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Measuring Ethical Values with AI for Better Teamwork

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Abstract: Do employees with high ethical and moral values perform better? Comparing personality characteristics, moral values, and risk-taking behavior with individual and team performance has long been researched. Until now, these determinants of individual personality have been measured through surveys. However, individuals are notoriously bad at self-assessment. Combining machine learning (ML) with social network analysis (SNA) and natural language processing (NLP), this research draws on email conversations to predict the personal values of individuals. These values are then compared with the individual and team performance of employees. This prediction builds on a two-layered ML model. Building on features of social network structure, network dynamics, and network content derived from email conversations, we predict personality characteristics, moral values, and the risk-taking behavior of employees. In turn, we use these values to predict individual and team performance. Our results indicate that more conscientious and less extroverted team members increase the performance of their teams. Willingness to take social risks decreases the performance of innovation teams in a healthcare environment. Similarly, a focus on values such as power and self-enhancement increases the team performance of a global services provider. In sum, the contributions of this paper are twofold: it first introduces a novel approach to measuring personal values based on "honest signals" in emails. Second, these values are then used to build better teams by identifying ideal personality characteristics for a chosen task.

Keywords: personality characteristics; ethics; business performance; honest signals; email analysis; machine learning; social network analysis; natural language processing; time series analysis

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1. Introduction

Do employees with high ethics and morals perform better? Extant research has tried for a long time to identify personality characteristics, moral values, and risk-taking behavior correlated with high-performing individuals and teams. Until now, these determinants of individual personality were measured through surveys, where individuals were asked to answer a series of questions to assess their characteristics. Existing research shows that certain characteristics are related to individual and team performance. For instance, it has been found that with regards to the FFI five-factor personality inventory, entrepreneurs are more conscientious, open, and extroverted, and less neurotic and agreeable than managers [1]. Similarly, the perceived fairness of executives has a positive influence on employee performance [2]. However, individuals are notoriously bad at self-assessment, either seeing themselves in too positive a light or being overly critical of themselves. AI and machine learning put new tools at the disposal of behavioral and organizational researchers, allowing them to automatically analyze electronic traces of individuals to predict their personality characteristics. Leveraging social network analysis (SNA) and natural language processing (NLP) enables researchers to gain deep insights into the personality of individuals, computing it automatically and then comparing the predicted personality characteristics with dependent variables of individual and team performance.

Foundational Research

In his seminal research Pentland [3] introduced the concept of honest signals. These are small signs of an individual, for instance, body signals, little words, or the way how words are spoken or sent electronically, that give away the true intent, personality, emotion, or personal values of the individual. We have applied this concept of honest signals to email, for instance, measuring the speed of response to a message as a predictor of the passion of an employee, while the speed with which others respond to her is a predictor of the respect she commands [4]. Similarly, the creativity of an individual can be measured by tracking the changes in the network position of the individual in the group network [4]. The validity of these constructs has been verified many times, applying it to employee satisfaction [5], individual and team creativity [6], customer satisfaction, the likelihood of leaving the company [5], personality characteristics, and risk-taking attitude [7]. In another project, we have shown that the moral values of individuals are correlated with their honest signals expressed in their emails [8]. In this project, we will apply these insights to first compute personality characteristics, ethical values, and risk attitudes from the emails of employees and then attempt to uncover the hidden relationship between the values of these individuals and their individual and team performance.

The present work builds on previous research examining the relationship between the concepts of honest signals and personal values measured with the same surveys as in the present paper. The first relevant study links honest signals to the traits of agreeableness, neuroticism, and openness to experience. Agreeableness, for example, is linked to greater centrality and shorter response time, neuroticism to lower centrality and a lower contribution index, and openness to experience to shorter response time [9]. In a further study, correlation and regression results demonstrate significant connections of honest signals for all five moral foundations of Haidt. According to this study, for example, positive and non-emotional language and "nudging by email" are predictive of a person's level of harm or care [8]. In sum, the study showed that honest signals account for 70% of the actors' moral values [8]. In terms of Schwartz's Values, the same study's correlation results show that the value of conservation is linked to increased responsiveness and social capital [8]. Unlike the current paper, the study has not examined the values that underpin Schwartz's dimensions. However, as these are underlying values of similar dimensions, it is presumed that they are likewise linked to honest signals. The final study on which this paper is based analyzes personality through the lens of DOSPERT values. Both email and DOSPERT survey data are collected, as in the other experiments, to investigate their relationship. The regression results suggest that honest signals can create significant predictions of people's risk attitudes [7]. In sum, the described studies indicate that email-based honest signals can be predictive of personal and moral values, as measured by the NEO FFI-R personality survey, the Schwartz's Values survey, the Haidt Moral Foundations questionnaire, and the DOSPERT risk-taking survey. This work builds on this previous research by developing machine learning models which predict individuals' personal and moral values by their honest signals. Hereby, these models serve as an intermediary step to predict the survey scores of employees and link these values to their performance.

2. Method

How can we predict individual and team performance based on email communication data? The goal of this research is to leverage the "wisdom of the crowd through AI" to identify personality characteristics, moral principles, and attitudes to risk predictive of employee performance, both on the individual and on the team level. These characteristics can then be used to measure and improve performance of employees, managers [2], and entrepreneurs [1]. Towards that goal, features suitable for machine learning need to be extracted from electronic communication archives such as email. In particular, features indicative of social network structure such as degree and betweenness centrality features indicative of network dynamics such as oscillation in betweenness centrality and contribution index, and features indicative of network content such as positivity and emotionality must be computed. These features are known as “honest signals” [3]. Honest signals are signals that people express unconsciously or uncontrollably. These signals are rooted in individuals and give meaningful insights and revelations about their behavior [3]. An overview and definitions of all studied honest signals are given in Table 1. These features are then compared with morality, personality, and risk attitude of individuals measured through the NEO FFI-R personality survey [10], the Schwartz’s Values survey [11], the Haidt Moral Foundations questionnaire [12], and the DOSPERT risk-taking survey [13] to build a machine learning model that will predict these dependent variables (morality, personality, and risk attitude) automatically.

Table 1. Definition of Honest Signals.

Signal	SNA/NLP Term	Definition	Calculation
Central Leadership	Degree Centrality	Number of actors each person is directly connected within a network [4]	Number of nearest neighbors from an actor both as senders and receivers in the network [4]
	Betweenness Centrality	Measure of the extent to which each actor acts as an information hub [4]	Likelihood to be on the shortest path between any two actors in the network [4]
	Closeness Centrality	Measure of the mean distance from a node to other nodes [7]	Mean shortest distance from one node to each other node [14]
	Reach2	Proxy for individual social capital [7]	Number of nodes an actor can reach in two steps [15]
Rotating Leadership	Betweenness Centrality Oscillation	Measure of how frequently actors change their network position in the team, from central to peripheral, and back [4]	Number of local maxima and minima in a node’s betweenness centrality curve [4]
Balanced Contribution	Contribution Index	Balance of communication in terms of sent and received messages [4]	Subtracting messages received from the messages sent and then dividing the result by the messages sent added to the messages received [4,7]
Rotating Contribution	Contribution Index Oscillation	Measure of how frequently actors change the balance of their communication [7]	Number of local maxima and minima in a node’s contribution index curve [7]
(Rapid) Response	Ego ART	Average number of hours sender takes to respond to emails [4]	Time until a frame is closed for the receiver after he has sent an email [4]
	Ego Nudges	Average number of follow-ups that the sender needs to send to receive a response from the receiver [4]	Number of pings until sender responds [4]
	Alter ART	Average number of hours receiver takes to respond to emails [4]	Time until a frame is closed for the sender, after he has sent an email [4]
	Alter Nudges	Average number of follow-ups that the receiver needs to send to receive a respond from the sender [4]	Number of pings until receiver responds [4]
Honest Language	Average Sentiment	Indicates positivity and negativity of communication [4]	Sentiment scores which are predicted through ML model trained on twitter data are averaged [4,16]
	Average Emotionality	Indicates the deviations from neutral sentiment [4]	Standard deviation of sentiment [4]
Shared Context	Average Complexity	Measure of complexity of word usage [4]	Information distribution using Term Frequency Inverse Document Frequency (TF/IDF), independent of single words [4]
	Average Influence	Measure of influence of word usage averaged over all messages—defined as speed with how quickly newly introduced words are picked up by others, normalized by TF/IDF [17]	Counting the popularity of a word within a message compared to all other messages in the community (using TF/IDF) [17]
	Total Influence	Measure of influence of word usage—the individual influence per message summed up over all messages of an actor [17]	Summing up influence measure (described above) over all messages of an actor [17]

The NEO FFI-R surveys the Big Five personality traits of openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism [10]. Schwartz's Values survey is based on Schwartz's Theory of Basic Human Values and measures the ten human values of importance for power, achievement, hedonism, stimulation, self-direction, universalism, benevolence, tradition, conformity, and security, as well as the two dimensions of self-transcendence and conservation [11]. The moral foundation questionnaire is based on the Theory of Moral Foundations and attempts to measure the moral concerns of individuals. These values include peoples' concern for care (or harm), fairness (or cheating), loyalty (or betrayal), authority (or subversion), and sanctity (or degradation) [12]. Last, the DOSPERT risk-taking survey measures peoples' risk-taking likelihood and perception in five behavioral domains. According to the DOSPERT scale, risk-taking decisions can be assessed by financial (e.g., investing in a speculative stock), health/safety (e.g., seatbelt usage), recreational (e.g., taking a skydiving class), ethical (e.g., cheating on an exam) and social risk decisions (e.g., confronting coworkers or family members) [13]. Further, this work defines the total risk likelihood and perception by the sum of the respective scores as an indicator of a person's overall risk-willingness [7].

The resulting models are then used to predict morality, personality, and risk attitude of large numbers of individuals through analyzing their emails and developing further models to predict employees' performance based on their personal and moral values. The described theoretical framework is presented in Figure 1.

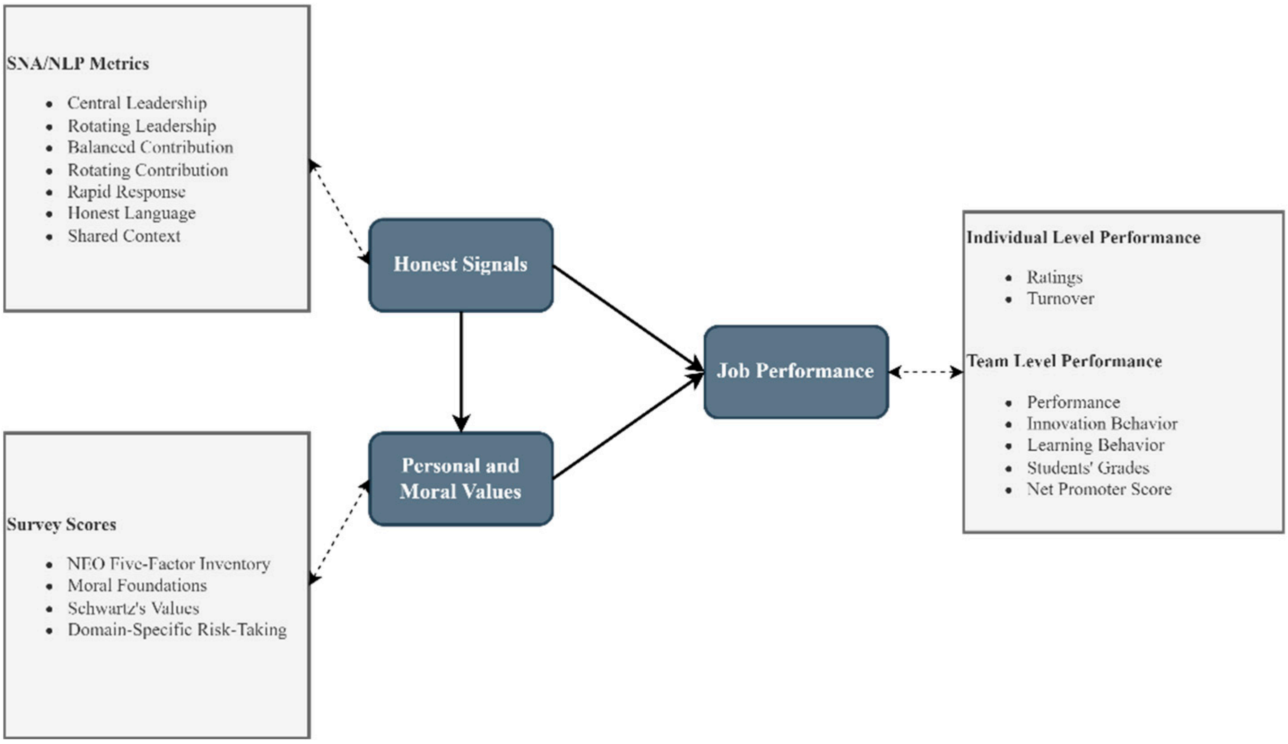

Figure 1. Theoretical Framework.

