What Makes Some Workplaces More Favorable to Remote Work? Unpacking Employee Experiences During COVID-19 Via Glassdoor

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ABSTRACT

The COVID-19 pandemic has altered the working culture at various organizations; what began as a public health safety measure, remote work is continuing to reshape work in America and beyond. However, remote work has fared differently for different workers and for different organizations, contributing to better work-life balance for some, while increased burnout for others. What aspects of an organization's culture make it less or more favorable to remote work? We answer this question by creating, analyzing, and subsequently releasing a large dataset of employee reviews shared anonymously on Glassdoor. Adopting a worker-centered approach grounded in organizational culture theory, we extract organizational cultural factors salient in the language of employee reviews of 52 Fortune 500 companies. Through a prediction task, we identify what distinguishes companies perceived to be desirable for remote work versus others, noted in company rankings following the pandemic. Our dataset and findings can serve to be valuable evidence-base and resources for efforts to define a new future of work post-pandemic.

CCS CONCEPTS

• **Information systems → Data mining**; • **Human-centered computing → Empirical studies in collaborative and social computing**.

KEYWORDS

datasets, text analysis, natural language processing

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1 INTRODUCTION

The COVID-19 pandemic has brought foundational changes in various facets of our lives. One of the most prominent impacts has been on the work culture of various organizations [19]. From the onset of the pandemic, due to public health measures to prevent its spread, organizations across different sectors were forced to adapt their existing work cultures to remote formats for the majority of the employees [6]. There is increasing evidence that working remotely has provided more flexibility, reduced commute, enabled employees to achieve greater work-life balance, as well as supported inclusivity at work [31], while ensuring public health safety and disease containment. Nonetheless, there have also been newer challenges on the front of collaboration, communication, and work environment [24], including how these challenges have been more pronounced for women and people of color with child- or elderly care responsibilities [52].

Ultimately, these experiences have been heavily shaped and influenced by the particular organization, its governing policies, and importantly, its prevailing *culture* [24]. While some organizations with supportive management and policies conducive to remote work have fared well during the pandemic, employees in organizations with lesser such support have struggled, evidence of which can be observed in recent phenomena such as "The Great Resignation" [35] or "Quiet Quitting" [25]. Noting these differences, a variety of surveys have curated lists and rankings of "best organizations" [23, 26, 42]. While such rankings help to identify desirable places that support remote work, they are inherently opaque – they do not provide an insight into factors contributing to or driving these rankings. These factors can include aspects about an organization's values, interpersonal relations, work styles, and so on [37]. Moreover, due to the survey based nature of such rankings, these assessments of workplaces can suffer from various forms of bias such response/non-response bias, social desirability bias, retrospective recall bias, and others [4].

Importantly, rankings of "best organizations" do not provide actionable information for cultural change in organizations. This issue is particularly a critical one. This is because, as the society returns to a *new normal* (pre-COVID-19 normal with changes), many organizations are considering the possibility of continuing supporting the measures surrounding remote work taken during the pandemic [44]. However, for the changes to be effective over a long period in the future, it is essential for organizations to adopt an evidence-based strategy – they need to understand their employees' experience during the COVID-19 pandemic and how remote work has fared for them. Equipped with feedback from employees, organizations can improve and adapt their culture [7] and enhance the working experience when it comes to remote or in-person work [20, 43, 45].

In light of the above, this paper asks the question: *what underlying attributes of the work culture of some organizations have made them more conducive to remote work during the pandemic, and what cultural factors tend to hinder this work style?* To answer this, we adopt the theoretical lens of organizational culture [50]. We analyze the difference between desirable and less-desirable organizations (referred to as DOs and LDOs respectively), as identified in company rankings capturing organizational conduciveness towards remote work. We provide the following contributions:

(1) We provide novel insights about the organizational culture of 52 Fortune 500 companies, leveraging over 140K anonymous employee review data from Glassdoor, spanning two years around the pandemic. make the processed review vectors and code files public here.[1]
(2) We develop two approaches to data augmentation towards a prediction task that identifies which inherent cultural attributes of an organization, from the pre-COVID-19 era, are associated with favorable perceptions towards remote work. Our best classifier predicts the remote work desirability of an organization with an accuracy of ~76% and F-1 score of ~73%. We also cover the important features/aspects that are key drivers behind perceptions of remote work, which can be used to provide insights to leadership and management across organizations.

2 RELATED WORK

2.1 COVID-19 and the Future of Work

The COVID-19 pandemic has altered the working culture of organizations [19]. Remote work was a relatively uncommon practice in most industries in the pre-pandemic era. However, the global nature of the pandemic and the risks it posed to public health forced many organizations to adapt to the remote work setup [31]. There have been mixed reactions towards this remote work culture. While employees have embraced the work schedule flexibility and reduced commute, increased distance has present challenges towards effective communication and collaboration [24, 31]. Women employees have been especially affected due to COVID-19. School and daycare center closures during large part of the pandemic increased childcare needs causing women employees to leave jobs to take care of the family [1]. Impacts on mental and physical health have been one of the primary concerns around remote work. Absence of physical exercise, communication with co-workers, satisfactory workstation setup, and blurring work-life balance caused decreased overall well-being of many employees [59].

