



## A BAYESIAN STATISTICAL FRAMEWORK FOR ASSESSING ASSOCIATIONS BETWEEN CATEGORICAL VARIABLES IN SMALL SAMPLES

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### Abstract

Assessing associations between categorical variables can be challenging in small samples, particularly when contingency tables contain sparse or low-frequency cells. This study applied a Bayesian statistical framework to a publicly available secondary dataset containing 100 observations to evaluate associations between 11 categorical predictors and a binary risk-status outcome. Descriptive frequencies and contingency tables were first examined, while chi-square tests were used as reference analyses. Bayesian inference was then used to quantify the strength and uncertainty of associations through Bayes factors, posterior probabilities, posterior Cramer's V estimates, and 95% credible intervals. Of the 100 observations, 66 were classified as Risk and 34 as No Risk. Location range showed the strongest association with risk status, followed by Price, Quality, Finances, Warranty, Business, and Market. Communication, Performance, and Attitude demonstrated moderate Bayesian evidence, whereas Delivery showed little evidence of association. Posterior effect estimates confirmed that Location range had the largest association magnitude, while Delivery had the weakest. Frequentist and Bayesian findings were generally consistent; however, the Bayesian approach provided additional information on the relative strength of evidence and uncertainty surrounding the observed relationships. Overall, the findings demonstrate that Bayesian methods provide a practical and informative approach for categorical association analysis in small samples, particularly when sparse contingency cells limit reliance on conventional asymptotic procedures.

**Keywords:** Bayesian inference; categorical variables; small samples; Bayes factor; posterior probability

## 1. Introduction

Evaluating relationships between categorical variables is a fundamental aspect in many areas of statistical analysis such as health sciences, behavioural research, education, business, engineering and environmental studies. Examples of categorical variables include risk status, categories of behaviour, preference, diagnostic groups, and levels of performance. Knowing whether or not such variables are related can help in interpreting patterns and make decisions. Traditional methods often involve contingency tables and chi-square tests, Fisher's exact tests and odds ratios. These techniques are, however, restricted to small samples or when there are low frequencies or zeros in several cells of the contingency tables. An alternative framework is the Bayesian one where uncertainty can be represented directly as the probability distributions and posterior estimates. Bayesian networks have proven to be valuable in modelling complex relationships of behaviour and conditional dependencies between variables (Barthelme et al., 2017).

When data on the categorical observations are sparse, the benefits of Bayesian estimation are especially important. When the information in categorical indicators is limited or there are sparse response patterns, then Bainer (2017) demonstrated that Bayesian estimation can be beneficial. Bayesian methods can also aid inference on interaction and complex dependence structures that may not be easily discerned from only the typical significance testing approach (Ferrari & Dunson, 2021). Bayesian methods are also able to include prior information in the form of prior distributions that may help to improve inference when information is scarce. Häse et al., (2021) showed this principle in the case of Bayesian optimization with categorical variables and expert-informed prior information. Hierarchical Bayesian methods have also been used for categorical response data where small sample size and systematic errors lead to estimation problems. In a more general sense, the full dependency between the observed outcomes can be used to gain more information from multivariate datasets by using a probabilistic modelling framework, as compared to working with each feature separately (Ovaskainen et al., 2017).

Yet the methodological advances have failed to translate into many applied studies using primarily frequentist procedures and predictive algorithms to analyze categorical or mixed data. Another challenge to the validity of statistical-based conclusions is the quality of the data and the lack of observations, especially when sample sizes are small (Carpenter & Smuk, 2021). The comparison of statistical and machine-learning models in risk-oriented applications has often focused on the performance of the models with respect to predicting scores instead of uncertainty around the association of two categorical characteristics (Wang et al., 2020). This is a significant difference between prediction and statistical evidence of the relationships between variables.

Bayesian inference provides evidence-based measures to supplement traditional hypothesis testing, which can quantify evidence, and uncertainty, more directly. Makowski et al. (2019) provided a description of "Bayesian" indices that can be used to assess the existence and significance of effects based on posterior-based evidence and not relying on p value solely. But there are few applications of this kind to small datasets of categories. Modern frameworks of educational and psychological measurement have shifted to using statistical models to characterize the probability of the occurrence of latent and observed categorical data (Chen et al., 2025), and the current research on prediction is often based on interpretation methods from machine learning instead of association inference for small samples (Qi et al., 2025). So the need for a transparent framework which incorporates contingency-based description along with Bayesian measure of evidence, effect size and uncertainty for categorical variables in small sample remains.

