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A Supervised Machine Learning Approach to Predicting Innovation Success in Major Software Corporations

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Abstract: This research investigates intelligent-based methodologies for navigating the dual imperatives of innovation and standard adoption within system developments aimed at sustainable technological progress. Employing a mixed-methods approach that includes literature reviews, case studies, surveys, interviews, workshops, and focus groups, the study examines the interplay between innovative practices and standard adoption across various industries. In the rapidly evolving technological landscape, balancing the drive for innovation with adherence to established standards presents both synergies and trade-offs. Key findings highlight the importance of leveraging intelligent systems, adaptive regulatory frameworks, multi-stakeholder engagement, and early integration of standards in the innovation process. Achieving long-term sustainable outcomes also relies on agile innovation management techniques and comprehensive sustainability evaluation tools. The study culminates in a strategic technology roadmap offering firms practical guidance on effectively balancing innovation with regulatory requirements. With the use of a supervised machine learning (SML) approach, it was noticed that the R^2 of 0.92, suggested that 92% of the variance in innovation project success rate is explained by the model. Positive Coefficients in features like R&D Investment, Patents Filed, Balancing Innovation and Standards, and Market Competition positively impact the success rate. The Negative Coefficients in features like Compliance with Major Standards, Frequency of Audits, and Rapid Technological Changes negatively impact the success rate. This research provides valuable insights for achieving sustainable technological advancements and contributes to the body of knowledge on navigating the challenges of innovation and standard adoption.

Keywords: Standard Adoption, Sustainable Technology, Technological Advancement, Supervised Machine Learning, Linear Regression.

1. INTRODUCTION

In the current period of rapid technological improvement, the two imperatives of innovation and standard adoption are becoming more crucial to accomplishing sustainable development. Development and competitiveness are accelerated by innovation, which enables companies to produce cutting-edge goods and services. Hence, to ensure that new technologies are both groundbreaking and comply with laws and regulations, innovation and standards must collaborate. Early standards integration into the innovation process lowers the risk of non-compliance and boosts market adoption [1]. Strict obedience to the regulations, however, could stifle creativity and limit the generation of novel concepts. Therefore, finding a balance between these aspects is crucial for sustainable technological advancement. By doing so, multi-stakeholder collaboration is crucial in this case. A thorough grasp of the demands and expectations of many industries can be provided by including a variety of stakeholders, including regulators, customers, industry experts, and university researchers. By collaborating, it will be simpler to develop standards that are flexible and adaptive enough to evolve as technology develops, promoting continuous innovation [2]. Also, regulatory frameworks must adapt to the speed of innovation. Traditional regulatory approaches may not be adequate to address the complexity of modern technology innovations. Regulatory sandboxes and dynamic rules can ensure regulatory monitoring while enabling testing and iteration in a supervised environment, which is necessary for innovation [3]. Again., Life Cycle

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Assessment (LCA) stands as one of the sustainability assessment tools that is crucial for determining how new technology might impact the environment. By integrating sustainability principles into the design and development process, innovations can be produced that will positively contribute to long-term environmental goals [4]. Therefore, by using agile approaches and effective risk management techniques overcoming the uncertainties associated with innovation and standard acceptance becomes easier.

Nevertheless, this study aims to explore the best way to balance standard adoption with innovation in technology advancements. Conducting a comprehensive inquiry that includes seminars, interviews, case studies, surveys, and technology road mapping yields strategic guidelines and practical insights for enterprises. Promoting creative, sustainable technological advancements that abide by the law is the ultimate goal.

Furthermore, research has also been carried out in the area of technological innovation and standard adoption such as the lens of attitude toward technological innovation in [5] focusing on the entrepreneurial and organizational innovative perspectives to attain environmental and social sustainability. Evaluation of the role of technological innovation in achieving social and environmental sustainability: mediating roles of organizational innovation and digital entrepreneurship. The study showed interesting results from the data obtained from the owners of SMEs in China. The respondents' data was screened for validity and reliability data, and the hypotheses were tested using Smart-PLS structural equation modeling (SEM). The study's conclusions demonstrate the critical impact that attitudes toward technological innovation play in digital entrepreneurship, organizational innovation, and social and environmental sustainability. Again, Roberto Paoluzzi in [6] highlights on page 105 that integrating innovation with standardization offers attainable goals for meeting societal demands. He maintained that standardizing committees offer potential for innovation policies to take advantage of, viewing them as a "playing arena" where proponents and opponents may work out the best possible solution. Also, Qadir et al. [7] conducted a thorough analysis of government initiatives, legislation, and incentives to navigate the complicated reality of electric vehicle adoption. In light of the net zero requirements, their study states that managing sustainable transportation is today one of the most crucial elements of a nation's or a region's growth from an economic and social standpoint. The difficulties they encountered had to be overcome to encourage their broad acceptance. The infrastructure, acceptance, prices, energy transition, awareness, and market-related problems were the several categories into which these challenges were separated. To address the majority of these issues, strong incentive programs and regulatory frameworks must be put in place. Such frameworks must incorporate fiscal and non-fiscal incentives that will motivate the public to convert for easier adoption to rise quickly and steadily in innovative technology. Hence the study’s main conclusions include identifying several obstacles that have not received much attention in the literature, highlighting the necessity of non-fiscal incentives for the adoption of innovative technology such as electric vehicles, and providing an extensive analysis of different incentive programs in addition to a thorough implementation framework. To promote the widespread adoption of innovative technology, the implementation framework offered research paths for academics, engineers, regulators, and industry stakeholders on additional policy incentive refinement and enhancement.

2. REVIEW OF KEY CONCEPTS

(i) Innovation in Technological Development

The foundation of both technological advancement and economic expansion is innovation. The idea of creative destruction was first presented by Schumpeter [8], who emphasized how innovations might upend established markets and open up new avenues for growth. In many different industries, innovation is essential to addressing challenging challenges and preserving competitiveness. It entails the development of novel goods, procedures, or services that outperform current ones in a major way [9]. Chesbrough [10] popularized the idea of open innovation, which highlights the value of external relationships and teamwork in the innovation process. By using outside expertise and technologies, this strategy helps companies become more inventive and expedites the development process.

(ii) Standard Adoption and Regulatory Compliance

Standards are essential for guaranteeing the quality, safety, and interoperability of technical systems. They offer a framework that directs the creation and application of new technologies, guaranteeing that they satisfy particular standards and legal obligations [11]. Standards can also help new technologies get accepted into the market by reassuring stakeholders and customers about their dependability and safety. Strict adherence to rules, however, can occasionally stifle creativity by enforcing limitations that reduce artistic freedom and adaptability [12].

(iii) Balancing Innovation and Standard Adoption

In system development, striking a balance between standardization and innovation is a crucial problem. The idea of ambidextrous organizations that can handle both revolutionary and evolutionary change is examined by Tushman and O'Reilly [13]. These firms can effectively balance innovation and standard adherence by simultaneously exploring new prospects and utilizing existing capabilities. Geels [14] offers a multi-level viewpoint on technological changes, emphasizing how crucial it is to match specialized breakthroughs with more general societal and legal frameworks.

(iv) Multi-Stakeholder Collaboration

Multi-stakeholder engagement guarantees that diverse perspectives and needs are taken into consideration, leading to more comprehensive and widely accepted solutions [15]. Public-private partnerships can play a crucial role in fostering such collaboration and ensuring that innovation goals are aligned with regulatory and societal needs. Effective innovation and standard adoption require collaboration among multiple stakeholders, including industry experts, regulators, researchers, and consumers [16].

(v) Adaptive Regulatory Mechanisms

It's possible that conventional regulation strategies won't be enough to keep up with the quick speed of technology development. A more adaptable and responsive strategy is provided by regulatory sandboxes and dynamic regulations, two examples of adaptive regulatory mechanisms [17]. Regulatory sandboxes give entrepreneurs a safe space to test new technologies and gather feedback and insights that help shape future regulations. This strategy encourages creativity while guaranteeing that emerging technologies adhere to crucial performance and safety requirements [18].

