Modeling Enterprise Productivity: A Regression Analysis on GenAI Adoption

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Enterprise GenAI Adoption & Workforce Impact Data

Dataset

- Over 100k records
- Collected from 2022 - 2024
- Anonymized companies across multiple industries

Key Data Fields

- Year Adopted
- Country
- Industry
- Company
- Gen AI tool adopted (ChatGPT, Gemini, Mixtral, LLaMA, and Groq)
- Employees impacted
- New Jobs
- Training Hours
- Percentage of change in Productivity
- Employee Sentiment

EDA

Adoption Year
- Most adoptions happened after 2022, medium is 2023

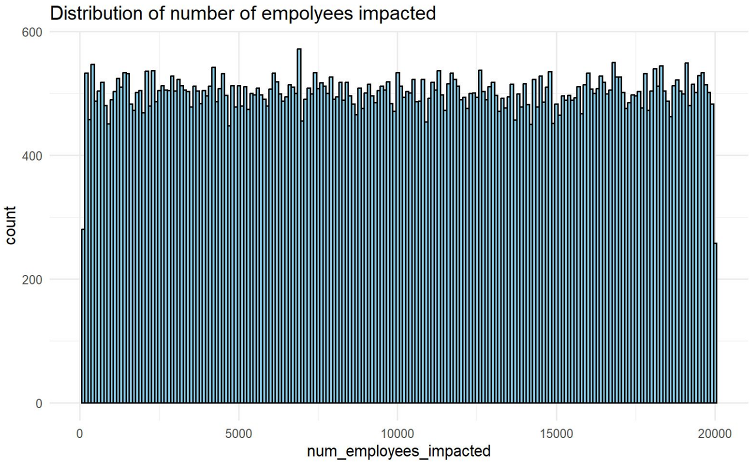
Productivity Change
- Range is 2% to 35%
- Average is 18.5%

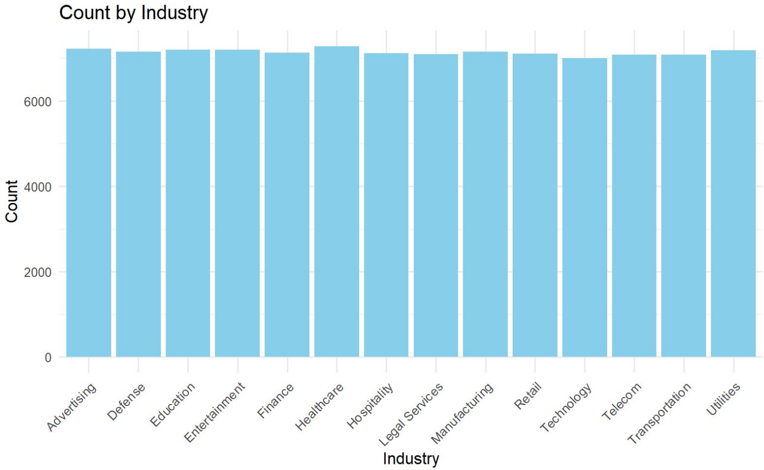
Training Hours
- Wide Variation from 500 to 25,000 hours
- Medium is 12,764 hours

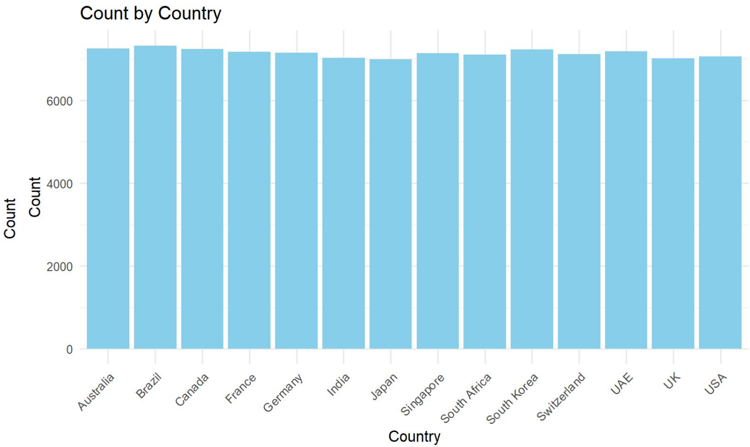
New Roles Created
- Range from 1 to 30 new roles
- Median is 16 roles created