Email archives of interactions of students participating in a multinational university course, professionals in a service firm as well as personal mailboxes are analyzed, where the same people have also answered the NEO FFI-R personality survey, the Schwartz's Values survey, the Haidt Moral Foundations questionnaire, and the DOSPERT risk-taking survey. In terms of FFI surveys, data of 81 people are analyzed, while 56 people are surveyed for Moral Foundations, 61 people for Schwartz's Values, and 49 people for DOSPERT values (Table 2). Constellation of the data sources underlying the targeted survey scores are given in the following table.

Table 2. Data Source Per Survey.

Survey	Data Source	Percentage	N
NEO FFI	Multinational university course	18.51%	15
	Professional service firm	2.47%	2
	Personal email boxes	79.01%	64
	Total	100%	81
Moral Foundations	Multinational university course	25.46%	14
	Professional service firm	1.82%	1
	Personal email boxes	72.73%	40
	Total	100%	56
Schwartz's Values	Multinational university course	22.95%	14
	Professional service firm	3.28%	2
	Personal email boxes	73.77%	45
	Total	100%	61
DOSPERT	Multinational university course	30.61%	15
	Professional service firm	4.08%	2
	Personal e-mail box	65.3%	32
	Total	100%	49

With the email data, the honest signals of these people, such as speed of response, SNA metrics, and emotionality, are computed. The "honest signals" are then used as features to predict FFI personality, Schwartz's Values, Moral Foundations, and DOSPERT attitudes to build a generally usable machine learning model that will predict these values from email. These models will be applied to separate datasets of employees of different industries in order to predict their personalities and link them with their performance. Similar to the case of building machine models for predicting personal values, usable machine learning models that will predict performance will be built. Hereby, email and various performance measure data of employees of health care firms, professional services as well as students are collected and analyzed. Table 3 shows the origin of data as well as the targeted performance variables.

Table 3. Data Sources for each study.

Data Source	Object of Study	Target
Health care	70 employees in 11 innovation teams	Team performance, learning behavior, and innovation behavior
Professional services	82 managers	Employee ratings (of two years)
Professional services	78 managers in 17 teams	Team net promoter score
Multinational university course	80 master's students in 20 teams	Student Teams Grades

Further, data are prepared by detecting and removing outliers, identifying and merging duplicate actors in the email network, and binning the target features into the three classes of "low", "medium", and "high" personality or performance scores. Binning is performed for the continuous target features based on normal distribution so that the lowest-scoring 16%, the highest-scoring 16%, and the remaining 84% are binned into one category each, while categorical performance variables, e.g., managers' ratings, are left in their natural state. After preparing the data, the process of developing the machine learning models is structured in the following way. First, a maximum of three input features are selected based on calculating the importance of the strongest correlating input features in order to avoid overfitting of the classification models. Then, the datasets are split into 90% training and 10% test data in order to ensure, in the context of the relatively small data sets, that instances of all three classes are present in the 10 folds during cross-validation as well as during testing. The classes of the training data are balanced via SMOTE, and different classification models, such as Logistic Regression, Support Vector Machines, Stochastic Gradient Descent, or XGBoost Classifiers (XGB), are approached and trained using 10-fold cross-validation (CV) [18–20]. Out of all approaches, the best-performing model is optimized using GridSearchCV before finally evaluating the model on the independent test set. Figure 2 describes this system setup.

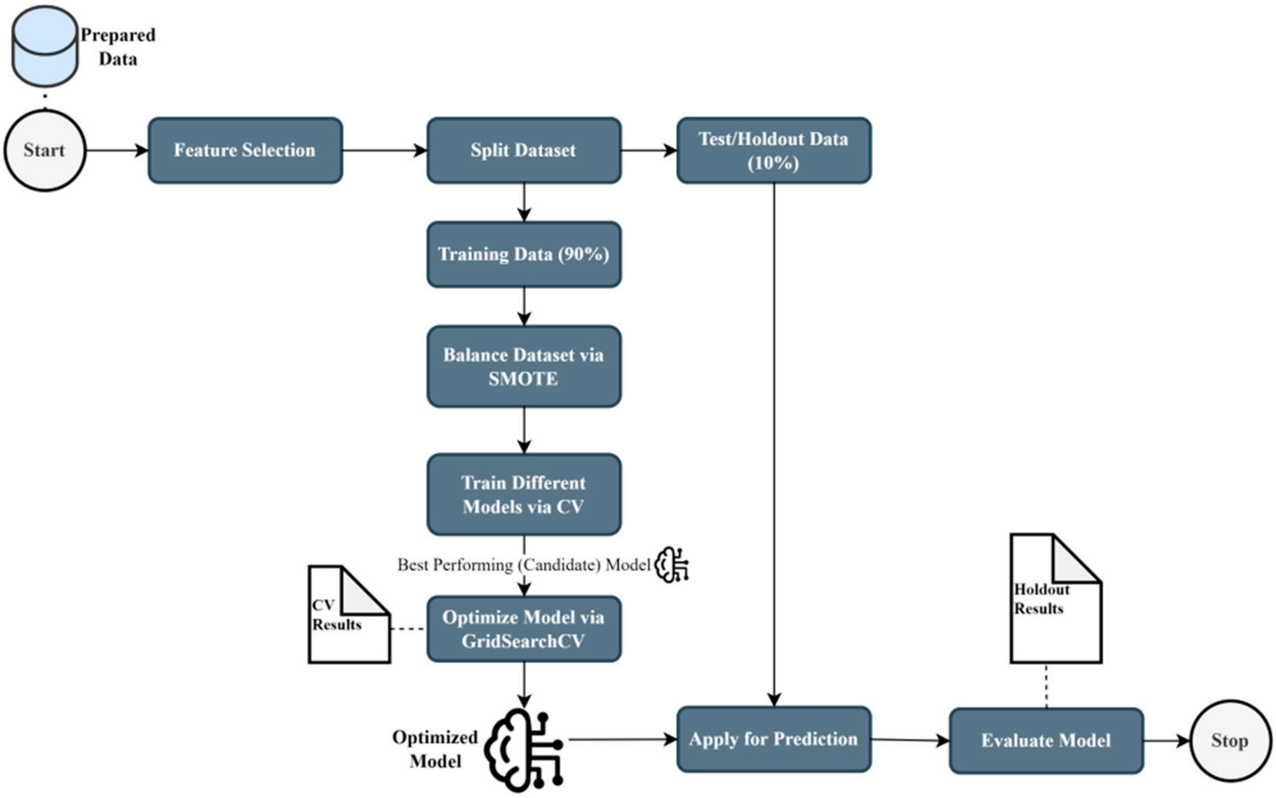

Figure 2. Modeling Setup.

Python and Jupyter Notebook are used for programming and coding tasks, including data preparation, modeling, and evaluation. Additionally, in terms of creating data statistics (e.g., correlation results), R and RStudio are used. Email data collection has been performed using Condor [21], a social network and semantic analysis software, before processing the data in Phoenix [22], a high-end analysis software to calculate and explore honest signals.

3. Results

3.1. Predicting Personal and Moral Values

Analyzing email and survey data of the cohort of students, employees in professional services, and actors in the personal mailbox, correlation results (see Appendix A) suggest relationships between honest signals and personalities. For example, the personality factor conscientiousness is associated with occupying central network positions at the significance level of 0.05, as indicated by betweenness (0.221 *) and degree centrality (0.227 *), while agreeable people tend to be positioned at peripheral positions.

Based on the most important and strongest correlating input features, the developed ML models for predicting survey ranks are shown in Table 3. In sum, the personal and moral values of agreeableness, conscientiousness, extraversion, openness to experience, neuroticism, authority/respect, fairness/reciprocity, harm/care, power, achievement, transcendence, recreational risk likelihood, social risk likelihood, social risk perception, ethical risk likelihood, ethical risk perception, and total risk likelihood result to be predictive through honest signals. For the remaining target values, no prediction model could be developed due to low validation metrics. Furthermore, a point to notice is that among all considered classification approaches, XGB classifiers indicate the best performance. Consequently, all valid models are represented by XGB models.

Regarding conscientiousness, for example, in addition to degree centrality, the oscillation of a person's betweenness centrality has proven to be a substantial predictor. The model's feature importance plot is shown in Figure 3. Accuracy scores of about 0.8 during CV and 0.889 on the holdout set, as well as a Cohen's kappa coefficient of 0.75, indicate that the model has a validly high performance.

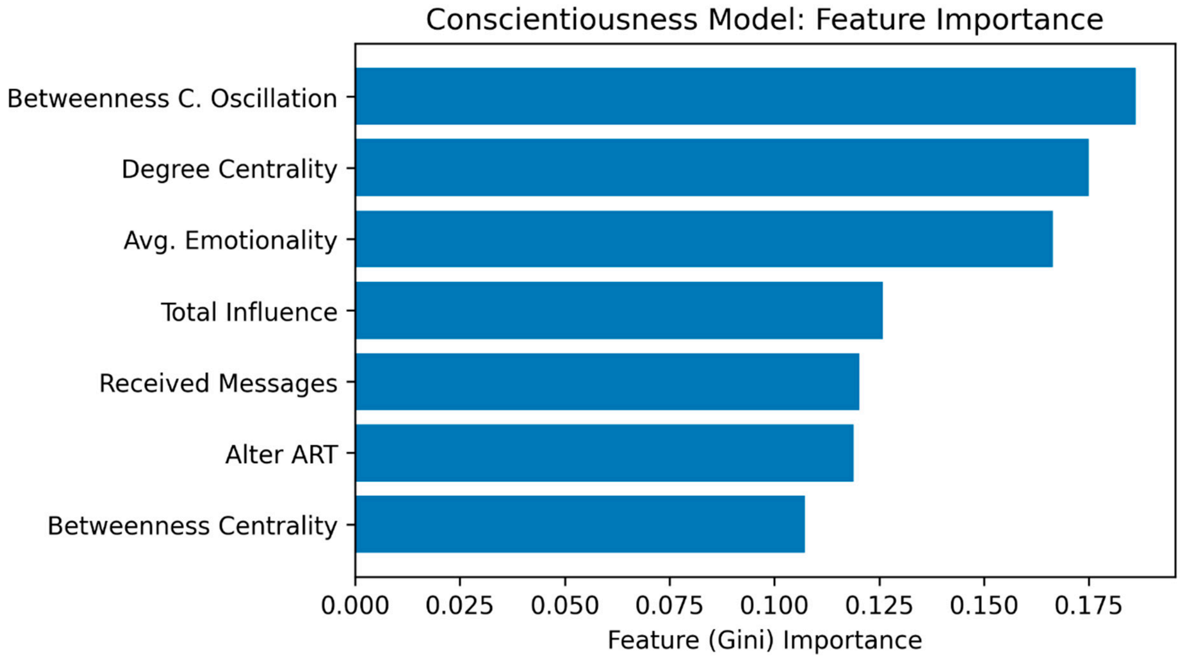

Figure 3. Feature Importance of Conscientiousness Model.

