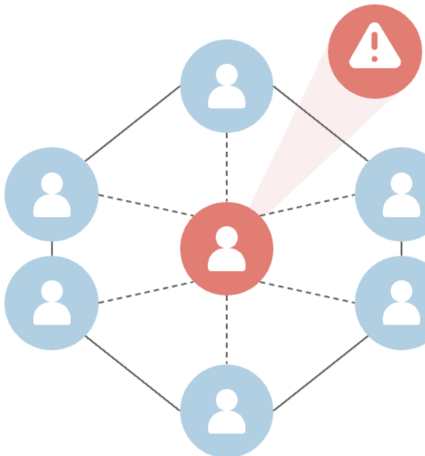

# Analysis of USPTO Examiner Attrition & Art Unit Movement

TALENT ANALYTICS TERM PROJECT
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# Part 1

## Data Preprocessing

In our journey to enhance the efficiency and equity of the USPTO, we've embarked on a detailed analysis, starting with a rigorous data preprocessing phase. This step was crucial for us in understanding the demographic landscape of the USPTO workforce. We achieved this by extracting unique examiner names to determine the examiner's gender through the 'gender' package, which assigns gender based on first names. Similarly, we could derive the examiner's race by last name using the 'wru' package. Both of these derived categories, race and gender, were then merged back into the main dataset to enrich it with the demographic details of the examiners.

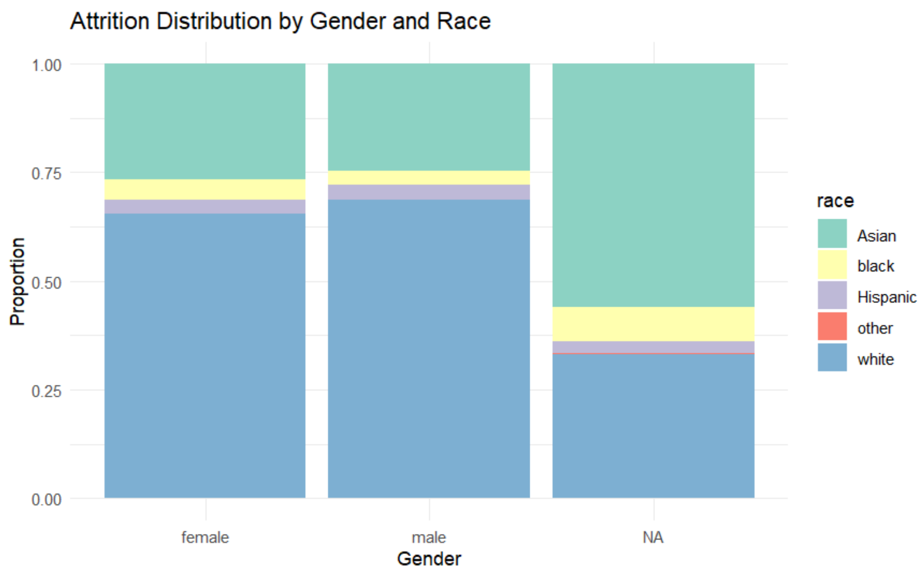
Subsequent steps focused on refining the dataset further: unnecessary columns were removed, and important dates such as filing and status update dates were converted to a consistent format using the 'lubridate' package. This conversion enabled the calculation of tenure for each examiner by determining the time interval between their earliest and latest recorded activities.

We transformed the data to reflect quarterly aggregates to create a panel dataset suitable for regression analysis. This process involved converting dates into quarters and summarizing application data—including new applications, abandonments, issues, and in-process applications—by examiner and quarter. Additionally, we aggregated information on the composition of art units, specifically total and female examiners, every quarter using averages. This aggregated data, along with gender and race information, was then integrated into the main dataset.