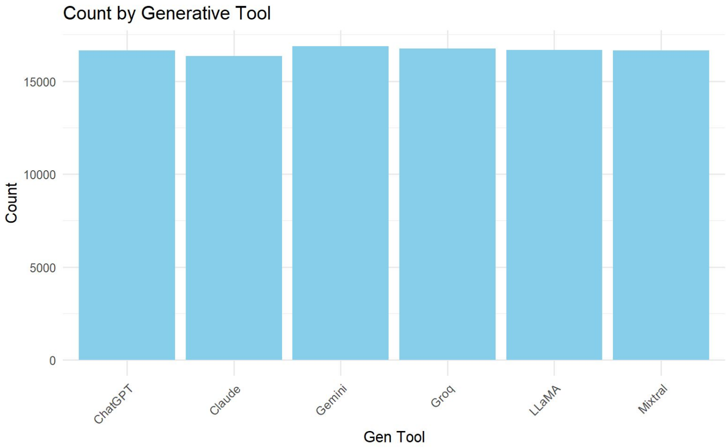
Employees Impacted
- Range from 100 to 20,000
- Median is 10,044 employees impacted

EDA Visualizations









Correlation Between Variables

- All variables show very weak and or no correlation with each other
- Low Multicollinearity
- Predictors are independent

Multiple Regression Model

Initial Model

- Dependent Variable: Productivity Change
- Predictor Variables: adoption year, training hours, new roles created, number of employees impacted, industry, country, and gen ai tool

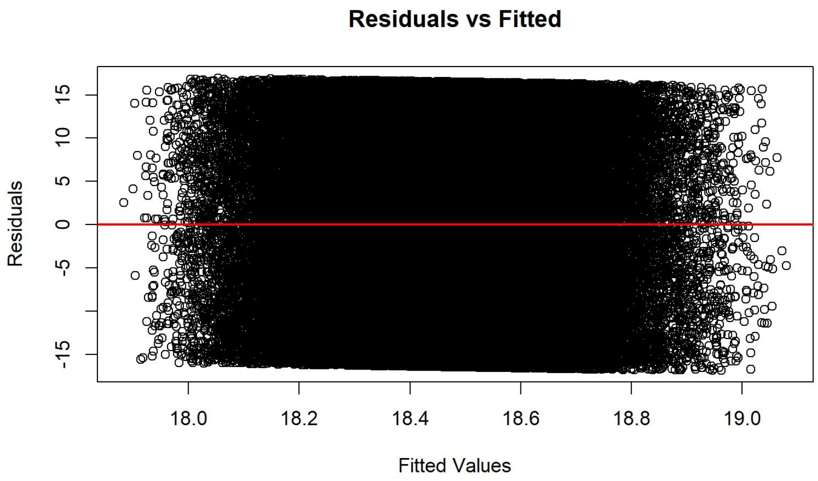
Key Findings

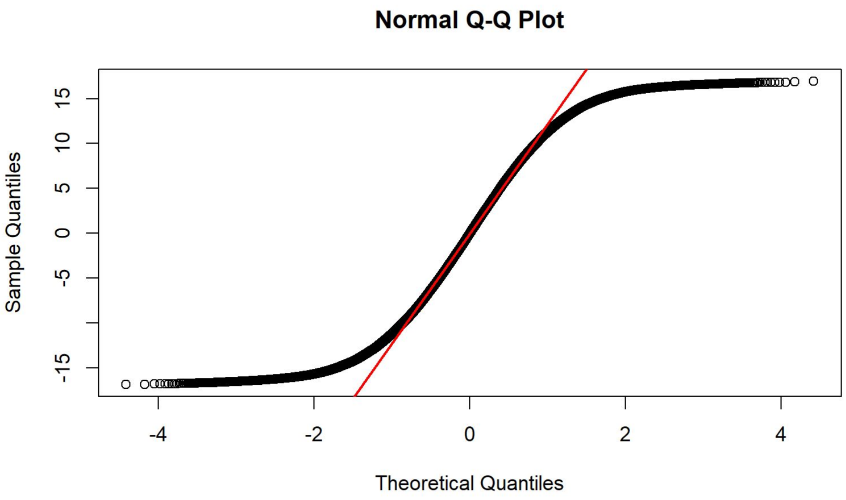
- R squared 0.00034: The model explains none of the variation in productivity change
- P-value 0.5162: The model is not statistically significant
- Residual Standard Error 9.5: Large error relative to the range 2%-35% in productivity change

