MACHINE LEARNING

A DATA DRIVEN BURNOUT RISK ANALYSIS

Date
5th January 2022

MACHINE LEARNING

A DATA DRIVEN BURNOUT RISK ANALYSIS

Date	5th January 2022
Authors	Everton Souto Lima Robin van Stokkum Wendela Hooftman Marloes van de Klauw
Projectnumber	060.38022
Reportnumber	TNO 2022 R10016
Contact TNO	Wendela Hooftman
Telephone	+31888665253
E-mail	Wendela.hooftman@tno.nl

Healthy Living
Schipholweg 77-89
2316 ZL Leiden
Postbus 3005
2301 DA Leiden
The Netherlands

www.tno.nl

T +31 88 866 90 00
info@tno.nl

Handelsregisternummer 27376655

Table of contents

1 Samenvatting

Dit rapport bevat een beschrijving van de aanleiding, methoden en resultaten van het project “Machine Learning: A Data Driven Burnout Risk Analysis”, uitgevoerd in het voorjaar van 2019. In dit project zijn moderne machine learning (ML) algoritmes gebruikt om op een data gedreven manier oorzaken te vinden van burn-out symptomen in het meerjarenbestand van de Nationale Enquête Arbeidsomstandigheden (NEA). De dataset gebruikt in dit onderzoek bestaat uit 111.761 respondenten en beslaat 21 verschillende domeinen omtrent de werksituatie van werknemers in Nederland.

Van de verschillende onderzochte algoritmes leidde eXtreme Gradient Boosting (XGBoost) tot de beste resultaten met een accuraatheid van 87% in het verklaren van burn-out symptomen. Het interpreteren van het resulterende ‘black box’ model is aan de hand van het Shapely Addictive Values (SHAP) gedaan, een recente techniek welke de complexe gevonden relaties overzichtelijk weergeeft. De resultaten laten zien dat burn-out symptomen gerelateerd zijn aan lage werkvoldoening, hoge taakeisen, weinig ervaren steun vanuit het management, lage algemene gezondheid en een slechte werk-privé balans. Ook behoren jongere werknemers, zeker in combinatie met kinderen, tot een risicogroep. Deze gevonden effecten zijn niet nieuw.

De toegevoegde waarde van Machine learning en XGBoost in het bijzonder, is dat ze vanuit de data laten zien dat burn-out symptomen in belangrijke mate tot stand komen op basis van telkens een unieke combinatie van factoren. Zo is de verklaring voor burn-out symptomen bijvoorbeeld voor sommige respondenten de combinatie van een slechte werk-privé balans met lage algemene gezondheid, terwijl het voor andere hoge taakeisen en lage werkvoldoening. Het inzichtelijk maken van deze combinaties is de meerwaarde van machine learning ten opzichte van conventionele statistische methoden, die hier niet goed mee overweg kunnen.

Aanvullend lieten de resultaten zien dat het erg lastig om burn-out symptomen met een korte vragenlijst te meten en het noodzakelijk is om een temporaal component mee te nemen in de zoektocht naar verklaringen van burn-out symptomen.

Concluderend laat dit rapport zien dat machine learning geschikt is om op een data gedreven manier verdiepende inzichten te genereren in grote surveyonderzoeken, ook wanneer de relaties tussen de variabelen complex en talrijk zijn. Ook is er gedemonstreerd hoe een resulterend model inzichtelijk kan worden weergegeven en geïnterpreteerd, klassiek een uitdaging van ML.

2 Introduction

Work related stress or occupational burnout is on the rise. In the Netherlands alone, estimates show that 9 million workdays are lost to stress related issues and nearly 1 million people risk suffering from burnout (e.g.: Factsheet Werkstress, 2015 and 2018). Moreover, research shows that occupational burnout contributes to poor health and is accompanied with health problems such as insomnia, depression, type 2 diabetes, coronary heart disease, and others (e.g.: Toker et al., 2012, Kiviimaki et al., 2012, Nyberg et al., 2014, Matsen et al., 2017). Consequently, obtaining insight into the causes of burnout is an important step in promoting work health, increasing productivity, promoting public health and consequently reducing costs of associated healthcare.

Since 2005 the Netherlands Working Conditions Survey (NWCS, ‘NEA’ in Dutch) had been conducted to monitor the employment situation of Dutch employees. The NCWS is executed by TNO and CBS and includes, but is not limited to, working conditions and health related outcomes such as burn-out symptoms, for Dutch employees. This rich dataset contains many questions capturing possible causes for burnout symptoms, such as overall wellbeing, availability of social support and perceived autonomy and many more (see Hooftman et al., 2019). However, many conventional statistical approaches popular in the social sciences (e.g.: regression, ANOVA, t-tests) fall short in a data-driven search for answers. This is because of the high number of variables available in a data and the possible non-polynomial (e.g.: non-linear, non-quadratic) relations between them. Machine learning, however, offers solutions for these shortcomings, allowing for high number of possible predictors and high complexity of relationships between them, enabling powerful data-driven inductive research.

Machine learning approaches use statistical methods to infer relationships from data and make predictions. In the last few years, machine learning methods have been successfully used to predict health risks and produce insight in health care settings (e.g.: Lundberg et al., 2018). However, the application of machine learning to burnout prediction has been limited to small datasets, single companies, or in student settings. Additionally, the techniques employed typically fail to generate insight as model produced by machine learning approaches can be difficult to interpret. This study sets out to just tackle that: using a large scale dataset in combination with state-of-the art machine learning algorithms to find actionable insights in burnout symptom prediction.