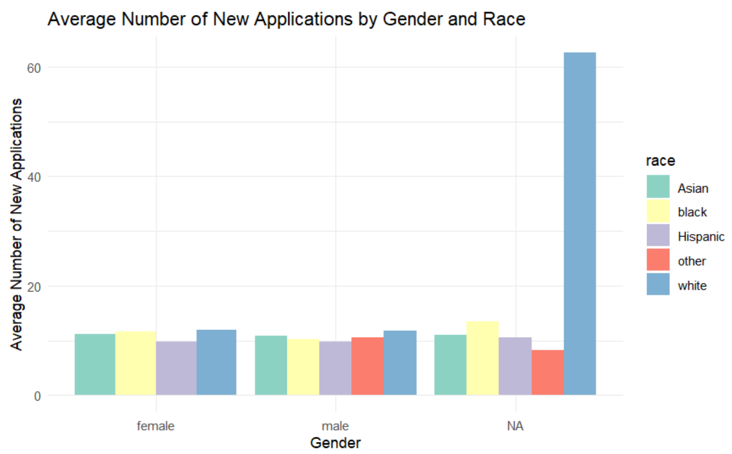
Finally, to explore patterns of mobility and potential indicators of examiner separation, variables indicating changes in art units and a flag for an examiner's last five quarters of activity were introduced.

## Analysis

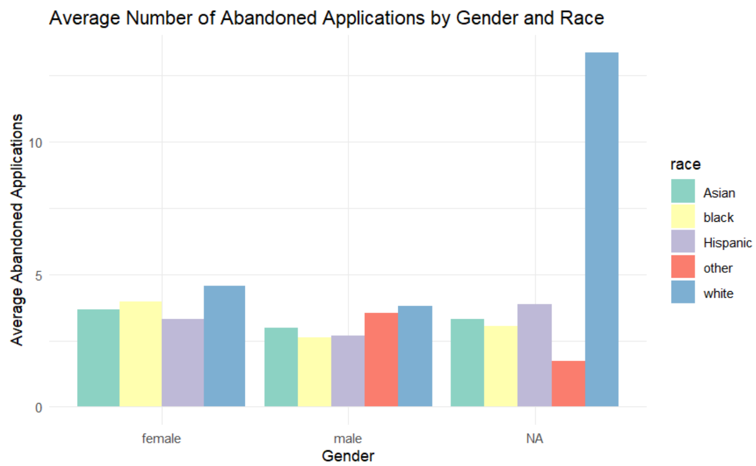
In the plots, NA represents the unknown gender as not only genders could be identified from the examiner's name. Considering they are unknown, they are kept out of analysis.



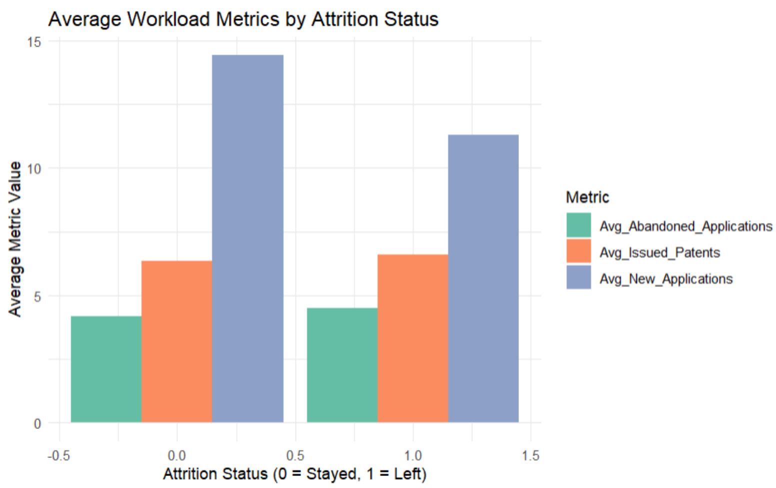
Attrition distribution among males and females by race is almost the same for both genders, with male whites slightly higher than female whites.



