2023 StackOverflow Annual Developer Survey Research

How age influences the adoption and perception of artificial intelligence technologies among industry professionals

How AI tools enhance the ability of software developers to predict and adapt to future trends in software development

BAN 690 Business Analytics Capstone Project
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1. Title

"How does age influence the adoption and perception of artificial intelligence technologies among industry professionals?"

"How do AI tools enhance the ability of software developers to predict and adapt to future trends in software development?"

2. Abstract

The study utilized the dataset from StackOverflow's 13th Annual Developer Survey in 2023, involving over 90,000 developers and users. Participants provided demographic information, work background, programming experience, and attitudes toward emerging technologies such as AI. This research aimed to explore how AI can assist developers in predicting and adapting to the future of software development, examining factors influencing their decisions and the role of demographic factors such as age, and how age influences the adoption and perception of artificial intelligence technologies among industry professionals. The study's target variables were AIBen, AISelect, and Age. Initially, the variables AIBen and AISelect were converted from a Likert scale to binary. Excel was used to clean the data, focusing on full-time developers employed older than 18 years. Improving the analysis required filtering, removing unnecessary variables, and dividing the columns. SAS Enterprise Miner was used for model development, which included handling missing values through imputation or removal and partitioning the data into a 60/40 train-test split for optimal results. The analytical techniques employed included Forward Regression, Backward Regression, Stepwise Regression, Decision Tree, Neural Network, DM Neural, Gradient Boosting, and HP Forest models. The Gradient Boosting (Boost2) model provided better results for the Age variable, while the Neural Network model excelled with the lowest Average Squared Error (ASE) for AIBen &AISent.

3. Introduction

In order to stay competitive in the rapidly changing world of technology, professionals in the field must constantly adjust to new programming languages, frameworks, and approaches. This study investigates how their age influences industry professionals' perceptions and adoption of artificial intelligence (AI) technologies.

We look at how various age groups interact with AI tools, how they perceive the technology differently, and what motivates them to incorporate AI into their daily tasks. We aim to comprehend how AI can help professionals of all ages navigate the quickly evolving technological landscape. Artificial intelligence's (AI) capacity to detect new patterns, forecast technology trends, and evaluate information from various sources presents a substantial opportunity to improve productivity and flexibility. This study sheds light on the strategic significance of incorporating AI into professional workflows catered to various demographics by looking at age-related variations.

We also recognize the broader field of autonomic computing, which refers to the management of systems by themselves with little assistance from humans. Autonomic computing has undergone a revolutionary change with the incorporation of AI and ML, which allows autonomous systems to learn, anticipate, and adjust.

We have selected the StackOverflow annual developer survey dataset for this study because it provides industry insights with up-to-date, precise, and AI-focused data. This dataset makes understanding the adoption and perception of AI across various age groups in the professional community possible.

We also aim to identify the particular opportunities and challenges each age group faces by investigating how age affects attitudes and perspectives regarding AI. Our objective is to provide practical insights that can guide creating inclusive and prosperous AI integration plans, improving trend prediction and developer productivity. This research aims to promote a more inclusive technological environment for all age groups by highlighting the transformative potential of AI in professional workflows and autonomic computing in particular.

4. Literature Review

4.1 **Age-related bias and artificial intelligence: a scoping review**

The research question addressed in the study was: "What is known about age-related bias in AI technology, how do AI systems encode, produce, or reinforce age-related bias, and what are the societal, legal, and ethical implications of age-related bias in AI systems?" The study concluded that age-related bias in AI is prevalent and often introduced during the early stages of data to algorithm development and the algorithm to user deployment phase. Machine learning models were found to have significant representation and evaluation biases, especially when used in applications like facial and age recognition systems. The application of biased AI systems can reinforce ageism, which has ethical ramifications. As a result, fairness and inclusivity for older adults must be given more consideration in the design and implementation of AI. The factors that were looked at included various biases, machine learning stages, and AI technology applications. This study is highly related to my research question, "How does age influence the adoption and perception of artificial intelligence technologies among industry professionals?" It provides a foundational understanding of age-related biases in AI systems, helping to address the challenges older professionals face with AI adoption and to develop strategies for more inclusive AI integration across age groups.

