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# Causality Guiding Survey Analysis: A Use Case on Cyberbullying

*Keywords:Causality; DAG; Bayesian Statistics; Cyberbullying; Adolescents*

## Extended Abstract

### Motivation

Surveys represent a widely used tool in social science research. However, the techniques traditionally employed to analyze the survey results can sometimes be problematic, especially when it comes to reporting on found correlations, insinuating underlying causal relationships. This is a common issue in research where it is impossible (or unethical) to perform a randomized control trial, and only observational studies are possible. We can easily exaggerate, minimize, or reverse causal effects if the data are not carefully treated and analyzed. Nevertheless, in recent years we are experiencing a flourishing of research and techniques based on causal inference. This scientific philosophy has the potential to help us better understand the issues we are researching and how the different variables (causally) affect each other. It also motivates researchers to raise more questions about the data and to explicitly present assumptions and hypotheses, fostering fruitful discussion.

Cyberbullying (CB) represents a relevant problem among youngsters nowadays. A monthly average of 10% of European youngsters are victims of cyberbullying (CB) [1], and 49% have encountered a circumstance involving CB at least once [2]. CB also represents a good example of the kind of research where interventional studies are not possible and where the interpretability and explainability of potential conclusions are especially important. In particular, preventing the potential risk of suffering CB faces four main problems: (i) the lack of data on the intrinsic motivations of minors while interacting on the Internet; (ii) the under-reporting of cyberbullying events occurring to minors; (iii) the possibility for multiple contributing factors, making it harder to identify those on which we can intervene to protect minors and incriminate the offenders; and (iv) the need to consider ethical constraints to protect the minors from unnecessary or harmful interventions.

### Methodology

With the aim of better understanding the CB phenomenon, our team surveyed minors in Madrid and Valencia (Spain) schools in 2022. We collected 665 responses from students between 13 and 17 years old (Mean=14.53, SD=0.88), where 50.6% identified themselves as males, 48.04% as females, and 1.36% as non-binary. In this survey, we gathered demographic data (e.g., age, gender, sexual orientation, migratory background), some questions about the participants' relationship with new technologies and the Internet (e.g., use of IoT devices, daily hours of the Internet), and, finally, some inquiries concerning situations related to cyberbullying or cyber-harassment.

Our work uses Bayesian Networks (BN) [3] to combine insights from literature, expert knowledge and survey data. The structure of the BN is represented as a directed acyclic graph (DAG) and encodes both the statistical and causal dependencies between variables (i.e., joint probability distributions). There are several examples in the literature that use BN to analyze survey data, especially in the field of customer satisfaction [4] [5] [6]. However, there are fewer examples of applying them to more complex social phenomena, such as CB [7].

In addition to applying causality-based techniques to surveys, our methodology also includes a procedure for comparing the different hypotheses of BN structures. It consists in performing a k-fold cross-validation and evaluating the BN structures through the (log) likelihood $L(\theta \mid X)$, where $\theta$ represents the BN with its fitted parameters, and $X$ represents unobserved data samples. In other words, we are measuring the probability that a given BN fitted with training data, is the underlying generating process which has produced the testing data. Hence, encouraging the choice of the BN model that best generalizes. Traditionally, the comparison between hypothetical BN structures has consisted of evaluating the goodness-of-fit to all the data. That is, checking how well the model fits all the available data. However, this entails great risks of overfitting the data, especially when the sample is small, as is often the case in Social Sciences.

**Results**

We have analyzed the survey data in an attempt to identify the underlying causal relationships among the measured variables, by comparing different plausible BN structures. These plausible BN structures are built using specific (qualitative) knowledge by CB experts and some causal discovery algorithms (*Bayesian Search, PC, Greedy Thick Thinning*). The causal discovery algorithms employed allowed us to force and prohibit some causal connections coming from expert knowledge or common sense (e.g., no variable can cause the participant's age or gender).

Figure 1 shows all the hypothetical BN structures we have compared in this work. Table 1 summarizes the results of the conducted experiments. The best results, both in training and testing, were obtained with one of the structures proposed by the CB experts. The results obtained are aligned with the BN literature, which suggests that causal discovery algorithms can be useful for the researcher to consider alternative structures, but do not usually produce optimal solutions [8].

**Implications**

Introducing a causality philosophy into a survey analysis is not an all-in-one tool. This is a modeling mindset that helps researchers to conduct more rigorous analyses and encourages them to ask more questions about the data and the issue we are confronting. Furthermore, it makes researchers’ assumptions explicit, promoting more discussion and open and honest science. This approach is especially important when dealing with sensitive research topics such as CB. The obtained results allow us to better understand the complex phenomenon of CB, thus being able to focus prevention efforts or interventions on people who are most at risk.