Society has recently started moving back to some form of pre-COVID-19 normalcy. However, some of the pandemic-era changes in working culture and styles, especially remote work policies, are expected to persist in varying intensities in different job sectors [44]. Consequently, both employees and employers are keen to evaluate if remote working cultures are viable and synergistic with the prevailing culture of their particular organizations. With this knowledge, employers can adapt organizational policies and employees can assess which workplaces may be sensitive to their situations and needs, in light of The Great Resignation [35]. As noted above, a variety of initiatives are therefore releasing rankings of "best organizations" with an eye to their attitudes towards and suitability for remote work [26] – however, not only are these rankings opaque, they lack often rely on surveys or expert-evaluation, rather than an employee-centered approach. We close this gap by adopting a theoretically-grounded strategy that uses anonymous employee reviews to quantify the inherent working culture of organizations, and then to assess the extent to which these cultural factors explain organizational rankings post-pandemic.

2.2 Social Media Studies of Organizations

Recently online websites have become a popular platform for employees to share their experiences, opinions and feelings [2, 30]. This has allowed researchers to understand a variety of aspects about work and workplaces. For instance, in an early work, De Choudhury and Counts [17] analyzed data from an internal microblogging tool at Microsoft, to find that positive affect expressed via interpersonal interactions on the platform transcended geographic and cultural homophily. Shami et al. [51] designed a tool Enterprise Social Pulse to analyze opinions and sentiments among employees, while Muller et al. [41] analyzed data for 44,000 IBM employees and to understand the dynamics of employee engagement.

Although social media platforms provide an insight into employee experience and feelings, these platforms are not anonymous, which may preclude candid and honest disclosure [14]. Glassdoor, a website where current and former employees of an organization can post anonymous reviews and ratings about their workplace, on the other hand, provides an opportunity for employees to share their experiences without significant concerns of impression management or negative professional repercussions. Lee and Kang [36] analyzed reviews on Glassdoor to extract factors affecting job satisfaction. They found that "Culture and Values" and "Senior Management" factors have the highest influence on both retention and turnover. In a more recent work Das Swain et al. [16] used multiple job descriptors to operationalize working culture in Glassdoor reviews, and validated it based on self-reported workplace and psychological constructs of information workers in multiple organizations. The proposed method explained the individual performance and citizenship behavior, beyond individual intrinsic attributes. Anonymity promotes candid responses and minimizes deceptive tendencies [21]. Hence, we use employee reviews shared on Glassdoor in order to understand employee experiences around the COVID-19 pandemic.

3 THEORETICAL LENS AND FRAMEWORK: ORGANIZATIONAL CULTURE

Our work draws upon the construct of organizational culture (OC) that has been a central theme in the field of organizational psychology. Several past early works have defined the organizational culture in different ways. According to [50], OC can be generally defined as: *A pattern of shared basic assumptions that the group learned as it solved its problems of external adaptation and internal integration, that has worked well enough to be considered valid and, therefore,*

[1] https://github.com/mohit3011/Remote-Work-Glassdoor

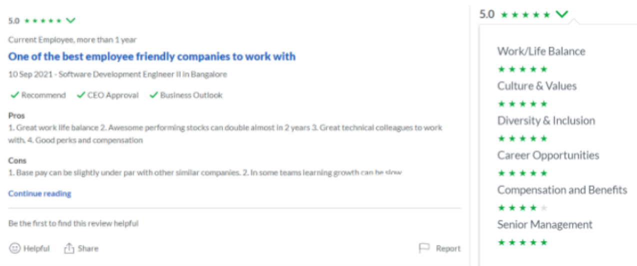

Figure 1: (Left) Sample Glassdoor review. (Right) detailed ratings displayed with mouse hover. The review contains information about 1) Review Title, 2) Date of Review, 3) Reviewer Designation/Title, 4) Location, 5) Categorical Ratings (Recommend, CEO Approval, Business Outlook), 6) Pros, 7) Cons, 8) Overall Rating, 9) Sub-Ratings (Work/Life Balance, Culture&Values, Diversity&Inclusion, Career Opportunities, Compensation and Benefits, Senior Management)

to be taught to new members as the correct way to perceive, think, and feel in relation to those problems. Other scholars have posited that OC emerges from the interplay of top-down expectations and bottom-up norms [15] and influences several key dimensions such as effectiveness, collaborations and innovation [43].

In light of these theoretical underpinnings, a variety of framework based studies have sought to quantify OC. Glaser et al. [27] presented a framework focusing of six key aspects related to organizational culture: teamwork-conflict,climate-morale, informational flow, involvement, supervision and meetings. In an other work [15] developed a theoretical model revealing that an ideal organizational culture promotes achievement-oriented, affiliative, humanistic, and self-actualizing thinking and behavioral styles. Scholars have, therefore, argued that OC can be a principled approach to making sense of employee perceptions and attitudes towards the workplace and the employer [8].

Inspired by this theoretical lens, we analyze employee reviews on Glassdoor in a principled manner, utilizing the approach proposed by Das Swain et al. [16]. This work allows us to establish an ontology of job aspects indicative of different organizational culture dimensions. The OC construct developed by Das Swain et al. [16] has been validated this construct with language used in 650k Glassdoor reviews. The proposed method has also been observed to explain the individual workplace performance [40] and organizational citizenship behavior of employees [53], beyond individual intrinsic attributes.

4 DATA COLLECTION AND PREPARATION

4.1 Data Collection

To get a suitable set of organizations that would allow addressing our research question adequately, we referred to the Fortune 500 list for the year 2021. Fortune publishes a list of top 500 companies based on the revenue and hence this list serves as a good indicator of popular market leaders. Additionally, we referred to multiple sources [23, 26, 42] to get various complementary as well as somewhat overlapping lists of companies that have been recognized as *'Best companies to work for'* during the pandemic, in light of remote work policies, as well as companies that have not been given such recognition.

