Capstone Design and Analysis
Fall 2024
Project Report - Microsoft Team 2

Ryan Stofer
Naveen Kumar Rajesh
Harold Yat Hin Ng
Kabir Snell
Steven Yang
Harry Kim

Sponsors
Ana Baratz - anabaratz@microsoft.com
Dalton Young - dyoung@microsoft.com
Onyi Okafor - onyi.okafor@microsoft.com
Phil Johnson - phil.johnson@microsoft.com

Instructors: Faisal Nawab, Brian G Vegetabile
December 11, 2024

Executive Summary:

Objective and Scope:

- The project aimed to evaluate the return on investment (ROI) of Microsoft's transition to a single-source knowledge base (SSKB) for internal customer support content.
- Initially focused on financial ROI, the scope evolved to assess operational efficiency and customer satisfaction.

Key Challenges:

- Dataset limitations, such as skewed distributions and aggregated metrics, required methodological adaptations.

Approach and Methodology:

- Metrics such as investigation time, investigation clicks, engagement time, and engagement rate were used as proxies for evaluating operational efficiency.
- Statistical models, including Generalized Linear Models (GLM), analyzed pre- and post-SSKB performance across ~60,000 support cases.
- Customer satisfaction trends were also evaluated through exploratory data analysis of aggregated metrics.

Findings:

- Efficiency Improvements:
  - Investigation time decreased by 12% post-SSKB implementation.
  - Investigation clicks reduced by 65%, indicating streamlined access to information.
- Engagement Metrics:
  - Declines in engagement rates, ~20%, and slight drops in average engagement time suggest areas for content quality improvement.
- Customer Satisfaction:
  - Increased or stable customer satisfaction scores post-SSKB transition, despite marginal variations in dissatisfaction rates across organizations.

Key Takeaways:

- The SSKB significantly reduced operational inefficiencies, particularly in investigation times and clicks.
- While customer satisfaction trends are promising, engagement metrics highlight opportunities for further refinement of the knowledge base.
- The several limitations of our project and data underscore the need for noting modeling assumptions.

Future Recommendations:

- Expand the dataset to include more data and granular metrics for deeper statistical analyses.
- Perform A/B testing on knowledge bases not ingested into the SSKB.
- Obtain financial data capable of translating our work into a dollar amount for stakeholders

Overview and Project Goals:

Understanding the value generated by internal resources is essential for making strategic decisions, especially when direct profits are difficult to measure. Without this insight, it becomes challenging to assess the performance of a customer support business—a problem at the core of our project.

Initially, our goal was to develop a methodology for calculating return on investment (ROI) for Microsoft's internal customer support knowledge base assets, focusing on the traditional concept of ROI as a financial value relative to cost. However, after discussions with our project sponsors, industry research, and a deeper analysis of our data, we expanded our approach to adopt a broader view of ROI.

Rather than focusing solely on financial returns, we shifted our attention to Microsoft's transition to a single-source knowledge base (SSKB) for its customer support teams. Our objective is now to evaluate the impact of this transition by analyzing key metrics related to customer support performance. Specifically, we aim to measure changes in metrics across case samples, articles, and ratings data, validating their statistical significance in terms of time savings. This report outlines our analysis, modeling, and findings on the effectiveness of the SSKB integration.

Background Information:

Internal support content encompasses documentation, resources, and knowledge assets developed for Microsoft support engineers, advocates, and other customer-facing roles. Unlike external support content designed for customer self-service, internal content is tailored to help teams efficiently resolve customer cases. This content typically includes troubleshooting guides, technical manuals, procedural documentation, FAQs, and training materials. Its primary goal is to enhance support staff productivity by providing accurate, accessible, and actionable information for resolving a wide range of issues effectively.

The success of internal support content is measured through key performance indicators (KPIs) such as case resolution time, content utilization, and satisfaction metrics. Examples of such KPIs include the percentage of cases resolved within 24 hours, average time to close a case, and customer satisfaction/dissatisfaction scores (CSAT and DSAT respectively). Furthermore, metrics like article visits, engaged visits, and helpful resolution rates gauge content effectiveness, while reductions in handling time quantify its impact on operational efficiency.

At Microsoft, internal support content is a cornerstone of case resolution, enabling support engineers and advocates to diagnose issues, collaborate, document solutions, and stay updated on product changes. Knowledge bases like Evergreen, SMC, and SXC store this content, ensuring it is indexed and easily retrievable. These systems play a critical role in providing support staff with the information needed for timely and effective customer interactions.

However, managing internal support content presents challenges. Its volume and complexity make updates and maintenance resource-intensive. Also, not all content is equally helpful or up-to-date, causing inefficiencies, and quantifying the ROI of internal content remains difficult. Up until the first quarter of the fiscal 2023-2024 year, Microsoft support teams faced challenges due to reliance on multiple, disconnected knowledge systems. This fragmented approach created inefficiencies, as case agents often had to consult several platforms to resolve complex issues.

To address these challenges, Microsoft implemented the SSKB to consolidate its internal support content into a unified platform. This initiative aims to improve consistency, eliminate redundant content, and enhance accessibility for support staff. By streamlining content creation and maintenance, the SSKB aimed to reduce overhead while ensuring teams can quickly find the information they need.

Key systems like Evergreen and SMC played pivotal roles in this transition. For instance, Evergreen, restricted to support personnel, includes a variety of support articles including Policy, Technical, and Non-Technical articles, with associated KPI metrics such as article visits and helpfulness surveys to measure its impact. Together, these knowledge bases were integrated into the SSKB to improve accessibility and consistency in handling customer cases.

However, the transition to the SSKB is still on-going. To preface, Microsoft's global support team, organized into five groups (Orgs 1-5), serves distinct customer segments, including Premier, Partner, Consumer, and Government (*Explanatory Figure 1*). These groups had a varying adoption rate for the SSKB (as of September 2024): Orgs 1, 3, and 4 achieved 70–90% adoption, while Orgs 2 and 5 lagged at 30–40%, reflecting differences in operational environments and resistance to change.

While Microsoft has not observed direct financial returns since the integration as of late, they have anecdotally noted improvements in case resolution efficiency. This suggests promising benefits but highlights the need for a more rigorous analysis.

To provide stakeholders with evidence of the SSKB's impact, Microsoft seeks a statistical evaluation of its effectiveness. Such an analysis would not only validate anecdotal observations but also identify the KPIs most influenced by the transition. This information will be critical for demonstrating the value of the SSKB and guiding future optimization efforts as they finalize their centralization of their entire knowledge base infrastructure.

Our Approach and Methodology:

The datasets' limitations were central to shaping our methodology. Inconsistent financial data, aggregated metrics, and a lack of behavioral granularity—such as detailed agent-level usage logs—restricted deeper insights. While we had access to financial data for organizations using Microsoft support services, our sponsor's advice on the irrelevance of monetary savings due to similar costs made it impractical to calculate a meaningful ROI within our time constraints. Additionally, many numerical features, such as engagement and investigation metrics, exhibited skewed and non-normal distributions, complicating the use of standard statistical models. These limitations necessitated a shift in focus from calculating direct ROI to evaluating the effectiveness of the transition to a single-source knowledge base through proxy metrics like operational efficiency and customer satisfaction.

Recognizing these constraints, we redefined "return" to focus on KPIs typically used for ROI calculation and applied this framework to analyze Microsoft's transition from pre-SSKB to post-SSKB. Furthermore, we assume that all organizations had a 100% adoption rate which allows us to focus on evaluating the impact of the SSKB transition without the confounding influence of uneven implementation, providing a clearer assessment of its potential effectiveness.