An individual's level of valuing authorities and respect, for example, is shown to be predictive through the signals of average influence and sentiment (Figure 4). The classification model reaches an accuracy score of 0.707 during CV and 0.833 during testing. Furthermore, ROC AUC scores of greater than 0.8 on both sets and Cohen's kappa score of 0.714 indicate accurate predictability.

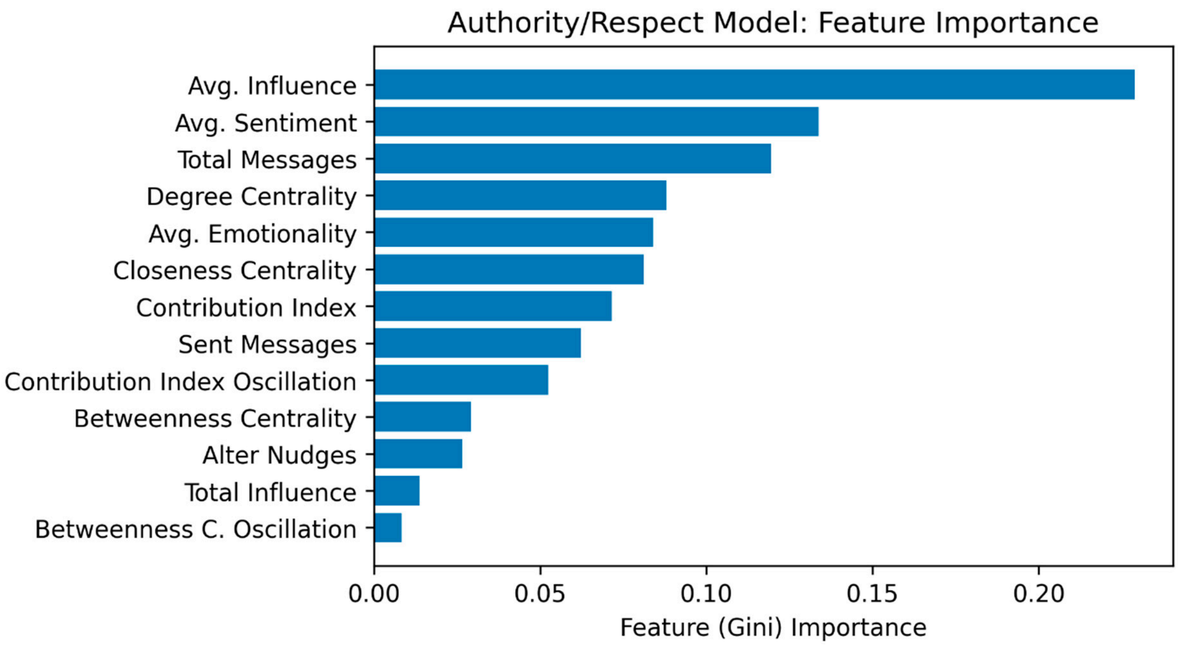

Figure 4. Feature Importance of Authority/Respect Model.

In terms of Schwartz's Values, modeling results show, for example, that the importance of power for people is predictable by the language metrics of complexity, emotionality, and influence per message (Figure 5). Beyond that, the second value of the dimension self-enhancement, which is achievement, can be predicted through the signals of betweenness centrality, contribution balance, and the number of sent messages (Figure 6). Both models for predicting an individual's relevance of power and achievement perform well, with an accuracy of 0.714 on the test set. Furthermore, both models perform well during CV, with an accuracy of 0.858 when predicting power and an accuracy of 0.793 when predicting achievement.

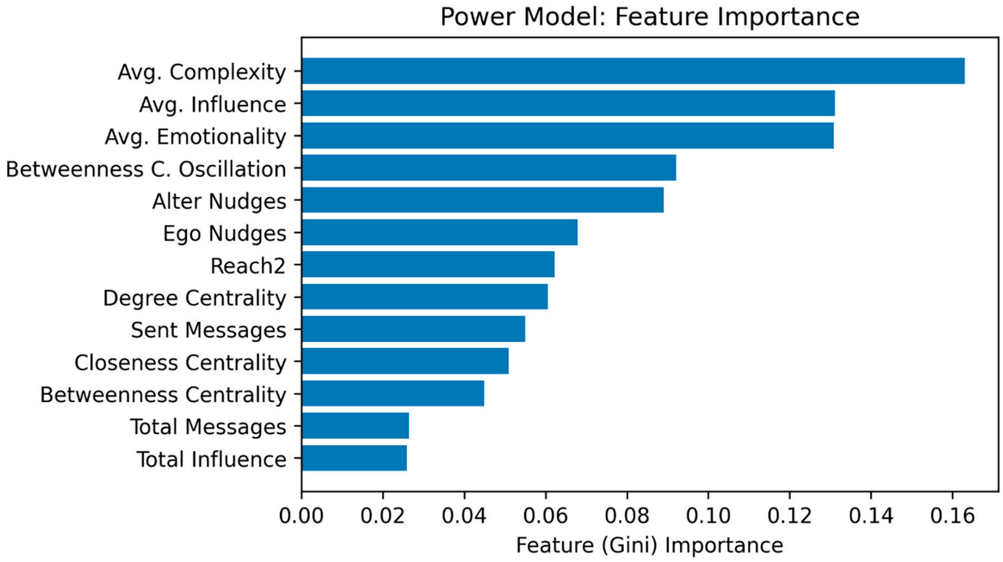

Figure 5. Feature Importance of Power Model.

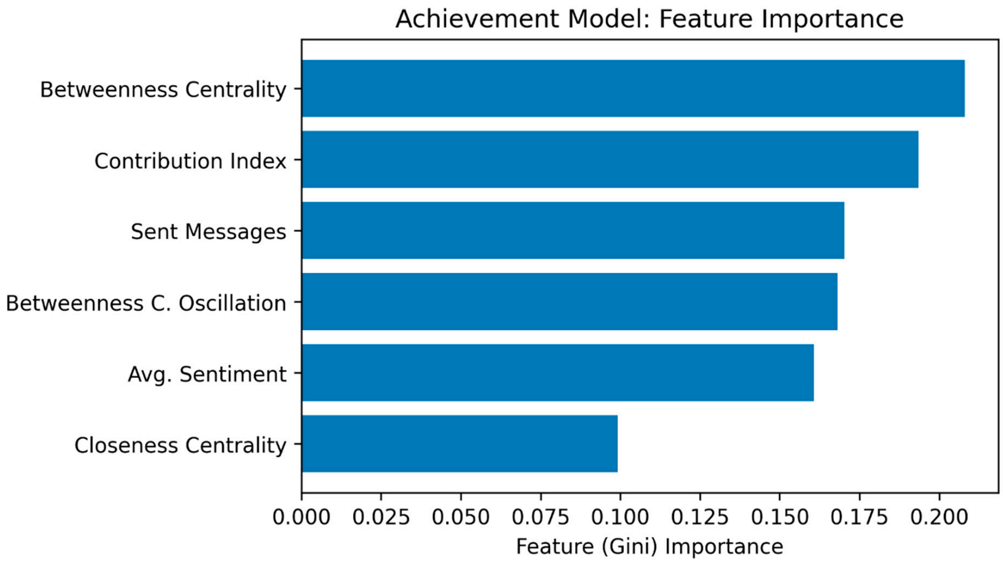

Figure 6. Feature Importance of Achievement Model.

Last, an exemplary DOSPERT value that is predictable by honest signals is social risk likelihood. The likelihood of engaging in social risks is predicted by the responsiveness of alters, as measured by their nudges and ART, as well as the person's betweenness centrality. With accuracy scores of 0.733 and 0.8 during CV and testing, as well as ROC AUC scores of greater than 0.9, the model indicates high prediction performance (see Table 4).

Table 4. Prediction Models for Personal and Moral Values.

Target	Predictors	Accuracy (CV)	Macro F1 (CV)	Macro Precision (CV)	Macro Recall (CV)	ROC AUC (CV)	Accuracy (Holdout)	Macro F1 (Holdout)	Macro Precision (Holdout)	Macro Recall (Holdout)	Cohen's Kappa (Holdout)	ROC AUC (Holdout)
Agreeableness	Betweenness C. Oscillation, Contribution Index, Total Influence	0.7	0.679	0.712	0.719	0.848	0.667	0.643	0.667	0.639	0.491	0.897
Conscientiousness	Betweenness C. Oscillation, Degree Centrality	0.797	0.785	0.794	0.804	0.911	0.889	0.863	0.952	0.833	0.75	0.86
Extraversion	Betweenness Centrality, Ego ART	0.681	0.658	0.674	0.688	0.8	0.667	0.6	0.6	0.6	0.438	0.621
Neuroticism	Betweenness C. Oscillation, Total Influence, Avg. Sentiment	0.785	0.763	0.791	0.778	0.894	0.667	0.631	0.711	0.722	0.413	0.823
Openness to Experience	Avg. Complexity, Ego Nudges, Reach2	0.687	0.648	0.67	0.674	0.848	0.667	0.631	0.6	0.722	0.4	0.794
Authority/Respect	Avg. Influence, Avg. Sentiment	0.707	0.683	0.721	0.74	0.901	0.833	0.841	0.917	0.833	0.714	0.843
Fairness/Reciprocity	Avg. Emotionality, Reach2, Ego Nudges	0.648	0.612	0.634	0.648	0.799	0.667	0.722	0.778	0.833	0.5	0.754
Harm/Care	Alter Nudges, Total Influence, Avg. Sentiment	0.752	0.739	0.758	0.778	0.889	0.667	0.722	0.833	0.778	0.5	0.917
Power	Avg. Complexity, Avg. Emotionality, Avg. Influence	0.858	0.849	0.875	0.874	0.968	0.714	0.6	0.6	0.6	0.364	0.7
Achievement	Betweenness Centrality, Contribution Index, Sent Messages	0.793	0.776	0.798	0.812	0.897	0.714	0.694	0.667	0.867	0.533	0.756
Transcendence	Degree Centrality, Avg. Emotionality, Total Influence	0.748	0.707	0.718	0.75	0.887	0.714	0.711	0.722	0.778	0.562	0.694
Recreational Risk Likelihood	Betweenness Centrality, Avg. Complexity, Contribution Index	0.814	0.798	0.813	0.813	0.912	0.8	0.822	0.833	0.889	0.688	0.98
Social Risk Likelihood	Alter ART, Alter Nudges, Betweenness Centrality	0.733	0.719	0.739	0.757	0.908	0.8	0.822	0.833	0.889	0.688	0.98
Social Risk Perceived	Alter Nudges, Closeness Centrality	0.623	0.594	0.666	0.633	0.762	0.8	0.556	0.5	0.667	0.643	0.75
Ethical Risk Likelihood	Betweenness C. Oscillation, Received Messages, Betweenness Centrality	0.67	0.655	0.68	0.693	0.834	0.8	0.822	0.833	0.889	0.688	0.944
Ethical Risk Perceived	Betweenness C. Oscillation, Avg. Complexity, Avg. Emotionality	0.803	0.779	0.806	0.822	0.931	0.8	0.822	0.833	0.889	0.688	0.98
Total Risk Likelihood	Contribution Index, Betweenness C. Oscillation, Total Influence	0.752	0.723	0.745	0.759	0.932	0.8	0.822	0.833	0.889	0.69	0.944

3.2. Predicting Job Performance

These models are then used with four different datasets to predict the personality characteristics of four cohorts of students in a seminar, managers of a global services firm, and health care professionals working on a healthcare innovation project. First, the predicted personality characteristics are correlated with individual and group performance, finding that, indeed, the personality characteristics of individuals and teams predict their performance (see Appendix B). Correlation results between personality values and performance show that both concepts are related. The prediction models for six different performance measures [17] are shown in Table 5. We find that, indeed, aggregated personality characteristics of team members predict the performance of their teams.