In this report we present an ensemble-based machine learning approach called XGBoost (Chen & Benely, 2015) that predicts the risk of burnout symptoms based on the aforementioned large multi-year questionnaire data (NWCS) and provide an explainable framework for identifying individual risk factors for burnout. In doing so, we were able to gain new insight on occupational burnout that can aid further research on its prevention and understanding.

3 Methods

Data used in the project was the NWCS (Nationale Enquête Arbeidsomstandigheden), based on collaboration between TNO, CBS and the ministry of Social Affairs and Employment.. This large scale survey is conducted every year since 2005. The resulting dataset used in this project consisted of the years 2005 through 2018. After preprocessing the data, the final sample size consisted of 111,761 respondents. The NWCS variables that were used are described in the appendix.

To achieve the best possible predictions of burnout symptoms using the NWCS dataset, several machine learning algorithms were employed. Of those, best performance was found by the eXtreme Gradient Boosting (XGBoost) algorithm, of which the results will be discussed in the next section. This highly versatile and powerful algorithm is one of the most popular in solving classification problems (such as having burnout symptoms or not) and is widely considered state-of-the-art (Chen & Guestrin, 2016, Chen & Benesty, 2015).

XGBoost belongs to a family of boosting algorithms which use the gradient boosting (GBM) framework at its core. Boosting is a technique were several weak learners are put in a sequence. A weak learner in this context is a simple model that performs only slightly better than a random guess. For example, a very small decision tree that only splits the sample in two categories, based on a single variable. This could be that people younger than a certain age have a slightly higher change of having a burnout, which then forms the basis for a weak learner. Several of these classification and regression trees (CART) are grown after another iteratively, aiming to reduce the misclassification rate of each subsequent tree. XGBoost is called a 'black-box' model, where the algorithm searches autonomously for the optimal combination of predictors to explain the outcome as well as possible.

Cross-validation was used to validate the results. To achieve this, the original dataset was split up in a training set of 100.584 subjects to estimate the models. A test of 11.177 subjects was used to validate the trained model and forms the basis of model performance statistics.

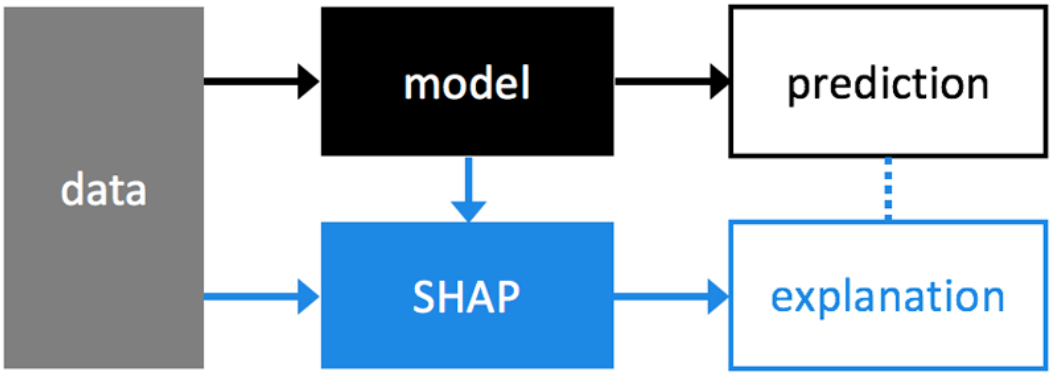

Figure 1: SHAP to explain the predictions of an arbitrary machine learning model.

Typically, black box machine learning algorithms have a trade-off between accuracy and explainability of the resulting model. This means that generally speaking, the better a model is in predicting a certain outcome, the harder it becomes to explain why the model resulted in a certain prediction. This can also be observed with the final model of this project. Given the numerous variables and trees used to make predictions, interpretation of the final set of tree models is complicated. To enhance insight in the model, rank variable importance, visualize the interesting effects and get a sense of the possible non-linear relationships and interactions within the data, we employed a SHAP (SHapley Additive exPlanations) model (visualized in Figure 1). SHAP is an novel approach which calculates the importance for each variable in the model for each individual test subject (Lundberg et al., 2018). This results in an importance score (or SHAP-value) for each of the variables for each of the individuals in the test data set. By aggregating these SHAP-values, one gets an overview of the most important predictors for the outcome variable, while enabling the investigation of complex (i.e.: higher order) interaction effects. Furthermore, it allows the prediction of new observations (e.g.: newly filled out NWCS questionnaires).

4 Results

This section presents the following results; (1) The overall performance of the model in predicting burnout symptoms. (2) A summary of relevant features chosen by the model. (3) A more detailed view of some of key risk factors of burnout. The Receiver Operator Curves (ROC) in Figure 2 show the overall performance of the model on the data used for training and on a holdout set. The hold out set, or test set, is a collection of observations (in this case, answers to the NWCS questionnaire) that the model has not seen before. This set has 11,117 (10% of the NWCS data selected after preprocessing). Moreover, there are 3,335 'burnout symptoms' samples (around 30% of the test set, as defined by Afl_Burnout > 3.2). The final model was is able to correctly classify 80% of samples, corresponding to an increase of 10% when compared to a model that assigned all samples to 'no burnout' group. Additionally, the model has a cross-validated AUC of 88% and hold out (test set) AUC of 87%. Consequently, while having limited accuracy, the model is able to capture the relationships present in the data more than a random model.

