

Using Machine Learning to Explore German PhD Researchers' Satisfaction with Supervision

Olga Lezhnina¹ and Gábor Kismihók²

Purpose

Doctoral researchers' wellbeing is predicted by a number of factors; according to the systematic literature review by Jackman et al. (2022), the crucial role is played by researchers' perception of supervision. The importance of supervision was discussed in literature (Casey et al., 2022; Kismihók et al., 2022).

In our forthcoming work (in press), we predict German PhD researchers' life satisfaction from a wide range of personal and institutional factors as measured by the National Academic Panel Study (NACAPS) in 2018 (Adrian et al., 2020). The design of the survey makes its sample representative of the German PhD research population (Briedis et al., 2020). We found, in accordance with previous research, that satisfaction with supervision is one of the most influential factors of PhD researchers' life satisfaction.

It is useful to know which particular aspects of supervision determine researchers' satisfaction with it, as previous studies emphasized various factors, such as frequency of supervision (Corner et al., 2017) or trusting relationships with the supervisor (Shield, 2023). For this goal, we proceeded with data analysis of the NACAPS 2018 dataset³.

Design

The NACAPS data of researchers doing PhD at the time of the survey (N = 21437) was used. We calculated the aggregate index of satisfaction with supervision out of three adsv12 items measuring the topic (overall satisfaction; with the supervisor; with institutional services for PhD researchers) and used it as the outcome variable. We conducted the regression task to

¹ Learning and Skill Analytics Research Group, Leibniz Information Centre for Science and Technology University Library, Hannover, Germany. CONTACT: Olga.Lezhnina@tib.eu

² Learning and Skill Analytics Research Group, Leibniz Information Centre for Science and Technology University Library, Hannover, Germany.

³ The data can be requested from the German Centre for Higher Education Research and Science Studies (DZHW). Descriptive statistics can be found in open access here <https://nacaps-datenportal.de/themenbereiche.html>

predict satisfaction with supervision from all other items of the survey related to supervision (26 items). Formulations of all items are in open access⁴.

We used machine learning techniques, which were developed to deal effectively with large datasets and therefore are increasingly used in mental health and wellbeing research (Shatte et al., 2019). Data analysis was conducted with Python, version 3.9.7. The gradient boosting regression model was built, and its performance assessed with the mean average error (MAE) and the R^2 (variance explained). Gradient boosting is a decision tree-based model that handles nonlinearity of the data and interactions between variables (Natekin & Knoll, 2013). Variable importance was calculated with the permutation importance metric (Molnar, 2019). The new model with the most important variables was built, and its performance assessed.

Partial dependence plots for predictors and pairs of predictors in the final model were built. These visualisations show the marginal effect that predictors have on the predicted outcome of the model. Thus, the nature of the relationship between the variable and the outcome (whether this it is linear, monotonic etc.) can be seen, as well as interactions between predictors in three-dimensional plots (Molnar, 2019).

Results

The initial gradient boosting regression model with 26 items of the supervision block explained 63% of variance, and the MAE was 0.43. The variable importance for the initial model is shown in Figure 1.

⁴ See the English version: [https://metadata.fdz.dzhw.eu/public/files/instruments/ins-nac2018-ins1\\$-1.0.0/attachments/nac2018_W1_VariableQuestionnaire_de.pdf](https://metadata.fdz.dzhw.eu/public/files/instruments/ins-nac2018-ins1$-1.0.0/attachments/nac2018_W1_VariableQuestionnaire_de.pdf)