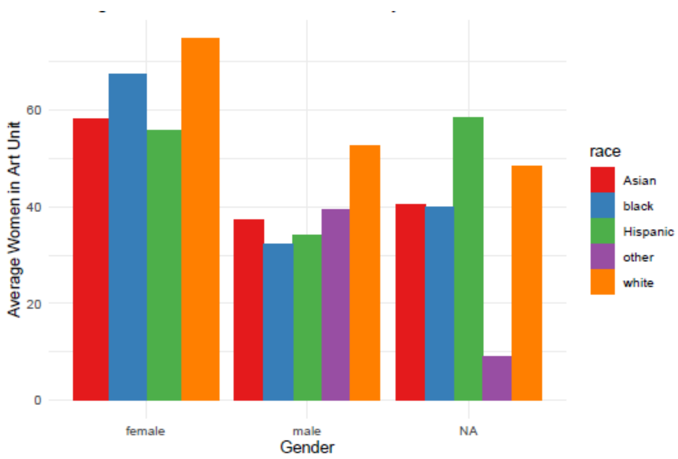

The average number of new applications is almost the same for both male and female races.




The average number of abandoned applications is slightly greater for female races compared to males.




It is observed than examiner who had higher average new application did not attrition



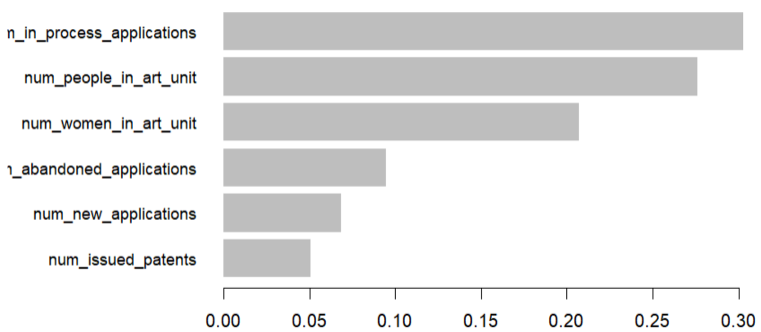

Female examiners had a higher number of other female examiners in their art units than males.

From the plots, we conclude that gender does not significantly influence attrition rates or the average number of new applications at the USPTO. However, a modest increase in abandoned applications among female examiners indicates potential differences in case outcomes by gender. The analysis also reveals that female examiners tend to be in Art Units with a higher presence of women.

**Modelling**

We used 2 XGBoost models to predict art unit movement and attrition. The purpose was to identify the features that most affect these decisions. We also used a causal model to see the effect gender has on attrition.

**Model 1:** We developed the first XGBoost model to forecast the probability of movement within Art Units and to predict if patent examiners would transition between units at the USPTO. To identify the most influential predictors, we conducted a feature importance analysis.



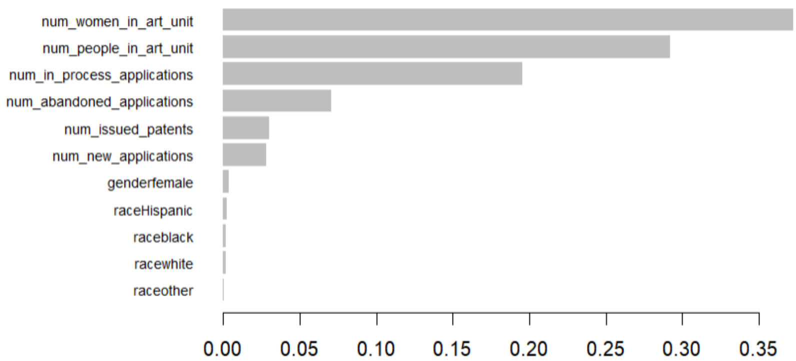

The analysis revealed that the quantity of applications currently in process (num_in_process_applications) is the primary factor influencing the likelihood of a unit change. Additionally, the total number of personnel within an Art Unit (num_people_in_art_unit) plays a significant role. In contrast, the presence of female examiners within an Art Unit (num_women_in_art_unit) holds lesser predictive value for movements, suggesting that the gender composition of a unit does not markedly impact Art Unit transitions.