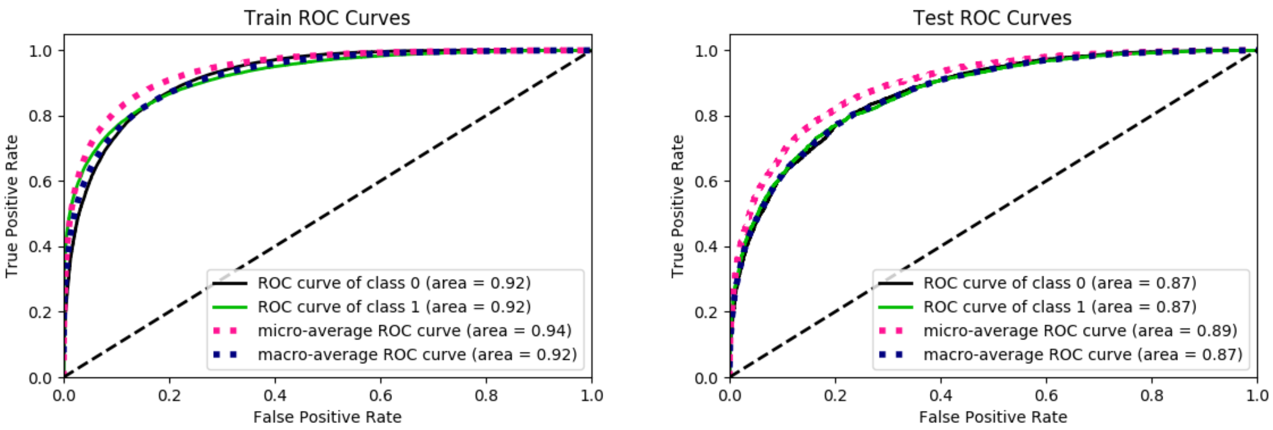

Figure 2: ROC for training (left) and test (right) data. The classes 0 and 1 correspond to 'no burnout symptoms' and 'burnout symptoms' respectively.

Importance of variables to burnout risk. Figure 3 provides details about variance importance, and overall impact on the model. In this figure variables are ranked according to their overall impact in the prediction (ordering in descending order in the y-axis), see the appendix for a further description of the variables. Colors indicate the value taken by the variable relative to the impact in the model. Moreover, values range from negative to positive values. Negative values correspond to a decreases in the log odds ratio, and consequently relate to a decrease in burnout risk. Similarly, positive values relate to an increase in the log odds and thus increase in risk of burnout symptoms.

The top 5 variables which were identified having the highest impact in the burnout symptoms prediction where: Emotional demanding work (Afl_Emotie), Psychological resilience (Compet_b), work satisfaction (TevrWrk), general health status (Afl_AlgGezDich-Goed or zeer Goed), and quantitative work demands (Afl_Werkdruk). From the colors assigned, we can see that emotional demanding work, and quantitative work demands range from blue (low score) to red (high score), indicating that an increase in these variables relates to an increase in burnout symptoms risk. In contrast, an increase in work enjoyment is related to a decrease in burnout symptoms risk.