The constructed ML models for predicting job performance are investigated using Partial Dependence Plots (PDP) to open the black boxes of the models and analyze how the input features of each model of job performance affect the prediction output [23]. Figure A3, for example, shows the PDP of the model that predicts team performance of innovation teams. On the left side, the effect of the average team level of extraversion is shown, while the effect of the average team level of conscientiousness is shown on the right side. The PDP of the model of team performance shows that the negative relationship already indicated by correlation is confirmed. The course of the input feature extraversion shows that with increasing extraversion of teams, the probability of employees being classified as "low" performing increases, and the respective class attains the highest probability of all three classes. At the same time, the probability of being "medium" performers decreases with increasing extraversion while it remains stable and unaffected for the class "high", indicating that the level of extraversion of a team does not change the likelihood of being classified as having a "high" performance rating. On the right side of the PDP, it is shown that for most levels of team conscientiousness, having a "medium" performance is most probable. However, with an increasing level of conscientiousness in a team, the probability of being classified as a "high" performer increases and becomes the most probable for higher values. Meanwhile, the curve of the "medium" class remains relatively stable, distinguished by some fluctuations. This indicates and supports the positive effect of conscientiousness on team performance. The positive effect of conscientiousness on job performance is also presented by the PDP of the model that predicts teams' learning behavior. When investigating the PDPs of the other performance models, the following effects can be observed. In terms of team innovation behavior, a team's importance for Schwartz's Value of power positively affects innovation behavior. Furthermore, the figure of the input feature measuring a team's likelihood to engage in risks shows that this attribute negatively affects the innovation behavior of teams. For customer satisfaction, we find that teams' agreeableness positively impacts the performance of teams, while additionally, teams' willingness for power has a moderately positive impact. When investigating the PDPs when predicting students' grades, a positive effect on teams' willingness to achieve and a negative effect on teams' respect for authorities are identified. At the individual level, we find that both the level of care as well as the total risk appetite of managers influence their performance positively. This can be explained by the idea that high levels of care indicate employees who are pro-socially motivated about the well-being of others. According to prior research, caring and pro-social behaviors at work can help both team leaders and team members by fostering positive team synergy, lowering the failure rate of a task that a team is working on, and enhancing team performance [24,25]. This is because pro-socially motivated employees are inspired to aid people who benefit from their work, including their coworkers, and are encouraged to cooperate efficiently, resulting in improved job outcomes [25,26]. The remaining PDPs are given in Appendix C.

Table 5. Prediction Models for Job Performance.

Target	Predictors	Accuracy (CV)	Macro F1 (CV)	Macro Precision (CV)	Macro Recall (CV)	ROC AUC (CV)	Accuracy (Holdout)	Macro F1 (Holdout)	Macro Precision (Holdout)	Macro Recall (Holdout)	Cohen's Kappa (Holdout)	ROC AUC (Holdout)
Team Performance	Team Avg. Extraversion, Team Avg. Conscientiousness	0.916	0.913	0.93	0.928	0.984	0.857	0.867	0.889	0.889	0.788	0.98
Team Learning	Team Avg. Conscientiousness	0.926	0.914	0.916	0.931	0.98	0.857	0.867	0.889	0.889	0.788	0.939
Team Innovation	Team Avg. Power, Team Avg. Total Risk Likelihood	0.83	0.809	0.852	0.86	0.969	0.857	0.852	0.933	0.833	0.731	0.969
Student Teams Grades	Team Avg. Achievement, Team Avg. Authority/Respect	0.702	0.676	0.776	0.72	0.854	0.75	0.767	0.889	0.778	0.556	0.828
Team NPS	Team Avg. Agreeableness, Team Avg. Power	0.807	0.767	0.796	0.809	0.92	0.75	0.756	0.778	0.833	0.636	0.861
First-Year Rating	Harm/Care, Total Risk Likelihood	0.652	0.623	0.667	0.657	0.657	0.778	0.775	0.8	0.833	0.571	0.833
Second-Year Rating	Harm/Care, Total Risk Likelihood	0.66	0.619	0.677	0.653	0.653	0.778	0.75	0.75	0.857	0.526	0.857

4. Discussion and Conclusions

Team performance scores of innovation teams, for example, show a positive correlation with the average conscientiousness level of a team at the significance level of 0.01 (0.347 **), indicating that teams consisting of employees with higher levels of conscientiousness are associated with higher performance (see Table A2). As evidenced by previous researchers, the positive effect of conscientiousness is explained to be due to peoples' autonomy and goal-setting behavior, which is advantageous to employee behaviors in terms of directing their actions [27–29].

Further, team performance indicates a negative relationship with the average extraversion level of the team at the significance level of 0.001 (−0.487 ***). This indicates that extroverted teams are related to worse performance than rather introverted teams. Opposed to existing research, which supports the idea that the energetic behavior and sociability of extroverts is a positive factor for job performance, this relationship shows that low levels of extroversion can also be beneficial on the job [30–33]. Further, we find that in terms of learning behavior, job performance of innovation teams is associated less agreeableness at the significance level of 0.05 (−0.298 *) and (again) less extraversion at the significance level of 0.001 (−0.625 ***). This suggests that having too much agreement within a team might be detrimental to their success because employees who have a very high level of agreeableness are less able to stand for themselves, face challenges or solve conflicts than employees who show a lower level of agreeableness. In addition, agreeableness implies less competitive and determined behavior as agreeable people avoid social conflicts and act rather unambitious [34]. Consequently, very agreeable employees do not pursue their own interests but behave in a manner that pleases their colleagues [35].

Furthermore, the innovativeness of teams is positively influenced by valuing Schwartz's Value of power. As a result, this relationship that valuing enhancement has a positive impact on professional success. An explanation is given by previous researchers suggesting that people with greater self-enhancement are defined by a competitive character due to its underlying value of achievement, which is advantageous for individual- and team-level job performance [11]. Consequently, the valuing of power leads to increased attainment, as those who value power aim to maximize their gain [36]. Apart from the studied innovation teams, agreeableness is, apart from valuing power and transcendence, positively related to customer satisfaction. While agreeableness may interfere with supervisors' performance assessments, it is beneficial in dealing with customers to increase their satisfaction. Teams can benefit from agreeable members due to their communicative, cooperative, and cohesive nature [37]. This personality trait is especially important in occupations that require teamwork or dealing with externals, e.g., in customer service [38,39].

Moreover, correlation results show a negative relationship between students' grades and the value of authority/respect at the significance level of 0.001 (0.366 **), indicating that receiving better grades is related to a lower value of respect for authority. We explain this relationship to exist due to the harmful effects of "blind obedience". People who just follow directions from superiors do not accept responsibility for their own activities. As a result, the employee's creativity, initiative, and contributions are harmed [40,41]. Additionally, there are negative implications for teams' performance. If everyone on the team has a high level of respect for authority, but there is no leader personality, this can be detrimental to the group. Existing research shows that successful teams require a leader personality who is reliable and whom the team can rely on as a problem solver, despite the need for respect [42]. Furthermore, apart from enhancement, students' performance shows a positive association with their recreational risk likelihood at the significance level of 0.05 (−0.285 *). This indicates that the trait of being risky and open to recreational activities can have a positive effect on students' performance as they are more open and engaged in tasks and can, therefore, foster new experiences [43,44]. People with a high level of openness are seen to obtain social and material advantages because of their enthusiasm to discover [44,45]. In terms of individual performance, manager ratings within the first year do not show a significant correlation with the studied traits. In the second year, managers' ratings show a significantly negative relationship with their level of extraversion. Similar to groups' performances, introverted managers may perform better than excessively extroverted managers. Beyond that, the positive relationship toward total risk likelihood at the significance level of 0.05 suggests that managers who show higher overall risk-taking attitudes are indicated to show better performance. Risk-taking can be helpful in general if performed reasonably for the following reasons. When people take a risk and succeed, they are usually rewarded more generously than when they choose a less risky option. By taking risks and failing, on the other hand, the individual learns something valuable about that decision and scenario and gains confidence in the future. According to previous research, successful risk-taking enhances outcomes in the workplace (e.g., being promoted), whereas failed risk-taking does not necessarily result in a disadvantage in the workplace [46].

Following the same modeling procedure as during modeling the personality models, feature selection is performed by studying the importance of features. Moreover, in the case of team-level job performance metrics, the team identification variable is examined during feature importance to control for team dynamics. Though teams' identification variable is never used as an input feature, the feature importance plots of all models which deal with team variables show that this variable always has importance. Resultingly, the models show that both individual-level and team-level performance can be predicted by peoples' personal and moral values. On the individual level, for example, the ratings of managers are to be determined by a manager's level of care and likelihood to engage in generally risky activities. As both ratings are predicted by the same traits, their predictiveness is stressed. Furthermore, both models have similarly valid performance metrics. Both models achieve evaluation metrics of greater than 0.6 during CV and an accuracy of 0.778 during testing. At the team level, innovation behavior of innovation teams, for example, shows to be predictive by the values of power and the teams' general likelihood to engage in risks

This study is the first to attempt to predict job performance through personal and moral values by building ML models based on individuals' communication data. In terms of the effects of personal or moral values on job performance, this research implicates that there are specific personal and moral values that are predictive of individual- or team-level job performance. Therefore, this work brings new insights and implications for factors that influence the performance of employees. Particularly, the following findings and explanations, which are also summarized in Figure 7, showing the predictability between variables through flows, are derived from the developed prediction models.

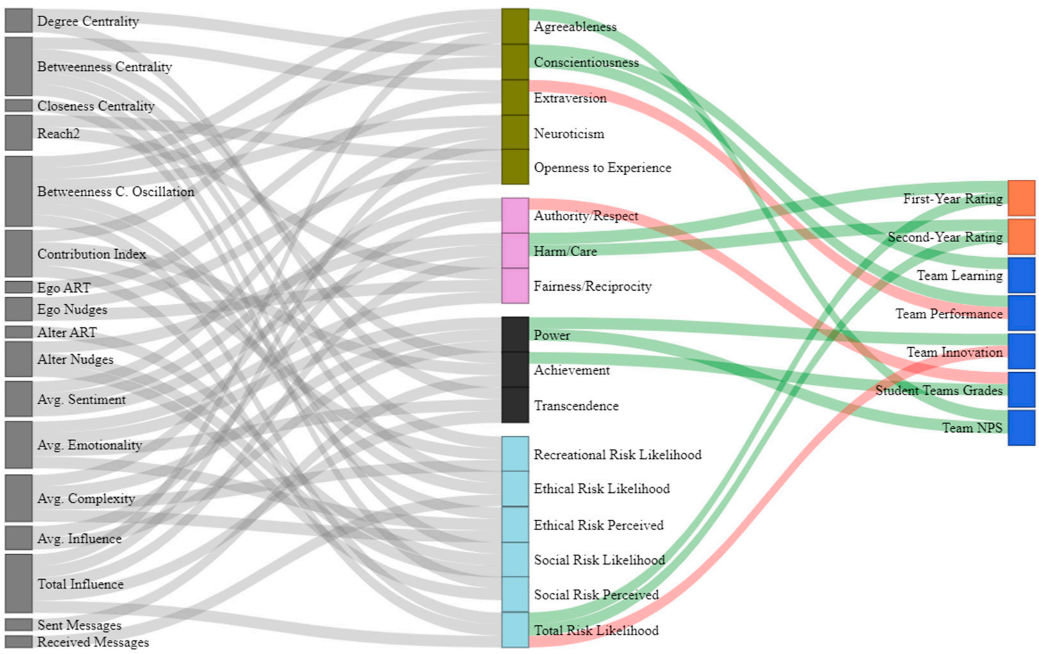

Figure 7. Summarized Prediction Results.