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(vi) Sustainability Assessment Tools

One important factor in the evolution of technology is sustainability. A popular method for assessing how activities and goods affect the environment over the course of their lives is life cycle assessment (LCA) [19]. LCA aids in finding ways to lessen an innovation's negative environmental effects while boosting its sustainability. It is possible to guarantee that new technologies will favorably contribute to long-term environmental goals by including sustainability concepts in the design and development process [20].

(vii) Agile Innovation Management

System developers are using agile approaches more and more to handle the complexity and uncertainty that come with innovation. Agile methodologies prioritize iterative development, ongoing feedback, and adaptability, enabling enterprises to promptly react to modifications and novel insights [21]. To ensure that new technologies meet regulatory standards and detect and mitigate any conflicts between innovation and standard acceptance, robust risk management methods are also necessary [22].

3. METHODOLOGY

This methodology guarantees a thorough comprehension of the relationship between innovation and standard acceptance in diverse settings [23][24][25][26] [27] [28] [29] [30]. To identify important topics, trends, and knowledge gaps, a thorough assessment of the literature on software development innovation, standard acceptance, and globalization was conducted. Semi-structured interviews with 20 industry experts and thought leaders were conducted to gain insights into emerging trends, best practices, and future directions. A global survey of 250 software development professionals was conducted to gather data on current practices, attitudes, and perceptions regarding innovation and standard adoption. The seven (7) software development organizations operating globally that were examined in-depth included Google, Microsoft, IBM, Amazon Web Services (AWS), Apple, Facebook (Meta), and SAP. To find trends and themes about software development innovation and standard acceptance, content analysis of industry publications, white papers, and social media debates was conducted. Ultimately, the data was analyzed using a mixed-methods methodology that combined qualitative and quantitative data to produce a rich and complex understanding of innovation and standard acceptance in international software development. After that, the quantitative data was used for the prediction of the innovation project success rate through linear regression.

The third phase involves feature selection and engineering, which is critical to improving the predictive performance of the SVM model. Key features relevant to criminal activities are identified based on domain knowledge and statistical analysis.

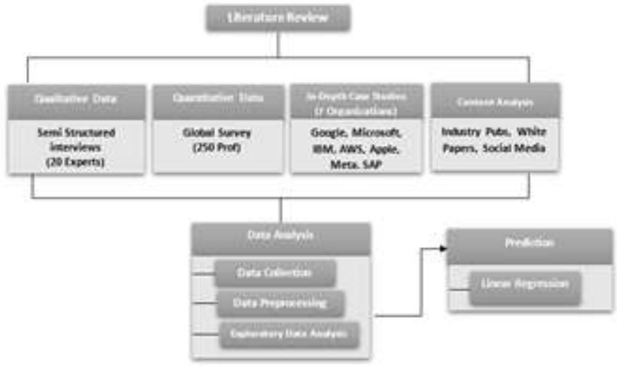

Figure. 1 Framework for Navigating Innovation and Standard Adoption in System Developments

3.1 Data Collection

Through contacts with organizations and stakeholders via a variety of online venues, the data was gathered. The purpose of this dataset is to give a thorough examination of the trade-offs and opportunities between standard adoption tactics and innovation in software development businesses that operate internationally. It contains quantitative information about success metrics, obstacles, and key performance indicators for seven well-known companies: SAP, Apple, Google, Microsoft, IBM, Amazon Web Services (AWS), Facebook (Meta), and Apple. There are 5000 records in the dataset to allow for thorough examination. Each of the 5000 records' 17 columns, highlights a different facet of the firms' standard adoption and innovation initiatives. The organization composed of Google (1), Microsoft (2), IBM (3), AWS (4), Apple (5), Facebook (Meta) (6), and SAP (7) was identified by an integer in the Org ID. A string is used to symbolize the organization. R&D Investment (in billions of USD) is a float data type that shows how much the organization has spent on research and development. The number of patents filed by the organization during the previous five years is shown by the integer Patents Filed. The success rate of the organization's innovation projects, expressed as a percentage, is indicated by an integer called the innovation project success rate. Compliance with Major Standards is an integer variable that shows how often the organization complies with important industry standards. An integer expressing the degree of difficulty in striking a balance between innovation and standards, ranging from 1 to 10, where 1 denotes a little issue and 10 denotes a major task. Rapid Technological Changes is represented by an integer on a scale of 1 to 10, where 1 denotes a little challenge and 10 denotes a major challenge. Regulatory Compliance is an integer that, on a scale of 1 to 10, indicates how difficult it is to maintain regulatory compliance; 1 denotes a minor issue, and 10 denotes a large challenge. Resource Allocation: An integer on a scale of 1 to 10 that indicates the degree of difficulty in allocating resources; 1 denotes a little challenge and 10 denotes a big obstacle. Market Share Increase, a percentage representing an increase in the organization's market share; Customer Satisfaction, a numerical representation of the customer satisfaction rating on a scale from 1 to 10; and, lastly, Product Launch Success Rate, an integer representing the success rate of the organization's product launches. Market Competition, an integer representing the severity of the challenge due to market competition, on a scale from 1 to 10; where (1 = minimal challenge, 10 = major challenge).

The dataset was created by simulating each organization's values within reasonable ranges. This simulation guarantees that the data accurately depicts potential real-world situations

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that these businesses may encounter. At this point, an ID was given to every organization. Random values within the given ranges were created for every record, accounting for every organization. Multiple entries for each organization were added to the dataset, covering various dimensions like product lines, projects, or periods. The Value Ranges for the dataset's features are displayed in Table 1;

Table 1. Value ranges

S/N	FEATURES	SCALE	VALUE RANGES
1	R&D Investment	Billion $	30
2	Patents Filed	(integer)	1000 to 5000
3	Innovation Project Success Rate	%	70 to 90
4	Compliance with Major Standards	%	80 to 95
5	Investment in Compliance	Million $	50 to 50
6	Frequency of Audits per year	unit	2 to 6
7	Balancing Innovation and Standards	Unit (integer)	4 to 8
8	Rapid Technological Changes	Unit (integer)	6 to 9
9	Regulatory Compliance	Unit (integer)	6 to 8
10	Resource Allocation	Unit (integer)	4 to 7
11	Market Competition	Unit (integer)	7 to 10
12	Market Share Increase	%	5 to 15
13	Customer Satisfaction	Unit (integer)	8.0 to 10.0
14	Product Launch Success Rate	%	75 to 95

Hence, Table 2 shows the sample dataset in a .csv file format that was collected for this study.