Collating these lists together, we considered a company as a 'Desirable Organization' if it had been listed in the 2021 Fortune 500 list and had also been listed in any of the aforementioned sources. Complementing this, we also prepared a list of companies ('Less-Desirable Organizations') that were a part of the 2021 Fortune 500 list but were not a part of any of the sources that enlist preferred places for remote work. Moreover, while selecting the companies for the DO and LDO sets, we made sure that these were of a similar size in terms of revenue and number of employees, again by consulting the Fortune 500 resource. Further, we consulted news articles and company pages for both of these sets to ensure that they indeed allowed remote work for at least some time (several months), following the start of the COVID-19 pandemic. This ensured that these companies' rankings in 2021 were, in some ways, reliant on their remote work policies. In total, we focused on 52 companies, of which 35 were in the 'Desirable' and 17 in the 'Less-Desirable' categories. Table A1 and Table A2 give this comprehensive list, including their job sectors, size, earnings/revenue, and headquarters of operation for companies in DO and LDO categories, respectively.

We include a note on the seeming small number of organizations considered in this work, although the above referenced tables indicate availability of rich data (reviews), in the order of tens of thousands (ref. Table 1), at the per-organizational level. One of the major challenges faced during the data collection process was the limited number of organizations listed in various surveys on friendliness to remote work, that served as the ground truth for our work. Furthermore, many organizations were common across the multiple survey resources of organizational rankings we considered. Hence, data augmentation was leveraged as a technique to overcome this challenge (as described in section 5.3).

Next, we collected company-specific data from Glassdoor.com.[2] For each company, we scraped the reviews from 1st March, 2019 till 1st March, 2021. This choice of the time period allowed us to effectively analyze the contrasting characteristics of the reviews between the *Pre-COVID-19* era (Before 1st March, 2020 and *Peri-COVID-19* era (After 1st March, 2020). Figure 1 presents a sample review obtained from Glassdoor (left image) and additional sub-ratings obtained through hovering over the ratings section of the review (right image). We collected all possible textual components of the review shown in Figure 1. including: *1) Review Title, 2) Date of Review, 3) Reviewer Designation/Title, 4) Location, 5) Categorical Ratings (Recommend, CEO Approval, Business Outlook), 6) Pros, 7) Cons, 8) Overall Rating, and 9) Sub-Ratings (Work/Life Balance, Culture&Values, Diversity&Inclusion, Career Opportunities, Compensation and Benefits, Senior Management).* Table 1 presents descriptive statistics of the collected data.

4.2 Data Cleaning and Processing

After collecting reviews for each company, we cleaned and processed the data to get the final dataset. Specifically, we removed punctuation, numerical digits and extra white spaces to obtain the clean text and we removed the reviews with any of the *Pros*, *Cons*,

[2] https://www.glassdoor.com/

	Total	DO	LDO
# Companies	52/34	35/24	17/10
# Reviews	141,049 / 74,239	93,492 / 52,127	47,557 / 22,112
Avg. #Reviews (per company)	~2,713 / ~2,184	~2,671 / ~2,172	~2,797 / ~2,211

Table 1: Comparative numbers for desirable companies (DO) and less-desirable companies (LDO). In total, we collected data for 52 organizations, out of which data belonging to 34 organizations was used for the prediction task after filtering out companies having ≤ 500 reviews in the *Pre-COVID-19* period. Numbers before '/' corresponds to 52 organizations, whereas the number after '/' corresponds to the 34 filtered organizations. ~ represents the rounding off approximation.

Review Title, *Overall Rating* sections as empty strings or null values. This step ensured that the final dataset only contains complete reviews. Additionally, we also filtered out reviews from former employees as we are only considering the experiences of the people who were working at the organization at the time of writing the review.

Next, we processed the data to add additional information to the cleaned dataset. For the *Pros* and *Cons* section each review, we added the sentiment label, sentiment score and Part-Of-Speech (POS) tagged tokens. For obtaining the sentiment label and score, we used the XLM-RoBERTa transformer model fine-tuned for the sentiment analysis task from Barbieri et al. [3]. Given, the text input, the model produces one of the three labels (Positive, Negative or Neutral) along with the softmax probability score. We added the sentiment label and sentiment probability score in the final dataset. We also added the tokens from the *Pros* and *Cons* sections along with their POS tags obtained using the spaCy POS-Tagger [54].

5 PREDICTION TASK

Next, we focus on answering whether the 'Desirable Companies' had some inherited qualities in the *Pre-COVID-19* period that helped them to be listed as top places to work during the COVID-19 pandemic. This we consider a valuable preceding analysis, since, to recall, our prediction task asks if there exists a relationship between the *Pre-COVID-19* culture of organizations and their *Peri-COVID-19* rankings. Specifically, we frame a prediction task where we utilize company-wise reviews shared between 1^{st} March, 2019 and 1^{st} March, 2020 from our Glassdoor dataset to identify if the corresponding company fared as desirable. While, one may argue that there might be additional features such as sentiments expressed in reviews that may impact the *Peri-COVID-19* ranking, our goal here is to study the relationship between organizational culture, as expressed in the Glassdoor reviews of a company, and its ranking. Moreover, it has been established in past studies that OC dimensions capture and encompasses diverse factors such as sentiments and attitudes of companies [16]; thus by looking at *Pre-COVID-19*, we are able to harness a variety of information embedded in the reviews. Specifically, we train classifiers on *Pre-COVID-19* review OC feature vectors to predict the labels for *Peri-COVID-19* review vectors. To tackle sparsity in this task, we filtered out all companies with ≤ 500 reviews during this period. This step left us with a total of 24 and 10 DOs and LDOs respectively, used in the ensuring prediction task.