Beginning with the predictors of job performance on the team level, the level of agreeableness in customer service, for example, is a positive predictor of customer satisfaction. This is explained by the cooperative spirit and pleasantness of agreeable individuals, which are highly valued by clients [38]. Meanwhile, conscientious people influence teamwork and performance positively and display higher learning behavior, validating earlier meta-analyses' findings that conscientiousness leads to autonomy and goal-directed conduct, which may lead to success in a variety of professions [27]. Extraversion, however, is found to be disadvantageous as it is a predictor for lower team performance and also shows negative associations with managers' performance. Even though these findings oppose earlier research, it does not imply that introverts always perform better than extroverts. Rather is suggested that the negative effect of extraversion in this paper is caused by the job characteristics of the studied jobs. As argued by further researchers, extroverts might perform worse than introverts in creative and inventive work environments because rather introverted people usually have greater analytical abilities, thinking, and reflection than more extroverted ones [47]. This leads to the conclusion that these might be particularly important characteristics in innovative and creative work environments, which are present for both studied innovation teams and managers and can therefore produce positive results in these jobs [48]. As a result, it is argued that excessive levels of extraversion lower job performance in creative and inventive environments. The trait of respecting and putting a high value on authorities has been found to have a negative effect on performance. Based on the characteristics of these traits, this work presents two probable explanations for the observed result. First, this effect is based on the notion that obedience and compliance are not necessarily the key to increased performance and success [40,41]. In the context of this research, it is assumed that a supervisor's instructions do not necessarily result in a better grade. Instead, the people's initiative, inventiveness, and capacity to work independently could be positively evaluated by the supervisor. An alternative or additional explanation is the notion that this attribute is associated with team members and teams that lack leaders under difficult conditions so that they perform worse than teams with a good constellation of leaders and respecters [42]. Another identified predictor of high team performance is self-enhancement, as shown by the underlying values of power and achievement. The explanation for this positive effect comes from the definition of these qualities. Self-enhancement characterizes those that are ambitious and seek to achieve and maximize the power they earn, among other things, through their work. As a result, activities that lead to great work performance follow this character [36,49]. For job performance on the individual level, the level of care of employees is found to be a predictor. It is implicated that caring managers perform better than employees who are more prone to harm. This is explained by the pro-social and motivational attitude of caring people, which enables employees and colleagues to work together efficiently, create a cooperative work culture and increase success in the workplace [24,25]. In terms of risk-taking attitudes, findings and predicting traits need more interpretation than the other values. Results suggest that while generally, high riskiness can be beneficial to individuals at work, it can also be detrimental to teams if this attitude is excessively present within the team. Therefore, in terms of general risk-taking likelihood, risk-averse members of teams are seen to be necessary to calibrate the team and team performance. Additional associations between honest signals, personal or moral values, and job performance are indicated by correlation analysis to provide answers to proposed hypotheses, but they are not discussed further because they are not used as predictors of job performance. However, there is also the suspicion that of these significant associations, other attributes might predict job performance, but they are not employed to avoid overfitting the models.

4.1. Implications for Research and Practice

Further, the following practical implications arise from the conducted study. First, the job performance predictors that emerged show that there are more variables than traditionally known job performance indicators. Apart from traditionally respected attributes that predict career success, such as social capital, present research argues that moral beliefs and qualities can also be a determinant of future job performance [50]. These determinants have a direct implication for employees, organizations, and their HR management. As previously discussed, certain personal or moral attributes can be beneficial while others can be disadvantageous in the workplace. For HR managers, this implies that, apart from the already widely distributed FFI tests, in the context of innovative and creative work environments, they should also assess moral beliefs, as measured by the Moral Foundations questionnaire, Schwartz's Values survey, or DOSPERT. Particularly, in terms of the individual job performance of managers, organizations should focus on hiring caring employees with a high-risk appetite, while in terms of teamwork, lower-risk appetite but self-willed and -enhanced team members should be the focus. In terms of the big five personality factors, this thesis supports the argument that conscientiousness is the most desirable personality trait of the NEO FFI. In terms of agreeableness, in jobs in which employees deal with externals, such as in customer service, employers should hire agreeable employees, while within organizations, argumentative employees are recommended. In addition, employers in innovative workplaces should realize that introverts may be valuable to businesses since they can contribute analytical talents that more outgoing people may lack. In this context, capturing survey scores through honest signals might open new doors for staff selection, allowing HR departments to avoid traditional surveys, which are prone to several biases, including response biases, social desirability, or varying reference standards [16,51]. As many HR managers already analyze various types of data to add value to the company by identifying traits and talents, the present ML models may serve as a further data-driven analysis tool for analyzing both traits of employees as well as their potential performance [52]. As an alternative to existing scientific ML models that can predict personality factors, e.g., predicting NEO FFI values from Facebook or smartphone sensor data, the attributes required for personnel selection can be determined by honest signals [51,53]. Models based on communication behavior have the advantage that they reveal personalities unintentionally and are difficult to fake. Following on from this, applicants' or employees' performance can be determined by applying the developed ML models. Especially important in cases when monitoring the job performance of employees is difficult, the developed ML models can be used to predict the performance of employees and possibly act when performance is predicted to become low. The input data can hereby be collected manually, for example, by conducting the surveys or by applying the first type of ML model to predict personal and moral values. The second approach should be feasible as email communication is usually present within organizations.

Regardless of the ML models, further important practical implications are made in terms of individual- and team-level job performance. Given that team dynamics may potentially play a relatively substantial role as judged by the feature importance of the ML models and that more significant connections are observed at the team level than at the individual level, this may imply the following. In terms of the studied job performance metrics, an individual's personal and moral values are not as essential as the constellation of personal and moral values within a team. The research demonstrates that organizations should not necessarily focus on an individual's personal and moral principles but that the constellation of individual values within a team or organization, as well as job demands, have a much greater impact on job performance.

4.2. Limitations and Future Research

The work presented is subject to limitations that should be addressed in future studies. Primarily, the results of this work are limited by the small amount of data as well as the methodology. Both the developed ML models for the prediction of personalities and for the prediction of job performance are based on small data sets. Consequently, this limits the generalization of the ML models and the results so that they may not present a general picture. The current work should be replicated on a wider scale with more data in the future to uncover more general models and outcomes. The limitations of our datasets also restricted our choice of model architecture, as one dataset predicted personal values from honest signals computed from email, and a second dataset compared email honest signals with individual and team performance. We hope that in future work, we will be able to obtain a combined dataset that includes all three variables, email, personal values, and individual and business performance.

Another data restriction is the collection of subjective data. Though the applied surveys are scientifically validated and widely distributed, the gathered data are self-reported and biased. Because of the biased data, ML may yield prediction models that are biased with inferior accuracy on real-world data [54,55]. Therefore, future research should focus on gathering data through more objective personality assessment methods. For example, there are real-life virtual simulations in which individuals go through various tasks to assess personality traits based on the individuals' choices during the tasks [56]. As also the performance ratings are not based on objective indicators, the research could also be replicated with objective key performance indicators. Furthermore, the present analysis is limited to the network of email data. Though emails fulfill the purpose of social networks, future research might expand the current study and approach to include other networks, such as LinkedIn or Slack [57].

Another limitation is given by the focus on personality and morality factors, as measured by the four surveys of NEO FFI-R, Moral Foundations questionnaire, Schwartz's Values survey, and DOSPERT. Though the applied surveys cover many different traits, it is suggested that in future research, further personal or moral values should be tested. As an extension, future research, for example, might use the Valued Living Questionnaire, which examines people's value systems and looks at people's values from a different viewpoint than the surveys in the current study [58].

Further, there are limitations in the methodology and modeling process. First, no control variables are observed, and the relationship between job performance and personal characteristics is simplified. Therefore, no clear statement regarding additional contextual factors which affect job performance in addition to the studied traits can be made. There may be additional explanatory variables and circumstances which contribute to the explanatory power of the results. Furthermore, the term job performance is generalized to different performance metrics of different industries and practices. Consequently, identified effects of this study may not be applicable to all industries. However, the study can be repeated, this time focusing on specific indicators of job performance and other explanatory variables, such as job requirements, age, or tenure, to provide more detailed explanations. For the differential effects of perceptions and likelihoods of risk-taking in certain domains on job performance, this research has not provided clear effects or possible explanations and brings the following limitations. First, the implied result of general risk-taking should be viewed with caution. There is a need for more research here since the observations do not quantify whether people profit from risk-taking in the workplace, whether they effectively take risks, or whether they are foolish about taking risks on the job. Further, though this study fails to find a relationship between attitudes toward financial, health, and ethical risk-taking and job performance, it is suggested that for a given risk domain, subjective risk perception and objective risk likelihood may have different implications for a given performance metric. People's risk perception and their likelihood to participate in each risk may have opposing effects on job performance. For example, risk-taking likelihood in the social domain is positively associated with team innovation behavior but negatively associated with team learning behavior, while the perception of social risks is negatively associated with team innovation behavior but positively associated with team learning behavior. This shows that the relationship between risk-taking in the objective and subjective sense is more complex than assumed. In addition to this, as shown by the correlation coefficients of recreational risk-taking likelihood, a given risk attitude can have both positive and negative effects on job performance. Therefore, it is assumed that (especially social) risk perceptions and likelihoods can have different effects on job performance, and the effect may additionally depend on factors that are not elaborated on in this thesis.

As a result, this thesis cannot exactly state if taking risks in certain domains predicts work performance. Instead, other elements, such as the work environment, job requirements, the actual outcome of risks, risk tolerance on the job, etc., are thought to play a role. Therefore, the effect of risk-taking attitudes on job performance is suggested to be researched in a more explanatory manner.

Last, limitations are given by binning target features for both types of ML models into three classes. This may overoptimize the accuracy and validity of predictions and lead to information loss. When larger data samples are available, regression models or classification models with more classes are recommended for making more comprehensive predictions. Furthermore, because some personal or moral values lack valid ML models and because some research subjects predict the same personality level for all participants, the link between personality and work performance cannot be examined for all studied personality and moral values. For future research, it is suggested that models for the traits that could not be developed in the current work be developed using an alternate approach to identify more ML models to predict personal or moral values and investigate the effects of the remaining traits on job performance. All in all, it can be said that the current study paves the way for more research into developing ML models for predicting personality, morality, and job performance, as well as into the causes of personality or moral characteristic effects at work.

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Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Institutional Review Board of MIT (protocol code 170181783) on 16 February 2017.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are not publicly available due to privacy restrictions of the participating institutions.

Acknowledgments: All the experiments conducted in this work have been approved by the Institutional Review Board (IRB) of the Massachusetts Institute of Technology (MIT).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Pearson Correlation between Personal/Moral Values and Honest Signals.