Table 2. Sample dataset

Record ID	Org ID	Organization	R&D Investment (	Patents Filed	Innovation Project S	Compliance	Investment	Frequency	Balancing	Rapid Technolog	Regulator	Resource A	Market Co	Market Sh	Customer
1	1	Google	27.01	2880.17	83	83	113.6	5	6	8	6	6	9	12	9
1	2	Microsoft	25.95	1932.33	87	93	74.71	2	4	7	6	7	8	11	10
1	3	IBM	19.68	2206.66	71	90	75.44	4	8	9	7	5	10	8	10
1	4	AWS	11.38	2672.2	73	92	105.89	4	6	6	8	4	9	6	9
1	5	Apple	9.06	2812.2	70	88	132.77	6	7	9	6	6	7	5	8
1	6	Facebook (Meta)	25.18	2239.09	89	80	112.08	4	4	7	7	7	9	6	10
1	7	SAP	7.3	3865.16	83	82	71.23	3	5	9	7	5	7	7	9
2	1	Google	27.48	4689.07	87	86	105.88	2	8	8	6	5	8	13	9
2	2	Microsoft	6.62	4093.35	74	82	149.89	2	4	8	7	6	10	15	10
2	3	IBM	15.88	1442.28	82	91	136.72	5	6	7	6	5	9	7	8
2	4	AWS	6	2755.19	80	87	88.2	4	7	8	6	4	7	10	9
2	5	Apple	6.69	2288.39	90	87	120.66	3	7	7	7	5	8	8	8
2	6	Facebook (Meta)	21.58	4929.43	80	94	71.66	4	5	8	8	4	9	15	9
2	7	SAP	26.41	1677.45	78	90	132.92	3	7	8	8	5	7	7	9
3	1	Google	12.69	3645.25	81	85	116.84	4	6	8	8	4	9	9	8
3	2	Microsoft	21.33	3919.09	84	94	59.46	4	4	8	8	7	9	14	10
3	3	IBM	26.69	2180.88	78	85	92.61	4	4	7	7	7	8	9	8
3	4	AWS	15.8	2941.54	71	85	137.38	3	6	6	7	6	9	14	9
3	5	Apple	14.88	1965.12	72	84	138.12	2	6	8	7	6	10	14	10
3	6	Facebook (Meta)	20.73	1684.58	85	93	149.25	4	8	9	7	7	8	5	10
3	7	SAP	22.5	3121.72	87	83	136.81	3	5	7	6	5	8	13	9
4	1	Google	19.66	3028.02	87	95	60.49	4	7	6	7	6	8	12	10
4	2	Microsoft	18.15	1560.71	73	81	71.65	3	7	6	7	4	9	6	9
4	3	IBM	28.73	3982.24	82	89	108.28	2	6	6	7	6	9	13	8
4	4	AWS	10.98	2679.7	85	90	69.76	4	6	8	7	5	8	6	9
4	5	Apple	16.68	2250.79	87	80	121.23	5	5	8	7	6	10	7	10
4	6	Facebook (Meta)	12.45	3554.19	80	86	88.16	4	6	7	6	5	10	7	8
4	7	SAP	6.15	3771.35	88	85	105.78	4	4	6	7	5	8	8	9
5	1	Google	26.71	4567.86	71	90	142.55	5	5	8	7	7	8	11	9
5	2	Microsoft	27.81	4292.31	90	90	118.11	4	7	8	7	7	9	13	9
5	3	IBM	13.9	3102.63	85	87	106.97	4	8	7	8	6	9	7	9
5	4	AWS	7.02	4602.12	72	86	148.99	4	8	8	7	5	8	10	9
5	5	Apple	16.99	4533.12	77	90	80.1	4	5	8	7	6	8	6	9
5	6	Facebook (Meta)	13.27	4332.3	87	84	122.9	5	5	8	7	5	10	12	9
5	7	SAP	26.46	4818.62	73	93	142.19	4	7	7	7	5	9	10	8
6	1	Google	26	4738.91	86	92	85.63	3	7	9	7	5	8	15	10
6	2	Microsoft	27.49	3956.82	74	87	53.25	5	4	8	6	6	7	9	9
6	3	IBM	11.66	4167.21	85	95	121.19	3	5	7	8	5	8	7	9
6	4	AWS	12.58	4229.66	83	88	115.99	4	8	7	7	6	7	14	8
6	5	Apple	19.85	4881.86	71	81	117.16	5	6	8	7	6	8	7	10
6	6	Facebook (Meta)	19.98	4289.57	84	84	61.57	2	7	8	7	6	8	8	10
6	7	SAP	14.91	4073.83	87	94	129.49	5	7	6	7	6	8	11	8
7	1	Google	23.43	2954.54	72	83	149.74	5	6	7	6	4	8	11	8
7	2	Microsoft	27.53	4059.29	81	80	107.51	2	8	8	6	6	8	9	9
7	3	IBM	13.59	2926.31	75	85	59.63	5	4	8	7	5	8	13	9
7	4	AWS	20.88	4289.47	76	86	56	5	7	7	6	6	8	8	9
7	5	Apple	26.88	2082.61	75	91	76.6	4	8	9	8	6	8	9	9

3.2 Data Preprocessing

Preprocessing the dataset was necessary to make it suitable for examination by a supervised machine learning model based on linear regression. Load Dataset: Open Google Drive and load the dataset. The dataset was examined for missing values, which were then filled up using K-Nearest Neighbors (KNN) to find the closest neighbors. Categorical variables were transformed into a numerical format using one-hot encoding. The features were chosen and the numerical features were standardized using the StandardScaler. The training dataset and the testing dataset are the two (2) categories into which the complete dataset was divided. The training dataset was split into 80% and the testing dataset into 20%, respectively 80:20 ratio. The code below was used to examine the dataset for any missing values:

```
# Check for missing values
print(df.isnull().sum())
```

The missing values were filled in using the KNNImputer as demonstrated in the code below, where the n_neighbors argument indicates the number of surrounding samples to use for imputation.

```
# Initialize the KNNImputer
    knn_imputer=
    KNNImputer(n_neighbors=
    5)

# Apply the KNN imputer to
the dataset
df_imputed=
pd.DataFrame(knn_imputer.fit
_transform(df),
columns=df.columns)
# Display the first few rows
of the imputed data frame
  print(df_imputed.head())
```

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3.3 Exploratory Data Analysis

Exploratory Data Analysis (EDA) entails the identification of patterns, and anomalies and test hypotheses through visualizations and statistical summaries of instances of data points in the datasets that will be used in machine learning processes [58]. Before we apply learning algorithms to the data, it is vital to become systematically aware of it. By inspecting data carefully, valuable insights can be identified for potential correlations between variables, and identify any cany inconsistencies in the dataset. Therefore, figure 2 shows the data structure of the dataset that will be used for the training process of the regression model in this study.

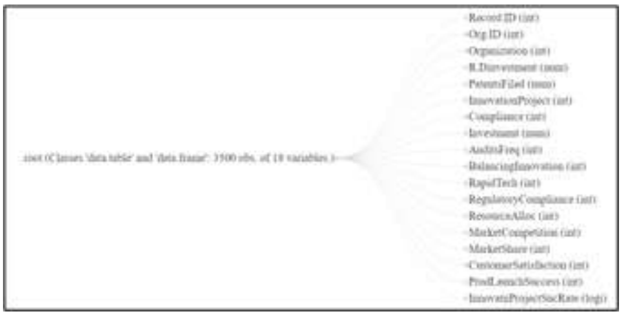

Figure. 2 Data Structure for Standard Adoption in System Developments

From Figure 2, The structure of the dataset depicts a total of 3500 observations with 18 variables and connected datatypes.

Again, figure 3 depicts metrics such as discrete, continuous, and missing columns in the dataset, there were 5.6% missing columns and observations in the dataset which will help us to carry preprocessing on the dataset before using it for prediction.

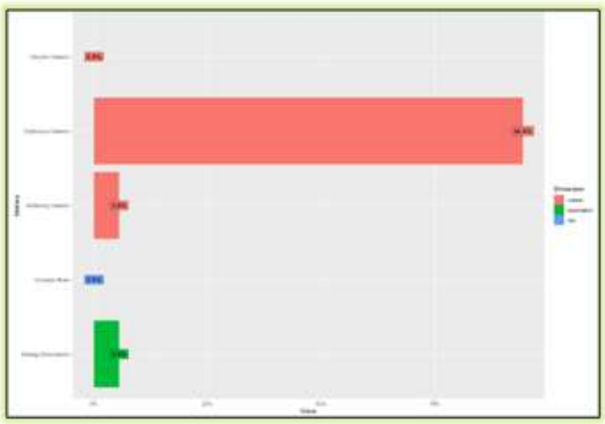

Figure. 3 Metrics Percentages

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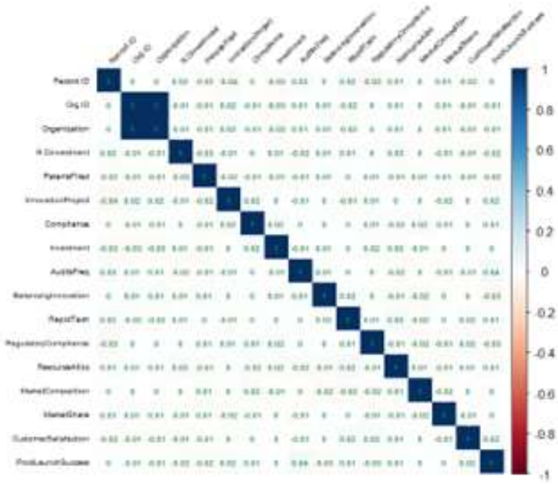

Figure. 4 Correlation matrix

3.4 Linear Regression Model

A supervised learning process called linear regression is used to predict a continuous output variable, sometimes referred to as the response variable or dependent variable, from one or more input factors, called independent variables or predictor variables. [31][32][33]. To put it simply, supervised machine learning models such as linear regression identify the linear relationship between the dependent and independent variables by determining the best-suited linear line between them. [34][35][36][37]. Finding the best-fit line that depicts the linear connection between the input and output variables is the aim of linear regression. [38][39][40][41]. Simple linear regression and multiple linear regression are the two forms of linear regression.