**Modelling Results:**

The model has high recall, accuracy, and precision, showing it predicts well. This means it's good at identifying correct predictions, making few mistakes in classification, and rarely misidentifying negatives as positives, making it reliable for forecasting Art Unit movements at the USPTO.

```
          Reference
Prediction      0      1
         0 121063   6005
         1  47812  16001

               Accuracy : 0.7181
                 95% CI : (0.716, 0.7201)
    No Information Rate : 0.8847
    P-Value [Acc > NIR] : 1

                  Kappa : 0.2431

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.7169
            Specificity : 0.7271
         Pos Pred Value : 0.9527
         Neg Pred Value : 0.2507
             Prevalence : 0.8847
         Detection Rate : 0.6342
   Detection Prevalence : 0.6657
      Balanced Accuracy : 0.7220
```

**Model 2:** Our second XGboost model was trained to predict the examiner's attrition. The feature importance analysis showed the following results:

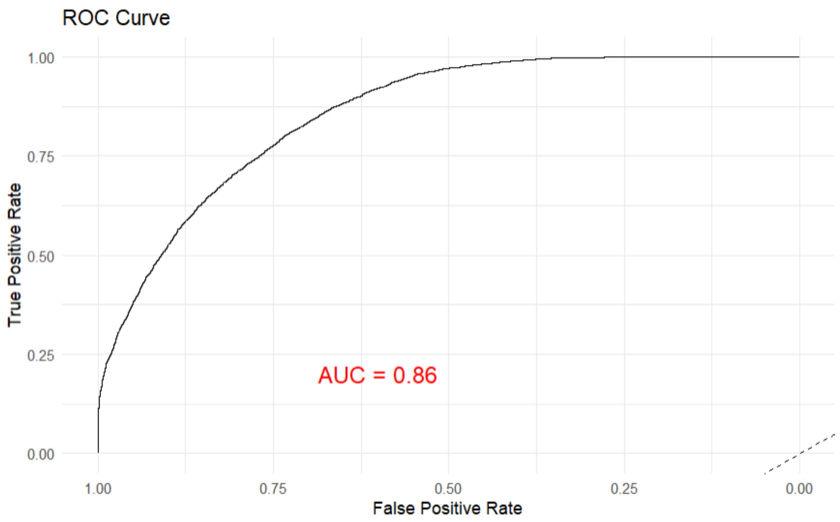



The most influential factors are the number of women and the total number of people in an art unit. This suggests that social dynamics and team size within an art unit might significantly influence examiner retention. The number of in-process and abandoned applications also affects attrition, hinting that workload and case outcomes could influence an examiner's decision to leave. Lesser importance is given to the number of new and issued applications and demographic factors like gender and race, indicating that these may have a relatively minor direct impact on attrition.

**Recall (0.8504956):** The model correctly identifies 85.05% of the true positive cases. This means that when an examiner's attrition is imminent, the model is quite effective at predicting it.

**Precision (0.2044477):** Of the cases where the model predicted attrition, only 20.44% were cases of attrition. This suggests that the model generates many false positives and is less reliable when it signals a potential attrition.

**Accuracy (0.7000955):** Overall, the model correctly predicts attrition (both true positives and true negatives) 70.01% of the time.




An AUC of 0.86 shows the model performs well. It means the model is effective at telling apart examiners who leave (positive class) from those who stay (negative class).

**Causal Forest Model:** The analysis conducted using a causal inference model sought to discern the average effect of gender, particularly female, on the probability of separation within the USPTO. The resulting Average Treatment Effect (ATE) was marginally negative, denoting that being female correlates with a slightly reduced likelihood of separation compared to their male counterparts.

**ATE (-0.001849595):** This minor negative ATE value suggests that being female does not play a significant role in an examiner's decision to leave the USPTO. The near-zero magnitude of the ATE implies that the differences in separation rates by gender are almost indistinguishable and likely do not warrant targeted gender-specific retention policies.