Overall, this shift in focus guided the development of our methodologies, ensuring alignment with the available data. To this end, we employed statistical methods to test various models and identify which variables in our customer support datasets are most significant in contributing to our ROI. The following sections outline the specific approaches used to pinpoint the most significant contributors to efficiency within the three datasets we were provided—customer support case dataset, Evergreen knowledge base data, and customer satisfaction data.

The first dataset that we investigated was the customer support case dataset. This dataset contains metrics for time (minutes), and number of clicks spent on each phase of the support case process (*Explanatory Figure 2*). Metrics in this dataset include but are not limited to: case opening time, case opening clicks, initial review time, initial review clicks, investigation time, investigation clicks, communication time, communication clicks, etc. This dataset contains 30,000 observations for each tooling phase period (pre-SSKB and post-SSKB) for a total of 60,000 support case records.

Through our domain research, conversations with our company sponsor, and preliminary EDA on this dataset, we determined that: investigation time and investigation clicks most accurately reflect the usability and accessibility of knowledge systems since they are strongly correlated with total case time ($r = .74$) and total case clicks ($r = .92$) (*EDA Figure 1*). Reductions in these metrics suggest improvements in workflow efficiency, with shorter resolution times enabling faster problem-solving and fewer clicks indicating streamlined access to relevant information.

Investigation time, defined as the duration spent by support agents analyzing, understanding, and resolving customer issues, is the largest contributor to total case resolution time. Its purpose is to enable agents to thoroughly diagnose the customer's problem, identify potential solutions, and prepare the necessary steps for resolution. Investigation typically occurs in between the initial and middle phases of case handling, where agents focus on gathering information, consulting relevant resources, and applying their expertise to address the issue. From a domain knowledge perspective, investigation time is expected to be the largest contributing factor to total case time since it often involves the most complex and cognitively demanding aspects of resolution, such as problem-solving, information retrieval, and decision-making. Moreover, this is the only phase of the case resolution process where agents directly use internal support articles, making it a critical focus for understanding knowledge base utilization.

Similarly, *investigation clicks*, defined as the number of interactions or clicks required by agents to retrieve relevant information from the internal knowledge base, were chosen as a complementary metric. Investigation clicks provide a quantitative measure of the effort needed to locate and access support articles during the investigation phase. By analyzing these clicks, we can evaluate the efficiency of the knowledge base system and its role in reducing cognitive load and operational effort for agents. Together, investigation time and clicks provide valuable insights into the effectiveness of the single-source knowledge base and its impact on case resolution efficiency.

To analyze investigation time and clicks, we fit a Generalized Linear Model (GLM) with a log link function to assess the impact of tooling phases and organizational differences. We chose a GLM model as both investigation time and clicks exhibited a non-normal distribution (*EDA Figure 2*). Furthermore, EDA revealed that the decreases in investigation time and clicks varied significantly across organizations (*EDA Figure 3*). For instance, Organization 3 exhibited the most substantial reduction in investigation time, whereas other organizations saw smaller, but still notable, improvements. Similarly, investigation clicks decreased more dramatically for some organizations than others, highlighting disparities in efficiency gains. These findings motivated the inclusion of organizational differences as a predictor in the model.

Moving away from the case dataset, we examined the Evergreen article data to analyze the effect of the SSKB transition on article-related metrics. Building on the findings of SSKB's impact on investigation time and clicks, we focused on understanding how the transition influenced article engagement metrics, particularly article efficiency and content discoverability.

Our main motivation to investigate engagement metrics stems from the fact that after doing some EDA histograms on these metrics across the different transition phases, we noticed significant decreases across the different article applicability types (*EDA Figure 4*). Also note that some articles applied to multiple groups such as Org 1, Org 2, and Org 5, and some in fact were even universal.

To assess article efficiency, we analyzed the *average engagement time* variable, which measures the average time (in seconds) an agent spends in an engaged visit to an article. In order for an article to be considered to have engagement, Microsoft has defined their engagement threshold to be the following: 15 seconds of dwell time with at least one interaction (e.g., scrolling or clicking within the article). This metric is crucial for identifying cases where agents are meaningfully engaging with the internal customer support articles. Due to the non-normality of our average engagement time metric (*EDA Figure 5*), we decided to fit a random forest model to understand how high of an importance, if any, the transitional period had on predicting engagement time.

For content discoverability, we focused on the *engagement rate* variable, calculated as the ratio of an article's engaged visits to its total article visits. This evaluates the discoverability of articles in providing insight into how often the articles were useful to agents in solving customer support cases. Note that based on our approach of calculating engagement rate, we assume that any engaged visit indicates the knowledge base successfully matched the agent with the article required to solve their case. To explore these metrics further, we performed EDA to examine their trends and distributions across transitional periods. Since we noticed that the engagement rate had a roughly normal distribution after fitting an inverse log (exponential) function (*EDA Figure 6*), we decided to fit a linear regression model with an exponential function and utilized bidirectional stepwise selection to find the most relevant variables for predicting engagement rate.

The last dataset we analyzed focused on customer satisfaction data aggregated monthly across all five organizations, covering the period from July 2023 to October 2024. This dataset provided key indicators related to customer satisfaction and, by implication, case resolution efficiency. Variables included the percentage of cases resolved within 24 hours, the average number of days to close a case, the average customer satisfaction rating (CSAT 5-Star Average), and the percentage of dissatisfied customers (DSAT %). While these metrics are essential for evaluating customer satisfaction and the effectiveness of the support process, the aggregated nature of the data limited our ability to conduct detailed statistical modeling due to a lack of individual-level variance. Instead, we focused on exploratory data analysis to identify trends and patterns.

Validation/Evaluation/Results/Demos:

The results of the gamma regression model for investigation time indicate significant effects of both the tooling phase and organization on investigation time (in minutes). The coefficient for the post-transition tooling phase is -0.042 ($p < 0.001$), representing an approximate 4.14% decrease in investigation time from the pre-transition baseline. These results suggest that transitioning to the SSKB resulted in a meaningful improvement in efficiency by reducing the time required for support agents to investigate internal content. The model also includes organizations as a predictor, which accounts for differences between organizations relative to the baseline of Org 1. While all organizations were significantly different when compared to the baseline Org 2 ($p > .05$) did not. This may be due to the fact that both Org 1 and Org 2 service the same customer base (*Explanatory Figure 1*). Overall, the model explains a substantial portion of the variance in investigation time, as evidenced by the reduction in deviance. Specifically, the null deviance of 25,782 decreases to a residual deviance of 13,722, reflecting a 46.8% reduction in deviance.

$$log(Investigation.Time.Mins) = \beta_0 + (\beta_1 * Tooling.Phase) + (\beta_2 * Org.Name)$$

Coefficient	Estimate	Std. Error	Pr(>|t|)
Intercept	5.383	0.007	$< 2e^{-16}$
Org 2	-0.020	0.011	0.0577
Org 3	-0.522	0.010	$< 2e^{-16}$
Org 4	-1.379	0.010	$< 2e^{-16}$
Org 5	-0.055	0.013	$3.40e^{-5}$
Post-Transition	-0.042	0.006	$3.67e^{-12}$

Figure 1: Results Table of GLM log-link model on Investigation Time

The results of the gamma regression model for investigation clicks also indicate a significant impact of the tooling phase on the number of clicks performed during the investigation process. The coefficient for the post-transition tooling phase is -1.057 ($p < 0.001$), which corresponds to a 65.16% decrease in investigation clicks from the pre-transition baseline. This substantial reduction highlights the effectiveness of the SSKB transition in streamlining access to relevant internal content, reducing the number of clicks required by support agents during investigations. Much like the results for investigation time, Org 2 displayed no significant change compared to the baseline, but interestingly Org 5 also displayed strong statistical evidence that it had so significant differences in investigation clicks compared to Org 1. Overall this model explains a significant portion of the variance in investigation clicks, as evidenced by a 47% reduction in deviance from the null deviance to the residual deviance. These findings demonstrate that the SSKB transition meaningfully reduces investigation clicks, validating its role in improving customer support efficiency.