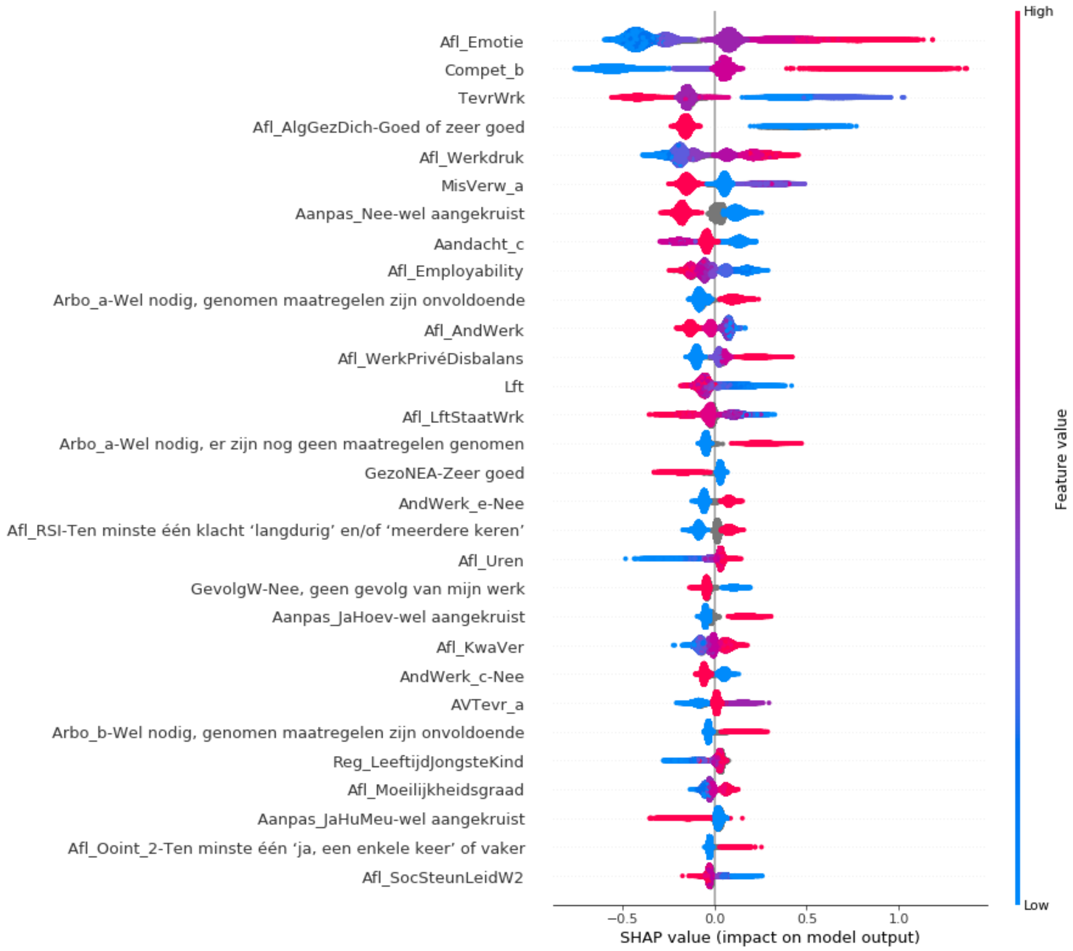

Figure 3: Figure shows the SHAP variable importance for the top 30 variables in the NWCS dataset. The x-axis shows the SHAP values for the different independent variables and colors indicate the value of the variable with the color grey indicating a missing value. A negative SHAP value is associated with a lower risk of burnout symptoms and a higher SHAP value with a higher risk. The variables shown are also ranked by their overall influence in the prediction.

Psychological resilience. The variable psychological resilience (Compet_b) suggests a relationship with burnout symptoms that is not in accordance with general expectation. This variable is measured as how strongly an individual agrees with the statement 'I can easily meet the psychological demands that my work places on me'. A more detailed view of the relationship of psychological resilience with the prediction is shown in Figure 4. In this figure values 1 through 4 correspond to strongly agree, agree, disagree, and strongly disagree respectively. We can note that answering strongly disagree has a relative strong impact in the model, and leads to an overall decrease risk of burnout symptoms. Figure 8 shows the variable measuring psychological resilience split out by burnout symptoms, and the unexpected relationship is immediately apparent. The 'disagree' category has a relatively high degree of having burnout symptoms, in line with expectation: one who is having difficulty coping with the psychological demands has a higher chance of suffering from burnout symptoms. However, the "strongly disagree" category has a similar and sometimes lower degree of people suffering from burnout symptoms than the "agree" category, contrasting with intuition. One interpretation of the relationship observed is that individuals that are able to properly assess their limits and needs have a lower risk of developing burnout symptoms. However, examining this further is out of the scope of this project (and possible data), but might be related to the problems of measuring self-reported burnout symptoms by means of survey research. More on this and possible use of more objective measures can be found in the discussion chapter.

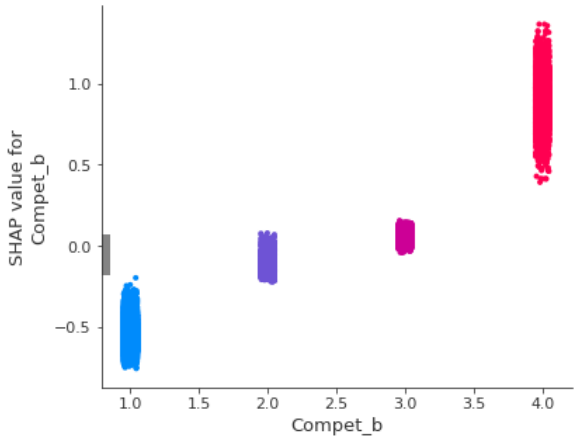

Figure 4: The answered value of Compet_b (x-axis) and the SHAP value of the same variable in the y-axis. Provides indication of how the model depends on the value of Compet_b variable. Colours are decorative. Grey values are points where the feature is missing. Higher SHAP value means higher change of burnout symptoms.

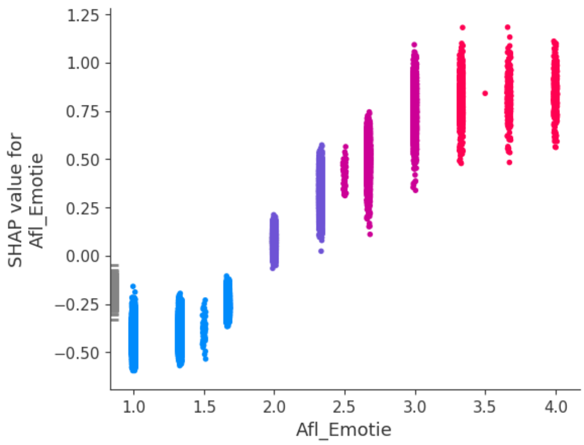

Figure 5: SHAP values for Afl_Emotie. Grey values are missings.