4.2 **Understanding Older Adults' Perceptions and Challenges in Using AI-enabled Everyday Technologies**

The research question addressed in the study was: "What are older adults' personal experiences with AI-enabled products, do they face any challenges in using these products, and what are their perceptions of AI technology?" According to the study's findings, older adults lack appropriate learning opportunities but are generally excited about using and learning about AI-enabled products. They also expressed worries that AI would surprise them, invade their privacy, and affect their ability to make decisions. As a result, they have conflicting opinions about AI and see it as both an ally and an enemy. The variables examined included older adults' experiences, challenges, perceptions, knowledge, trust, and motivations regarding AI-enabled products. This study is pertinent to my research question, as it provides valuable insights into how older adults perceive and interact with AI, highlighting the importance of addressing age-specific concerns and barriers. These findings can inform my exploration of AI adoption and perception among different age groups within the professional community, ensuring that strategies are tailored to meet the unique needs of older professionals.

4.3 **AI for next generation computing: Emerging trends and future directions**

This research paper explores the integration of AI and Machine Learning (ML) techniques with autonomic computing across various paradigms, including cloud, fog, edge, serverless, and quantum computing. The authors recommend AI-autonomic computing to reduce maintenance costs and increase system stability by enabling systems to self-manage, adapt, and optimize independently, thereby reducing human intervention. The independent variables include types of autonomic behaviors (self-configuration, self-optimization, self-protection, self-healing), AI and ML techniques for data analysis and system optimization, different computing paradigms, and system performance metrics. Because it provides a comprehensive understanding of current methods, upcoming developments, real-world applications, and the advantages of lower maintenance costs and human intervention, this research is relevant. It provides a framework for creating new AI-based autonomic computing solutions and refining the ones that already exist, especially in terms of boosting optimization and self-management capabilities. In addition, this study explores future directions and useful applications of AI across a range of computing paradigms, highlighting the strategic importance of incorporating AI into software development processes. This demonstrates why my research is essential to comprehending how AI will affect software development in the future.

4.4 **Trust In AI and The Perception of AI**

Heysun Choung, Prabu David, and Arun Ross's research paper is titled "Trust in AI and Its Role in the Acceptance of AI Technologies." The study was divided into two parts: the first focused on college students as the focus group and asked questions about their trust in AI voice assistants; the second section examined AI's usability and attitudes toward it, asking a representative sample of the US population. The study examined two dimensions: functionality and human-like trust. It found that both have a favorable effect on how AI tools are perceived. An outstanding summary and supporting information are provided by this research study. The study, however, was based on data from two distinct populations: US citizens in general and college students. This research paper is meaningful for my study because it tests the influence of trust and perception on the acceptance of AI tools in people but through different demographics. This is helpful since it will give a detailed insight into essential factors that influence the adoption of AI, therefore generalizing it across the study of software developers' attitudes toward AI. Applying this research to a comparison is more relevant because developers are more familiar with the technology than other professions. This provides a foundation to show how trust and ease of use affect the acceptance of AI in a technically proficient population.

5. **Data Analysis**

For this research, the dataset was obtained from the Stack Overflow Developer Survey 2023. The specific dataset used is called survey_results_public.csv, which contains responses from a broad range of software developers around the world.

The dataset is in CSV (Comma-Separated Values) format and comprises 89,184 rows (observations) and 83 columns (input variables). The key variables analyzed in this study include Age, Employment, YearsCodePro, AISearchHaveWorkedWith, AISearchWantToWorkWith, AIDevHaveWorkedWith, AIDevWantToWorkWith, AISelect, AISent, AIBen, Industry. These variables offer insights into the current state of software development practices and trends, making the dataset a valuable resource for investigating the impact of AI on forecasting and adapting to future trends in the field.