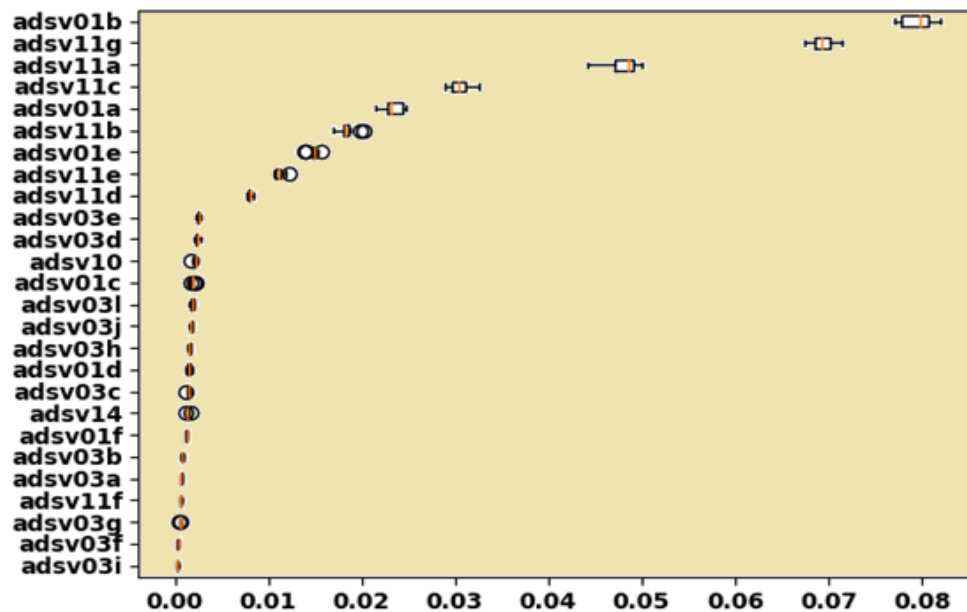


Figure 1. Variable Importance for the Initial Model.

Note: The permutation variable importance (the X axis) is the decrease in the model score (the R^2) when the variable values are randomly shuffled.

The new model was built with three most important variables. The model was still well-performing: it explained 58% of variance, and the MAE was 0.46. The variable importance for this final model is presented in Figure 2.

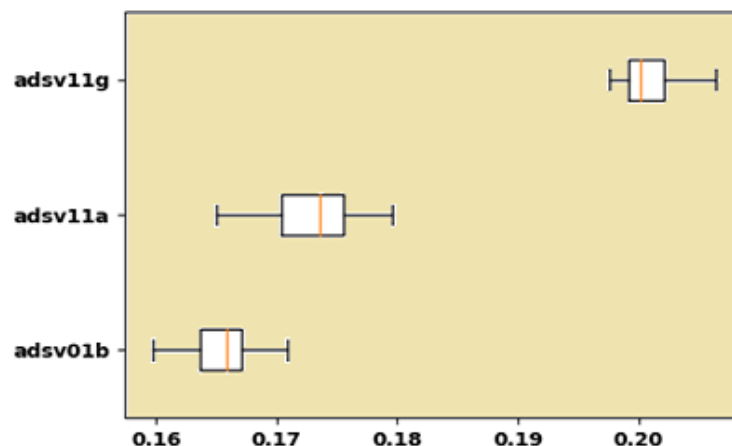


Figure 2. Variable Importance for the Final Model.

Note: The permutation variable importance (the X axis) is the decrease in the model score (the R^2) when the variable values are randomly shuffled.

Three most important variables were items formulated as follows: (1) adsv11g: “My supervisor inspires me”; (2) adsv11a: “My supervisor behaves as if (s)he is dedicated”; (3)

adsv01b: “There are/were phases of my doctorate in which I received insufficient advice”.
Partial dependence plots for the predictors are presented in Figure 3.

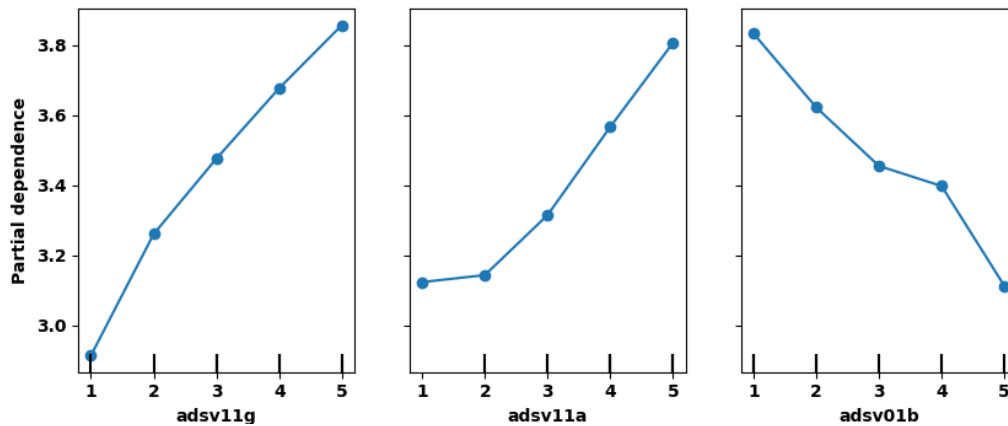


Figure 3. Partial Dependence Plots for Predictors.

Note: The partial dependence (the Y axis) is the marginal effect that the predictor has on the outcome variable. The X axis shows the values of the predictor.