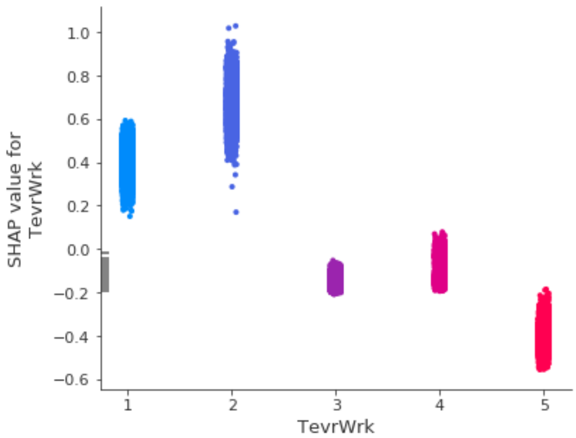

Figure 6: SHAP of Overall Job Satisfaction. Grey values are missing.

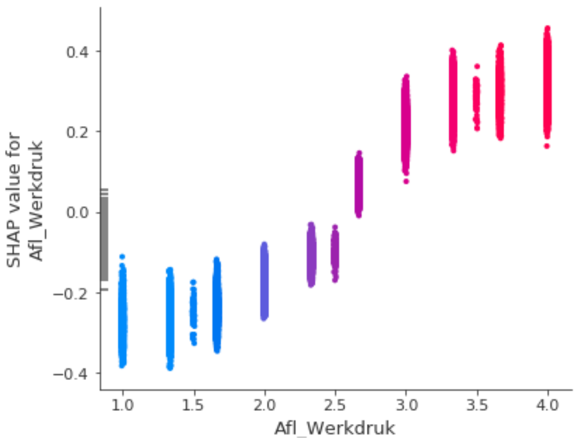

Figure 7: SHAP of Work Pressure scale. Grey is missing values.

Figure 8: Psychological Resilience by burnout symptoms for 2010 - 2017

Challenging the theory. In contrast of our expectations, many of the predictors often named in theories explaining burnout were not found to be of great importance. For example, the work-related stress model or work balance theory (Wiezer et. al., 2012) identifies an imbalance of job demands and resources as an important cause for burnout symptoms. These demands and requirements are made up of from different elements, which are depicted in Figure 9. Some of the elements from the figure indeed pop up in the results, but the majority does not.

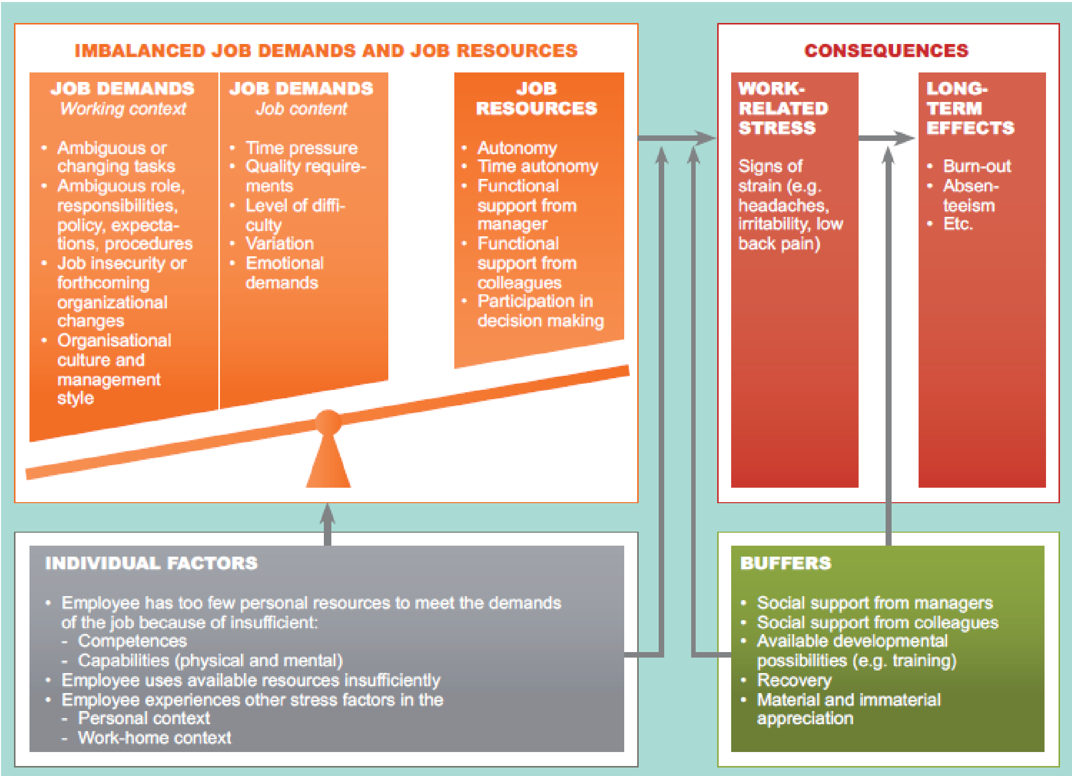

Figure 9: Work Balance Model; Wiezer et.al., 2012

From the Working Context, only “Job insecurity or forthcoming organizational changes” seems to be of importance for burnout symptoms. From the context of Job Demands, only “Emotional demands” play a significant role, although it remains ambiguous what that means on an individual level. Furthermore, from the Job Resources, we do not see any of the variables play an important role in explaining burnout symptoms. From the individual factors we see two strong predictors of burnout symptoms in both theory and empirical results: competence and work-home balance. In addition, social support from colleagues, recovery and material appreciation, the buffers, were not found to be important, both in direct relation with burnout symptoms or in statistical buffering (e.g.: interacting or moderating). More on these factors can be found in the Appendix.