Coefficient

- None of the predictors were statistically significant: In this linear model, no single factor strongly predicts productivity change

Residual Plots





Prediction Test for Initial Model

Actual	Predicted	Error
25.2	18.42	+6.78
27.5	18.31	+9.19
11.5	18.33	-6.83
7.0	18.53	-11.53
2.5	18.40	-15.90

- Predictions cluster at 18 regardless of actuals
- Model lacks variation in productivity change
- Model lacks predictive power

Multicollinearity

- Checked to ensure variables were useful and not redundant
- Used VIF to check for multicollinearity
- Found no redundancy: each variable contributes its own information

	GVIF	Df	GVIF^(1/(2*Df))
adoption_year	1.000235	1	1.000117
training_hours	1.000327	1	1.000164
new_roles_created	1.000313	1	1.000157
num_employees_impacted	1.000389	1	1.000194
industry	1.002895	13	1.000111
country	1.003191	13	1.000123
gen_tool	1.001461	5	1.000146

Stepwise Regression

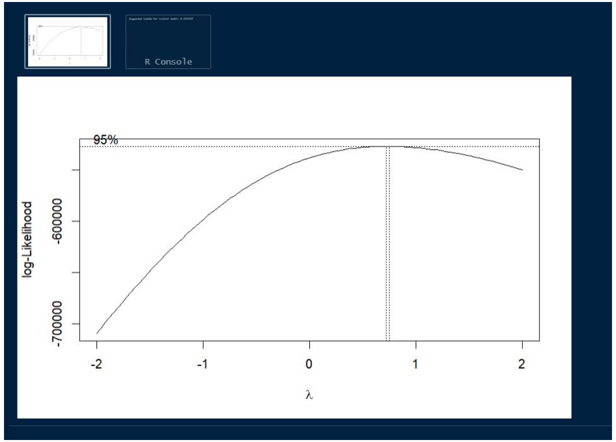
- Ran backward, forward and combined stepwise regression, seeking to improve quality of the model
- Intercept-only outcome: no variables were statistically significant in helping predict productivity change
- Our best 'model' is simply the average change in productivity

```
Start:  AIC=450876.5
productivity_change ~ training_hours + new_roles_created + num_employees_impacted +
    industry + gen_tool

                         Df Sum of Sq     RSS    AIC
- industry               13    636.92 9077607 450858
- gen_tool                5    721.19 9077691 450874
- training_hours          1      1.26 9076971 450875
- num_employees_impacted  1     68.88 9077039 450875
- new_roles_created       1    101.71 9077071 450876
<none>                                9076970 450877
```

Box Cox Analysis

- Checked to see if we needed to 'straighten out' our data in relation to the response variable
- Box Cox Analysis: tells us what type of transformation
- Results showed we could only yield marginal improvements, no transformation required



Final Model

Final Model Summary & Evaluation

Objective

To evaluate the final regression model to understand the relationship between GenAI adoption factors and productivity change.

Dataset & Sampling:

- Original dataset: 1000+ companies
- Final model built on a **sample of 500 observations**
- Seed: 2025 for reproducibility

Model Used:

Multiple Linear Regression

- Predictors: training_hours, new_roles_created, num_employees_impacted, industry, gen_tool