The first two variables influenced participants' satisfaction with supervision positively, and the last one negatively. Partial dependence plots for pairs of predictors (Figure 4) show interactions between them.

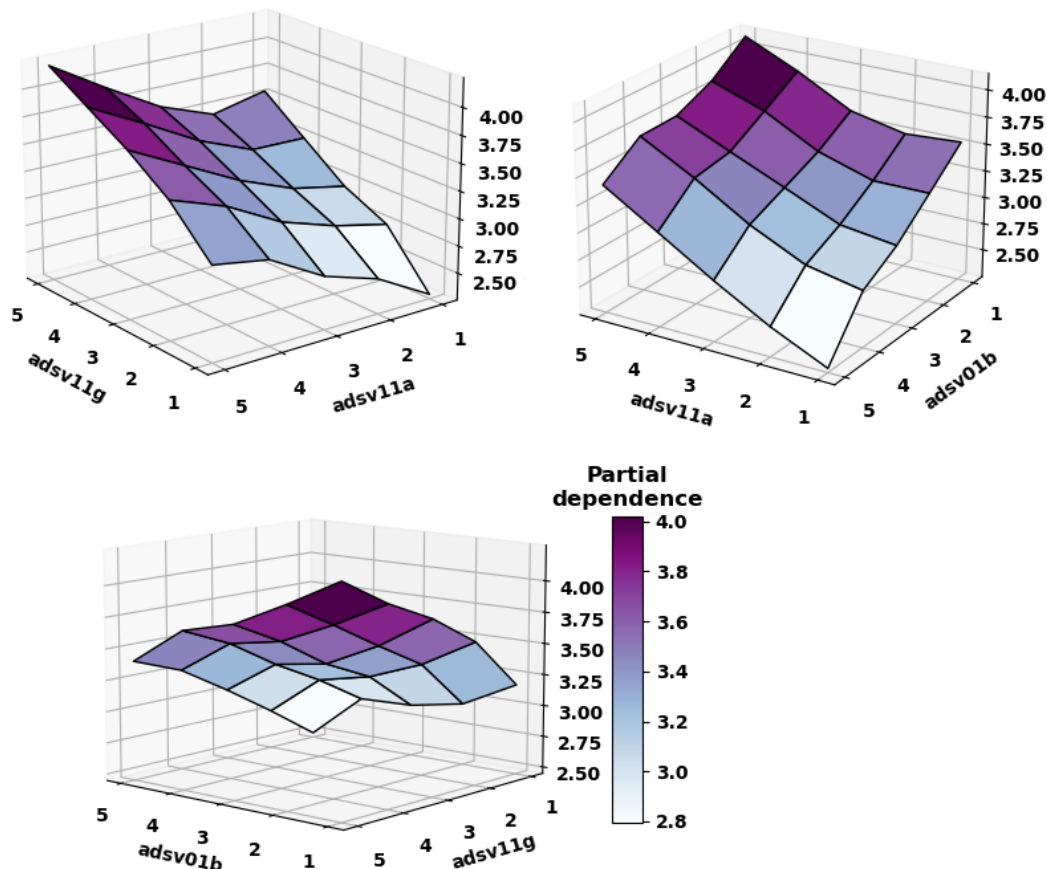


Figure 4. Partial Dependence Plots for Pairs of Predictors.

Note: The partial dependence (see the colour code in the legend) is the marginal effect that the predictor has on the outcome variable. The X and Y axes show the values of the predictors.

Thus, we discerned three out of 26 supervision-related variables that were most important for participants' satisfaction with supervision. The partial dependence plots illustrated their relationships with the predicted outcome and interactions with each other.

Implications

For evidence-based interventions, methodologically rigorous analysis of high quality data is required. Large-scale surveys, such as NACAPS, provide researchers with large amounts of data, and machine learning models are helpful for obtaining data-driven results and making predictions about the new data.

As satisfaction with supervision was an important predictor of German PhD researchers' life satisfaction, we explored in detail what the participants perceived as satisfactory supervision. We could conclude that the most influential factors were the supervisor being (i) inspiring and

(ii) dedicated, and providing (iii) constant reliable support. Other variables, such as details of supervisory agreement (items advs03), or regularity of appointments with the supervisor (adsv01e), were much less important for the participants' satisfaction with supervision.

These findings might inform development of interventions aimed at enhancing PhD researchers' satisfaction with supervision, which in turn is a crucial factor of their wellbeing. Further research on this topic is needed at the international level, as our findings relate to German doctoral researchers, and country-level differences are possible.

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