6. **Data Preparation**

Initially, the dataset comprised 83 variables and 89,184 rows. We first converted the CSV file into an XLSX file to facilitate data manipulation in Excel. Then, we identified which variables were meaningful for our analysis and which were not. Consequently, we dropped multiple columns that could have been more useful, such as administrative questions related to the survey itself or questions about the technology not pertinent to our research on the impact of AI, including database tools, web frameworks, and some developer background information.

Moreover, we filtered the data. For the variable 'Age,' we included only observations for individuals who were 18 years or older. We also focused on retaining only industry professionals working for at least one year but, at most, 50 years who were employed full-time. We excluded all data related to part-time employees or self-employed individuals. Additionally, we converted this variable from character to numeric by replacing values such as '25-34 years old' with '25-34', and similarly for other age ranges. There were two observations greater than 50 years old that counted as missing values. Using Python, we replaced those two missing values with the median for 'Age,' which was 25.0. There were some missing values across different variables that SAS did not recognize due to their representation as 'NA' values. These were treated as text rather than missing values. We addressed this by removing all instances of 'NA.'

We transformed the variables for how developers perceive AI, namely AIBen, AISent, and AI Select, from a Likert scale to binary values. We used AIBen, AISent, and Age as target variables for our analysis in SAS Enterprise Miner. These columns were encoded with 1 if the perception or trust was positive and 0 if it was undecided or negative. Through these steps, we reduced the dataset from over 89,000 observations to 3,694 while retaining 11 relevant variables. To ensure these changes were reflected correctly, instead of hiding values in Excel, we exported the filtered observations into a new spreadsheet. We then imported this cleaned Excel file into SAS Enterprise Miner using a File Import node. After importing, we added a Save Data node and ran it to save the data. We provided a filename prefix and assigned a name to the library in SAS. Subsequently, we modified the 'Project Start Code' to include the library name and the directory (LIBNAME CapsProj 'K:\Students\dcavada\BAN690\DataSources' ;) and executed it. The new data source was created and added to the project diagram.

Our analysis of the interval variables revealed varying levels of skewness. 'AISelect' exhibited a significant left skew with skewness of -2.85709, indicating most values were concentrated at the higher end of the scale. Conversely, 'YearsCodePro' had a skewness of 1.264261, indicating a right skew and suggesting a concentration of values toward the lower end. 'AIBen' showed a skewness of -0.89717, indicating a less pronounced left skew. After attempting data transformation using the log function in Python, it was determined that fixing the skewness did not yield significant improvements in the models, so the data was retained in its original form. However, 'AISent' exhibited an extremely high kurtosis of 77.18509, indicating a high concentration of values and significant outliers, which were subsequently removed in Python to ensure the robustness of our analysis (see Appendix 10.5).

7. **Analytic Models**

For Data analysis, we have developed models for our target variables: AIBen, AISent, and Age. In short, we imported the file, selected target variables, defined input variables, and rejected some of the variables not needed for the analysis. We then ran the StatExplore node to analyze the file and get basic information about the dataset.
We partitioned the dataset into training and validation subsets to prepare for modeling using the Data Partition node. We opted for a 60/40 split: the training set (60%) was used to build and train the model, while the validation set (40%) was used to evaluate the model's performance and ensure its reliability. We experimented with other partitions, such as 70/30, but found that the 60/40 split better-balanced training and validation, ensuring robust model evaluation without overfitting.

After Data Partition, to prepare the dataset for Regression analysis, I also used the impute node to ensure that missing values were imputed correctly using Mean for numerical values and Mode for Categorical variables. The following steps were to run four different types of regressions, more specifically, Stepwise Regression, Backward Regression, Forward Regression, and Standard Regression. Besides regressions, we also run the Decision Tree Node and Neural Network Node. To compare all of them, we used the model comparison node. For all five nodes, we used the Average Square Error rate as the selection criterion.