In conclusion, the comprehensive analysis of USPTO examiner attrition and the Art Unit movement suggests that organizational and social dynamics play a more pivotal role than gender in these phenomena. The data reveals only minor differences in attrition rates between male and female examiners, indicating that environmental factors such as the number of colleagues and the volume of ongoing applications play a more significant role in influencing attrition. While female examiners have a slightly lower propensity to leave, the effect is so minimal that it does not necessitate gender-specific interventions. Essentially, our analysis did not uncover instances of gender-based discrimination. The predictive models employed exhibit strong recall and accuracy, highlighting their utility in identifying at-risk examiners and potential areas for policy improvement. Overall, the USPTO might benefit more from focusing on workload management and team composition rather than gender-focused strategies to enhance examiner retention and reduce movement within Art Units.

## Part 2

During our research, we discovered a plethora of people analytics software available on the market. While some applications, such as HireRoad and Applied, are more geared toward finding the right talent, others are focused on promoting workplace equity and reducing pay gaps, namely, Syndio, Diversion and PayAnalytics. A standout application was Betterworks, an AI-powered people analytics application that combines both aspects of talent recruitment and promoting workplace equity. As the initial hypotheses in Part 1, social factors such as gender and ethnicity could play an important role in USPTO's examiner attrition, which significantly impacts the processing time of patent applications. Below are the ways that Betterworks can be used to address this issue.

Betterworks' analytics and AI capabilities would be applied to identifying areas of concern within the USPTO's workforce dynamics:

1. Diversity and Inclusion Dashboards: Betterworks offers granular breakdowns of examiner demographics, including promotions and attrition rates, shedding light on any disparities related to gender, race, age, or other protected characteristics. For instance, it can reveal discrepancies in promotional timelines based on gender.
2. Bias in Performance Reviews: Leveraging AI, Betterworks can analyze language patterns in performance reviews to detect subtle biases in the distribution of praise and criticism across demographic groups, unveiling systemic issues.

If examiners attrite, Bettrerworks' features would allow USPTO to understand what are the drivers of inequality and attrition:

1. Sentiment Analysis: The platform's AI gauges sentiment from employee surveys, providing insights into perceived fairness and identifying groups facing greater barriers to progress.
2. Exit Interview Insights: Betterworks categorizes anonymized exit interview data to identify patterns in reasons for leaving among different demographics, signalling disparities in workplace experiences.
3. Career Roadmap Mapping: Betterworks' Career Roadmap feature encompasses tracking internal career moves, which reveals stagnation in certain groups, such as women, who may be less likely to move across art units, thus hindering their promotion opportunities.

Furthermore, Betterworks facilitates action and progress measurement:

1. Goal-Setting and Calibration: USPTO can set specific equity targets, like improving women's or a minority group's representation in leadership, and individual managers can have goals tied to promoting equity in their teams.
2. Nudging and Interventions: AI-generated nudges can highlight potential unconscious bias during reviews or remind managers of diverse candidates for promotion opportunities, showcasing Generative AI's potential for promoting workplace equity
3. Tracking Effectiveness: Regular updates to equity dashboards within Betterworks enable the USPTO to monitor the success of initiatives in reducing gender pay gaps, increasing representation in leadership, and more.

As discussed in Part 1 later, workload and anxiety were considered more likely to cause examiner attrition than social factors. Below are the ways that Betterworks can be integrated into USPTO to address this issue.

