.00

Table 3. Sampling diagnosis and model summary for the extended model. The sampling diagnosis metrics are defined similar to Table 2. Each beta value in this table represents a variable's coefficient in the logit's regression equation, as defined on page 4.

Table 4. The effect matrix of language consistency levels (columns) over family happiness logits (rows) based on the extended model.

4. Conclusion and Discussion

This study investigated the factors influencing family happiness in Turkey by using the robust capabilities of Bayesian networks. We explored how variables such as frequency of visits, gift-giving, proximity to relatives, and family arguments interact to shape family happiness in Turkey, a culturally diverse nation that bridges Eastern and Western traditions. Our analysis provided several key findings that both align with and expand upon existing literature.

Our results demonstrate a strong positive relationship between frequent family visits and happiness, which is consistent with past research that emphasizes the importance of close familial ties (e.g., Bjarnason & Haartsen, 2023). The proximity of family members was also shown to be another critical factor, with closer living distances indicating higher happiness levels. This is well-supported by the work of Adjei et al., (2016) and Bjarnason and Haartsen (2023), who highlighted the psychological comfort derived from living near family. Our study builds on this by showing how proximity interacts with other variables like visiting frequency to influence overall happiness. Larsen (2014) demonstrates similar results. Our study

extends this understanding by acknowledging that these variables are interdependent rather than isolated, with their effects mediated through a causal network.

One unexpected result was the slight positive association between family arguments and happiness. While this contrasts with earlier studies that link conflict to reduced well-being (e.g., Hajdu & Hajdu, 2015), it may suggest that constructive disagreements allow communication and understanding, or it might indicate the presence of unaccounted confounders in the data. Patterson (2002) also underscores the importance of resilience and adaptive mechanisms in family relationships, which may be relevant to this outcome. It should be noted that a key limitation of this study is the inability to distinguish between argument types. For example, families involved in constructive disagreements may experience a completely different level of happiness compared to those engaged in physical or verbal and emotionally damaging conflicts. This limitation could partially account for the counterintuitive results regarding the effect of arguments in happiness, and more research is necessary to better understand this component.

Our model also demonstrated interesting patterns in the relationship between linguistic consistency and family happiness. Families who spoke a non-native language only inside the home had the highest probabilities of achieving high happiness levels (4 or 5). This aligns with De Houwer (2015, 2017) and Müller et al. (2020), who showed the emotional and cultural benefits of families with linguistic diversity. Such families are more likely to demonstrate resilience in dealing with challenges to strengthen their bonds. On the other hand, families speaking only their native language both inside and outside the home had the highest probability of moderate happiness (level 3), which suggests that the absence of linguistic challenges might reduce their shared struggles, which gave them a lower probability compared to other families who speak their non-native language. Patterson's (2002) study mentioned similar observations on the role of overcoming challenges in closeness and commitment.

It should be noted that while our method provides useful extensions to the past literature, limitations remain. Beyond our limitations in investigating the effects of argument types, including additional socio-cultural variables may refine our understanding of family well-being. Elements such as socioeconomic status were not included in our analysis due to the methodological constraints and may influence the observed relationships. Future research could consider Bayesian Structural Equation Modeling (SEM) and Bayesian Hierarchical Models, which can incorporate latent variables and multilevel structures for a greater depth of analysis.

5. Acknowledgment

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