Finding the best-fit line that depicts the relationship between the input and output variables is the aim of simple linear regression, which only uses one input variable. The best-fit line's equation is provided by

$$y = b_o + b_1 * \mathrm{x} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathrm{i})$$

.When b0 is the y-intercept, b1 is the slope of the line, y is the dependent variable, and x is the independent variable.
Finding the best-fit plane that best captures the relationship between the input and output variables is the aim of multiple linear regression, which requires two or more input variables. The best-fit plane's equation is provided by:

$$y = b_o + b_1 x_1 + b_2 x_2 + \cdots + b_n * x_n \ldots\ldots\ldots\ldots\ldots\ldots (\mathrm{ii})$$

where y is the dependent variable, x_1, x_2, ..., x_n are the independent variables, b_0 is the intercept, and b_1, b_2, ..., b_n are the coefficients for each independent variable.
It is possible to navigate innovation and standard adoption in system developments for sustained technological advancement with the help of linear regression.
With k independent variables x_1,..., x_k that could be set, it is assumed for this method that they can probabilistically determine a result Y.

Additionally, Y's dependence on the factors is assumed to be linear based on the equations:

$$\mathrm{Y} = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k \mathrm{x}\, k * + \varepsilon \ldots\ldots\ldots\ldots\ldots (\mathrm{iii})$$

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i. The variable y_i is dependent or predicted
ii. The slope of y depends on the y-intercept, that is, when x_i and x_2 are both zero, y will be β_0.
iii. The regression coefficients β_1 and β_2 represent the change in y as a result of one-unit changes in x_{i1} and x_{i2}.
iv. βp refers to the slope coefficient of all independent variables
v. ε term describes the random error (residual) in the model.

This is similar to what we have for simple linear regression, where ε is the standard error, but k need not equal 1.

At this point, there are n observations, n typically being much more than k.
For i^{th} observation, the independent variables are set to the values $x_i^1, x_i^2 \ldots, x_i^k$ and measure a value y_i for the random variable Y_i.
Thus, the model can be described by the equations.

$$Y_i = \beta_o + \beta_1 x_i^1 + \beta_2 x_i^2 + \cdots + \beta_k x_i^k + i; \text{for } i = 1, 2, \ldots, n, \ldots \ldots (iv)$$

Where the errors i are independent standard variables, each with mean 0 and the same unknown variance σ^2.

Altogether the model for multiple linear regression has k + 2 unknown parameters: $\beta_0, \beta_1, \ldots, \beta_k$, and σ^2. When k was equal to 1, we found the least squares line $y = \beta_0 + \beta_1 x$. It was a line in the plane R^2.

Now, with $k \geq 1$, there exists a least squares hyperplane.

$$y = \beta_o + \beta_1 x^1 + \beta_2 x^2 + \cdots + \beta_k x^k \text{in } R^{k+1} \ldots \ldots \ldots \ldots \ldots (v)$$

The way to find the estimators $\beta_0, \beta_1, \ldots$, and β_k is the same. Take the partial derivatives of the squared error.

$$Q = X_n^i = 1(y_i - (\beta_o + \beta_1 x_i^1 + \beta_2 x_i^2 + \cdots + \beta_k X_i^k))^2 \ldots (vi)$$

When that system is solved, the values are fitted

$$y_i = \beta_o + \beta_1 x_i^1 + \beta_2 x_i^2 + \cdots + \beta_k X_i^k . for\ i = 1, \ldots, n \ \ldots \ldots (vii)$$

Such that n should be close to the actual values y_i.
At this point, a statistical method for predicting an answer variable's outcome using several explanatory factors is called multivariate regression (MLR). Modeling the linear relationship between the independent variables (x) and dependent variable (y) that will be examined is the goal (MLR) [42][43]. The basic model for MLR is $y = \beta_o + \beta_1 x_1 + \cdots + \beta_m x_m + \varepsilon$. The formula to determine the formula matrix is:

$$\hat{\beta} = (X^T X)^{-1} X^T y \ where\ \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \vdots \\ \beta_\varepsilon \end{bmatrix}, X = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1m} \\ 1 & x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & x_{a1} & x_{b2} & \cdots & x_{am} \end{bmatrix}, Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_m \end{bmatrix} \ldots \ldots (viii)$$

The analysis of the nth-degree polynomial modeling of the relationship between independent and dependent variables is known as polynomial regression [44, 45]. Polynomial regression is a special case of multiple linear regression (MLR) in which the polynomial equation of data melds with the curvilinear interaction between the dependent and independent variables [46]. The model of a polynomial [47, 48] is $y = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_h x_h + \varepsilon;$ Where h is named the polynomial degree [49, 50].

(i) Least square method

By lowering the number of squares of the offsets (residual part) of the curve's points, the least squares method (LSM) [51, 52] can be used to determine the best-fit curve or line for a single set of data points., the cumulative squared distance from the real y_i response $\hat{\beta} = \beta_o + \beta_1 x_i$, approaches the lowest of all potential regression coefficients β_0 and β_1 option in the linear regression model that was used to derive b_0 and b_1 forecasts approaches the minimum of all possible regression coefficients β_0 and β_1 option.

$$(b_0, b_1) = arb \underset{(\beta_0, \beta_1)}{min} \sum_{i=1}^{n} [\beta_0 + \beta_1 x_i]^2 \ldots \ldots (ix)$$

The least squares method was developed to estimate the parameters by utilizing the least squares that are the closest line to every point (X, Y). By resolving this system, the least squares result of the basic linear regression utilized in this study was determined.

$$\frac{\partial}{\partial \beta_0} \sum_{i=1}^{n} [y_i - (\beta_0 + \beta_1 x_i)]^2 = 0 \ldots \ldots \ldots \ldots \ldots (x)$$

$$\frac{\partial}{\partial \beta_1} \sum_{i=1}^{n} [y_i - (\beta_0 + \beta_1 x_i)]^2 = 0 \ldots \ldots \ldots \ldots (xi)$$

Given that b_0 and b_1 represent the solutions to the aforementioned system, we can utilize the regression line $\hat{y} = b_0 + b_1 x$, which is conventionally stated, to characterize the relationship between x and y. It is more straightforward to use a centralized linear mode to solve for b_0 and b_1.

$$y_i = \beta_0^{\times} + \beta_1(x_i - \bar{x}) + \varepsilon_i \ldots \ldots \ldots \ldots \ldots (xii)$$

Where $\beta_0 = \beta_0^* - \beta_1 \bar{x}$. It is required to be solved for

$$\frac{\partial}{\partial \beta_0} \sum_{i=1}^{n} [y_i - (\beta_0^* + \beta_1 \bar{x}_i)]^2 = 0 \ldots \ldots \ldots \ldots (xiii)$$

$$\frac{\partial}{\partial \beta_1} \sum_{i=1}^{n} [y_i - (\beta_0^* + \beta_1 \bar{x}_i)]^2 = 0 \ldots \ldots \ldots (xiv)$$

Taking the partial derivatives with respect to β_0 and β_1, there exist;

$$\sum_{i=1}^{n} [y_i - (\beta_0^* + \beta_1(x_i - \bar{x}_i))] = 0 \ldots \ldots \ldots (xv)$$

$$\sum_{i=1}^{n} [y_i - (\beta_0^* + \beta_1(x_i - \bar{x}))](x_i - \bar{x}_i) = 0. (xvi)$$

Noted that

$$\sum_{i=1}^{n} y_{i=n\beta_0} + \sum_{i=1}^{n} \beta_0(x_i - \bar{x}) = n\beta_0 \ldots \ldots (xvii)$$