5.1 Organizational Culture Descriptors and Review Text Transformation

On the company review data, to obtain theoretically-grounded linguistic cues for the prediction task that are situated in the organizational behavior and psychology literature, we adopted the approach proposed by Das Swain et al. [16], to obtain 7 job aspect descriptors, or categories, capturing 41 OC dimensions derived from the Occupational Information Network (O*Net) [47]. O*Net is an online repository that contains information related to the different aspects of work including various OC descriptors (refer to Table 2 for detailed descriptions).

After collecting the descriptions for each of the 41 OC dimensions, we transformed the description into a 50-dimensional word-embedding vector. Specifically, we used GloVe pre-trained word embeddings trained on the Wikipedia corpus with 6B tokens [46]. We took a similar approach in encoding the text present separately in *Pros* and *Cons* section for each review. For each review, we created two separate sentence level 50 dimension word embedding vector for the *Pros* and *Cons* section respectively. As an alternative approach, we also experimented with transformer based sentence embeddings such Sentence-BERT [48]. However, many reviews present in our dataset were between 1-2 sentences that covered different aspects related to the employer and workplace, making it hard for the model to encode the information efficiently.

5.2 Feature Vectors

Next, to get the prominent OC dimensions present in each review which could be valuable for the prediction task, we used cosine similarity as a measure of overlap between the 41 OC dimension vectors and the sentence word embedding vectors from *Pros* and *Cons* section for each review. Higher cosine similarity would indicate that the sentence is semantically similar to the description of the particular OC dimension. While raw text obtained from reviews can be used to extract important keywords common across reviews of DOs and LDOs, these keywords cannot be used to fully explain the importance of different OC dimensions. This problem exacerbates when different and ambiguous keywords are used to describe a particular OC dimension that eventually leads to worsen performance for topic modelling methods. However, with our method of using feature vectors based on GloVe handles this problem through semantic similarity between the reviews and OC dimensions. We retained all reviews having a cosine similarity of more than 0.90 with any of the OC dimensions. Hence, a review can express facets related to multiple OC dimensions. Table 3 presents a few examples of reviews and corresponding OC dimensions.

We then computed a 41 dimensional feature vector for each company j where each dimension represents the difference in the fraction of Pro reviews (among the total reviews for j) ($N_p(j)$) that are semantically similar to a particular OC dimension i and the fraction of Con reviews ($N_c(j)$) that are semantically similar to the same OC dimension i. Mathematically, the feature $d_i(j)$

O*Net Category	**OC Dimensions**
Interests	conventional, enterprising, social
Work Values	relationships, support, achievement, independence, recognition, working conditions
Work Activities	assisting and caring for others, establishing and maintaining interpersonal relationships, guiding, directing, and motivating subordinates, monitoring and controlling resources, training and teaching others, coaching and developing others, developing and building teams, resolving conflicts and negotiating with others
Social Skills	instructing, service orientation
Structural Job Characteristics*	consequence of error, importance of being exact or accurate, level of competition, work schedules, frequency of decision making, freedom to make decisions, structured versus unstructured work
Work Styles	concern for others, leadership, social orientation, independence, integrity, stress tolerance, self control, adaptability/flexibility, cooperation, initiative, achievement
Interpersonal Relationships*	frequency of conflict situations, face-to-face discussions, responsibility for outcomes and results, work with work group or team

Table 2: Org. descriptors from O*Net to represent the dimensions of OC. The category column indicates the O*Net category of the descriptors. Categories with '*' are subcategories within the "Work Context" category.

Review Text	Review Type	OC Dimension
poor work conditions, poor management, no benefits for part time team members.	Cons	Working Conditions
good work culture, management is supportive, good infrastructure, job security, transport facility with escords, salary as per industry standards, management values your opinion.	Pros	Support
benefits for part-time employees. they work with your schedule! open door policy with management, they will listen to your concerns at any time. great working atmosphere, coworkers are very friendly.	Pros	Working Conditions
people are friendly and always willing to help	Pros	Service Orientation
Constant changes to the job requirements and compensation plan. management treats employees like children rather than executives. too many people trying to make decisions regarding the process to reach individual goals. micromanagement is at an all time high!	Cons	Independence
i have personally experienced my colleague telling that, you should not explain others about internal design of your code, it makes them to learn it, it means there is a replacement for you, they can come and fill your shoes	Cons	Relationships

Table 3: Reviews for which the word-vector representation of one of the sentences in *Pros* or *Cons* section shows a cosine similarity ≥ 0.90 with the corresponding OC dimension. A review can exhibit aspects related to multiple OC dimensions, but here we present only one OC dimension per review for clarity.

representing the i^{th} OC dimension for company j ($1 \leq m \leq 41$) is given as:

$$d_i(j) = N_p(j) \sim OC_i - N_c(j) \sim OC_i \quad (1)$$

Next, we assigned ground truth labels to each company's 41 dimension vector, based on whether the company appeared in the DO or LDO list.

5.3 Data Augmentation

One of the challenges we note towards the prediction task is the limited size of training examples, comprising just 24 DOs (positive examples; also the majority class) and 10 LDOs (negative examples). To address this issue, we developed a data augmentation approach tailored to our specific task, drawing from the field of computer vision [32]. We experimented with different techniques to first increase the sample size of the majority class (DOs). Specifically, we used adversarial data augmentation through introducing noise to the samples in the majority class. We experimented with two different approaches of noise introduction– 1) convex-combination of samples, and 2) Gaussian noise addition to samples.

The first approach produces a synthetic sample using a convex combination of any two samples belong to the majority class. Mathematically, a new synthetic sample (v_{syn}) is generated from two samples v_1 and v_2 using $v_{syn} = r_1 * v_1 + r_2 * v_2$ where r_1 and r_2 are random real numbers such that $r_1 + r_2 = 1; 0 < r_1, r_2 < 1$. In the second approach, we added Gaussian noise to the samples in the second approach. Here, we add Gaussian noise to randomly chosen samples to create the new synthetic vectors.