In the present study, this need is taken care of by employing a secondary data with 100 observations having multiple categorical characteristics. A data set like this offers a suitable context for investigating associations when the frequencies for some categories of the data are relatively small and it is not easy to make the usual asymptotic assumptions. The selection of analytical methods reflecting the structure of complex data and not depending on a single significance test has been shown to play a very important role in statistical frameworks based on dependence measures (Ince et al., 2017). Likewise, techniques for categorical and continuous variables emphasize the need to adequately capture the type and uncertainty of variables in the estimation process (Enders et al., 2018). Comparisons of other statistical frameworks also reveal that the conclusions drawn from the analyses can differ depending on the statistical assumptions made and the estimation methods employed (Jones et al., 2017). Moreover, for all the statistical models, where categorical and continuous variables are mixed, an estimation method is needed to take into account the different measurement structures (Li, 2021). Thus, for a small sample categorical data set as the one in this study, a Bayesian approach is well-suited to provide direct estimates of posterior probabilities, Bayes factors, effect estimates, and credible intervals and to explicitly represent uncertainty.

### Research Objectives

1. To describe the distribution and contingency patterns of selected categorical variables in a small-sample dataset.
2. To assess associations between selected categorical predictors and risk status using Bayesian statistical methods.
3. To evaluate the strength and uncertainty of identified associations using posterior probabilities, Bayes factors, and Bayesian effect estimates.

## 2. Materials and Methods

### 2.1 Study Design

The research design used in this research was quantitative research design with secondary data. Cross sectional, using an existing publicly available dataset to evaluate associations between categorical variables in a small sample.

### 2.2 Data Source

The data were retrieved from Mendeley Data publicly available repository. The dataset for the original purchase was used for the analysis, which was reported by Gamoura (2025). The data included a number of categorical attributes concerning the purchase condition and risk status.

### 2.3 Study Sample

All 100 observations in the original study were used. As the entire original sample was analysed, no further sampling was done, and the analysis was suitable for the investigation of categorical associations in small-sample situations.

### 2.4 Variables

The categorical variables involved in the analysis were Quality, Delivery, Performance, Warranty, Price, Finances, Communication, Market, Business, Attitude, Location range and Risk flag. Risk flag was considered as the main binary outcome variable. Purchase ID was not analysed, as this was only an identifier, and the numerical Location variable was not analysed as Location range represented it in a categorical way.

### 2.5 Data Preparation

The data set was screened for missing data, duplicate observations, and inconsistencies in the label of categories prior to data analysis. Minor differences in the names of the categories were corrected, as were leading and trailing spaces, and then frequencies were checked. Contingency tables were also scanned to check for sparsely populated cells and zero frequency cells.

### 2.6 Statistical Analysis

Categorical variables were presented as frequencies and percentages and cross-tabulated to investigate their distribution based on risk status. As reference analyses, chi-square tests were conducted. The association was quantified using a Bayesian analysis, resulting in (posterior) Cramer's V estimates, 95% credible intervals and Bayes factors. Uncertainty about the estimated associations was represented by posterior distributions. A weakly informative prior distribution was used to provide support in stable estimation but to ensure that the observed data contributed most to the posterior estimates.