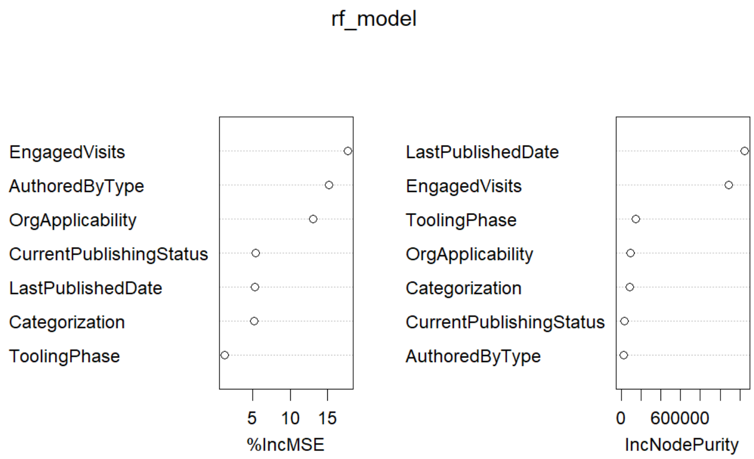
$$log(Investigation.Clicks) = \beta_0 + (\beta_1 * Tooling.Phase) + (\beta_2 * Org.Name)$$

Coefficient	Estimate	Std. Error	Pr(>|t|)
Intercept	5.383	0.007	< $2e^{-16}$
Org 2	-0.020	0.011	0.0577
Org 3	-0.522	0.010	< $2e^{-16}$
Org 4	-1.379	0.010	< $2e^{-16}$
Org 5	-0.055	0.013	$3.40e^{-5}$
Post-Transition	-0.042	0.006	$3.67e^{-12}$

Figure 2: Results Table of GLM log-link model on Investigation Clicks

The residual diagnostics for both the investigation time and investigation clicks models indicate that the gamma regression models are reasonably good fits for the data (*Validation Figure 1 and Validation Figure 2*). In both cases, the residual histogram shows that the residuals primarily follow a normal distribution, with only a slight positive skew, which is expected given the positively skewed nature of the response variable. Similarly, the normal Q-Q plots reveal that the residuals closely align with a normal distribution, with some deviations observed at the tails. These deviations suggest that while the model captures the central tendency and variability of the data well, it may struggle to fully account for extreme values. One possible explanation for this could be the lack of agent level data. Individual customer support agent experience could influence investigation times and clicks. This represents a potential area for future model improvement. However, the overall adherence of the residuals to a normal distribution supports the appropriateness of the gamma regression models with a log link function, affirming their utility in evaluating the impact of the tooling phase on investigation time.

For our Evergreen dataset, our random forest model showed that the tooling phase was not as large of a predictor of average engaged time as expected. Engaged visits had the most weight for predicting engagement time, with the highest increased mean square error of 152.89 and node purity of 1,089,938.07. This shows us that in the random forest model, changes in the engaged visits have a much higher chance of changing the predicted engagement time, and that changes in engaged visits have a larger magnitude of change on the engagement time. Other variables that had a large effect on engagement were the types of authors and the article's organization applicability. However, since the R^2 value of our model was relatively poor (0.12), we believe that further improvements can be made if given more data to build a more efficient and effective model.



	%IncMSE	IncNodePurity
OrgApplicability	53.959824	89324.82
CurrentPublishingStatus	6.049904	29518.55
Categorization	31.325851	85051.11
AuthoredByType	48.012138	27646.18
LastPublishedDate	44.339629	1249139.76
EngagedVisits	152.893673	1089938.07
ToolingPhase	6.461936	149359.71

Figure 3 & 4: Variable Importance Feature Plot for Random Forest model on Average Engagement Time and associated numerical metrics

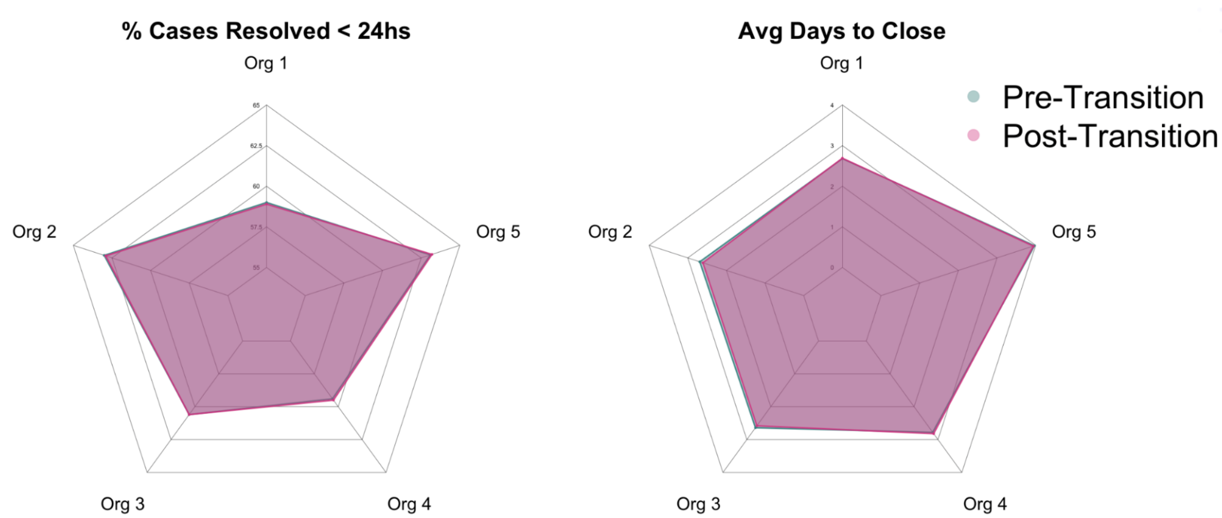
Examining the significance of each of the variables in the linear regression model for engagement rate, the transitional period variable had the lowest p-value (< 2e-16) and an extreme t-score of -34.924, suggesting that the transitional period was a highly influential factor in predicting engagement rate. Furthermore, the transitional period variable had a negative coefficient suggesting that the model predicts article engagement to decrease, on average, by 20% following the transition period. Notably, all other variables in the model, including organization applicability and categorization, impacted the engagement rate negatively. These results highlight the significant negative influence of the transitional period on the engagement rate and the positive influence of the last published date on the article engagement rate. However, it is important to note that, while the model had a low p-value and R-squared value, the variables are statistically significant in predicting engagement rate. Nonetheless, the linear regression model only accounts for 12.7 variance in the engagement rate, suggesting other influencers of engagement rate outside the model.

```
Coefficients:
                                                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)                                      1.180e+00  1.290e-01   9.149  < 2e-16 ***
OrgApplicabilityOrg3                            -3.165e-02  1.788e-02  -1.770  0.07674 .  
OrgApplicabilityOrg4                            -5.792e-02  2.030e-02  -2.853  0.00434 ** 
OrgApplicabilityUniversal                       -1.704e-02  1.177e-02  -1.447  0.14780    
CategorizationNontechnical                      -1.038e-01  4.584e-02  -2.264  0.02358 *  
CategorizationNontechnical||MS internal operations -1.676e-01  2.151e-01  -0.779  0.43607    
CategorizationPPP                               -9.596e-02  4.718e-02  -2.034  0.04199 *  
CategorizationTechnical                         -5.294e-02  4.704e-02  -1.125  0.26041    
CategorizationUnclassified                      -1.401e-02  4.619e-02  -0.303  0.76164    
LastPublishedDate                                4.683e-05  6.197e-06   7.557 4.51e-14 ***
PeriodPost_Transition                           -2.141e-01  6.130e-03 -34.924  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2974 on 9414 degrees of freedom
Multiple R-squared:  0.1277,	Adjusted R-squared:  0.1268 
F-statistic: 137.8 on 10 and 9414 DF,  p-value: < 2.2e-16
```