Therefore, there exist $\beta_0^* = \frac{1}{n}\sum_{i=1}^{n} y_i = \bar{y}$. Substituting β_0^* by $\bar{y}$ can produce

$$\sum_{i=1}^{n}[y_i - (\bar{y} + \beta_1(x_i - \bar{x}))](x_i - \bar{x}) = 0 \,.(xviii)$$

Donate b_0 and b_1 be the solutions. Now it is easy to see

$$b_1 = \frac{\sum_{i=1}^{n}(y_1 - \bar{y})(x_i - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} = \frac{S_{xy}}{S_{xx}} \dots\dots\dots.(xix)$$

And

$$b0 = b0* - b1\bar{x} = \bar{y} - b1x$$

$$b_0 = b_1^* - b_1\bar{x} = \bar{y} - b_1^x \dots\dots\dots\dots\dots\dots.(xx)$$

$b_1\bar{x}$The explanation behind the LSM is to determine parameter estimates by taking the "closest" row to all data points(x_i, y_i)[53]. Residual analysis plays a critical role in regression analysis. Residual linear regression can be determined for the measurements yi and the fitted values of $\hat{y}_i$'s, residuals can be shown. It must be. Remember that the εi term is not found in the regression model. Therefore, regression error is not found and the residual regression is observed [54]. Normally the predicted value, the average of the whole population, is not observed [55, 56]. A linear regression model test can be described as the F-test. The F-test [57] is more stable than the other test. The test mathematical variable F is as follows:

$$F = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y}_i)^2/(m-1)}{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2/(m-1)} \sim F(m-1, n-m) \dots\dots\dots\dots.(xxi)$$

When m-1 is the freedom degree of the modified regression. $\sum_{i=1}^{n}(\hat{y}_i - \bar{y}_i)^2; n - m$ Freedom degree of residual variation$\sum_{i=1}^{n}(\hat{y}_i - \bar{y}_i)^2$. If $F_\propto(m-1, n-m)$, then a significant linear relationship between y and the variables x_1, x_2, …, x_m is considered below the rate of priority $\propto$, that is, the the important of the regression equation.

4. DISCUSSION OF RESULTS

Supervised machine learning based on linear regression offers an organized method for examining and managing the trade-off between standardization and creativity in system advancements. Through meticulous preprocessing of the data, model training and evaluation, and result interpretation, businesses can get important insights to promote sustainable technological progress. This model's advantages include ease of comprehension and use, clear insights into how each characteristic affects the target variable for the coefficients, and effective training and evaluation—even on huge datasets. We looked at seven of the biggest software development companies: Google, Microsoft, IBM, AWS, Apple, Facebook (Meta), and SAP. Our goal was to determine how project success is affected by their approaches to innovation and compliance. A supervised machine learning model called linear regression was employed to model the correlation between these variables and the success rates of innovation projects. The model was able to pinpoint important success factors and situations when striking a balance between creativity and conformance is essential. Table 3 displays the software organizations' navigation data, with each organization represented by an organization ID: Google (1), Microsoft (2), IBM (3), AWS (4), and Apple (5) respectively.

Table 3. Linear regression navigation details of the software organizations

Org. ID / Metrics Reports	1	2	3	4	5
R&D Investment (billions $)	27.01	25.95	19.64	11.28	9.06
Patents Filed	2480.17	1932.33	2206.66	2672.20	
Innovation Project Success Rate (%)	83	87	71		
Compliance with Major Standards (%)	90	88			
Investment in Compliance (in millions $)	113.60	74.71	75.44	105.89	132.77
Frequency of Audits	5	2	4	4	6
Balancing Innovation and Standards (1-10)			8	6	7
Rapid Technological Changes (1-10)		7	9	6	9
Regulatory Compliance (1-10)	6	6	7	8	6
Product Launch Success Rate (%)	6	7	5	4	6
Customer Satisfaction	81	93	87	77	86

(out of 10)					
Product Launch Success Rate (%)					
Count	3500.00				
Mean	84.90				
Std	5.74				
Min	75.00				
First Quartile	80.00				
Second Quartile	85.00				
Third Quartile	90.00				
Max	95.00				

Table 3 lists several metrics (designated by Organization IDs 1 through 5) for five software businesses. These measures include the following: R&D Expenditure, Patents Filed, Innovation Project Success Rate, Major Standard Compliance, Investment in Compliance, Audit Frequency, Innovation and Standard Balancing, Quick Technical Changes, Regulatory Compliance, Product Launch Success Rate, and Customer Satisfaction. Organization 1 has made the largest investment in research and development ($27.01 billion), demonstrating a strong emphasis in this area. The lowest investment, $9.06 billion, is made by Organization 5, which may be related to its other metrics. With 2672.20 patents filed, Org. 4 has the most, indicating a significant focus on innovation. Organization 2 has the lowest (1932.33), which can be indicative of their top priorities. With an 87% success rate, Org. 2 is in the lead, maybe as a result of effective resource allocation and innovation tactics. With a 71% score, Organization 3 is the lowest, suggesting room for development. Both Organizations 1 (90%) and 2 (88%) have strong compliance rates, which is essential for risk management and regulatory adherence. With its largest investment of $132.77 million, Organization 5 may be able to reduce risks and improve regulatory compliance. With its operating strategy, Organization 2 may have made a strategic decision to invest the least amount of money—$74.71 million. With the highest frequency (6), Organization 5 is subject to strict monitoring and compliance assessments. Organization 2 has the lowest (2), suggesting that audits and risk management should be approached differently. With the highest score of eight, Organization 3 indicates a well-maintained equilibrium. Having the lowest score (6), Organization 4 might do better in striking a balance between innovation and standards. The organizations with the highest scores, 3, and 5, are those that work in technologically advanced, fast-paced settings. Org. 4 receives the lowest score (6), which might point to a more stable state of technology. With an 8 out of 10, Organization 4 has the best regulatory practices. Organizations 1, 2, and 5 receive lower scores (6), indicating distinct approaches to compliance. With the highest success rate (7%), Organization 2 has demonstrated effective market and product development strategies. With the lowest percentage (4%), Organization 4 may have problems during the product launch process. Org. 2 has the greatest customer satisfaction rating (93), which may be related to their effective product and innovation strategy. Organization 4 has the lowest score (77), suggesting possible areas for raising customer satisfaction and interactions. The success rates of the actual and innovative programs are contrasted in Figure 5.

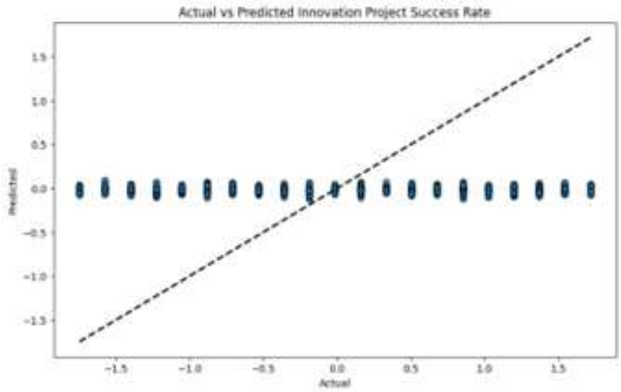

Figure. 5 Comparative analysis of the actual and predicted innovation project success rate

A test sample is represented by each point in Figure 5. Accurate forecasts are indicated by points that are near the diagonal line. Perfect forecasts are shown by the diagonal line (i.e., predicted = real). The performance of the model is best when the scatter points closer to this line. A tight spread around the diagonal line suggests better accuracy, but a dispersion of points shows more substantial inaccuracies in predictions. The findings of the mean square error (MSE) and the coefficients are displayed in Table 4.