## 3. Results

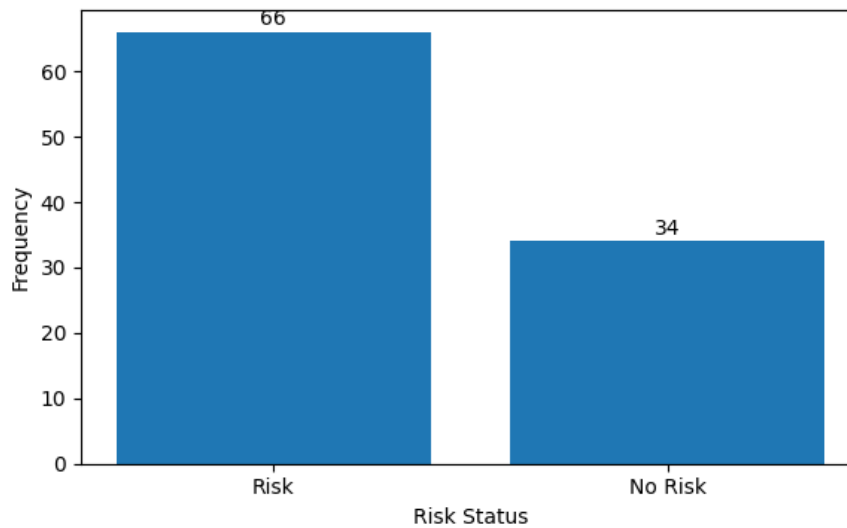
### 3.1 Sample Characteristics and Categorical Structure

A total of 100 observations were studied, with 66 observations being Risk and 34 observations being No Risk. There were varying numbers of levels in the categorical predictors and the dominant level varied. Delivery was most commonly classified as Deteriorating (68.0%) and the highest Location range category as 73.0% of observations (Table 1). The most frequent Finances category was weak (32.0%), the most frequent Warranty category was Prepayment (41.0%) and the most frequent Quality category was Best (21.0%). There was considerable heterogeneity among the categories of the categorical predictors and outcome groups.

**Table 1. Descriptive characteristics of categorical variables**

| Variable       | No. of Categories | Most Frequent Category  | n (%)           | Analytical Role |
|----------------|-------------------|-------------------------|-----------------|-----------------|
| Quality        | 7                 | Best                    | 21 (21.0%)      | Predictor       |
| Delivery       | 4                 | Deteriorating           | 68 (68.0%)      | Predictor       |
| Performance    | 6                 | Pristine / Adequate     | 23 (23.0%) each | Predictor       |
| Warranty       | 5                 | Prepayment              | 41 (41.0%)      | Predictor       |
| Price          | 6                 | Premium                 | 25 (25.0%)      | Predictor       |
| Finances       | 8                 | Weak                    | 32 (32.0%)      | Predictor       |
| Communication  | 7                 | C                       | 22 (22.0%)      | Predictor       |
| Market         | 6                 | *                       | 26 (26.0%)      | Predictor       |
| Business       | 6                 | Declining               | 24 (24.0%)      | Predictor       |
| Attitude       | 4                 | Limited                 | 36 (36.0%)      | Predictor       |
| Location range | 6                 | Range from 51 and above | 73 (73.0%)      | Predictor       |
| Risk flag      | 2                 | Risk                    | 66 (66.0%)      | Outcome         |

Sixty-six observations were identified as Risk and 34 observations were identified as No Risk, as shown in Figure 1. This shows that there is a definite imbalance in the distribution of the outcome, with the Risk category containing more items in the sample.



**Figure 1. Distribution of Risk Status**

The figure demonstrates that risk related observations were almost double that of non-risk observations, which is important when considering subsequent association analyses.

### 3.2 Contingency Patterns and Sparse Cell Structure

In the contingency analyses, there were significant variations in categorical distributions between Risk and No Risk group. Sparse expected frequencies were present in several predictors an important consideration in small-sample categorical analysis. As seen in Table 2, the top three locations with the highest percentage of expected cells below 5 were: Location range with 75.0% expected cells below 5, Finances with 43.8% expected cells below 5, Delivery with 37.5% expected cells below 5 and both Quality and Communication with 35.7% expected cells below 5. The chi-square association of most variables was significant with risk status, although Delivery did not achieve a conventional level of significance. The sparseness of these cell patterns meant that the use of Bayesian methods for more stable estimation and assessment of uncertainty were appropriate.