8. **Results**

8.1 **Age**

Fit Statistics

Selected Model	Predecessor Node	Model Node	Model Description	Target	Target Label	Selection Criterion: Valid: Average Squared Error	Train: Total Degrees of Freedom	Train: Degrees of Freedom for Error	Train: Model Degrees of Freedom	Train: Number of Estimated Weights	Train: Akaike's Information Criterion	Train: Schwarz's Bayesian Criterion	Train: Average Squared Error	Train: Maximum Absolute Error	Train: Divisor for ASE	Train: Sum of Frequencies	Train: Root Average Squared Error	Train: Sum of Squared Errors	Train: Sum of Case Weights Times Freq	Train: Final Prediction Error
Y	Reg2	Reg2	Backward ...	Age		22.90232	2216	2203	13	13	7182.968	7257.113	25.27154	37.38685	2216	2216	5.02708	56001.73	2216	25.56
	Reg3	Reg3	Forward Re...	Age		22.90232	2216	2203	13	13	7182.968	7257.113	25.27154	37.38685	2216	2216	5.02708	56001.73	2216	25.56
	Reg4	Reg4	Stepwise R...	Age		22.90232	2216	2203	13	13	7182.968	7257.113	25.27154	37.38685	2216	2216	5.02708	56001.73	2216	25.56
	Reg	Reg	Regression	Age		23.25961	2216	2167	49	49	7223.37	7502.839	24.91374	36.66801	2216	2216	4.991367	55208.85	2216	26.040
	Tree	Tree	Decision Tr...	Age		23.30059	2216	.	.	.	.	.	24.77068	33.32013	2216	2216	4.977015	54891.82	.	
	Neural	Neural	Neural Net...	Age		24.34337	2216	2062	154	154	7456.634	8334.966	25.17667	31.65531	2216	2216	5.017636	55791.5	2216	28.93
	Boost2	Boost2	Gradient Bo...	Age		25.13634	2216	.	.	.	.	.	19.75176	31.07781	2216	2216	4.444295	43769.89	2216	
	DMNeural	DMNeural	DMNeural	Age		27.54828	2216	2195	.	21	7515.379	7635.152	29.15025	35.49377	2216	2216	5.399097	64596.95	.	29.708
	HPDMForest	HPDMForest	HP Forest	Age		31.19674	.	.	.	.	.	.	32.39871	29.1724	2216	2216	5.691986	71795.54	.	

The decision tree analysis highlights the importance of 'YearsCodePro' as a crucial factor impacting the estimation of age. The tree displays discrete nodes with widely differing average ages according to years of experience with professional coding. For instance, developers with over 12.5 years of experience are noticeably older than those with less than 6.5 years. This division suggests that developers with more experience may view AI tools differently and adopt them at a faster pace than developers with less experience. With the lowest Average Squared Error (ASE) of 19.75176, the highest absolute error of 31.07781, and the lowest Root Mean Squared Error (RMSE) of 4.444295, we would like to draw attention to Gradient Boosting (Boost2)'s superior performance in predicting 'Age'. Neural Networks (Neural) also demonstrated competitive performance with lower Akaike's Information Criterion (AIC) and Schwarz's Bayesian Criterion (SBC) values, indicating a good balance between model fit and complexity. Decision tree analysis's segmentation—especially the impact of 'YearsCodePro' on age prediction—illustrates how artificial intelligence (AI) can recognize and take advantage of key factors that influence developer behavior and technology adoption. This knowledge is essential for developing more focused and successful adoption strategies by adjusting AI tools and resources to the varying levels of experience within the developer community. For instance, developers with over 12.5 years of experience are noticeably older than those with less than 6.5 years. This division suggests that developers with greater experience may view AI tools differently and adopt them at a different rate.