Figure 5: Results Table of linear regression model with exponential transformation on Engagement Rate

The analysis of the aggregated monthly performance metrics across the five organizations, using radar charts to compare pre-SSKB with post-SSKB, revealed several key trends. The percentage of cases resolved within 24 hours and the average number of days to close a case remained relatively unchanged across the tooling phase. This finding contradicts the results observed in the investigation time analysis, although it is important to note that only using “days” as a time metric may not be precise enough to capture subtle, yet significant improvements in efficiency. In terms of customer satisfaction, all organizations experienced up to a 0.5% increase in their CSAT 5-star average, suggesting that the SSKB transition may have contributed to a better customer experience, but more analysis is needed to be done to check significance. However, when examining dissatisfaction, Organizations 1 and 2 showed a significant decrease in their DSAT percentages (1.5% and 6% respectively), while 3, 4, and 5 experienced marginal increases. These variations highlight the potential for further investigation to determine whether these changes are statistically significant and whether they are driven by factors beyond the SSKB transition.



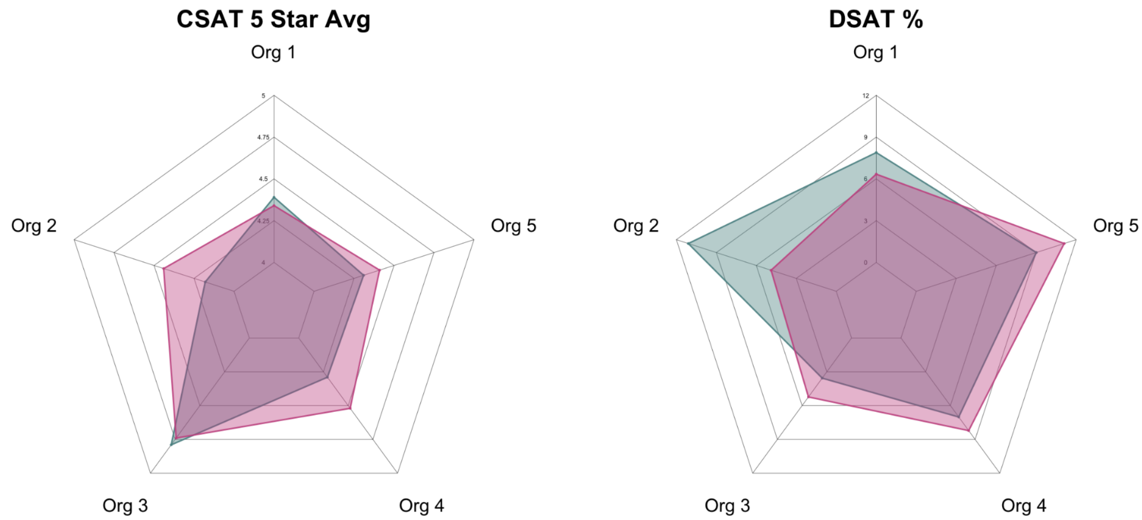


Figure 6: Radar Plots for Customer Satisfaction metrics

<u>Conclusion/Next Steps:</u>

Our project assessed the impact of Microsoft's investment into their SSKB for their internal support content by analyzing key metrics across case sample, article, and rating datasets before and after the transition period. Our primary objective was to determine whether the transition into an SSKB significantly influenced metrics such as case investigation time, clicks, article engagement duration, and engagement rates. By analyzing the changes in the key metrics and fitting various statistical models, we evaluated whether the transition was a significant factor in predicting these changes, highlighting its influence on case resolution efficiency.

Our analysis highlighted an overall decrease across all key metrics, including case investigation time and clicks, and article engagement time and engagement rate after the transition into an SSKB. While the transitional period was statistically significant in predicting case investigation time, clicks, and article engagement rate, it did not show significance in predicting article engagement time in our models. These findings suggest while the transition into an SSKB had a notable impact on certain KPI variables, its effect on article engagement time requires further investigation given the importance of engagement time in determining article engaged visits.

While our models and analysis gave valuable insights into the impact of Microsoft's transition to an SSKB, several limitations influenced the results. At the project level, the lack of consistent financial data prevented us from conducting a cost-benefit analysis of the transition and ultimately ROI calculation. Additionally, because the data was aggregated, we were unable to get behavioral insights at an agent level, such as the difference in case resolution efficiency based on experience and training time. For the analysis and modeling, limitations included the non-normal distribution of the data and the presence of irrelevant or inaccurate features, both of which affected model performance. Alleviating these limitations in future work could lead to more comprehensive and accurate evaluations of the impact of SSKB.

In addition to addressing the assumptions made in our current analysis, several areas for future work could significantly expand and refine our evaluation of the SSKB. One major limitation in our analysis stemmed from the aggregated nature of the customer satisfaction data, which restricted the depth of our insights. By shifting to case-level customer satisfaction data, we could conduct a more detailed examination, identifying specific factors that influence satisfaction and uncovering patterns not visible in generalized metrics. This would allow us to provide more meaningful and actionable insights into how the SSKB affects customer experiences.

Another promising avenue involves incorporating agent-specific data. In our current analysis, we implicitly assumed uniformity among agents handling support cases, despite the clear variability in expertise, training, and tenure across individuals. Access to agent-level data would enable us to analyze how these factors influence case resolution efficiency and which groups of agents were most impacted by the transition to the SSKB. This would provide valuable context for tailoring future training programs and optimizing agent performance.