We tested the efficacy of both approaches by generating $\binom{n}{2}$ synthetic examples for the majority class where n is the original number of samples in the majority class. We validated the coherence of this synthetic data with the original dataset through Spearman's correlation coefficient (ρ). More elaborately, we computed the average of the vectors of samples in the majority class in the original dataset (v_{avg}). We used v_{avg} and the set of synthetically generated vectors (v_{syn}) to computed ρ across each of the 41 OC dimensions. We found that the first approach outperformed the second, in that it yielded higher correlation (ρ) between the synthetic and original examples, in both training (ρ=0.696 vs. ρ=0.458 respectively) and test sets (ρ=0.685 vs. ρ=0.397 respectively).

Method	Accuracy	Recall	Precision	F-1
SVM	0.74 ± 0.02	0.74 ± 0.02	0.74 ± 0.01	0.71 ± 0.02
LR	**0.76± 0.02**	**0.76± 0.02**	**0.75± 0.01**	**0.73± 0.02**
XGBoost	0.70 ± 0.03	0.70 ± 0.03	0.65 ± 0.05	0.63 ± 0.04
2-Layer MLP	0.51 ± 0.02	0.51 ± 0.02	0.27 ± 0.05	0.34 ± 0.03

Table 4: Results for the prediction task with Convex Combination based majority oversampling.

Method	Accuracy	Recall	Precision	F-1
SVM	0.68 ± 0.02	0.68 ± 0.02	**0.81± 0.01**	0.64 ± 0.03
LR	**0.72± 0.03**	**0.72± 0.03**	0.73 ± 0.02	**0.69± 0.03**
XGBoost	0.66 ± 0.05	0.66 ± 0.05	0.65 ± 0.08	0.60 ± 0.07
2-Layer MLP	0.50 ± 0.02	0.50 ± 0.02	0.26 ± 0.04	0.34 ± 0.02

Table 5: Results for the prediction task with Gaussian Noise based majority oversampling.

In addition to increasing the size of the majority class, we also used the Synthetic Minority Oversampling Technique (SMOTE) [13] to oversample the minority class (LDOs).

5.4 Prediction Approach and Results

We performed the task of binary classification with conventional statistical as well as deep learning based methods. The selection of these methods was based on the success of deep learning methods and the effectiveness of traditional methods such as (SVM, Logistic Regression) while working with small datasets such as ours [12, 57]. We used stratified 5-fold cross-validation for each classifier ensuring separate data augmentation for the train, test and validation sets (in case of deep learning-based method). This ensured that there was no leakage of information to the classifier. Since we used the above described adversarial data augmentation which is random in nature, we performed the 5-fold cross-validation for 1,000 runs for the classifiers to ensure the generalizability of results. Specifically, we experimented with statistical methods such as Support Vector Machines (SVM), Logistic Regression (LR), and XGBoost and a 2-layer MLP as a deep learning baseline. We performed hyper-parameter tuning for each classifier, keeping F-1 score as the metric (more information in Appendix A). In our prediction task, for SVM, we used a linear kernel along with $C = 0.5$ whereas for the Logistic Regression classifier, we used $C = 0.5$ with a 'liblinear' solver having 'l2' penalty as a regularization. For the XGBoost classifier, we used $gamma = 0.25$, learning rate=0.1, max depth=5, reg lambda=1, subsample=0.8. We experimented with vanilla 2-layer Multi-Layer Perceptron (MLP) as a deep learning based classifier. We used 64:16:20 as the train:validation:test split to train the classifier using the Adam optimizer [33] with learning rate $=2e^{-5}$. We trained the MLP model for 20 epochs in each fold. We used macro F-1 score as metric for the hyperparameter tuning. We have provided the code file used in the experimentation here.[3]

Tables 4 and 5 present the results for the above binary classification task with the convex combination and Gaussian noise based data augmentation respectively. The LR classifier outperformed the other methods in both cases of data augmentation, except on the precision with Gaussian noise based data augmentation. On the other hand, the 2-Layer MLP based classifier performed the worst, confirming the intuition that traditional non-deep learning classifiers may be more suited in situations with limited dataset sizes. As observed in Tables 4 and 5, the Logistic Regression based classifier performs with an F-1 score ≥ 73% indicating the existence of inherited differences between the DOs and LDOs from the *Pre*-COVID era that likely impacted their respective employees' working culture during the COVID-19 period as well.

O*Net Category	F-1 Score Change
Interests	-0.012
Work Values	-0.102
Work Activities	0.000
Social Skills	0.000
Structural Job Characteristics	-0.047
Work Styles	0.001
Interpersonal relationships	0.000

Table 6: OC categories with the F-1 feature permutation score (rounded to three decimals). The score is calculated as the difference of F-1 score with permuted (shuffled) test set and F-1 score with non-permuted (unshuffled) test set averaged over 5 folds and 1000 runs. Lower score signifies more importance of the respective O*Net category.

6 PERMUTATION FEATURE IMPORTANCE

We performed the permutation feature importance experiment to analyze the most influential OC dimensions. Permutation feature importance measures the increase in the prediction error of the model after permuting the values of the particular feature. Thus the drop in the model score is indicative of how much the model depends on the feature. We used the Logistic Regression classifier due to it's better performance in the prediction task. For this analysis, we use the 7 theoretically-coherent O*Net job aspect descriptors (categories) as shown in Table 2. We shuffled the values across each OC dimension in a particular OC category to observe the change in the macro F-1 score in comparison to the control set (unshuffled test set). Since, there exists a factor of randomness due to the data augmentation techniques we used, we repeated the permutation feature importance experiment for five folds for 1000 runs.