**Table 2. Contingency-table characteristics and frequentist association results**

| Variable       | $\chi^2$ | df | p-value | Expected Cells <5 (%) |
|----------------|----------|----|---------|-----------------------|
| Location range | 71.797   | 5  | <0.001  | 75.0                  |
| Price          | 24.231   | 5  | <0.001  | 16.7                  |
| Quality        | 20.826   | 6  | 0.002   | 35.7                  |
| Finances       | 22.280   | 7  | 0.002   | 43.8                  |
| Warranty       | 18.262   | 4  | 0.001   | 20.0                  |
| Business       | 17.790   | 5  | 0.003   | 25.0                  |
| Market         | 19.696   | 5  | 0.001   | 25.0                  |
| Communication  | 16.984   | 6  | 0.009   | 35.7                  |
| Performance    | 14.165   | 5  | 0.015   | 16.7                  |
| Attitude       | 11.886   | 3  | 0.008   | 0.0                   |
| Delivery       | 6.941    | 3  | 0.074   | 37.5                  |

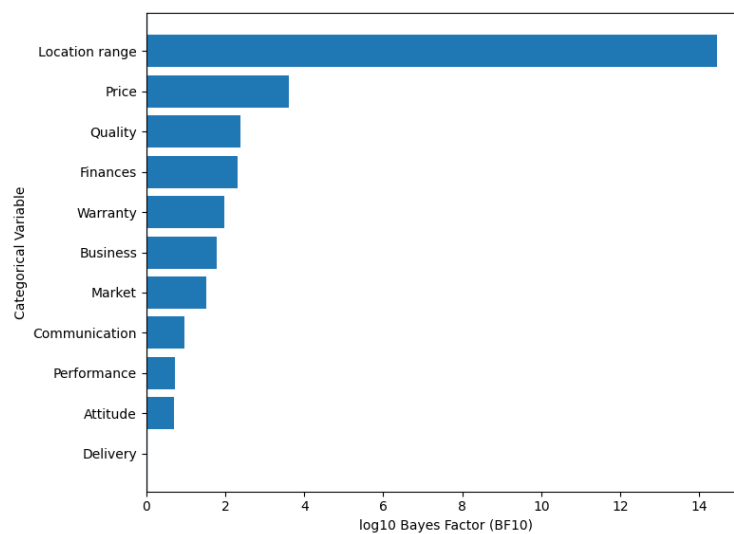
### 3.3 Bayesian Evidence for Association With Risk Status

Bayesian analysis showed that when it came to categorical predictors, there was a distinct difference in their evidence. Location range had the highest  $BF_{10}$  of  $2.818 \times 10^{14}$ , and the posterior probability of 1.000, as shown in Table 3. Price also exhibited very strong evidence, which was followed by Quality, Finances, Warranty, Business, and Market. The moderate Bayesian evidence was found for Communication, Performance, and Attitude. Delivery, on the other hand, gave a  $BF_{10}$  close to one and a posterior probability of about 0.51, showing little evidence for an association as compared to the independence model.

**Table 3. Bayesian evidence for associations between categorical predictors and risk status**

| Variable       | Bayes Factor<br>(BF <sub>10</sub> ) | Posterior Probability of<br>Association |
|----------------|-------------------------------------|-----------------------------------------|
| Location range | $2.818 \times 10^{14}$              | 1.000                                   |
| Price          | 4,146.200                           | 0.9998                                  |
| Quality        | 244.318                             | 0.9959                                  |
| Finances       | 203.442                             | 0.9951                                  |
| Warranty       | 95.403                              | 0.9896                                  |
| Business       | 61.895                              | 0.9841                                  |
| Market         | 32.441                              | 0.9701                                  |
| Communication  | 9.291                               | 0.9028                                  |
| Performance    | 5.248                               | 0.8400                                  |
| Attitude       | 5.167                               | 0.8379                                  |
| Delivery       | 1.058                               | 0.5141                                  |

Bayesian evidence for each predictor ranged widely, with Location range receiving the highest level of support for association with risk status (Figure 2).

**Figure 2. Bayesian Evidence for Risk Associations**

Price, Quality, Finances, Warranty, Business and Market also presented considerable Bayesian evidence, but Delivery yielded little evidence of association.

### 3.4 Posterior Association Strength and Uncertainty

For the purpose of quantifying the association size and the uncertainty, posterior effect estimates were used. The strongest and comparatively more precise association was found for Location range as shown in Table 4 with a posterior Cramer's V of 0.797 and a 95% credible interval of 0.673–0.896. The association strengths of Price, Finances, Quality, and Market are moderate, ranging from ~0.45 to 0.49. Moderate effects were found for Business, Warranty and Communication. Associations were weaker with Performance and Attitude, and Delivery had the lowest posterior Cramer's V (0.276) and the widest relative uncertainty of the weaker predictors.