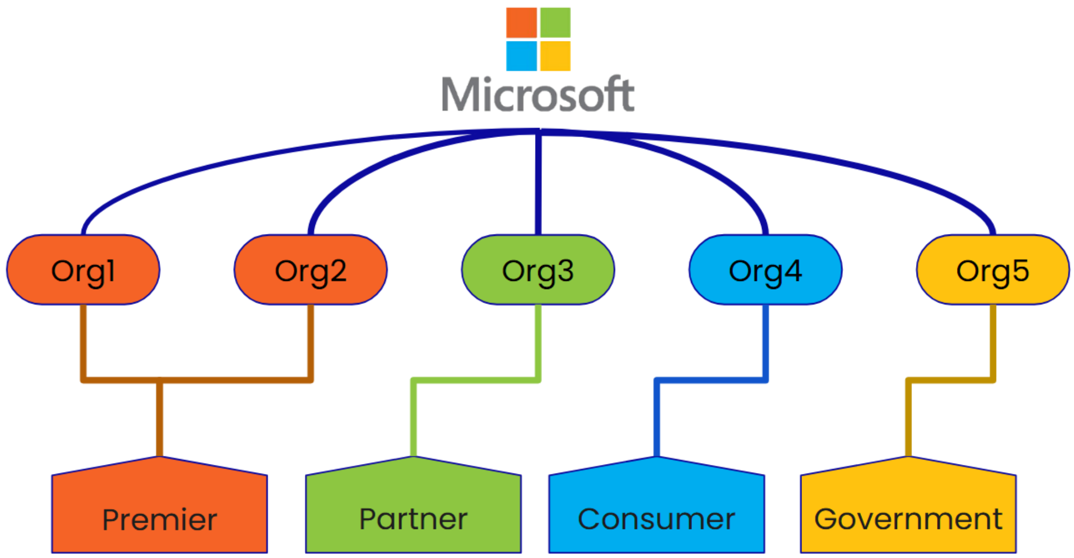
The scale and scope of the dataset used in our analysis also present an opportunity for improvement. Although we worked with limited features and a relatively small dataset, Microsoft processes millions of cases monthly across its organizations. Expanding the dataset to include a larger sample size and additional features would allow us to train more complex machine learning models and conduct deeper analyses. While our current models, such as GLM and random forest, were intentionally simple and interpretable, a larger and richer dataset could support more advanced techniques for uncovering nuanced patterns in the data.

Additionally, our analysis highlighted that not all knowledge bases were ingested into the SSKB. A future direction could involve conducting A/B testing with knowledge bases that were and were not integrated. This approach would allow us to directly compare KPIs between the varying KBs and better isolate the effects of the SSKB on article metrics. A/B testing is a standard practice in the industry for evaluating changes and applying it here would enhance the robustness of our findings.

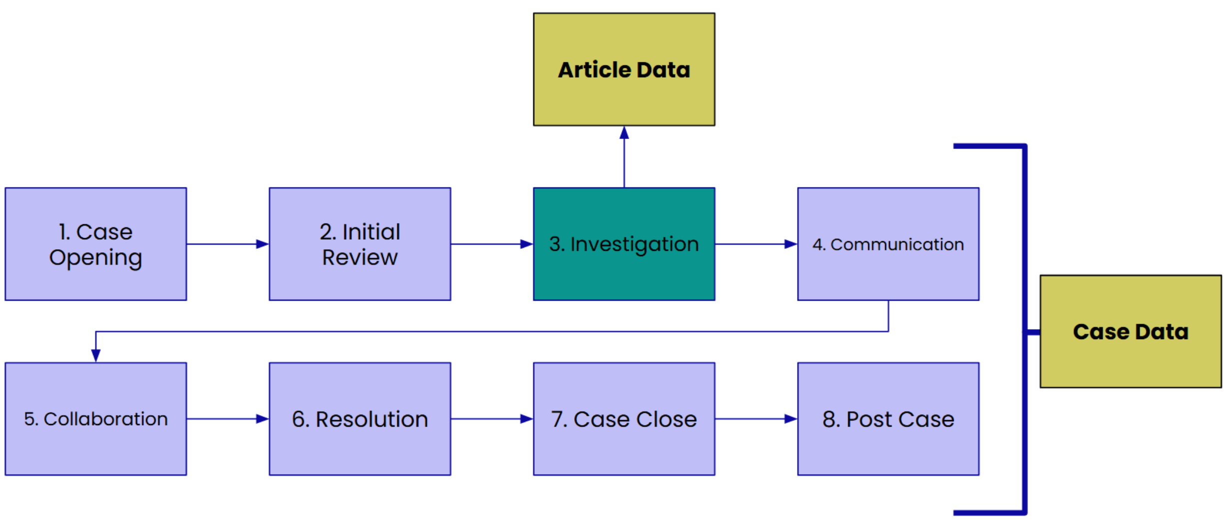
Finally, while our analysis focused on operational metrics, it is crucial to consider the financial implications of the SSKB transition. Investors and stakeholders are particularly interested in understanding the monetary gains associated with such initiatives. If financial data were available, we could translate our findings into concrete dollar amounts, such as quantifying the impact of reduced article handling times or faster case resolutions in terms of cost savings. This would allow us to communicate the value of the SSKB integration more effectively, aligning our analysis with the priorities of decision-makers and helping to optimize future investments in Microsoft's support infrastructure. By pursuing these future directions, we can build on our current work to provide a more comprehensive evaluation of the SSKB and its broader implications for Microsoft's customer support strategy.

A2. Explanatory Figures

Explanatory Figure 1: Org. Hierarchy of Microsoft Customer Support and customer base