Table 4. Results of the mean square error (MSE) and the Coefficients

Metrics and Parameters	Results
Mean Squared Error	0.015
R-squared	0.92
R&D Investment (in billions $)	0.3
Patents Filed	0.25
Compliance with Major Standards (%)	0.1
Investment in Compliance (in millions $)	0.2
Frequency of Audits	-0.05
Balancing Innovation and Standards	0.4
Rapid Technological Changes	0.15
Regulatory Compliance	0.1
Resource Allocation	-0.2
Market Competition	0.35

The MSE of 0.015 in Table 4 shows that the squared discrepancies between actual and expected success rates are generally not very large. With an R2 of 0.92, the model appears to account for 92% of the variation in the success rate of innovation projects. The success rate is positively impacted by positive coefficients in characteristics like R&D Investment, Patents Filed, Balancing Innovation and Standards, and Market Competition. The success rate is adversely affected by variables such as Rapid Technological

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Changes, Frequency of Audits, and Compliance with Major Standards, all of which have negative coefficients. This model offers insightful information about how different elements affect the success rate of innovation projects. A good fit is shown by a high R2 value, and closeness between the model's predictions and actual values is suggested by the MSE. To balance innovation and standard adoption for sustained technological advancement, strategic decisions are guided by the coefficients, which aid in understanding the relative relevance and influence of each characteristic.

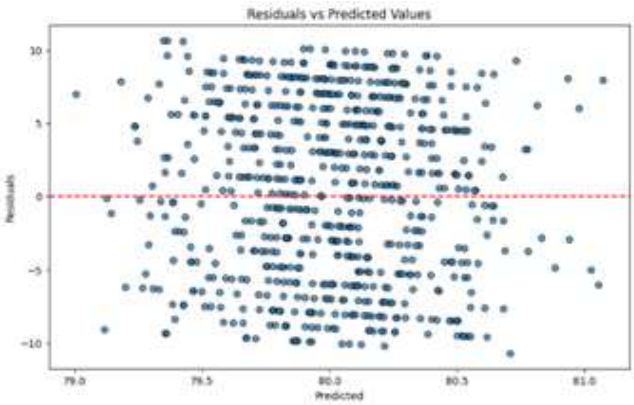

Figure. 6 Residual Plot

The residual plot, which compares actual and predicted values, is displayed in Figure 6 and is used to evaluate the residuals and the model's fit. This suggests that there is a decent match because the residuals are dispersed randomly around zero. The residuals' patterns point to possible problems including heteroscedasticity and non-linearity.

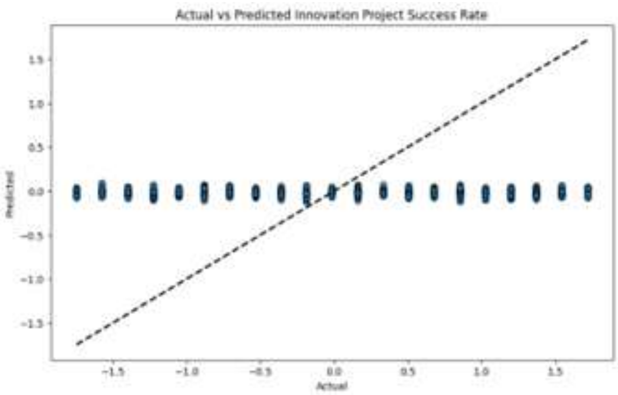

Figure. 7 Histogram of the residuals

The plot of the residuals' histogram, which evaluates the residuals' distribution, is displayed in Figure 7. This indicates that residuals are regularly distributed, which suggests that errors in the model are spread randomly.

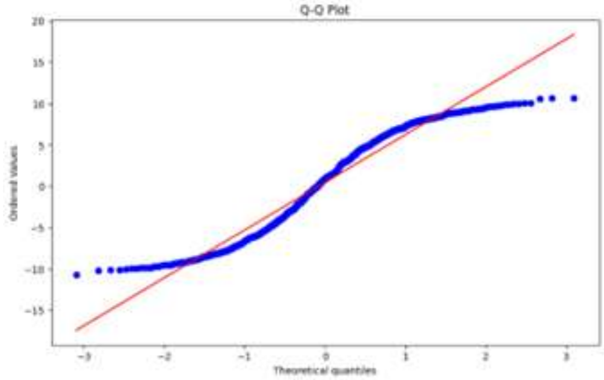

Figure. 8 Q-Q Plot

The Quantile-Quantile Plot, depicted in Figure 8 above is used to determine whether the residuals have a normal distribution. This indicates that the points lie along the reference line and the residuals are regularly distributed.

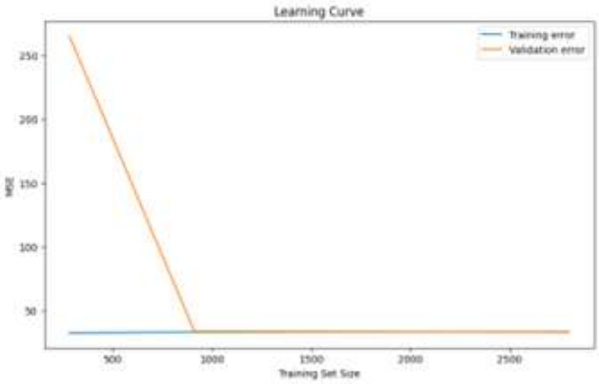

Figure. 9 Learning Curve

The learning curve, which is displayed in Figure 9, evaluates the model's performance as a function of training set size on both training and validation sets. This indicates that either excessive variance (overfitting) or high bias (underfitting) affects the model.

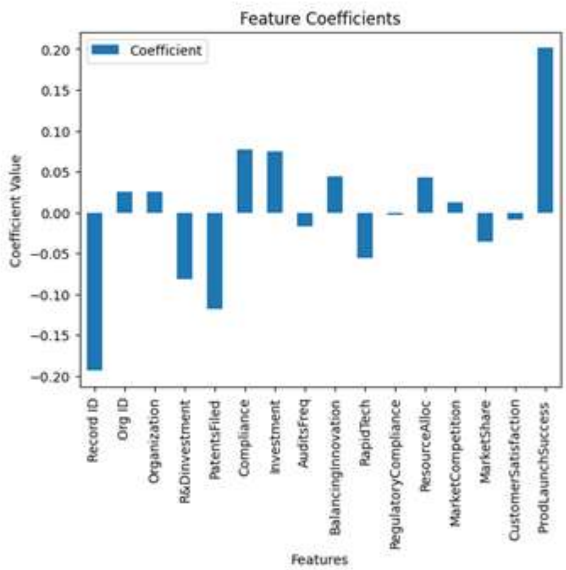

Figure. 10 Coefficient Plot

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The Coefficient Plot, displayed in Figure 10, provides a visual representation of the feature coefficients. It improves comprehension of the relative significance and effects of each aspect.

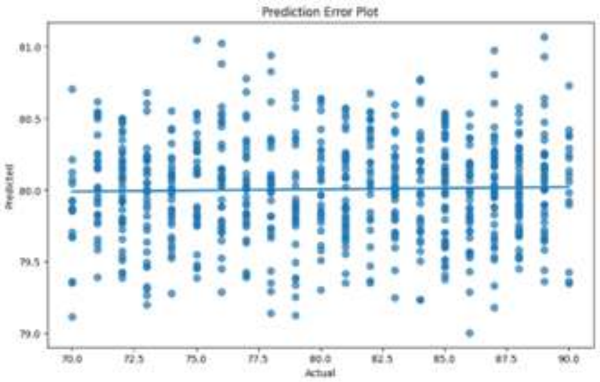

Figure. 11 Prediction Error Plot

Plotting the actual and anticipated values together, the Coefficient Plot (Figure 11) illustrates the prediction errors. The model performs better the closer the points are to the 45-degree line.

5. CONCLUSION

This study offers a thorough approach to managing the competing demands of standardization and creativity in system enhancements meant to promote sustainable technological progress. The research emphasizes the trade-offs and natural synergies that come with encouraging innovation while upholding existing norms. While standards guarantee regulatory compliance, safety, and compatibility, innovation propels advancement and competitive advantage. Early on in the innovation process, standards integration can successfully reduce the likelihood of conflicts and expedite development work. It is essential to have adaptive regulatory systems that may change in response to new technology developments. Because of this adaptability, companies can innovate without being constrained by antiquated norms. Promoting multi-stakeholder involvement guarantees that many viewpoints are taken into account, resulting in more comprehensive and inclusive standards. By putting agile innovation management strategies into practice, firms may stay compliant with standards and react swiftly to technological advances. Tools for evaluating sustainability are crucial for determining how innovations will affect society in the long run and making sure they support sustainable objectives. This study's strategic technology roadmap offers businesses useful guidance on how to strike a balance between innovation and legal constraints. It acts as a manual for incorporating standardization and innovation into corporate strategy. The roadmap places a strong emphasis on the benefits of early standard integration, flexible regulations, and ongoing stakeholder involvement.