8.2 **AI Sentiment (AISent)**

Fit Statistics

Selected Model	Predecessor Node	Model Node	Model Description	Target Variable	Target Label	Selection Criterion: Train: Average Squared Error	Train: Akaike's Information Criterion	Train: Average Squared Error	Train: Average Error Function	Train: Degrees of Freedom for Error	Train: Model Degrees of Freedom	Train: Total Degrees of Freedom	Train: Divisor for ASE	Train: Error Function	Train: Final Prediction Error	Train: Maximum Absolute Error	Train: Mean Square Error	Train: Sum of Frequencies	Train: Number of Estimate Weights	Train: Root Average Sum of Squares
Y	Neural	Neural	Neural Net...	AISent	AISent	0.010757	-9921.4	0.010757	0.010757	2155	61	2216	2216	23.83697	0.011366	0.996062	0.011061	2216	61	0.1037
	DMNeural	DMNeural	DMNeural	AISent	AISent	0.011439	-9869.05	0.011439	0.011439	2197	.	2216	2216	25.34973	0.011637	0.992434	0.011538	2216	19	0.1069
	Reg	Reg	Regression	AISent	AISent	0.011452	-9866.56	0.011452	0.011452	2197	19	2216	2216	25.37829	0.01165	0.994507	0.011551	2216	19	0.1070
	Boost	Boost	Gradient Bo...	AISent	AISent	0.011457	.	0.011457	.	.	.	2216	2216	.	.	0.98944	.	2216	.	0.1070
	HPDMForest	HPDMForest	HP Forest	AISent	AISent	0.011488	.	0.011488	.	.	.	.	2216	.	.	0.992207	.	2216	.	0.1071
	Reg2	Reg2	Backward ...	AISent	AISent	0.011514	-9888.68	0.011514	0.011514	2214	2	2216	2216	25.51465	0.011535	0.991085	0.011524	2216	2	0.1073
	Reg3	Reg3	Forward Re...	AISent	AISent	0.011514	-9888.68	0.011514	0.011514	2214	2	2216	2216	25.51465	0.011535	0.991085	0.011524	2216	2	0.1073
	Reg4	Reg4	Stepwise R...	AISent	AISent	0.011514	-9888.68	0.011514	0.011514	2214	2	2216	2216	25.51465	0.011535	0.991085	0.011524	2216	2	0.1073

The examination of different AI models for 'AISent' prediction provides important new information about how well these tools work to improve software developers' capacity for trend prediction and adaptation. Neural Networks (Neural) and decision tree-based models, including Gradient Boosting (Boost) and High-Performance Decision Forest (HPDMForest), performed better than the other models tested in a number of important metrics. With the lowest Average Squared Error (ASE) of 0.010757 and Mean Squared Error (MSE) of 0.011061, the Neural Network model performed exceptionally well, demonstrating high accuracy and robustness. With an ASE of 0.011488 and an MSE of 0.011092, HPDMForest demonstrated strong predictive capability and performed well as well. With an ASE of 0.011457 and an MSE of 0.011457, gradient boosting further demonstrated its efficacy as a predictive model. The predictive accuracy of the more complex models was not matched by the simpler regression models, despite being easier to understand. These results emphasize the value of utilizing cutting-edge AI models, which are essential for developers to foresee and adjust to future trends since they can analyze enormous datasets, spot patterns, and provide accurate forecasts. Developers' ability to predict the future is greatly improved by the thoughtful integration of AI, especially Neural Networks and Gradient Boosting, which helps them stay competitive in the quickly changing tech industry.