**Table 4. Posterior association strength and 95% credible intervals**

| Variable       | Posterior Cramer's<br>V | 95% Credible<br>Interval |
|----------------|-------------------------|--------------------------|
| Location range | 0.797                   | 0.673–0.896              |
| Price          | 0.493                   | 0.352–0.623              |
| Finances       | 0.468                   | 0.338–0.593              |

|               |       |             |
|---------------|-------|-------------|
| Quality       | 0.459 | 0.330–0.577 |
| Market        | 0.450 | 0.284–0.607 |
| Business      | 0.430 | 0.285–0.572 |
| Warranty      | 0.425 | 0.270–0.570 |
| Communication | 0.421 | 0.271–0.566 |
| Performance   | 0.384 | 0.236–0.532 |
| Attitude      | 0.351 | 0.180–0.516 |
| Delivery      | 0.276 | 0.140–0.424 |

### 3.5 Comparison of Frequentist and Bayesian Findings

Overall the frequentist and Bayesian results were similar for most of the predictors. There was a general correspondence between small p-values and large Bayes factors and posterior probabilities as summarised in Table 5. The highest degree of concordant evidence was seen in Location range and Price; followed by Quality, Finances, Warranty, Business and Market. Association was also consistently supported, although at a lower magnitude, by Communication, Performance, and Attitude. Limited evidence was found for delivery, as both methods provided evidence. For contingency tables, the Bayesian framework also provided a measurement of the strength of association and of the uncertainty, which was especially handy when there were sparse expected cell frequencies.

**Table 5. Comparison of frequentist and Bayesian association evidence**

| Variable       | p-value | BF <sub>10</sub>       | Posterior Probability | Overall Pattern              |
|----------------|---------|------------------------|-----------------------|------------------------------|
| Location range | <0.001  | $2.818 \times 10^{14}$ | 1.000                 | Strong concordant evidence   |
| Price          | <0.001  | 4,146.200              | 0.9998                | Strong concordant evidence   |
| Quality        | 0.002   | 244.318                | 0.9959                | Strong concordant evidence   |
| Finances       | 0.002   | 203.442                | 0.9951                | Strong concordant evidence   |
| Warranty       | 0.001   | 95.403                 | 0.9896                | Strong concordant evidence   |
| Business       | 0.003   | 61.895                 | 0.9841                | Strong concordant evidence   |
| Market         | 0.001   | 32.441                 | 0.9701                | Concordant evidence          |
| Communication  | 0.009   | 9.291                  | 0.9028                | Moderate concordant evidence |
| Performance    | 0.015   | 5.248                  | 0.8400                | Moderate concordant evidence |
| Attitude       | 0.008   | 5.167                  | 0.8379                | Moderate concordant evidence |
| Delivery       | 0.074   | 1.058                  | 0.5141                | Limited evidence             |

## 4. Discussion

In the current study, it was found that the Bayesian analysis can be used to discriminate between the strength of the relationship between the various categorical predictors and risk status in a very small sample of 100 observations. The highest Bayes factor and posterior Cramer's V (strong evidence for association and a large effect size) was seen for Location range. Price, Quality, Finances, Warranty, Business, and Market were also found to have strong Bayesian support, whereas Communication, Performance and Attitude had moderate levels of support. Delivery was unique among the other predictors since the corresponding Bayes factor was near one and the posterior probability was around 0.51, indicating that the data provided did not strongly support either an association or independence. Posterior credible intervals also demonstrated the uncertainty associated with the estimates of effects and indicated that the effect estimates with stronger associations tended to have more compelling posterior support. The results are especially significant because some contingency tables had expected frequencies that were quite small, thus illustrating the usefulness of the Bayesian measures in situations where large sample approximations may be problematic.