Some other important factors found in the academic literature to be of importance for explaining burnout symptoms that were not found in the NWCS dataset are listed here. Safe psychosocial work environment (with the exception of harassment by coworkers), job crafting ability, giving meaning to one’s job, effective self-governance & self-management, fulfillment of primary needs, psychological and social capital were not found to play an important role.

Instead, importance is given to psychological stressful work environment, high work demand, and poor work-life balance. Absenteeism (HoevaakV), low management support (Afl_SocSteunW2), are also identified as having a relationship with burnout symptoms which agrees with previous research. Additionally, young employees with children appear at a higher risk of developing burnout symptoms (Figure 10), an aspect theorical models do not capture (individual life situation or stage, demand at home). Furthermore, an interaction between age and burnout symptoms was also observed, with employees age ranging 20 – 30- years having the highest associated risk with burnout symptoms. A significant drop in risk is also observed at around retirement age (Appendix). Additional variables were extracted from the data to better investigate the influence of work context. Variables such as workplace inequality, in gender or nationality, median income, median age, etc. However, these were observed to offer relative low importance by the model with regard to burnout symptoms prediction.

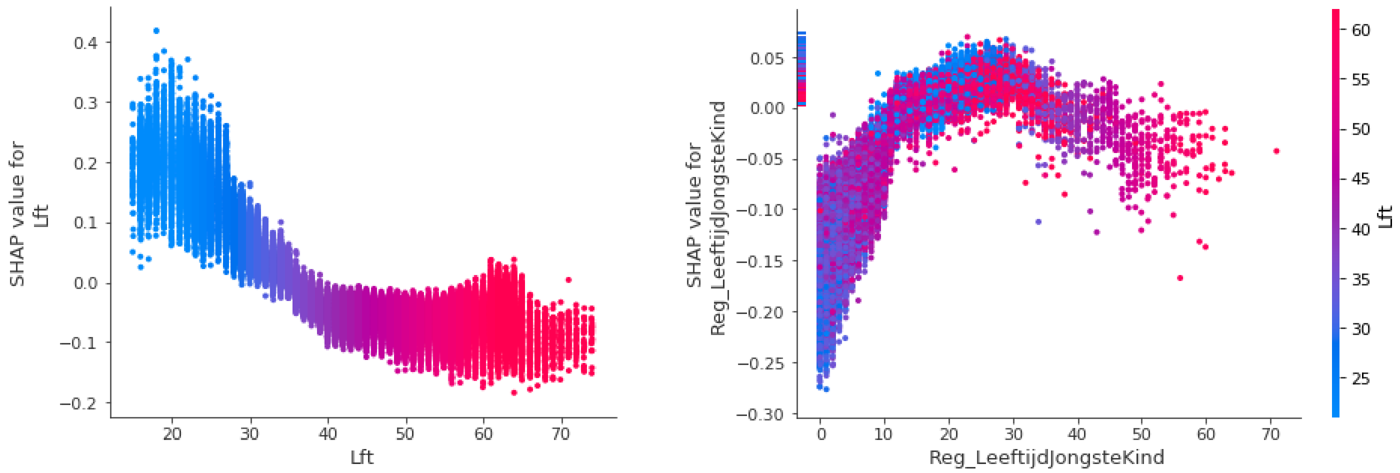

Figure 10: SHAP values for Lft (Age), Reg_LeeftijdJongsteKind (Age of youngest child).

Individualized prediction. Using the Shaply Additive Explanations (Shap) method we can gain insight into the predictions made by the model. Shap is a paradigm offering insights and model explanations (see methods section for additional details). For individual predictions, influence diagrams offer insight into the influence of observed variables in a sample (Figure 4). The contribution of variables can be read from the diagram. On the left variables that contribute to a higher risk of burnout symptoms are shown in read. On the right, variables that decrease the risk of burnout symptoms are shown in blue. In Figure 4, the prediction of burnout symptoms risk for two individuals is shown. The first individual, is determined to be of a low risk of burnout symptoms, due to high work enjoyment, low emotional stress at work, and low work-pressure. The second prediction, shows that this individual is at a higher risk, due to relative high work demand and not having excellent health.

5 Discussion

The results presented indicate occupational stress and burnout symptoms are related to emotional stress at work, low work enjoyment, high work demand, and low overall health. Also, an important predictor for occupational burnout symptoms is poor work-life balance. Furthermore, young employees appear to be at a higher risk, with children also playing a role in increasing risk of occupational burnout symptoms. The link with absenteeism is also present in the model, as is low management support.