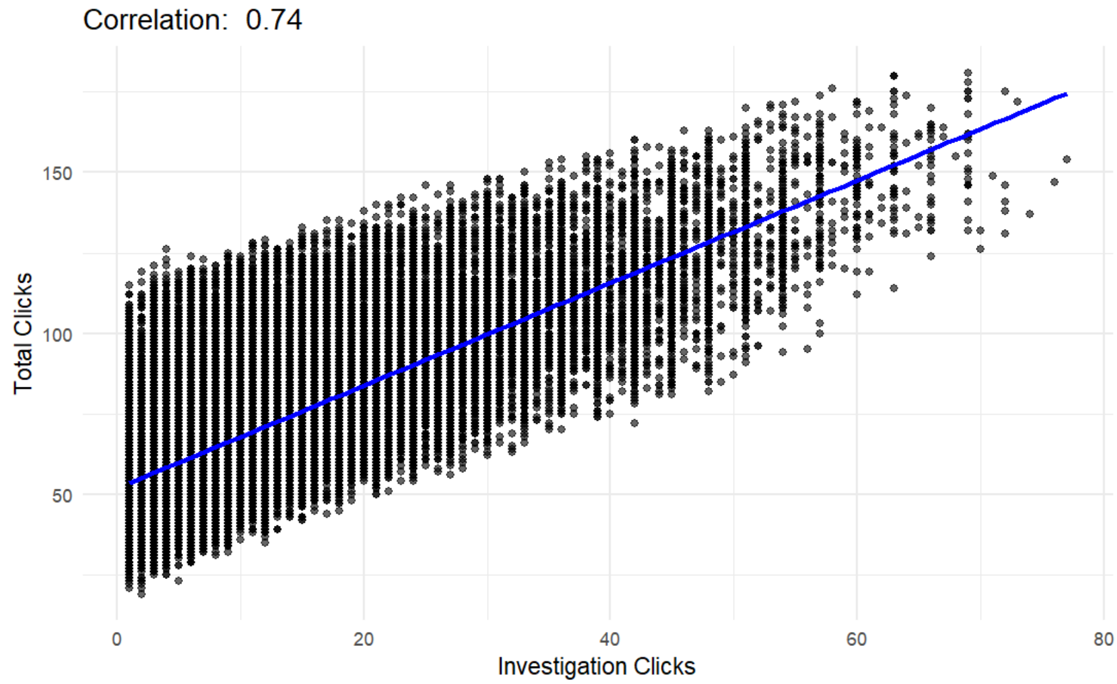


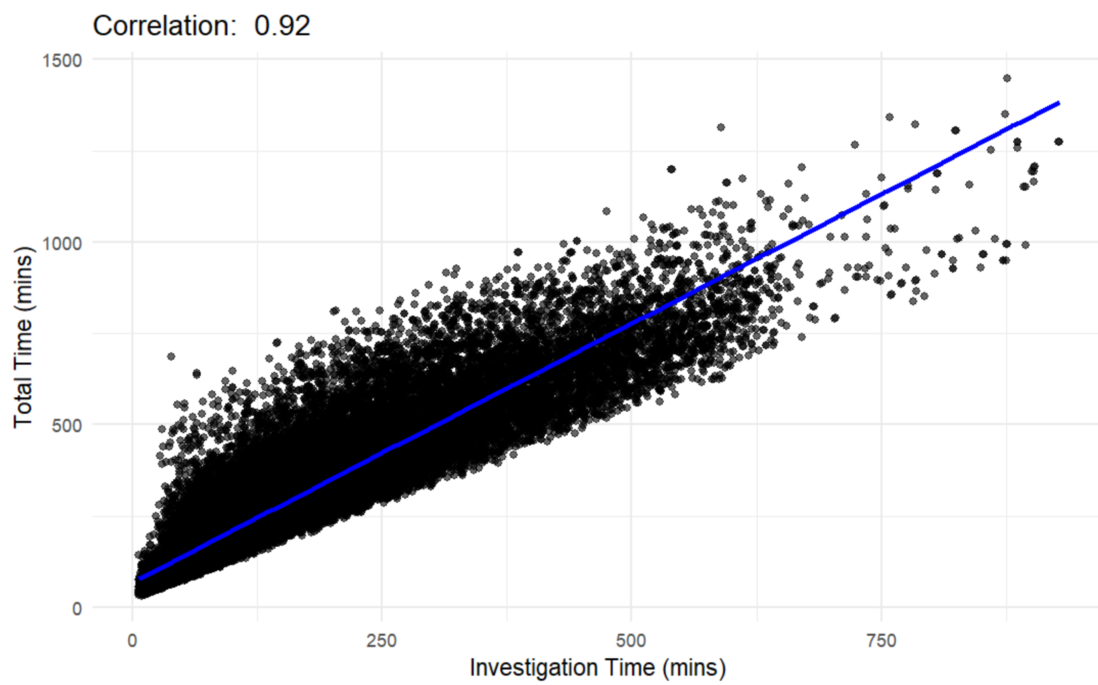
Explanatory Figure 2: Support Case Process Timeline and connection to datasets used



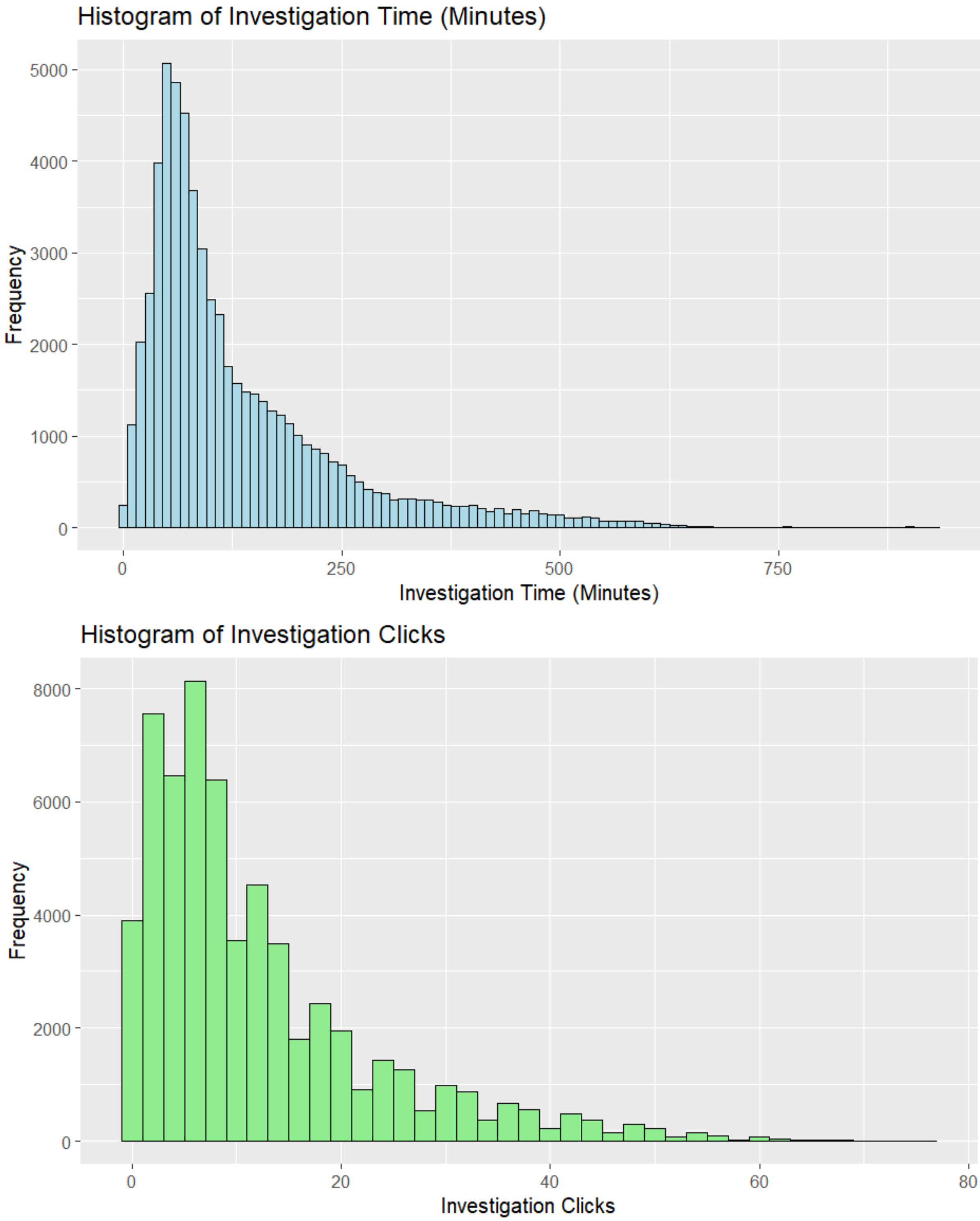
B. Exploratory Data Analysis

EDA Figure 1: Correlation plots between Investigation Clicks/Time vs Total Clicks/Time