8.3 **AI Benefits (AIBen)**

Fit Statistics

Selected Model	Predecessor Node	Model Node	Model Description	Target Variable	Target Label	Selection Criterion: Valid: Average Squared Error	Train: Akaike's Information Criterion	Train: Average Squared Error	Train: Average Error Function	Train: Degrees of Freedom for Error	Train: Model Degrees of Freedom	Train: Total Degrees of Freedom	Train: Divisor for ASE	Train: Error Function	Train: Final Prediction Error	Train: Maximum Absolute Error	Train: Mean Square Error	Train: Sum of Frequencies	Train: Number of Estimate Weights	Train: Root Average Sum of Squares
Y	Reg	Reg	Regression	AIBen	AIBen	0.214564	-3520.01	0.200769	0.200769	2197	19	2216	2216	444.9042	0.204242	0.895244	0.202505	2216	19	0.4480
	HPDMForest	HPDMForest	HP Forest	AIBen	AIBen	0.214976	.	0.201774	.	.	.	.	2216	.	.	0.758001	.	2216	.	0.4491
	Tree	Tree	Decision Tr...	AIBen	AIBen	0.215153	.	0.202746	.	.	.	2216	2216	.	.	0.724121	.	2216	.	0.4502
	Reg2	Reg2	Backward ...	AIBen	AIBen	0.215153	-3532.3	0.202746	0.202746	2214	2	2216	2216	449.2846	0.203112	0.724121	0.202929	2216	2	0.4502
	Reg3	Reg3	Forward Re...	AIBen	AIBen	0.215153	-3532.3	0.202746	0.202746	2214	2	2216	2216	449.2846	0.203112	0.724121	0.202929	2216	2	0.4502
	Reg4	Reg4	Stepwise R...	AIBen	AIBen	0.215153	-3532.3	0.202746	0.202746	2214	2	2216	2216	449.2846	0.203112	0.724121	0.202929	2216	2	0.4502
	DMNeural	DMNeural	DMNeural	AIBen	AIBen	0.215239	-3514.27	0.200927	0.200927	2195	.	2216	2216	445.2545	0.204772	0.857256	0.202849	2216	21	0.4482
	Boost	Boost	Gradient Bo...	AIBen	AIBen	0.215517	.	0.200499	.	.	.	2216	2216	.	.	0.744134	.	2216	.	0.4477
	Neural	Neural	Neural Net...	AIBen	AIBen	0.220793	-3489.63	0.195969	0.195969	2155	61	2216	2216	434.2684	0.207064	0.888002	0.201517	2216	61	0.4426

The analysis of AI models for 'AIBen' prediction highlights the remarkable results of the Neural Network (Neural) model, which had the lowest Mean Squared Error (MSE) at 0.201517 and Average Squared Error (ASE) at 0.195969. These figures demonstrate the high accuracy and dependability of the neural network model. With ASEs of 0.201774 and 0.200499, respectively, the High-Performance Decision Forest (HPDMForest) and Gradient Boosting (Boost) models also demonstrated impressive performance. On the other hand, the Decision Tree (Tree) and the less complex regression models (Reg2, Reg3, Reg4) had higher ASEs of approximately 0.202746, indicating lower precision in comparison to the more complex models. The Gradient Boosting model additionally demonstrated a low Maximum Absolute

Error of 0.744134, further supporting its predictive strength. These results indicate that advanced AI models like Neural Networks and Gradient Boosting are more effective in processing data, recognizing patterns, and delivering accurate predictions. This capability significantly enhances software developers' ability to anticipate and adapt to future trends, thereby boosting their productivity and competitive advantage in the rapidly changing technological landscape.

9. **References**

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10. **Appendices**

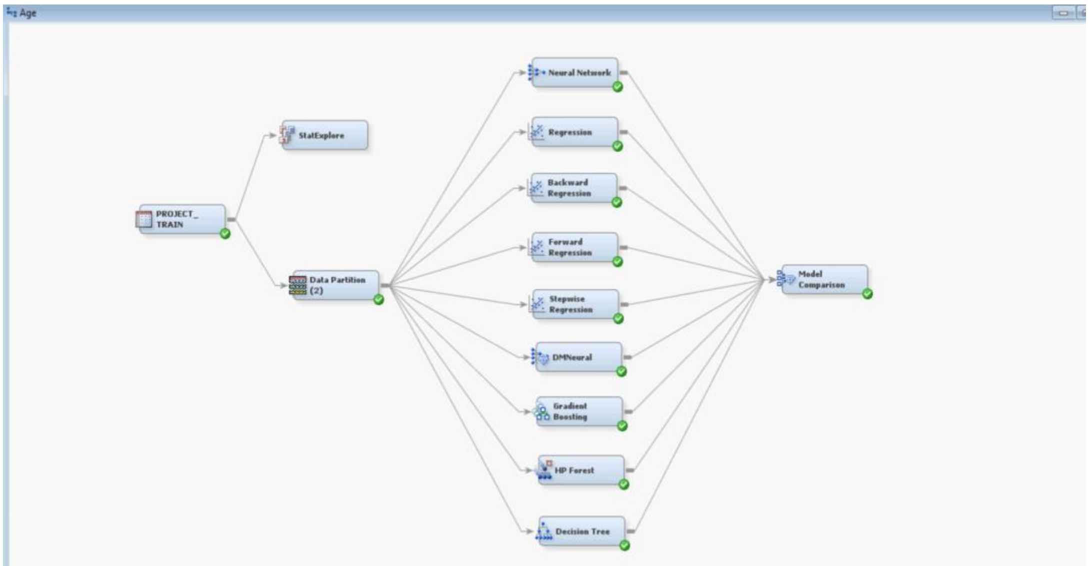
10.1. **Path to SAS Project and Files in Citrix**