Variables		Alter ART	Alter Nudges	Between-ness Centrality	Between-ness C. Oscilla-tion	Closeness Centrality	Avg. Com-plexity	Contribu-tion Index	Contribu-tion Index Osc.	Degree Central-ity	Ego ART	Ego Nudges	Avg. Emo-tionality	Avg. Influence	Total Influence	Received Messages	Sent Messages	Total Messages	Reach 2	Avg. Senti-ment
Agreeableness	*Pearson Correlation*	0.021	−0.134	−0.226 *	−0.362 ***	−0.286 **	−0.147	−0.196	−0.228 *	−0.243 *	−0.045	−0.048	−0.165	−0.262 *	−0.221 *	−0.059	−0.316 **	−0.177	−0.091	−0.169
	N	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81
Conscien−tiousness	*Pearson Correlation*	0.209	0.183	0.221 *	0.180	0.084	0.107	−0.073	0.135	0.227 *	0.091	0.156	0.180	0.076	0.180	0.200	0.128	0.194	0.134	0.038
	N	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81
Extraversion	*Pearson Correlation*	−0.076	−0.050	0.147	0.105	−0.059	−0.045	−0.020	−0.030	0.090	−0.162	−0.085	−0.018	−0.050	0.006	−0.047	0.026	−0.015	−0.106	−0.068
	N	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81
Neuroticism	*Pearson Correlation*	−0.021	−0.091	−0.200	−0.311 **	−0.021	−0.092	−0.030	0.028	−0.132	−0.002	−0.069	−0.048	−0.038	−0.113	0.041	−0.044	−0.005	−0.008	−0.102
	N	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81
Openness to Experience	*Pearson Correlation*	0.039	−0.058	0.003	0.063	−0.097	−0.071	−0.193	−0.096	0.007	0.011	−0.084	−0.041	−0.069	0.001	−0.051	−0.099	−0.066	−0.090	−0.150
	N	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81	81
Authority/ Respect	*Pearson Correlation*	−0.077	−0.271 *	−0.278 *	−0.323 *	−0.360 **	−0.228	−0.443 ***	−0.360 **	−0.304 *	−0.028	−0.197	−0.319 *	−0.310 *	−0.272 *	−0.207	−0.365 **	−0.287 *	−0.234	−0.421 **
	N	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55
Fairness/ Reciprocity	*Pearson Correlation*	0.201	0.258	0.139	0.185	0.072	0.333 *	−0.104	0.234	0.156	0.124	0.330 *	0.305 *	0.265	0.231	0.218	0.100	0.177	0.374 **	0.110
	N	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55
Harm/Care	*Pearson Correlation*	0.335 *	0.524 ***	0.393 **	0.459 ***	0.468 ***	0.533 ***	0.104	0.410 **	0.383 **	0.252	0.483 ***	0.472 ***	0.434 ***	0.392**	0.322 *	0.380 **	0.366 **	0.55 ***	0.332 *
	N	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55
Ingroup/ Loyalty	*Pearson Correlation*	0.36 **	0.430 **	0.305 *	0.212	0.465 ***	0.399 **	−0.077	0.186	0.294 *	0.186	0.371 **	0.479 ***	0.353 **	0.169	0.127	0.228	0.188	0.420 **	0.337 *
	N	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55
Purity/ Sanctity	*Pearson Correlation*	0.205	0.121	0.103	0.064	0.043	0.191	−0.137	0.174	0.102	0.073	0.149	0.089	0.086	0.122	0.126	0.101	0.118	0.156	−0.002
	N	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55	55
Power	*Pearson Correlation*	−0.173	−0.319 *	−0.379 **	−0.461 ***	−0.377 **	−0.419 ***	−0.022	−0.231	−0.278 *	−0.174	−0.268 *	−0.389 **	−0.444 ***	−0.345 **	−0.237	−0.310 *	−0.291 *	−0.341 **	−0.242
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61
Achieve−ment	*Pearson Correlation*	−0.037	−0.090	−0.258 *	−0.315 *	−0.245	−0.128	−0.331 **	−0.088	−0.186	0.054	0.032	−0.138	−0.121	−0.152	−0.055	−0.268 *	−0.153	−0.078	−0.200
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61
Hedonism	*Pearson Correlation*	−0.029	0.036	0.051	−0.214	0.108	−0.026	0.139	0.047	0.048	0.087	0.051	0.018	−0.041	−0.037	0.087	0.078	0.081	0.036	0.09
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61

Table A1. *Cont.*

Variables		Alter ART	Alter Nudges	Betweenness Centrality	Betweenness C. Oscillation	Closeness Centrality	Avg. Complexity	Contribution Index	Contribution Index Osc.	Degree Centrality	Ego ART	Ego Nudges	Avg. Emotionality	Avg. Influence	Total Influence	Received Messages	Sent Messages	Total Messages	Reach 2	Avg. Sentiment
Stimulation	*Pearson Correlation*	−0.035	−0.033	0.053	0.028	0.088	−0.055	0.082	0.143	0.076	0.156	0.007	0.052	−0.014	0.029	0.053	0.043	0.053	0.005	−0.016
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61
Self−Direction	*Pearson Correlation*	0.097	0.134	0.098	0.125	0.122	0.053	0.156	0.200	0.190	0.116	0.141	0.178	0.032	0.106	0.153	0.14	0.158	0.119	0.114
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61
Universalism	*Pearson Correlation*	−0.099	0.111	0.106	0.276 *	0.031	0.054	0.033	0.194	0.277 *	0.120	0.061	0.110	0.119	0.211	0.115	0.145	0.144	0.051	0.152
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61
Benevolence	*Pearson Correlation*	0.222	0.202	0.251	0.320 *	0.123	0.155	−0.021	0.223	0.310 *	0.136	0.175	0.249	0.141	0.240	0.173	0.204	0.205	0.141	0.116
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61
Tradition	*Pearson Correlation*	−0.059	−0.084	−0.145	−0.154	−0.155	−0.138	−0.137	−0.123	−0.081	0.040	−0.021	−0.108	−0.220	−0.220	−0.054	−0.163	−0.109	−0.084	−0.256 *
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61
Conformity	*Pearson Correlation*	−0.047	−0.030	−0.248	−0.053	−0.261 *	−0.083	−0.312 *	−0.039	−0.131	0.201	0.105	−0.078	−0.037	−0.102	−0.018	−0.214	−0.109	−0.011	−0.235
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61
Security	*Pearson Correlation*	0.109	0.262 *	0.044	0.189	0.126	0.180	−0.100	0.180	0.187	0.242	0.316 *	0.263 *	0.154	0.113	0.160	0.106	0.147	0.211	0.026
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61
Tran-scen-dence	*Pearson Correlation*	0.120	0.293 *	0.292 *	0.488 ***	0.267 *	0.281 *	0.031	0.213	0.329 **	0.112	0.180	0.281 *	0.301 *	0.318 *	0.181	0.279 *	0.247	0.221	0.166
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61
Conserva−tion	*Pearson Correlation*	−0.191	−0.204	−0.226	−0.263 *	−0.309 *	−0.245	−0.336 **	−0.206	−0.236	−0.010	−0.069	−0.217	−0.188	−0.277 *	−0.150	−0.293 *	−0.226	−0.202	−0.297 *
	N	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61	61
Ethical Risk Likelihood	*Pearson Correlation*	−0.122	−0.028	−0.257	−0.228	0.025	−0.070	0.020	−0.189	−0.190	0.056	−0.071	0.060	−0.039	−0.271	−0.292 *	−0.200	−0.273	0.003	0.020
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
Ethical Risk Perceived	*Pearson Correlation*	−0.156	−0.296 *	−0.379 **	−0.437 **	−0.310 *	−0.298 *	0.046	−0.274	−0.385 **	−0.296 *	−0.326*	−0.363*	−0.248	−0.264	−0.122	−0.236	−0.195	−0.250	−0.190
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
Financial Risk Likelihood	*Pearson Correlation*	−0.137	−0.143	−0.403 **	−0.377 **	−0.351 *	−0.140	−0.369 **	−0.282 *	−0.316 *	−0.178	−0.164	−0.076	−0.193	−0.387 **	−0.231	0.470 ***	−0.354 *	−0.088	−0.298 *
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
Financial Risk Perceived	*Pearson Correlation*	0.41 **	0.442 **	0.314 *	0.297 *	0.362*	0.444 **	0.070	0.168	0.363*	−0.046	0.244	0.418 **	0.163	0.243	0.235	0.293 *	0.282 *	0.378 **	0.360 *
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49

Table A1. *Cont.*

Variables		Alter ART	Alter Nudges	Betweenness Centrality	Betweenness C. Oscillation	Closeness Centrality	Avg. Complexity	Contribution Index	Contribution Index Osc.	Degree Centrality	Ego ART	Ego Nudges	Avg. Emotionality	Avg. Influence	Total Influence	Received Messages	Sent Messages	Total Messages	Reach 2	Avg. Sentiment
Health Risk Likelihood	*Pearson Correlation*	−0.136	−0.219	0.009	−0.129	−0.108	−0.191	−0.079	−0.114	−0.067	−0.194	−0.263	−0.089	−0.110	−0.109	−0.173	−0.086	−0.144	−0.202	−0.045
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
Health Risk Perceived	*Pearson Correlation*	0.254	0.237	0.089	0.321*	0.077	0.255	−0.044	−0.015	0.146	0.148	0.249	0.033	0.117	0.125	0.103	0.089	0.103	0.170	−0.013
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
Recreational Risk Likelihood	*Pearson Correlation*	−0.142	−0.188	−0.371 **	−0.308 *	−0.435 **	−0.236	−0.461 ***	−0.185	−0.354 *	−0.090	−0.085	−0.121	−0.013	−0.210	−0.107	−0.408 **	−0.251	−0.134	−0.255
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
Recreational Risk Perceived	*Pearson Correlation*	0.294 *	0.162	0.338 *	0.164	0.367 **	0.225	0.411 **	0.048	0.289 *	−0.109	0.006	0.087	−0.085	0.075	0.082	0.290 *	0.182	0.065	0.210
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
Social Risk Likelihood	*Pearson Correlation*	0.352 *	0.311 *	0.430 **	0.345 *	0.349 *	0.341 *	0.008	0.301 *	0.407 **	0.082	0.285 *	0.367 **	0.290 *	0.203	0.354 *	0.254	0.350 *	0.341 *	0.304 *
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
Social Risk Perceived	*Pearson Correlation*	0.211	0.201	0.115	0.133	0.225	0.178	−0.015	−0.057	0.080	−0.073	−0.019	0.216	0.156	−0.036	−0.105	−0.005	−0.055	0.127	0.096
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
Total Risk Likelihood	*Pearson Correlation*	−0.009	0.013	−0.185	−0.210	−0.031	0.008	−0.197	−0.104	−0.143	−0.034	−0.012	0.130	0.124	−0.251	−0.140	−0.267	−0.200	0.102	−0.001
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
Total Risk Perceived	*Pearson Correlation*	0.288 *	0.200	0.112	0.203	0.135	0.209	−0.003	0.041	0.110	0.015	0.156	0.139	0.089	0.131	0.206	0.132	0.191	0.191	0.111
	N	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Appendix B

Table A2. Pearson Correlation between Personal/Moral Values and Job Performance.

Variables	Team Performance		Team Innovation		Team Learning		Student Grades		Team NPS		First-Year Rating		Second-Year Rating	
	Pearson Correlation	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*
Alter ART	−0.178	70	0.322 **	70	−0.148	70	−0.008	80	−0.147	78	0.086	82	−0.106	82
Alter Nudges	0.150	70	−0.161	70	0.104	70	−0.146	80	−0.304 **	78	0.163	82	0.006	82

Table A2. *Cont.*

Variables	Team Performance		Team Innovation		Team Learning		Student Grades		Team NPS		First-Year Rating		Second-Year Rating	
	Pearson Correlation	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*
Betweenness Centrality	0.223	70	−0.120	70	0.254 *	70	−0.176	80	−0.010	78	0.024	82	−0.135	82
Betweenness C. Oscillation	0.102	70	−0.095	70	0.133	70	−0.072	80	−0.126	78	0.054	82	0.035	82
Closeness Centrality	0.097	70	−0.251 *	70	0.137	70	−0.009	80	−0.185	78	0.027	82	−0.030	82
Avg. Complexity	−0.289 *	70	0.086	70	−0.366 **	70	0.035	80	0.066	78	0.066	82	0.078	82
Contribution Index	0.108	70	0.040	70	0.200	70	0.056	80	0.057	78	−0.056	82	−0.050	82
Contribution Index Oscillation	0.096	70	−0.111	70	0.112	70	0.017	80	−0.190	78	0.045	82	−0.060	82
Degree Centrality	0.131	70	−0.190	70	0.192	70	−0.131	80	−0.103	78	0.013	82	−0.125	82
Ego ART	−0.150	70	0.179	70	−0.065	70	−0.140	80	−0.176	78	0.140	82	−0.182	82
Ego Nudges	−0.020	70	0.071	70	−0.106	70	−0.065	80	0.040	78	−0.103	82	0.018	82
Avg. Emotionality	0.163	70	0.011	70	0.281 *	70	0.248 *	80	0.213	78	0.099	82	−0.145	82
Avg. Influence	0.024	70	−0.176	70	−0.057	70	−0.063	80	0.077	78	0.031	82	−0.039	82
Total Influence	0.098	70	−0.143	70	0.112	70	−0.121	80	−0.270 *	78	−0.035	82	−0.124	82
Received Messages	0.174	70	−0.096	70	0.201	70	−0.096	80	−0.224 *	78	−0.053	82	0.051	82
Sent Messages	0.232	70	−0.051	70	0.248 *	70	−0.091	80	−0.278 *	78	−0.047	82	0.023	82
Total Messages	0.195	70	−0.084	70	0.219	70	−0.112	80	−0.241 *	78	−0.053	82	0.045	82
Reach2	0.027	70	−0.178	70	−0.016	70	−0.363 ***	80	0.074	78	−0.058	82	−0.059	82
Avg. Sentiment	0.086	70	−0.107	70	0.108	70	−0.143	80	0.129	78	−0.025	82	−0.053	82
Agreeableness	−0.093	70	−0.249 *	70	−0.147	70	−0.035	80	0.105	78	0.017	82	−0.071	82
Neuroticism	–	70	–	70	–	70	0.058	80	−0.186	78	−0.051	82	−0.020	82
Extraversion	−0.178	70	−0.034	70	−0.229	70	0.010	80	0.030	78	0.100	82	0.253 *	82
Openness to Experience	–	70	–	70	–	70	0.067	80	–	78	–	82	–	82
Conscientiousness	0.074	70	0.002	70	0.057	70	−0.129	80	0.119	78	−0.035	82	0.117	82
Authority/Respect	−0.045	70	−0.128	70	0.053	70	0.188	80	−0.025	78	0.123	82	0.042	82
Fairness/Reciprocity	–	70	–	70	–	70	0.068	80	–	78	–	82	–	82
Harm/Care	0.034	70	0.051	70	−0.048	70	0.016	80	0.083	78	−0.187	82	−0.162	82
Power	0.098	70	0.179	70	0.098	70	0.061	80	0.266 *	78	−0.041	82	−0.068	82