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| | Naive-BN | Bayesian Search-BN | PC-BN | Greedy Thick Thinning-BN | 1st Experts proposal-BN | 2nd Experts proposal-BN |
|---|---|---|---|---|---|---|
| Mean Log Likelihood [Training sets] | -4103.8 | -4034.9 | -3987.8 | -4003.9 | -3990.8 | **-3933.9** |
| Mean Log Likelihood [Testing sets] | -1089.1 | -1073.1 | -1064.9 | -1067.4 | -1071.8 | **-1061.8** |

**Table 1.** BN architecture comparison results. A k-fold cross validation was performed with k=5. The mean of the (log) likelihoods is shown. The higher the (log) likelihood, the better. The experts' second proposal obtains the best results in both training and testing sets.

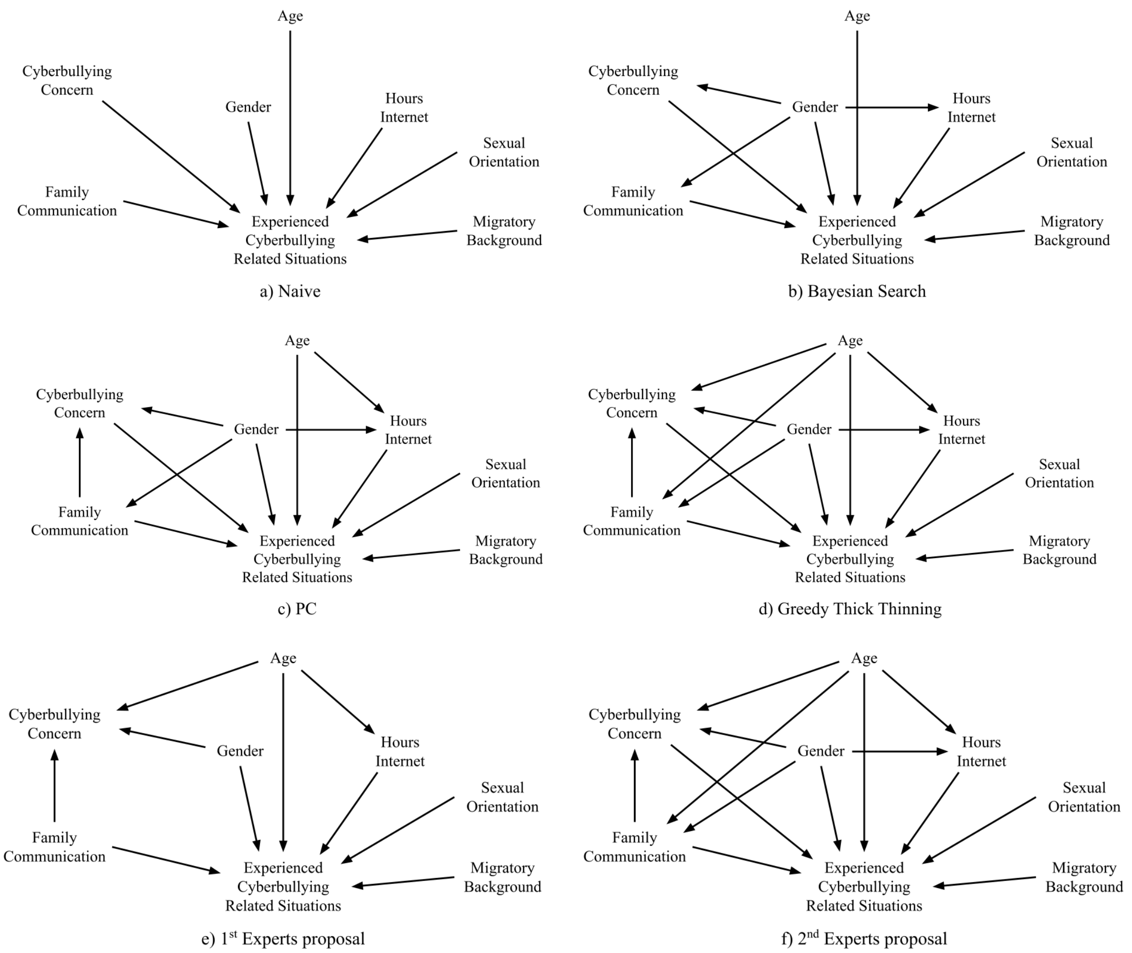


**Figure 1.** Bayesian Network structures that have been compared in this paper. Structures a), b), c) and d) have been derived using causal discovery algorithms. When using these algorithms, we have forced and prohibited some causal connections, coming from expert knowledge or common sense (e.g., no other variable can causally affect *age* or *gender*). Structures e) and f) have been derived solely from expert knowledge.