Table 6 presents the change in F-1 score between the permuted and non-permuted test sets. We observe considerable decrease in the F-1 scores among the *Interests*, *Work Values*, *Structural Job Characteristics* categories. This implies that these OC categories played a significant role in the prediction task; these OC attributes from the *Pre-COVID* period were strongly associated with *Peri-COVID* perceptions of which companies were desirable. The other categories differed marginally. These findings are inline with organizational

[3]https://github.com/mohit3011/Remote-Work-Glassdoor

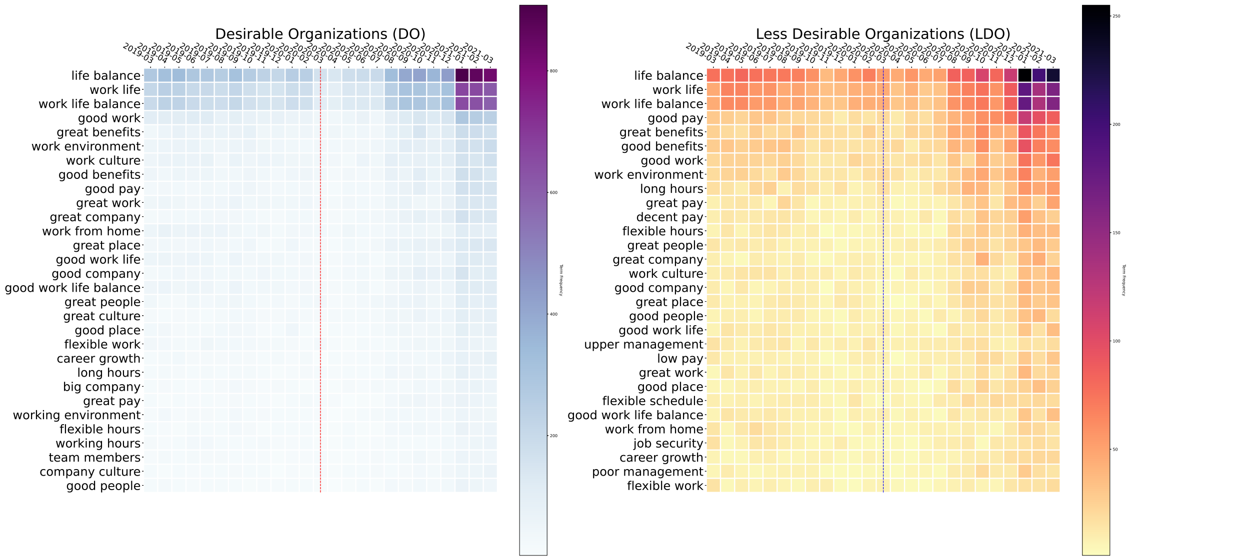

Figure 2: Frequency heatmap presenting the net occurrences of 30 most popular phrases in the review sections of DOs (Left) and LDOs (Right), aggregated monthly between 1^{st}March, 2019 - 1^{st}March, 2021. To the left of the red line is the *Pre-COVID* period, and to the right, *Peri-COVID*.

psychology literature, which we describe below. To structure this theoretically-grounded analysis, we make use of prominent linguistic phrases present in *Pros* and *Cons* section for DO and LDO during for the entire duration of our study. For this, we preprocessed the additionally associated POS Tagged tokens from the *Pros* and *Cons* sections of the respective company reviews, and further removed punctuation and stopwords to get clean data. Then, we used the methodology proposed in Handler et al. [28] to combine the tokens in Noun Phrases. The proposed method (NPFST) uses a finite-state transducer (FST) to extract interpretable phrases with a high recall. Figure 2 presents the net frequency heatmap of the top 30 phrases per month among the *Pros* and *Cons* section of the reviews for DOs and LDOs respectively.

Interests. One of the top predictive features for us was Interests. A culture that nurtures employees' interests can manifest in many ways. For example, enabling individuals to have the authority, initiative, and ability to manage their own work is known to create a sense of ownership and responsibility toward the organization [18]. Rodríguez-Escudero et al. [49] suggested that role conflict and role ambiguity, on the other hand, diminish employees' interest in work and therefore are negatively related the teamwork and job satisfaction. The DOs persistently scored higher for the OC dimensions corresponding to Interests, indicating a culture that espoused employees to inculcate passion, curiosity, and enjoyment in their work. Notice that phrases like "great work" and "good work life" in Figure 2 are not only present in the reviews *Pre-COVID* but also sustain in the *Peri-COVID* period. In a shift to remote work, these qualities likely kept employees engaged and appreciative of their workplaces, resulting in positive attitudes captured in the rankings.

Work Values. Employees' decision-making authority has an important role in creating an effective organizational culture [58]. The strong relationship between reward and recognition and its importance for job satisfaction of employees has also been explained by various theorists from around the world such as Maslow's need hierarchy theory [38] and Herzberg two factor theory [29]. Supportive leadership has been recognized as an influential factor towards development of employees [5, 11]. We found DOs to recognize these values, as also captured by the OC dimensions corresponding to the Work Values category. For instance, phrases like "great culture", "good benefits", "great people" and "working environment" in Figure 2 are highly prominent before the pandemic, so are they afterward. This likely made employees more conducive to diverse (including remote) work styles in the *Peri-COVID* period.