Table A2. *Cont.*

Variables	Team Performance		Team Innovation		Team Learning		Student Grades		Team NPS		First-Year Rating		Second-Year Rating	
	Pearson Correlation	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*
Achievement	–	70	–	70	–	70	−0.220 *	80	–	78	–	82	–	82
Transcendence	−0.008	70	−0.003	70	−0.031	70	0.046	80	0.152	78	0.190	82	0.035	82
Ethical Risk Likelihood	–	70	–	70	–	70	0.007	80	–	78	–	82	–	82
Ethical Risk Perceived	0.032	70	−0.242 *	70	0.062	70	–	80	−0.099	78	0.094	82	−0.078	82
Recreational Risk Likelihood	0.018	70	−0.101	70	−0.013	70	−0.122	80	–	78	0.094	82	−0.078	82
Social Risk Likelihood	−0.142	70	0.190	70	−0.192	70	0.131	80	−0.084	78	0.041	82	−0.096	82
Social Risk Perceived	0.040	70	−0.143	70	0.068	70	0.089	80	–	78	–	82	–	82
Total Risk Likelihood	−0.103	70	−0.116	70	−0.032	70	0.041	80	−0.145	78	−0.178	82	−0.224 *	82
Team Avg. Alter ART	−0.375 **	70	0.679 ***	70	−0.312 **	70	−0.013	80	−0.341 **	78				
Team Avg. Alter Nudges	0.380 **	70	−0.410 ***	70	0.264 *	70	−0.293 **	80	−0.435 ***	78				
Team Avg. Betweenness Centrality	0.505 ***	70	−0.271 *	70	0.573 ***	70	−0.383 ***	80	−0.028	78				
Team Avg. Betweenness C. Oscillation	0.229	70	−0.214	70	0.299 *	70	−0.096	80	−0.160	78				
Team Avg. Closeness Centrality	0.200	70	−0.517 ***	70	0.282 *	70	−0.013	80	−0.242 *	78				
Team Avg. Avg. Complexity	−0.565 ***	70	0.169	70	−0.715 ***	70	0.061	80	0.081	78				
Team Avg. Contribution Index	0.329 **	70	0.121	70	0.611 ***	70	0.144	80	0.090	78				
Team Avg. Contribution Index Oscillation	0.216	70	−0.250 *	70	0.252 *	70	0.024	80	−0.274 *	78				
Team Avg. Degree Centrality	0.269 *	70	−0.391 ***	70	0.395 ***	70	−0.182	80	−0.251 *	78				
Team Avg. Ego ART	−0.443 ***	70	0.529 ***	70	−0.192	70	−0.218	80	−0.291 **	78				
Team Avg. Ego Nudges	−0.066	70	0.236 *	70	−0.352 **	70	−0.098	80	0.060	78				
Team Avg. Avg. Emotionality	0.438 ***	70	0.031	70	0.756 ***	70	0.564 ***	80	0.296 **	78				
Team Avg. Avg. Influence	0.052	70	−0.373 **	70	−0.120	70	−0.117	80	0.130	78				
Team Avg. Total Influence	0.216	70	−0.316 **	70	0.249 *	70	−0.163	80	−0.466 ***	78				
Team Avg. Received Messages	0.415 ***	70	−0.228	70	0.478 ***	70	−0.106	80	−0.296 **	78				
Team Avg. Sent Messages	0.551 ***	70	−0.122	70	0.590 ***	70	−0.152	80	−0.431 ***	78				
Team Avg. Total Messages	0.461 ***	70	−0.198	70	0.518 ***	70	−0.123	80	−0.325 **	78				
Team Avg. Reach2	0.057	70	−0.384 **	70	−0.035	70	−0.372 ***	80	0.120	78				
Team Avg. Avg. Sentiment	0.250 *	70	−0.310 **	70	0.314 **	70	−0.265*	80	0.231 *	78				
Team Avg. Agreeableness	−0.188	70	−0.504 ***	70	−0.298 *	70	−0.054	80	0.395 ***	78				

Table A2. *Cont.*

Variables	Team Performance		Team Innovation		Team Learning		Student Grades		Team NPS		First-Year Rating		Second-Year Rating	
	Pearson Correlation	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*	*Pearson Correlation*	*N*
Team Avg. Neuroticism	–	70	–	70	–	70	0.122	80	−0.306 **	78				
Team Avg. Extraversion	−0.487 ***	70	−0.093	70	−0.625 ***	70	0.020	80	0.064	78				
Team Avg. Openness to Experience	–	70	–	70	–	70	0.104	80	–	78				
Team Avg. Conscientiousness	0.347 **	70	0.007	70	0.267 *	70	−0.208	80	0.217	78				
Team Avg. Authority/Respect	−0.081	70	−0.228	70	0.095	70	0.366 ***	80	−0.063	78				
Team Avg. Fairness/Reciprocity	–	70	–	70	–	70	0.116	80	–	78				
Team Avg. Harm/Care	0.090	70	0.136	70	−0.129	70	0.025	80	0.169	78				
Team Avg. Power	0.187	70	0.341 **	70	0.186	70	0.111	80	0.611 ***	78				
Team Avg. Achievement	–	70	–	70	–	70	−0.418 ***	80	–	78				
Team Avg. Transcendence	−0.022	70	−0.008	70	−0.081	70	0.070	80	0.262 *	78				
Team Avg. Ethical Risk Likelihood	–	70	–	70	–	70	0.011	80	–	78				
Team Avg. Ethical Risk Perceived	0.076	70	−0.576 ***	70	0.149	70	–	80	−0.147	78				
Team Avg. Recreational Risk Likelihood	0.057	70	−0.322 **	70	−0.041	70	−0.285 *	80	–	78				
Team Avg. Social Risk Likelihood	−0.419 ***	70	0.561 ***	70	−0.569 ***	70	0.205	80	−0.202	78				
Team Avg. Social Risk Perceived	0.141	70	−0.503 ***	70	0.240 *	70	0.157	80	–	78				
Team Avg. Total Risk Likelihood	−0.265 *	70	−0.297 *	70	−0.081	70	0.068	80	−0.267 *	78				

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Appendix C

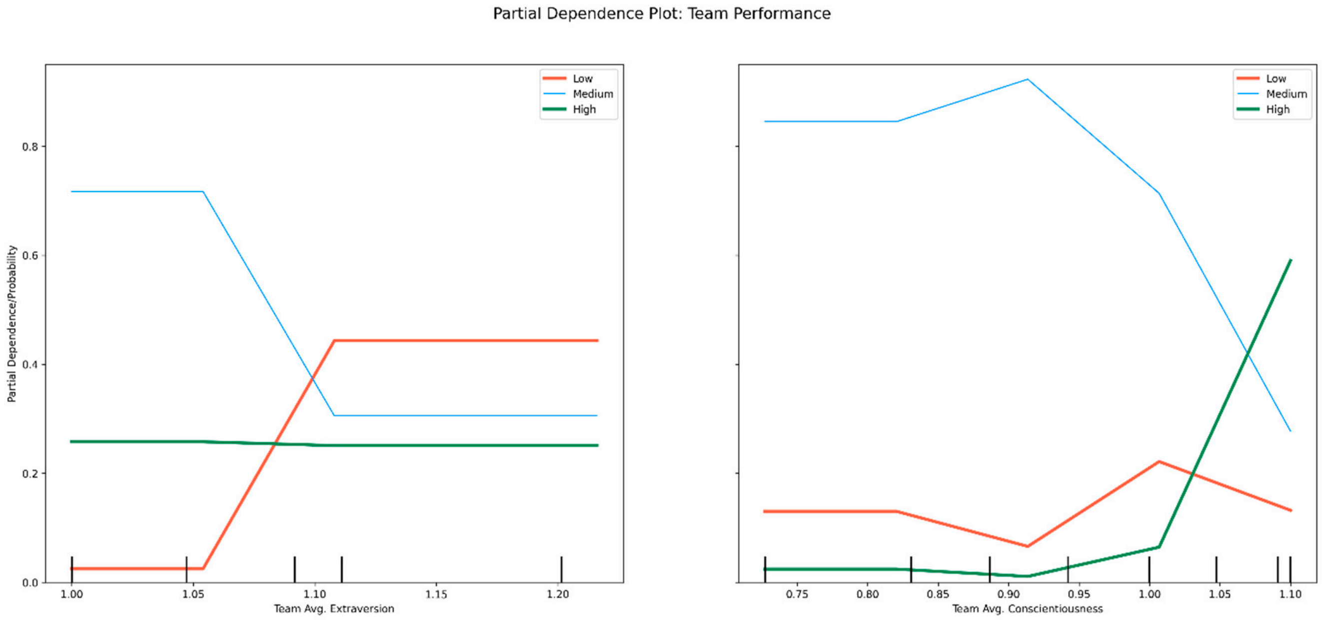

Figure A1. PDP of Team Performance Model.

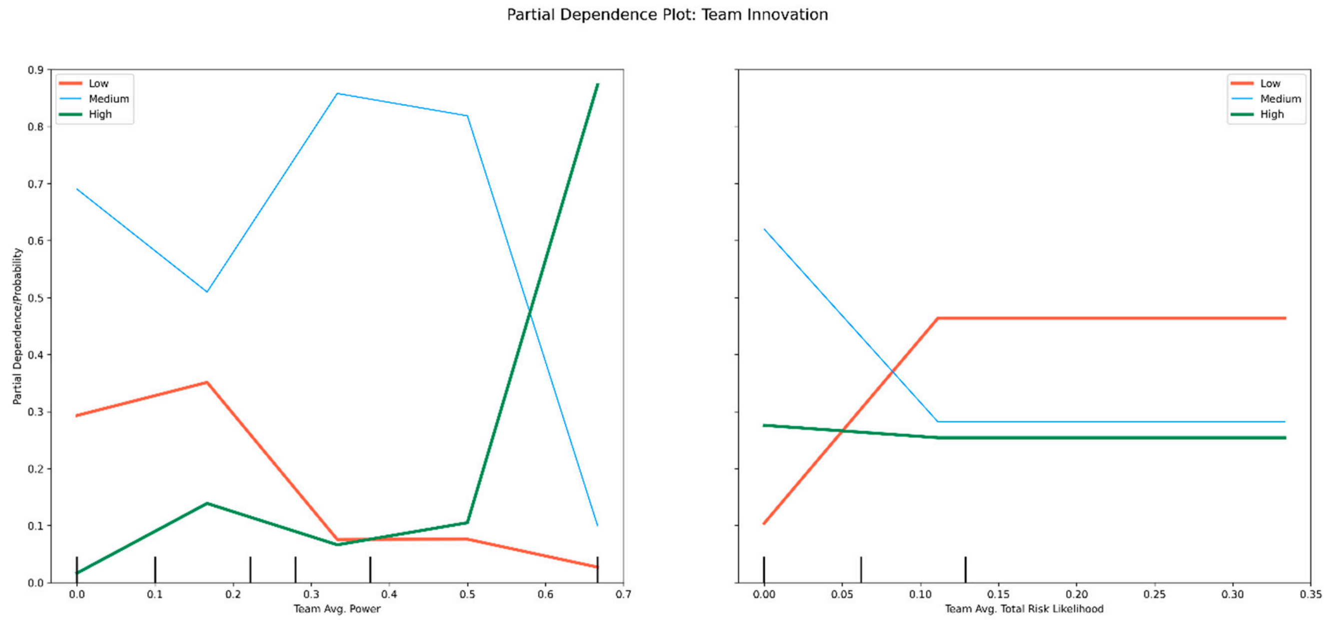

Figure A2. PDP of Team Innovation Model.