What the Data Told Us

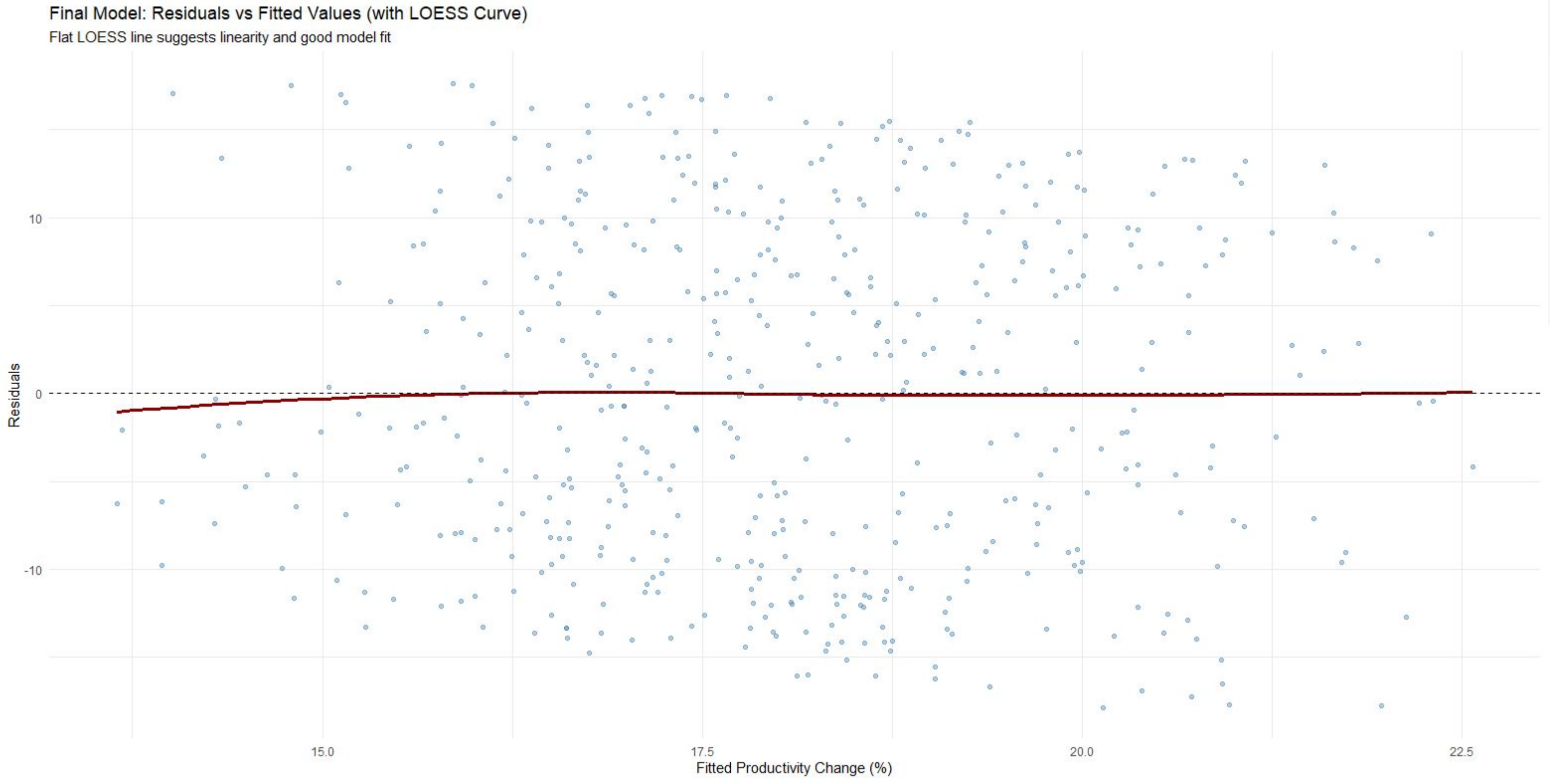
After testing many combinations of factors, we built a final model to see what influences productivity the most when companies adopt GenAI tools.

Here's what we found:

- Surprisingly, **no single factor** stood out as a strong predictor.
- Variables like **training hours**, **industry type**, or **number of employees affected** didn't clearly drive productivity changes.
- While we expected more training or certain industries to show bigger gains, the results showed that productivity **varied widely** even when those factors were similar.

This suggests that real productivity gains might come from deeper organizational changes, not just the visible factors like training quantity or tool type.

What the Model Got Right (and Missed)



Final Model Visualization Insights

- The **flatness of the line** is actually a good sign, it means the model isn't favoring any specific group.
- But the **spread of the points** is large, meaning our predictions were often quite far off.

Why This Matters:

Our model wasn't "wrong," but it struggled to find strong patterns in the data, likely because the **true drivers of productivity aren't captured in the dataset.**

Conclusion

Final Reflections & What's Next

3 Takeaways

1

Productivity change is a complex outcome, it may depend on how GenAI is used, company culture, leadership, and employee readiness.

2

The data we used was clean and structured, but lacked the human and qualitative factors (like how well training was absorbed or if employees embrace change).

3

This analysis shows that not all insights come from just numbers, sometimes, the absence of strong patterns is itself a finding.