Structural Job Characteristics. Zubair et al. [60] showed that organizations that provide the employees with the freedom to make decisions and put forward their ideas usually have more creative employees with higher morale. Such cultural characteristics seem to have been prevalent in DOs prior to the pandemic, as can be observed from phrases like "flexible work" and "work culture" in Figure 2. In contrast, the LDOs included not only lesser usage of these phrase *Pre-COVID*, but also greater use of phrases like "poor management" indicative of general dissatisfaction prevalent in their cultures. We conjecture these cultural factors to have positively (or negatively) shaped the workplace perceptions of employees in DOs (or LDOs) after the start of the pandemic and when a switch to remote work was implemented.

7 DISCUSSION AND CONCLUSION

We presented a first computational study analyzing the differences between desirable and less-desirable organizations, particularly in the backdrop of the COVID-19 pandemic's remote work policies. We collected data for 52 organizations between 1^{st} March, 2019 and 1^{st} March, 2021 from Glassdoor amounting to over 140K reviews. Drawing on the organizational psychology literature, we used company specific Glassdoor reviews to quantify and identify which OC factors were associated with rankings favorable or less unfavorable towards remote work. We observed common themes such as 'Work/Life Balance' and 'Benefits/Pay' to be prominent among the reviews for the DO's we considered in this work. In contrast, themes such as 'Leadership/Upper Management' were more prevalent in the LDO's. Our best classification model, based on statistical and deep learning methods, correctly predicted the remote work desirability of an organization with a accuracy of ~76%. Lastly, we performed a qualitative analysis revealing the influential OC dimensions for the classification task.

Our work appropriates a hitherto less explored language dataset – Glassdoor reviews – to investigate a hitherto less studied phenomenon – organizational culture of companies and its role in helping define an organization's future of work after the pandemic. Our theoretically-grounded approach provides, to the best of our knowledge, the first insights computationally analyzing differences in organizational culture among different companies, based on less-biased, anonymous employees' self-reported workplace experiences. Through our prediction task, we observed that DOs had some inherited qualities like excellent work-life balance, good compensation, and better ways to inculcate and nurture employee interest – these cultural attributes were positively associated with a more favorable remote work culture following the pandemic. To be successful in the *Peri-COVID* era, our findings indicate that decisions of allowing remote work need to be coupled with policies of improved work-life balance and employee agency. Moreover, we noted that organizational work culture in the *Peri-COVID* era needs to tackle elements contributing to toxic cultures such as failure to promote diversity, equity, and inclusion, workers feeling disrespected, and unethical behaviors. These observations collectively gel well with recent reports that have investigated the causes behind The Great Resignation, unearthing that for many employees who quit or retired during the pandemic, flexibility and amicability of the work environment mattered more than conventional aspects like compensation and job growth [25]. Summarily, we believe the that our findings can help understand employee experience and needs in a more holistic manner, surrounding relevant events that impact the future of work.

8 LIMITATIONS

Although novel, our study suffers from a few limitations. The first limitation is related to the data availability. Although we had tens of thousands of reviews available per company and the companies were diverse in their job sectors, we worked with a mere 52 DOs and LDOs which posed significant challenges towards training a classifier. To overcome this issue, we developed and used two synthetic data generation and oversampling techniques. Future work can consider additional real world data sources to gain a broader understanding across multiple companies that are diverse across sectors, revenue, and workforce.

Secondly, our study relies on Glassdoor data which may suffer from self-selection or participation bias. During the data collection we observed that while employees of some organizations were highly active on the platform, there were some organizations with not so prominent presence on Glassdoor. Future studies can augment Glassdoor data with additional information, such as that gained from company-specific social media, news, and surveys. Finally, our study is correlational, and further research is needed to situate whether any of the cultural factors we identified causally led to better or poorer remote working conditions.

9 PRIVACY, ETHICS, AND BROADER IMPACT

The approach used in our study follows the best practices noted in internet research ethics research [22, 56]. First, for collecting the Glassdoor reviews corresponding to the 52 companies, we provided a user agent string that made our intentions clear and provided a way for the administrators to contact us with questions or concerns. We requested data at a reasonable rate and strived never to be confused with a distributed denial of service (DDoS) attack. Using a parsimonious approach [34], we saved only the data we needed from the page that was relevant to our analysis. In addition, we refrained from using or reporting any personally identifiable information in our analysis or the results, to minimize potential harm to any individual's privacy [39, 55]. We also paraphrased raw text presented in the paper to reduce traceability to the review author, as advocated by [9, 10].

As noted in the previous section, we anticipate our work to contribute meaningfully to supporting remote work related decision-making in organizations, in the aftermath of the COVID-19 pandemic. With our approach and findings, an organization's upper management and administration can be in a better position to adapt their policies to support a healthier culture that facilitates remote work. Furthermore, by releasing our Glassdoor dataset associated with their respective organizational culture vector representations, our work can inspire future investigations that bring computational linguistic approaches to studies of the future of work.

That said, we are mindful of abuses and unintended negative consequences resulting from our work. We caution against using our findings "as-is" to evaluate the organizational culture of companies against the backdrop of the pandemic. Our work is best used in tandem with additional sources of complementary information. We have refrained from directly reporting which companies have better or poorer cultures that were associated with their respective rankings after the pandemic, since our intention was to prevent slandering any particular organization. Our work is best interpreted in the aggregate as a means to support evidence-based decision-making of company policies that, through a computational analysis of anonymous employee reviews, can support a worker-centered culture towards a post-COVID-19 "new normal."