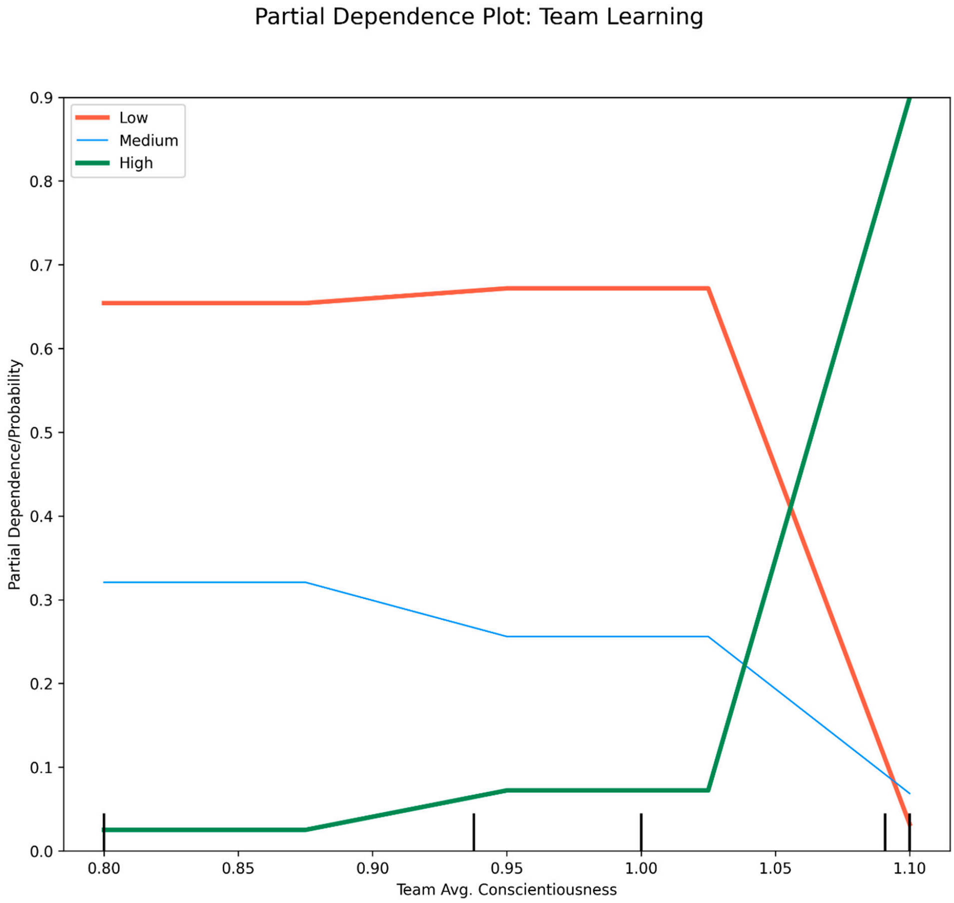

Figure A3. PDP of Team Learning Model.

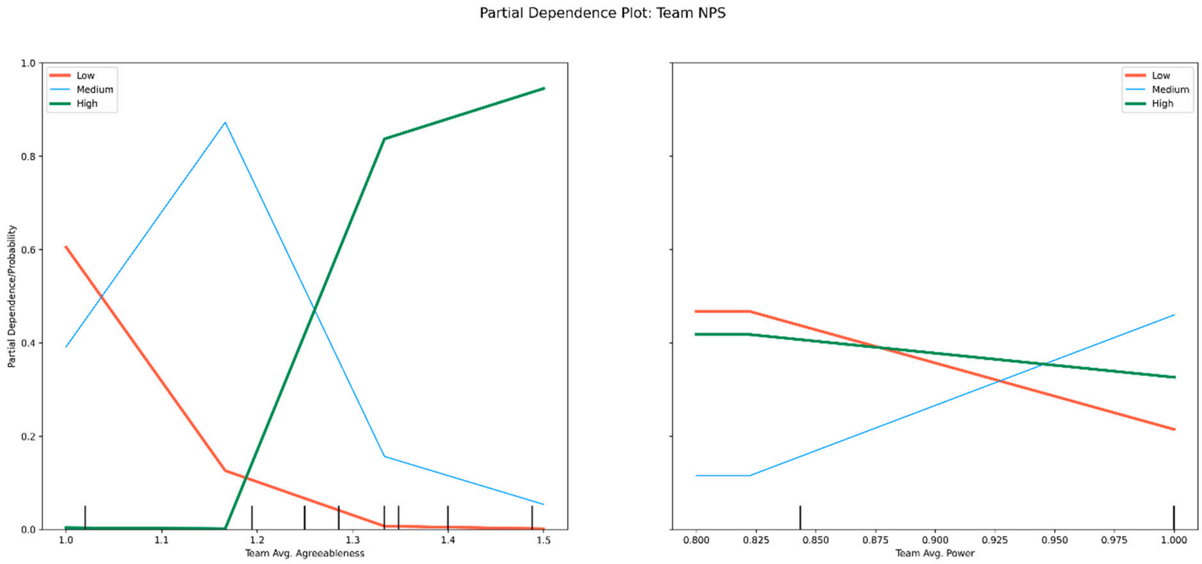

Figure A4. PDP of Team NPS Model.

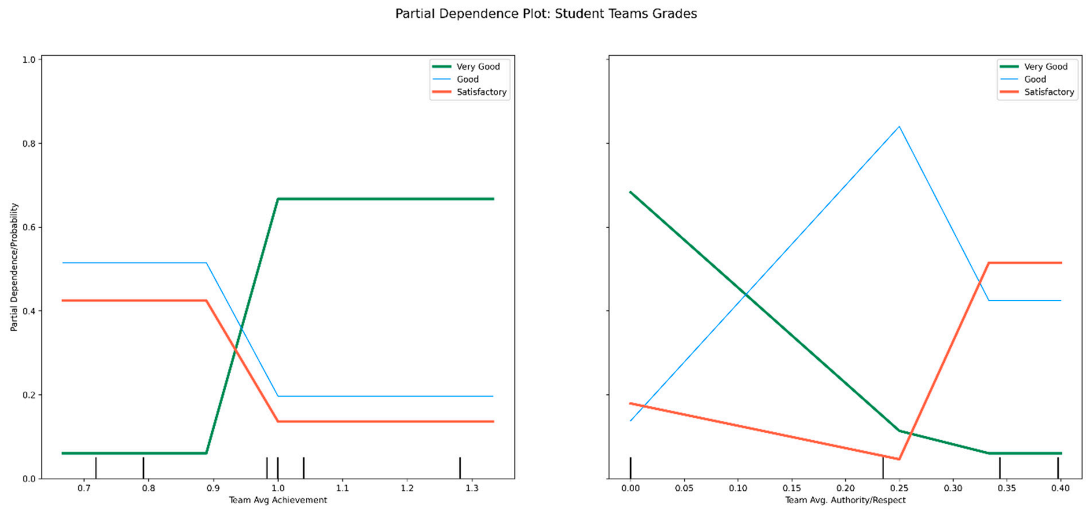

Figure A5. PDP of Student Teams Grades Model.

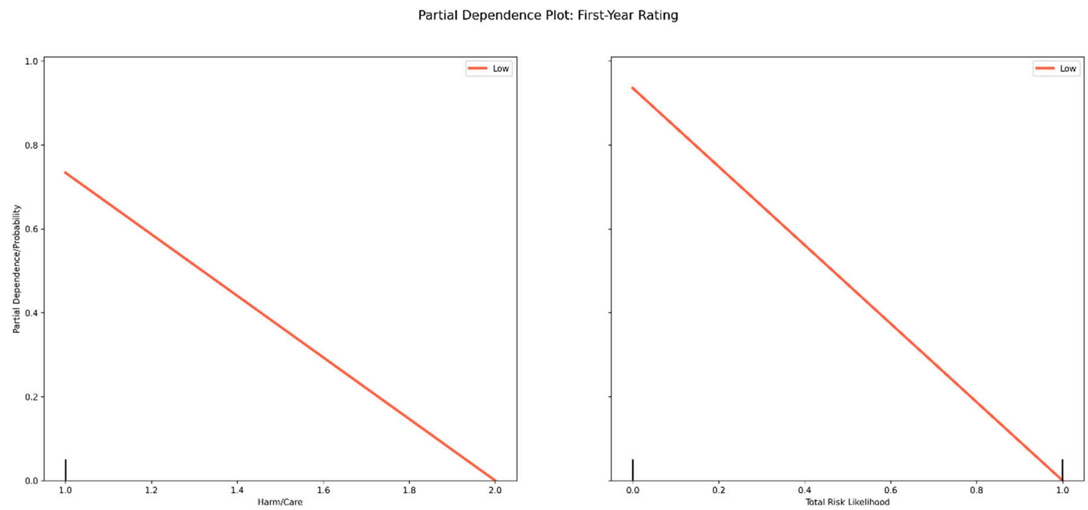

Figure A6. PDP of First–Year Rating Model.

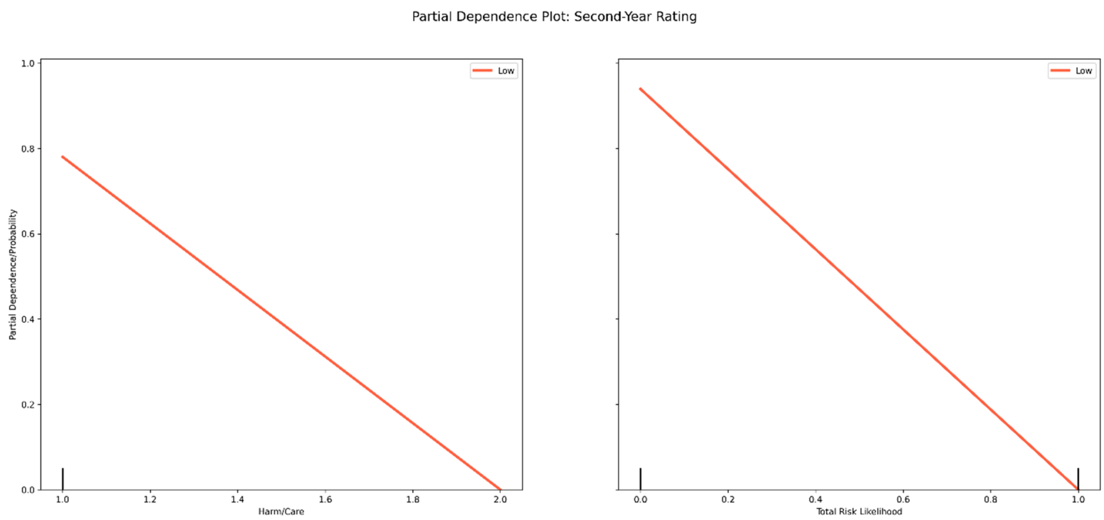

Figure A7. PDP of Second–Year Rating Model.

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