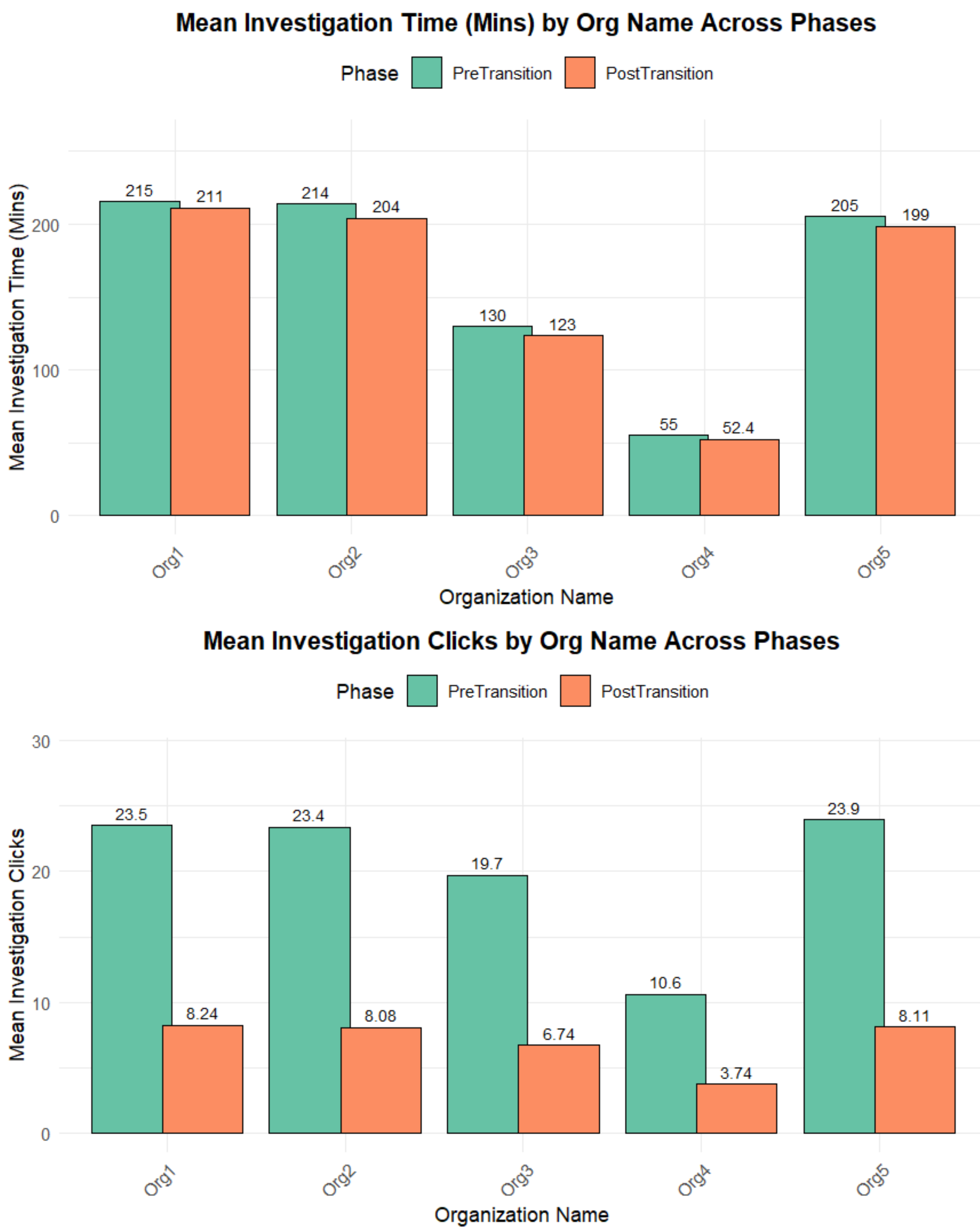




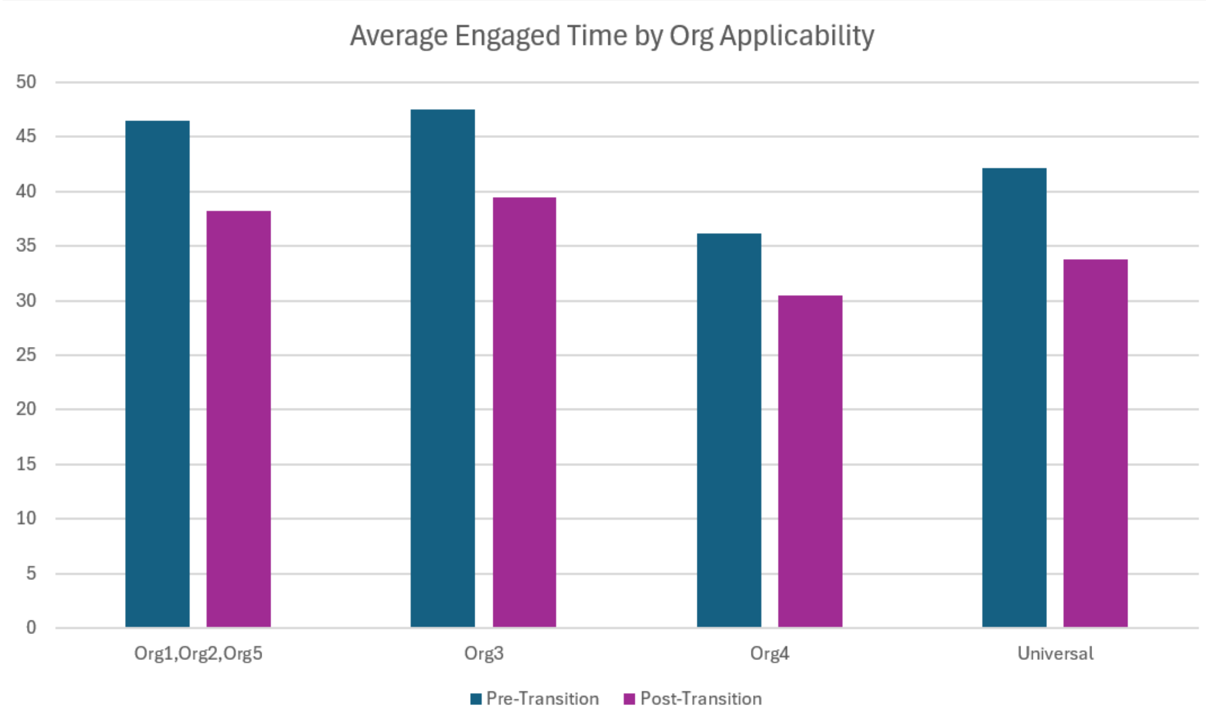
EDA Figure 2: Histogram of Investigation Time in minutes and Investigation Clicks

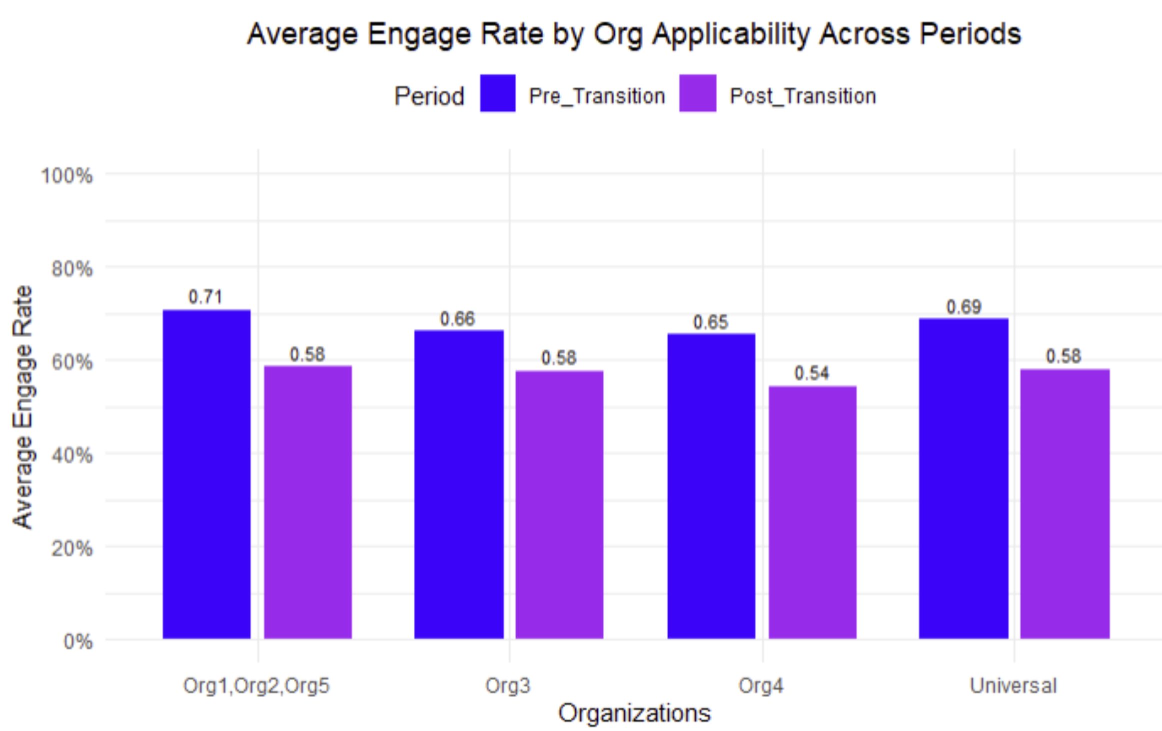


EDA Figure 3: Mean Investigation Time and Investigation Clicks by Orgs. across tooling phases