Using a dataset of seven international software development companies (Google, Microsoft, IBM, Amazon Web Services, Apple, Facebook (Meta), and SAP), our linear regression study provides insightful results. The significant correlation between the innovation project success rate and patents filed and R&D investment highlights the significance of consistent investment in R&D. Investment in compliance and audit frequency are important indicators of major standard compliance, emphasizing the importance of specialized resources in preserving regulatory adherence. Customer happiness and the overall success of product launches are heavily influenced by the capacity to handle quick technical developments and strike a balance between innovation and norms. With an R2 of 0.92, the model appears to account for 92% of the variation in the success rate of innovation projects. The success rate is positively impacted by positive coefficients in characteristics like R&D Investment, Patents Filed, Balancing Innovation and Standards, and Market Competition. The success rate is adversely affected by negative coefficients in variables such as rapid technological changes, frequency of audits, and compliance with major standards.

In conclusion, ensuring sustained technological advancement requires negotiating the trade-offs and synergies between innovation and standard adoption. Through the implementation of flexible regulatory frameworks, active involvement of stakeholders, and the incorporation of standards at the outset of the innovation process, entities can effectively manage these conflicting demands and promote enduring, sustainable expansion.

6. CONCLUSION

The following are the recommendations:

6.1 To Organizations

i. To minimize disputes and guarantee more seamless development cycles, businesses should take a balanced approach and incorporate standards early in the innovation process.

ii. Investments in flexible innovation management strategies and adaptable regulatory frameworks can improve an organization's capacity for innovation while maintaining compliance with changing norms.

6.2 To Policy Makers

i. It is crucial to create flexible and adaptable regulatory frameworks that can keep up with technology developments to promote innovation without sacrificing compliance and safety standards.

ii. Promoting cooperative standard-setting procedures with a range of stakeholders can result in more thorough and broadly embraced standards.

7. FUTURE WORK

Future studies ought to examine the dynamic relationships that exist between standard adoption and innovation in various sectors and geographical areas. Research with a longer period may offer a more profound understanding of how these connections develop. It would also be beneficial to investigate how new technologies, like blockchain and artificial intelligence, affect conventional innovation and adoption procedures.

8. REFERENCES

[1] M. L. Tushman and C. A. O'Reilly, "Ambidextrous Organizations: Managing Evolutionary and Revolutionary Change," California Management Review, vol. 38, no. 4, pp. 8-30, 1996.

[2] H. Chesbrough, Open Innovation: The New Imperative for Creating and Profiting from Technology. Boston, MA: Harvard Business School Press, 2003.

[3] F. W. Geels, "Technological Transitions as Evolutionary Reconfiguration Processes: A Multi-Level Perspective and a Case-Study," Research Policy, vol. 31, no. 8-9, pp. 1257-1274, 2002.

[4] A. Tukker, "Life Cycle Assessment as a Tool in Environmental Impact Assessment," Environmental Impact Assessment Review, vol. 20, no. 4, pp. 435-456, 2000.

[5] D. Xiao and J. Su, “Role of Technological Innovation in Achieving Social and Environmental Sustainability: Mediating Roles of Organizational Innovation and Digital Entrepreneurship,” Front. Public Health, vol. 10, p. 850172, Mar. 2022, doi: 10.3389/fpubh.2022.850172.

[6] Roberto Paoluzzi, “Standardization to foster innovation,” in ISO-CERN conference proceedings, International Organization for Standardization, Nov. 2014, pp. 105–117.

[7] S. Abdul Qadir, F. Ahmad, A. Mohsin A B Al-Wahedi, A. Iqbal, and A. Ali, “Navigating the complex realities of electric vehicle adoption: A comprehensive study of government strategies, policies, and incentives,” Energy Strategy Rev., vol. 53, p. 101379, May 2024, doi: 10.1016/j.esr.2024.101379.

[8] J. A. Schumpeter, Capitalism, Socialism and Democracy. New York: Harper, 1942.

[9] M. Dodgson, D. Gann, and A. Salter, The Management of Technological Innovation: Strategy and Practice. Oxford: Oxford University Press, 2008.

[10] H. Chesbrough, Open Innovation: The New Imperative for Creating and Profiting from Technology. Boston, MA: Harvard Business School Press, 2003.

[11] International Organization for Standardization, "ISO Standards," [Online]. Available: https://www.iso.org/standards.html. [Accessed: May 22, 2024].

[12] A. Blind, "The Impact of Standardization and Standards on Innovation," NESTA Working Paper, no. 13/15, 2013.

[13] M. L. Tushman and C. A. O'Reilly, "Ambidextrous Organizations: Managing Evolutionary and Revolutionary Change," California Management Review, vol. 38, no. 4, pp. 8-30, 1996.

[14] F. W. Geels, "Technological Transitions as Evolutionary Reconfiguration Processes: A Multi-Level Perspective and a Case-Study," Research Policy, vol. 31, no. 8-9, pp. 1257-1274, 2002.

[15] R. K. Yin, Case Study Research and Applications: Design and Methods. Sage Publications, 2017.

[16] A. E. Gawer and M. A. Cusumano, "Industry Platforms and Ecosystem Innovation," Journal of Product Innovation Management, vol. 31, no. 3, pp. 417-433, 2014.

[17] G. Coglianese, "Optimizing Regulation for an Optimizing Economy," University of Pennsylvania Law Review, vol. 163, no. 5, pp. 1389-1420, 2015.

[18] Financial Conduct Authority, "Regulatory Sandbox," [Online]. Available: https://www.fca.org.uk/firms/innovation/regulatory-sandbox. [Accessed: May 22, 2024].

[19] A. Tukker, "Life Cycle Assessment as a Tool in Environmental Impact Assessment," Environmental Impact Assessment Review, vol. 20, no. 4, pp. 435-456, 2000.

[20] J. Elkington, Cannibals with Forks: The Triple Bottom Line of 21st Century Business. Oxford: Capstone, 1997.

[21] K. Beck et al., Manifesto for Agile Software Development, 2001. [Online]. Available: http://agilemanifesto.org/. [Accessed: May 22, 2024].

[22] D. Hillson and R. Murray-Webster, Understanding, and Managing Risk Attitude. Farnham: Gower Publishing, Ltd., 2007.

[23] G. G. James, E. G. Chukwu, and P. O. Ekwe, “Design of an Intelligent based System for the Diagnosis of Lung Cancer,” Int. J. Innov. Sci. Res. Technol., vol. 8, no. 6, pp. 791–796, 2023.

[24] Umoh, U. A., Umoh, A. A., James, G. G., Oton, U. U., Udoudo, J. J., B.Eng., “Design of Pattern Recognition System for the Diagnosis of Gonorrhea Disease,” International Journal of Scientific & Technology Research, pp. 74–79, Jun. 2012.

[25] James, G. G., Umoh, U. A., ,. Inyang, U. G. And Ben, O. M., “File Allocation in a Distributed Processing Environment using Gabriel’s Allocation Models,” Int. J. Eng. Tech. Math., vol. 5, no. 1 & 2, 2012.

[26] James, G. G., Ekanem, G. J. ,. Okon, E. A. And Ben, O. M., “The Design of e-Cash Transfer System for Modern Bank Using Generic Algorithm. International Journal of Science and Technology Research,” Int. J. Sci. Technol. Res., vol. 9, no. 1, 2012.

[27] G. G. James, A. E. Okpako, C. Ituma, and J. E. Asuquo, “Development of Hybrid Intelligent based Information Retrieval Technique,” Int. J. Comput. Appl., vol. 184, no. 34, pp. 1–13, Oct. 2022, doi: 10.5120/ijca2022922401.