K:\Students\dcavada\BAN690

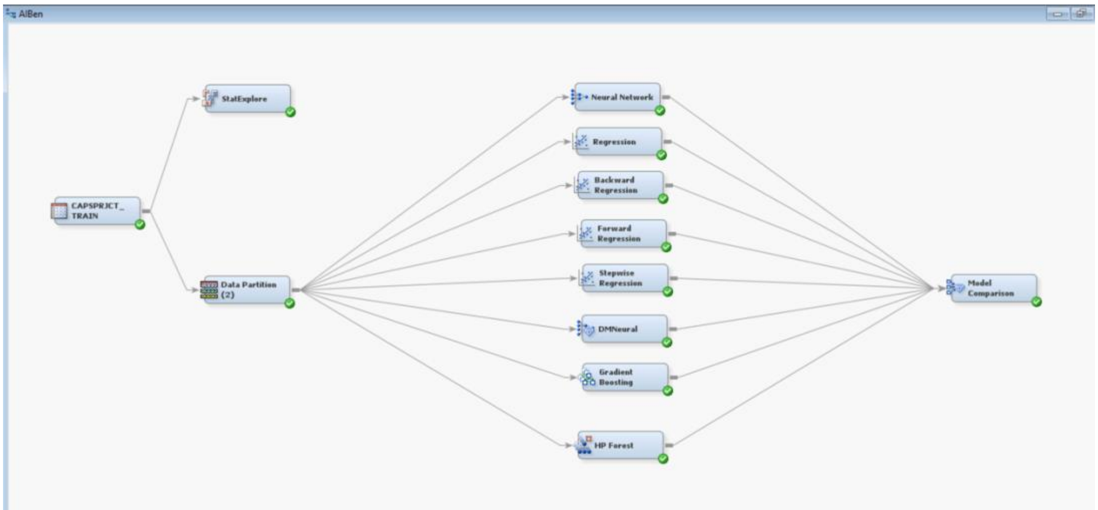
10.2. **Variables Table**

Variable Name	SAS Level	SAS Role	Missing Values	Missing Value Method	Number of Levels	Skewness Value	Kurtosis Value
Age	Target/Input	Interval	2	Replaced MV's with the Median	6		
Employment	Text	Nominal	0	Deleted Rows with NA's	1		
YearsCodePro	Input	Interval	0	Deleted Rows with NA's	50	1.264261	1.485312
AISearchHaveWorkedWith	Text	Nominal	0	Deleted Rows with NA's	100		
AISearchWantToWorkWith	Text	Nominal	0	Deleted Rows with NA's	128		
AIDevHaveWorkedWith	Text	Nominal	0	Deleted Rows with NA's	49		
AIDevWantToWorkWith	Text	Nominal	0	Deleted Rows with NA's	115		
AISelect	Input	Interval	0	Deleted Rows with NA's	2	-2.85709	6.16629
AISent	Input/Target/Rejected	Interval	0	Deleted Rows with NA's	2		
AIBen	Input/Target/Rejected	Interval	0	Deleted Rows with NA's	2	-0.89717	-1.19573
Industry	Input	Nominal	0	Deleted Rows with NA's	12		