Limitations. A limitation of this study is the measurement of burnout symptoms. Since the concept of burnout symptoms was explicitly asked using only a small set of items, people who are actually developing burnout symptoms but are ignoring the signs, might fall in the ‘no burnout symptoms’ category where they in fact are suffering from the onset of burnout symptoms. Additionally, there are many other factors playing a role in the development of burnout symptoms which are not considered here. Examples of these are life style and personal development such as coping strategies. Furthermore, to accurately study the coming about of burnout symptoms, a cohort study (a longitudinal) dataset considering many years of measurement is necessary. The CODI cohort fork of the NWCS consisting of 3 years (thus three measurements) showed significant changes over time in terms of burnout symptoms using a mixed logistic model, but these showed noisy and unstable when predictors of high importance of the XGBoost model were introduced in the model. This implies that burnout symptoms are relatively difficult to predict over time given the constraints of the current dataset. However, to properly dive into the effects-over-time relation of burnout symptoms, an additional study is necessary given the complexity of the data and the many different dynamics associated with the causes of burnouts.

Further research. A possible solution to have more reliable and accurate measurements of stress and burnout is to incorporate objective measurements of behavior. An example of where this is done successfully is the TNO SWELL project (Koldijk et al., 2016). Here, a set of objective measures, such as posture, keyboard typing behavior and facial expressions was used to predict stress related behavior using machine learning with good results (accuracy of ~90%).

Overall, our current model provides results that challenge established theoretical burnout model(s). However, they might also form the basis of a first step of combining both data and knowledge in novel ways. Developments in data science and statistics allow for data driven insights impossible up until recently. Given the complexity of explaining burnout symptoms, these innovative methods allow to gain more insights from data and might form the basis for furthering our understanding of the phenomena by aptly combining data and theory.

A next step in theory development surrounding burnout symptoms should be geared towards modelling the phenomenon as being the result of an intricate, dynamic network of many of the aforementioned concepts (ranging from behavioral, mental, resources, organizational traits and personal experience). By modelling burnouts as being the result of a Complex System (CS) allows us to close the gap between data and theory by accommodating its highly complex nature. A possible way forward would be to empirically investigate burnout symptoms as part of a network.

This network sees burnout symptoms as the results of a set of dynamically interacting factors. Here, subjective measures (e.g.: survey data) and objective measures (e.g.: sensors and software) could be combined to optimize results. Using a CS approach, it would be possible to try to model each of the possible links to all those aforementioned factors, using a step-by-step fashion.

6 References

Chen, T., He, T., Benesty, M., Khotilovich, V., & Tang, Y. (2015). Xgboost: extreme gradient boosting. R package version 0.4-2, 1-4.

Chen, T., & Guestrin, C. (2016, August). Xgboost: A scalable tree boosting system. In Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining (pp. 785-794). ACM.

Factsheet week van de Werkstress 2015: http://www.monitorarbeid.tno.nl/dynamics/modules/SFIL0100/view.php?fil_Id=149 retrieved on 03-07-2019.

Factsheet week van de Werkstress 2018: https://www.monitorarbeid.tno.nl/dynamics/modules/SPUB0102/view.php?pub_Id=100593&att_Id=4911 retrieved on 03-07-2019.

Hooftman W.E., Mars G.M.J., Janssen, B., De Vroome, E.M.M., Janssen B.J.M., Pleijers A.J.S.F.. Ramaekers M.M.M.J. & Bossche, S.N.J. van den (2019). Nationale Enquête Arbeidsomstandigheden 2018: Methodologie en globale resultaten. Leiden/Heerlen: TNO/CBS.

Kivimäki, M., Nyberg, S. T., Batty, G. D., Fransson, E. I., Heikkilä, K., Alfredsson, L., ... & Clays, E. (2012). Job strain as a risk factor for coronary heart disease: a collaborative meta-analysis of individual participant data. *The Lancet*, 380(9852), 1491-1497.

Koldijk, S., Kraaij, W., & Neerincx, M. A. (2016). Deriving requirements for pervasive well-being technology from work stress and intervention theory: framework and case study. *JMIR mHealth and uHealth*, 4(3), e79.

Lundberg, S. M., Erion, G. G., & Lee, S. I. (2018). Consistent individualized feature attribution for tree ensembles. *arXiv preprint arXiv:1802.03888.*

Madsen, I. E., Nyberg, S. T., Hanson, L. M., Ferrie, J. E., Ahola, K., Alfredsson, L., ... & Chastang, J. F. (2017). Job strain as a risk factor for clinical depression: systematic review and meta-analysis with additional individual participant data. *Psychological medicine*, *47*(8), 1342-1356.

Nyberg, S. T., Fransson, E. I., Heikkilä, K., Ahola, K., Alfredsson, L., Bjorner, J. B., ... & Hamer, M. (2014). Job strain as a risk factor for type 2 diabetes: a pooled analysis of 124,808 men and women. *Diabetes care*, *37*(8), 2268-2275.

Schaufeli, W.B. & D. van Dierendonck (2000). Handleiding van de Utrechtse Burnout Schaal (ubos). Lisse: Swets & Zeitlinger.

Toker, S., Melamed, S., Berliner, S., Zeltser, D., & Shapira, I. (2012). Burnout and risk of coronary heart disease: a prospective study of 8838 employees. *Psychosomatic Medicine*, 74(8), 840-847.

Wiezer N., Schelvis R., van Zwieten M., Kraan K., Klauw, M., Houtman I., Kwantes J.H. en Bakhuys Roozeboom M. (2012) Werkdruk. TNO: Hoofddorp.

Appendix Variables used

For a detailed description of the variables in the NWCS see Hooftman et al (2019). A short description of relevant variables and their relation with burn-out symptoms is given below.