1. Pulse Surveys and Sentiment Analysis: Regular, targeted surveys within Betterworks can track changes in employee stress levels and feelings of being overwhelmed. The AI's sentiment analysis helps uncover the most common pain points mentioned.
2. Work Distribution Insights: Betterworks can track workload distribution across individual examiners and teams. This reveals disparities or overburdening in specific technology areas or work units.
3. Feedback Channels: The platform allows examiners to give anonymous, structured feedback on workload pressures and specific anxieties they may face.
4. Performance Reviews Focused on Well-being: Betterworks facilitates conversations about output stress and burnout risks. Managers can be prompted to discuss workload balance during review cycles.
5. Targeted Development: If analysis reveals skills gaps contribute to work stress (e.g., examiners struggling with a new invention ), Betterworks can track and encourage participation in specific upskilling programs.
6. Wellness Initiatives: Participation in wellbeing programs offered by the USPTO can be tracked in Betterworks. This helps see if targeted resources impact work experience and, importantly, if those experiencing the highest stress access them.
7. Ongoing Monitoring: As the USPTO implements workload balancing policies or stress reduction initiatives, regular pulse surveys within Betterworks can gauge their effectiveness from the employee perspective.
8. Correlating Attrition: Tracking workload data and sentiment alongside attrition rates reveals whether improved balance significantly influences retention.
9. Peer Recognition: Stress often results from feeling invisible – use Betterworks to highlight successful teamwork, collaboration, and support in handling heavy workloads.
10. Knowledge Sharing: Encourage creating informal support communities within the platform to reduce the isolation of dealing with work-related stress.

Even though Betterworks offers powerful analytical solutions and AI capabilities, there remain some key considerations in implementing Betterworks, which include the following:

1. **Transparent Communication:** USPTO needs to communicate internally that data collection aims for progress, not individual scrutiny, and results will guide systemic improvements for a fairer workplace. Otherwise, examiners might resist change.
2. **Involving Examiners:** Engage diverse group representatives in discussions about results and solutions to ensure initiatives reflect real-world experiences and concerns.
3. Data Privacy: Assure employees that the data is anonymized and aggregated solely for workplace **equity improvements.**

Given all the advantages of an AI-powered people analytics solution like Betterworks, it's essential to acknowledge its limitations. The root causes need to be identified by combining the quantitative insights offered by AI solutions and traditional qualitative methods. While software identifies discrepancies, qualitative methods like interviews and focus groups remain necessary to uncover the reasons behind attrition. An AI-powered people analytics solution is not a panacea for solving equity/anxiety issues, which often stem from long-standing biases and culture at an institution like USPTO. This calls for sustained effort and broader USPTO leadership action, which includes hiring, process simplification, or technology enhancements that reduce bottlenecks. Overall, Betterworks offers valuable data-driven insights into USPTO workplace dynamics, aiding in the identification of disparities, progress tracking, and fostering a more equitable environment, thus potentially reducing attrition driven by lack of opportunity or unfairness and reducing the application backlog over time.

**Part 2 Bonus**

**Embedding Approach to addressing social factor-related bias in USPTO patent examination time and examiner attrition**

To recall the problems we try to prove and solve, here is a brief summarisation: Examiners' racial bias towards minority applicants leads to lower approval rates and longer examination times for applications from minority groups. On the other hand, examiners' demographic characteristics, particularly gender and race/ethnicity, may systematically influence their work dynamics, including mobility, promotion, and attrition, posing ethical challenges and legal risks for the agency, with attrition impacting patent examination time. Apart from the applications mentioned earlier, there can be an approach that combines the word embedding techniques, on which the Large Language Models rely, and the traditional statistical tests to monitor and solve the gender/ethnicity-related bias in patent examination time and examiner attrition.

First, prepare a dataset of successful and unsuccessful applications containing information on applicants' race, gender and application text. Get the vocabulary of the text data through tokenization, removing stop words, stemming, and lemmatization.

Utilize pre-trained word embeddings from OpenAI API or train a large language model to obtain the embedding layers on the text data to represent the semantic meaning of words and phrases in a high-dimensional vector space. The first option involves using Open AI's pre-trained model whose word embedding has been obtained. The second option uses a newly trained language model based on only the application text data. One may access packages of Cohere through the Langchain interface to customize a language model to obtain the embedding layer, which shall be different than the Open AI's embeddings.