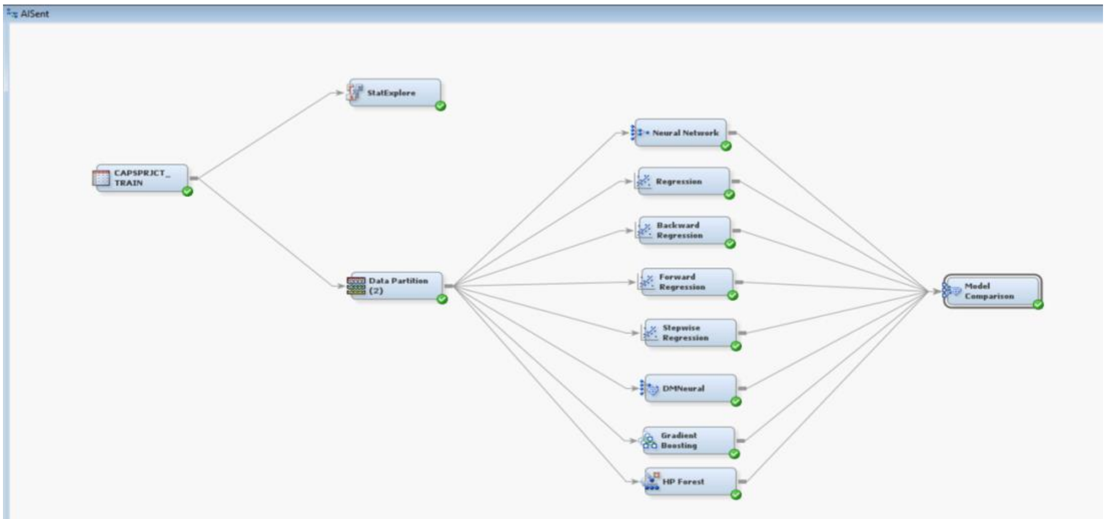
10.3. **Age Diagram**



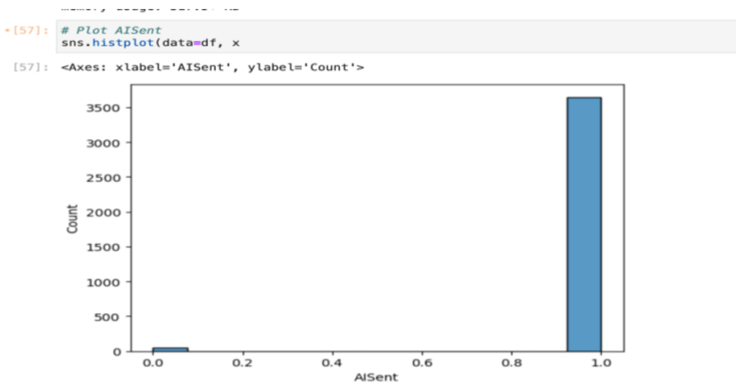
10.4. **AIBen Diagram**

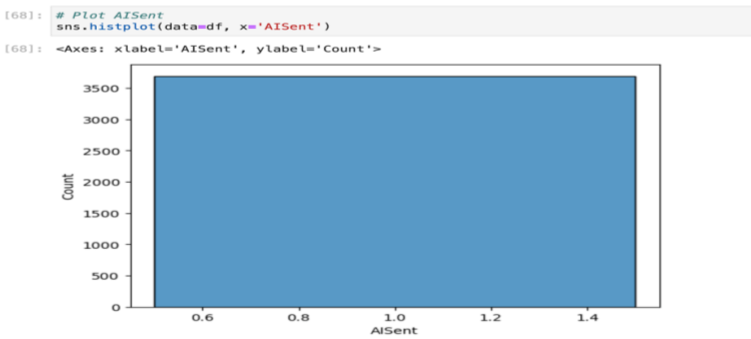


10.5. **AISent Diagram**



10.5 **AISent Outliers Removed**





10.6 **AISent Variable – Question**

How much do you trust the accuracy of the output from AI tools as part of your development workflow?

- Highly trust
- Somewhat trust
- Neither trust nor distrust
- Somewhat distrust
- Highly distrust

10.7 **AIBen Variable - Question**

How favorable is your stance on using AI tools as part of your development workflow?

- Very favorable
- Favorable
- Indifferent
- Unfavorable
- Very unfavorable
- Unsure

10.8 **Age Decision Tree**