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APPENDIX A

For SVM, we experimented with kernel types: 'sigmoid', 'poly', 'rbf' and 'C' values between 0.1-100. For XgBoost we used hyper-parameter tuning for max_depth from 3-7, learning_rate from 0.05-0.1, gamma from 0-1, reg_lambda from 0-10, and scale_pos_weight from 1-5. For Logistic Regression, we experimented with max_iter from 100 to 700, 'C' values between 0.01-1 and solvers from 'liblinear', 'saga', 'newton-cg','lbfgs'.

For the Neural Network based method, we experimented with different learning rates from e^{-5} to $3e^{-5}$ along with epoch between 20-35.

Name	Sector	Size (No. of Employees)	Revenue (Million USD)	Headquarters
AbbVie	Biotech & Pharmaceuticals	47,000	45,804	North Chicago, IL (USA)
Adobe	Computer Hardware Development	22,516	12,868	San Jose, CA (USA)
American Express	Financial Transaction Processing	63,700	38,185	New York, NY (USA)
Bank of America	Banking & Lending	212,505	93,753	Charlotte, NC (USA)
Burlington Stores	Department, Clothing & Shoe Stores	35,246	5,764	Burlington, NJ (USA)
Capital One	Banking & Lending	51,985	31,643	Mc Lean, VA (USA)
CarMax	Motor Vehicle Dealers	27,050	21,424	Richmond, VA (USA)
Cisco Systems	Enterprise Software & Network Solutions	77,500	49,301	San Jose, CA (USA)
Comcast	Telecommunications Services	168,000	103,564	Philadelphia, PA (USA)
Dell	Information Technology Support Services	158,000	94,224	Round Rock, TX (USA)
Delta Air Lines	Airlines, Airports & Air Transportation	74,000	17,095	Atlanta, GA (USA)
Dow	Chemical Manufacturing	35,700	38,542	Midland, MI (USA)
Edward Jones	Investment & Asset Management	50,000	10,165	Saint Louis, MO (USA)
Farmers Insurance Group	Insurance Carriers	10,004	11,869	Woodland Hills, CA (USA)
HP Inc.	Computer Hardware Development	53,000	56,639	Palo Alto, CA (USA)
Humana	Insurance Carriers	48,700	77,155	Louisville, KY (USA)
IBM	Information Technology Support Services	364,800	73,620	Armonk, NY (USA)
Intuit	Computer Hardware Development	11,950	7,679	Palo Alto, CA (USA)
IQVIA	Biotech & Pharmaceuticals	70,000	11,359	Durham, NC (USA)
Marriott International	Hotels & Resorts	121,000	10,571	Bethesda, MD (USA)
Mastercard	Financial Transaction Processing	21,000	15,301	Purchase, NY (USA)
Merck	Biotech & Pharmaceuticals	73,500	47,994	Rahway, NJ (USA)
Nationwide	Insurance Carriers	25,391	41,929	Columbus, OH (USA)
NVIDIA	Computer Hardware Development	18,975	16,675	Santa Clara, CA (USA)
Oracle	Enterprise Software & Network Solutions	135,000	39,068	Austin, TX (USA)
Progressive	Insurance Carriers	43,326	42,658	Cleveland, OH (USA)
Publix	Insurance Carriers	227,000	45,204	Lakeland, FL (USA)
Rocket Companies	Banking & Lending	24,000	15,980	Detroit, MI (USA)
Salesforce	Enterprise Software & Network Solutions	56,606	21,252	San Francisco, CA (USA)
Stryker	Health Care Products Manufacturing	43,000	14,351	Portage, MI (USA)
Target	General Merchandise & Superstores	409,000	93,561	Minneapolis, MN (USA)
Thermo Fisher Scientific	Biotech & Pharmaceuticals	84,362	32,218	Waltham, MA (USA)
UnitedHealth Group	Healthcare Services & Hospitals	330,000	257,141	Minnetonka, MN (USA)
USAA	Insurance Carriers	35,935	36,296	San Antonio, TX (USA)
Williams-Sonoma	Home Furniture & Housewares Stores	16,600	6,783	San Francisco, CA (USA)

Table A1: Details of companies in the DO category.

Name	Sector	Size (No. of Employees)	Revenue (Million USD)	Headquarters
AT&T	Telecommunications Services	230,760	171,760	Dallas, TX (USA)
Boeing	Aerospace & Defence	141,000	58,158	Chicago, IL (USA)
Cigna	Healthcare Services & Hospitals	72,963	160,401	Bloomfield, CT (USA)
Citi	Investment & Asset Management	210,153	88,839	New York, NY (USA)
DISH	Cable, Internet & Telephone Providers	13,500	15,493	Englewood, CO (USA)
Dollar General	Retail Shops	158,000	33,746	Goodlettsville, TN (USA)
DXC Technology	Information Technology Support Services	138,000	19,577	Tysons Corner, VA (USA)
Kraft Heinz	Food & Beverage Manufacturing	38,000	26,185	Chicago, IL (USA)
Kroger	Retail	465,000	132,498	Cincinnati, OH (USA)
MetLife	Insurance Agencies & Brokerages	46,500	67,842	New York, NY (USA)
Sprouts Farmers Market	Food & Beverage Stores	33,000	6,468	Phoenix, AZ (USA)
TJX	Department, Clothing & Shoe Stores	320,000	32,137	Framingham, MA (USA)
Union Pacific	Taxi & Car Services	30,960	19,533	Omaha, NE (USA)
Verizon	Telecommunications Services	132,200	128,292	New York, NY (USA)
Visa Inc.	Information Technology Support Services	20,500	21,846	Foster City, CA (USA)
Walmart	General Merchandise & Superstores	2,300,000	559,151	Bentonville, AR (USA)
Xerox	Information Technology Support Services	24,700	7,022	Norwalk, CT (USA)

Table A2: Details of companies in the LDO category.