Next, aggregate word embeddings to obtain document-level embeddings for patent applications and applicant language. This can be achieved through techniques such as padding and averaging or weighted averaging of word embeddings within each document.

Compute the similarity between pairs of documents using cosine similarity or other distance metrics in the embedding space among all applications. This would result in an n-by-n similarity matrix, with n being the number of applications, and each row or column has the race and success/failure state attached to it. Filter the column and row of the matrix by two criteria: race (minority or not) and success (approved or not). Get the similarity distribution by plotting the values from the filtered matrix in a histogram. One can visually inspect the distributions of the similarity scores to decide which statistical test to use. For example, suppose the distribution approximates a bell curve. In that case, one can conduct paired sample t-tests to see if the average of the similarity is significantly different between different combinations (i.e. Successful applications: Minority vs non-Minority, Minority vs Minority, non-Minority vs non-Minority. Rejected Applications: Minority vs non-Minority, Minority vs Minority, non-Minority vs non-Minority, Successful-Rejected Applications: Minority vs non-Minority, non-Minority vs Minority, Minority vs Minority, non-Minority vs non-Minority). If, say, the rejected minority group's similarity score is statistically different from that of a successful minority group, then the quality of the application text made a difference. If the rejected minority group's similarity score is not statistically different from that of the successful majority group, then the racial factor as the control variable suggests the likely presence of racial bias.

The reason for using a t-test is that all the data points are treated as samples from a historical time-series point of view, meaning that there would be more data in the past and the future. In this light, it would be beneficial to include a timestamp for each instance to conduct moving-window analysis and monitor bias existence in real-time.

To address the examiner attrition problem, we can use a similar embedding approach in which the text corpus needs to shift towards documents about or generated by individual examiners, such as performance review work emails (if USPTO allows using these to infer something about individual examiner's workload/style), other internal communication and feedback to patent applications. The documents would be labelled "pre-attrition" or "active," depending on whether the text was produced in a certain timeframe before the examiner left or within a period in which examiners were active. The same gender and ethnicity-related labels applied here as well.

For preprocessing and embedding, the same techniques of tokenization and padding are applied in this case, too. Pre-trained or customized embeddings on the text data may produce some differences. We'd calculate the similarity between individual examiner documents and filter the similarity matrix based on their gender, ethnicity and the "pre-attrition" or "active" label. The goal is to see if language patterns indicate someone is at risk of attrition. Therefore, instead of race/patent success, we'd filter the matrix rows/columns with gender, ethnicity, attrition (active vs. pre-attrition) and other social or organizational factors such as pay and years in an organization. Similar to the previous analysis, t-tests could reveal differences in mean similarity between different groups. However, this assumes certain distributions so that non-parametric tests might be safer given the exploratory nature. It might also be advisable to filter instances based on cross-demographics to see if intersectionality exists in examiner attrition. For example, women of colour may leave at higher rates and display different patterns in the text data.

To improve examination efficiency and reduce bias, one can integrate LLM into the patent examination workflow as a decision-support tool for examiners. A customized LLM model such as the one that Open AI provides can analyze the language used in patent applications and examiner decisions to provide real-time feedback and suggestions to examiners. To reduce racial bias, ensure that the LLM is trained on a diverse dataset that includes patent applications from various applicants, including minority groups. Since certain minority groups may be under-represented relative to the population, we can oversample these under-represented applications in the training data fed to LLM. By exposing the model to a diverse set of linguistic patterns and contexts, it can develop a more nuanced understanding of language and reduce the risk of perpetuating biases. Using techniques such as retrieval-augmented generation can reduce the risk of LLM hallucinations or produce biased output that impairs workplace inclusiveness. Similarly, LLMs can be deployed to promote workplace equity at USPTO. Performance review may be conducted about an LLM output based on real-time performance KPI data, reducing the risk of human bias.

## References

1. Betterworks. (2023, September 21). Resources library. https://www.betterworks.com/resources-library/