- **Burn-out symptoms**: Burn-out symptoms are measured with 5 questions based on the POLs. The questions are adapted from the Utrecht Burnout Inventory (Schaufeli & van Dierendonck, 2000). Questions are rated on a 1 (never) to 7 (every day) scale. 3.2 is used as a cut-off point for burnout symptoms.
- **Compet_b**: psychological resilience 'I can easily meet the psychological demands that my work places on me'. Contrasting to intuition, a higher score on this question is associated with a higher chance of having burnout symptoms. Further investigation of this relation can be found below (under Compet_b paragraph).
- **Afl_Emotie**: Emotionally demanding work [scale 1 (never)- 4 (always)]. Higher value on this scale is associated with a higher probability of having burnout symptoms.
- **TevrWrk**: Work satisfaction (scale 1 (very dissatisfied) – 5 (very satisfied) Higher value on this scale is associated with a lower probability of having burnout symptoms.
- **Afl_Werkdruk**: Quantitative demands, [scale 1 (never)- 4 (always)] based on 4 questions, e.g. I have to work at a high pace Higher value on this scale is associated with a higher probability of having burnout symptoms. The effect of the dichotomous variabele (Afl_Werkdruk_di) is similar to the continuous scale, but with a milder effect.
- **Afl_AlgGezDich**: General Health, dichotomized into 0 (bad) vs 1 ((very) good. Agreeing with having a bad health (scoring a '1') is associated with a higher probability of having burnout symptoms.
- **GezoNEA**: Different name for the previous variable "Afl_AlgGezDich".
- **Aandacht_c**: "Does your work requires a lot of attention from you?" Vergt uw werk veel aandacht van u].

  Higher value on this scale is associated with a higher probability of having burnout symptoms. Interestingly enough, this item is part of the scale "**Afl_Moeilijkheidsgraad**" (cognitive demands), which is not appearing high on the list of variables. Apparently, this specific question is much stronger related with burnout symptoms than the scale of which it is part.
- **GevolgW**- Workrelatedness of complaints Lower value, meaning 'No', is associated with lower probability of having burnout symptoms.
- **Afl_AndWerk**: Tendency to change job, scale based on 5 items e.g. "Are you at risk for losing your job?". Agreeing with the binary question options 'yes' leads to a higher probability of having burnout symptoms.
- **Afl_WerkPrivéDisbalans**: Work-Home balance [scale: 1=never - 4=very often; 2 items]". Higher score (meaning more disbalance has little influence on the outcome, but lower score (meaning better balance) can be of strong influence on reducing the probability of burnout symptoms.
- **MisVerw_a**: Are you missing or neglecting family(activities) because of your work??". One of the items of the "**WerkPrivéDisbalans**" variable. Works in a similar fashion.
- **Alf_Employability**: Employability [scale: 1=low - 4=high; 4 items]. E.g. I could easily get an new job at another employer. Lower self-reported value of employability reduces burnout symptoms. This is because the direction of the scale is reversed.

- **Afl_RSI** -Long term complaints of the neck, shoulders, arms/elbows or wrist/hands (RSI) Having long term RSI problems is associated with a higher probability of burnout symptoms.
- **Arbo_c**: OSH measures for prolonged computerwork“”. Agreeing with the need for more OSH measurements is associated with a higher probability of having burnout symptoms.
- **Lft**: Age. Lower age has a positive effect on reducing burnout symptoms, although being old itself is not associated with a high probability of burnout symptoms.
- **AflStaatWerk**: Age until it is perceived that de work can be - physically and mentally - continued [Subgroup: All ages; excl. those who do not know it (yet) . When people expect that they are not able to work for till a high, they have an increased probability of having burnout symptoms.
- **Afl_Ooint_2**: Unwanted behavior (e.g. sexual, verbal, physical) by colleagues. [4 items, dichotomized into 0=never, 1=at least once]. Lower score means no unwanted behavior. Higher score is associated with burnout symptoms.
- **AndWerk_e**: Would you still work with this company in 5 years. Similar to AflStaatWerk.
- **Aanpas_JaHoev**: Need for adaptations in the amount of work. When crossed as important, this answer has a strong association with having burnout symptoms.
- **Afl_KwaVer**: Skill ageing [scale: 1=low - 5=high; 3 items]”. Higher score is related to higher probability of burnout symptoms.
- **HoevaakV**: Frequency of work absenteeism (no absenteeism=0)
- **Afl_SocSteunLeidW2**: Supervisor social support Counter-intuitively, less social support is associated with lower probability of having burnout symptoms.
- **RedenW**: In your opinion, what was the most important reason in the work that (partly) led to the occurrence of these complaints? [Subgroup: "Ever absent and partly or mainly due to work"].This question is only valid for those who were absent for some time at work. When the reason was workstress or workpressure, the probability of burnout symptoms is higher.
- **AVTevr_a**: satisfaction with the interestingness of the work. People scoring around the median have the highest association with having burnout symptoms. This is a U-shape relationship with the peak of the bell-curve around 2.5.
- **Afl_Beroepsziekte_Prevalentie**: Having at least one occupational disease (prevalence) [based on 13 items]”. Having a work-related disease is associated weakly with having no burnout symptoms.
- **Reg_LeeftijdJongsteKind**: Age of the youngest child Having a young kid lowers the probability of having burnout symptoms, yet the negative impact of having older children is relatively small.

TNO.NL