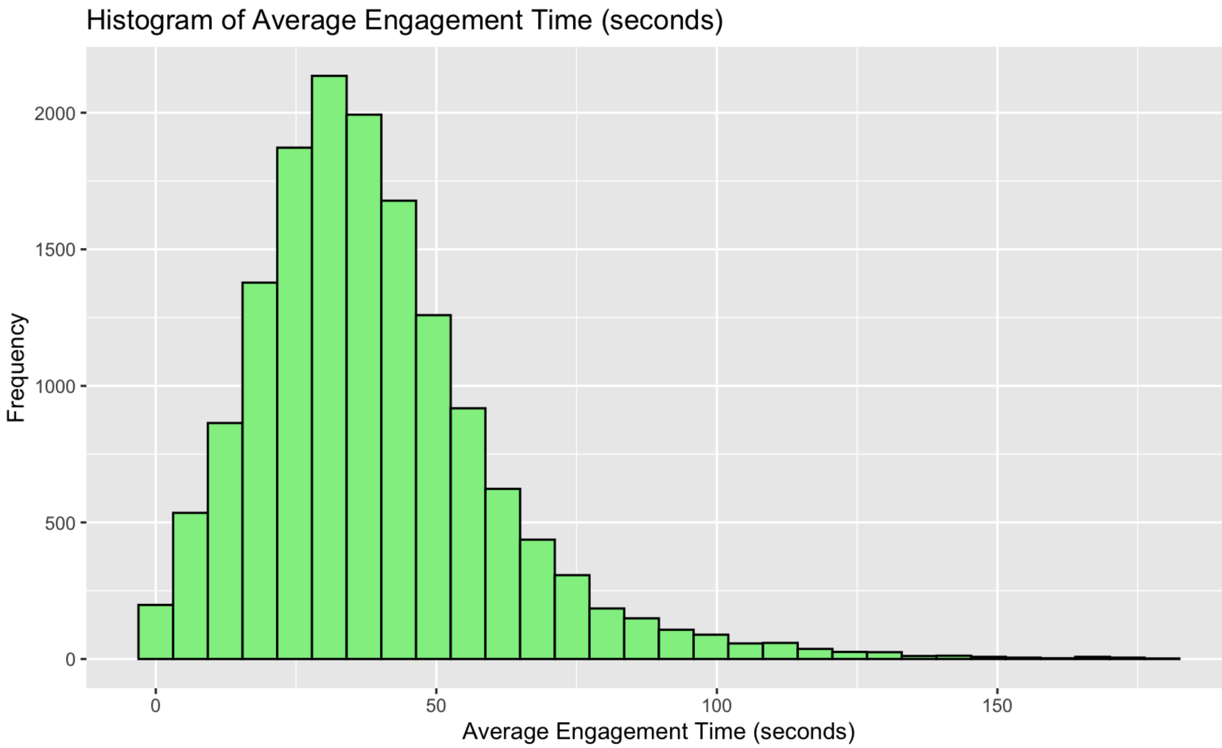


EDA Figure 4: Histograms of Average Engaged Time and Engagement Rate of Evergreen Articles across Tooling Phases

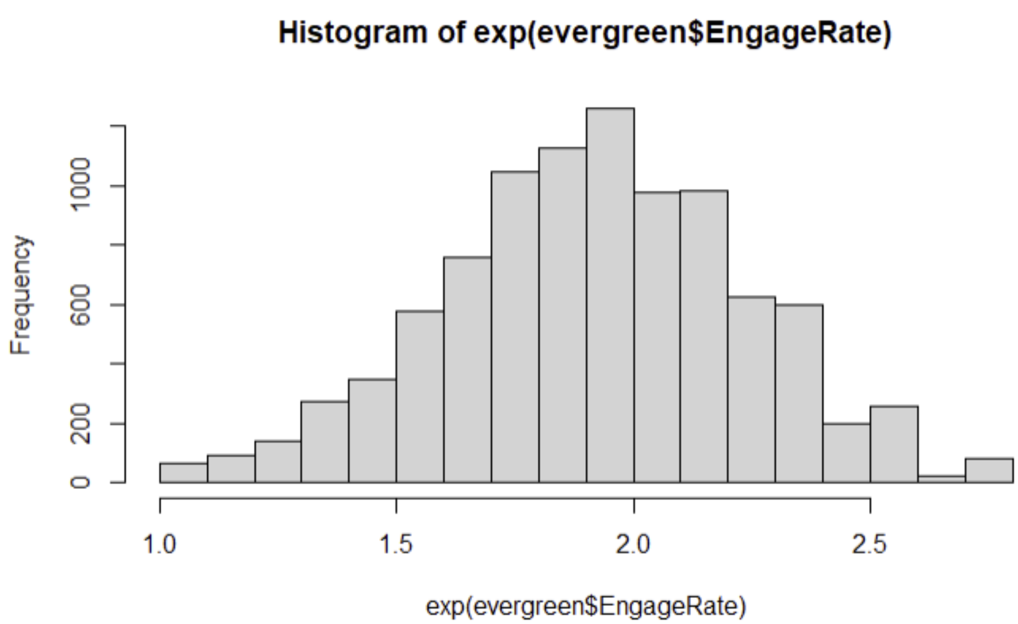




EDA Figure 5: Histogram of Average Engagement Time

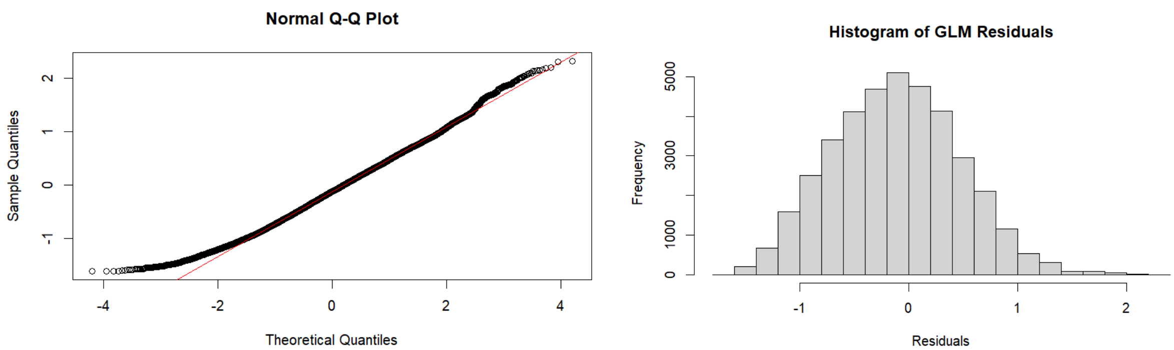


EDA Figure 6: Distribution of Engagement Rate after applying an log inverse (exponential) transformation



C. Modeling Results & Validation

Validation Figure 1: Residual histogram and residual Q-Q plot for investigation time model



Validation Figure 2: Residual histogram and residual Q-Q plot for investigation clicks model