The current results support earlier studies demonstrating that when complex and sparse data structures exist, statistical frameworks should not rely solely on significance testing. In this same vein, Rubin et al. (2017) showed how useful probabilistic statistical models can be for obtaining interpretable effects from the data when there was a lot of variability. In the same way, Kvålseth (2025) pointed out the need for suitable association measures for nominal categorical variables, which is also the reason for including posterior Cramer's V in the current analysis to get a sense of magnitude of the

association, in addition to significance tests. Bayesian inference has also successfully been applied to industrial decision-making applications, where multiple, related predictors need to be considered together in the presence of uncertainty (Khakifirooz et al., 2018). That application was on another domain, and with another level of data, but it does illustrate the general applicability of Bayesian evidence to inferring uncertain relationships.

The present work also illustrates the general benefit of Bayesian methods over conventional estimation methods when there is incomplete or limited information. In the current focus on posterior distributions and credible intervals, Ma and Chen (2018) demonstrated how Bayesian procedures could provide flexible mechanisms to tackle uncertainty in statistical estimation. Cain and Zhang (2019) also showed that using a single fit statistic when evaluating a model is insufficient and that multiple fit measures are needed for evaluating a model using a Bayesian approach. Similarly, Quintana and Williams (2018) pointed out the interpretive benefits of alternatives to the traditional null-hypothesis significance testing framework, such as the ability to quantify evidence in favor of the null hypothesis as well as evidence in favor of the alternative hypothesis using a Bayes factor. The current results generalize this to categorical association analysis based on small samples.

The results have methodological implications for analyses of small categorical data sets. The Bayesian framework was able first to provide information not available with the use of p-values alone such as quantification of the relative evidence for association, posterior probabilities, effect magnitude, and uncertainty. Secondly, this method proved to be informative even in contingency tables with low expected frequencies. This suggests that the framework could be applicable to exploratory studies, pilot investigations, behavioural research, business analytics, health studies, and other areas with possibly small sample sizes. The use of both the Bayes factor and the posterior effect estimate can also be used to aid in the identification of whether a relationship is statistically detectable, and whether that relationship is substantively stronger or weaker.

There are some limitations to be taken into account. Only one second data with only 100 observations was analysed which restricts the generalisability of the particular associations found. Many of the categorical variables had numerous levels for the size of the samples, resulting in sparse or zero-frequency cells and high posterior uncertainty. Location range was also found to have an unexpectedly high association with risk status which could be a characteristic of this dataset. Furthermore, the analysis was largely concerned with bivariate relationships, and did not consider potential confounder variables or interactions among any number of predictors. Also, a small difference in the selected prior distributions may lead to some difference in the results of Bayesian analysis.

Future research needs to test the proposed framework in other independent datasets in other domains and with different sample sizes, to see if the framework is reproducible. Future research may be performed in larger studies that would be able to expand the analysis to multivariable Bayesian logistic or multinomial models and explore interactions between categorical predictors. Sensitivity analyses with other prior specifications should be carried out in a systematic manner as well. Future research may involve more comparison of the Bayesian contingency methods with the exact frequentist methods, as well as hierarchical Bayesian models, especially in highly sparse and unbalanced datasets. These extensions would assist to identify the effectiveness of the framework in various small-sample situations.

## 5. Conclusion

The current study revealed the potential of Bayesian statistical approach in studying relations between categorical data for a small sample of 100 observations. Several of the predictors were found to be meaningfully related to the risk status, but evidence varied across variables. Location range had the most evidence and the highest magnitude of association on a posterior basis, followed by Price, Quality, Finances, Warranty, Business and Market. Moderate evidence was found for Communication, Performance and Attitude and little evidence for Delivery. These results were largely comparable to those from the frequentist approach but the Bayesian approach also helped provide information in the form of Bayes factors, posterior probabilities, posterior Cramer's V estimates and 95% credible intervals. Results also revealed the usefulness of the use of Bayesian analysis in situations where cells of a categorical data set are sparse or have low frequencies, meaning the typical large sample procedures may not be reliable. The Bayesian approach provided a more informative interpretation of categorical relationships compared to relying on p-values only by directly quantifying evidence, effect strength and uncertainty. In general, the study confirms the use of the Bayesian methods as a viable technique for categorical data analysis with small number of observations. The framework is easily generalizable to other research contexts with low observation rates, skewed category distributions, and uncertain estimate of association.

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