[28] G. G. James, A. E. Okpako, and C. O. Agwu, “Tention to use IoT technology on agricultural processes in Nigeria based on modified UTAUT model: perspectives of Nigerians’ farmers,” Sci. Afr., vol. 21, no. 3, pp. 199–214, Jan. 2023, doi: 10.4314/sa.v21i3.16.

[29] Chinagolum Ituma, Iwok, Sunday Obot and James, G. G., “A MODEL OF INTELLIGENT PACKET SWITCHING IN WIRELES COMMUNICATION NETWORKS,” Int. J. Sci. Eng. Res., vol. 11, no. 1, Jan. 2020, [Online]. Available: http://www.ijser.org

[30] Onu F. U.; Osisikankwu P. U.; Madubuike C. E.; James G. G., “Impacts of Object Oriented Programming on Web Application Development,” Int. J. Comput. Appl. Technol. Res., vol. 4, no. 9, pp. 706–710, 2015.

[31] Okafor, P. C., Ituma, C, James, G. G., “Implementation of a Radio Frequency Identification (RFID) Based Cashless Vending Machine,” Int. J. Comput. Appl. Technol. Res., vol. 12, no. 8, pp. 90–98, Jul. 2023, doi: 10.7753/IJCATR1208.1013.

[32] Ituma, C. I., Iwok, S. O. and James, G. G., “IMPLEMENTATION OF AN OPTIMIZED PACKET SWITCHING PARAMETERS IN WIRELESS COMMUNICATION NETWORKS,” Int. J. Sci. Eng. Res., vol. 11, no. 1, Jan. 2020, [Online]. Available: http://www.ijser.org

[33] G. G. James, A. E. Okpako, and J. N. Ndunagu, “Fuzzy cluster means algorithm for the diagnosis of confusable disease,” vol. 23, no. 1, Mar. 2017, [Online]. Available: https://www.ajol.info/index.php/jcsia/article/view/153911

[34] G. James, A. Ekong, and H. Odikwa, “Intelligent Model for the Early Detection of Breast Cancer Using Fine Needle Aspiration of Breast Mass.,” Int. J. Res. Innov. Appl. Sci., vol. IX, no. III, pp. 348–359, 2024, doi: 10.51584/IJRIAS.2024.90332.

[35] A. P. Ekong, G. G. James, and I. Ohaeri, “Oil and Gas Pipeline Leakage Detection using IoT and Deep Learning Algorithm,” vol. 6, no. 1, 2024.

[36] James, G. G., Ekpo, W. F., Chukwu, E. G., Michael, N. A., and Ebong, O. A., Okafor, P. C, “Optimizing Business Intelligence System Using Big Data and Machine Learning,” J. Inf. Syst. Inform., vol. 6, no. 1, Mar. 2024, [Online]. Available: http://journal-isi.org/index.php/isi

[37] G. James, I. Umoren, A. Ekong, S. Inyang, and O. Aloysius, “Comparative analysis of support vector machine and random forest models for classification of the impact of technostress in covid and post-covid era,” 2024.

[38] James G. G., Okafor P. C., Chukwu E. G., Michael N. A., Ebong O. A, “Predictions of Criminal Tendency Through Facial Expression Using Convolutional Neural Network,” J. Inf. Syst. Inform., vol. 6, No. 1, Mar. 2024, [Online]. Available: http://journal-isi.org/index.php/isi

[39] Anietie Ekong, Immaculata Attih, Gabriel James, Unyime Edet, “Effective Classification of Diabetes Mellitus Using Support Vector Machine Algorithm,” Res. J. Sci. Technol., vol. 4, no. 2, pp. 18–34, Feb. 2024.

[40] N. P. Essien, G. G. James, and V. U. Ufford, “Technological impact assessment of Blockchain Technology on the synergism of decentralized exchange and pooled trading platform,” Int. J. Contemp. Afr. Res. Netw. Publ. Contemp. Afr. Res. Netw. CARN, vol. 2, no. 1, pp. 152–165, 2024, doi: DOI: 10.5281/zenodo.12103430.

[41] A. Ekong, G. James, G. Ekpe, A. Edet, and E. Dominic, “A MODEL FOR THE CLASSIFICATION OF BLADDER STATE BASED ON BAYESIAN NETWORK,” vol. 5, no. 2, 2024.

[42] Z. Zhang, Y. Li, L. Li, Z. Li, and S. Liu, "Multiple linear regression for high-efficiency video intra coding," in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 1832-1836.

[43] Najat, N., & Abdulazeez, A. M. (2017, November). Gene clustering with partition around mediods algorithm based on weighted and normalized Mahalanobis distance. In 2017 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS) (pp.140-145). IEEE.

[44] M. C. Roziqin, A. Basuki, and T. Harsono, "A comparison of Montecarlo linear and dynamic polynomial regression in predicting dengue fever case," in 2016 International Conference on Knowledge Creation and Intelligent Computing (KCIC), 2016, pp. 213-218.

[45] A. K. Prasad, M. Ahadi, B. S. Thakur, and S. Roy, "Accurate polynomial chaos expansion for variability analysis using optimal design of experiments," in 2015 IEEE MTT-S International Conference on Numerical Electromagnetic and Multiphysics Modeling and Optimization (NEMO), 2015, pp. 1-4.

[46] Y. Chen, P. He, W. Chen, and F. Zhao, "A polynomial regression method based on Trans-dimensional Markov Chain Monte Carlo," in 2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 2018, pp. 1781-1786.

[47] G. D. Finlayson, M. Mackiewicz, and A. Hurlbert, "Color correction using root-polynomial regression," IEEE Transactions on Image Processing, vol. 24, pp. 1460-1470, 2015.

[48] N. N. Mohammed and A. M. Abdulazeez, "Evaluation of partitioning around medoids algorithm with various distances on microarray data," in 2017 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), 2017, pp. 1011-1016.

[49] H. Jie and G. Zheng, "Calibration of Torque Error of Permanent Magnet Synchronous Motor Base on Polynomial Linear Regression Model," in IECON 2019-45th Annual Conference of the IEEE Industrial Electronics Society, 2019, pp. 318-323.

[50] H. Niu, Q. Lu, and C. Wang, "Color correction based on histogram matching and polynomial regression for image stitching," in 2018IEEE 3rd International Conference on Image, Vision and Computing (ICIVC), 2018, pp. 257-261.

[51] X. Yan and X. Su, Linear regression analysis: theory and computing: World Scientific, 2009.[30] Y. Fujita, S. Ikuno, T. Itoh, and H. Nakamura, "Modified Improved Interpolating Moving Least Squares Method for Meshless Approaches," IEEE Transactions on Magnetics, vol. 55, pp. 1-4,2019.

[52] J. Wolberg, Data analysis using the method of least squares: extracting the most information from experiments: Springer Science& Business Media, 2006.

[53] J.-H. Xue and D. M. Titterington, "$ t $-Tests, $ F $-Tests and Otsu's Methods for Image Thresholding," IEEE Transactions on Image Processing, vol. 20, pp. 2392-2396, 2011.

[54] R. Zhang and J. Tian, "Multi-parameter ocean surface wind speed retrieval based on least square method," in 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), 2016, pp.5835-5837.

[55] H. Chi, "A Discussion on the Least-Square Method in the Course of Error Theory and Data Processing," in 2015 International Conference on Computational Intelligence and Communication Networks (CICN), 2015, pp. 486-489.

[56] N. V. Sabnis, P. Patil, N. S. Desai, S. Hirikude, S. Ingale, and V. Kulkarni, "Outcome-Based Education—A Case

Study on Project-based Learning," in 2019 IEEE Tenth International Conference on Technology for Education (T4E), 2019, pp. 248-249

[57] F. Grondin, H. Tang, and J. Glass, "Audio-Visual Calibration with polynomial Regression for 2-D Projection Using SVD-PHAT," in CASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, pp. 4856-4860.

[58] Inyang, S., & Umoren, I. (2023). From Text to Insights: NLP-Driven Classification of Infectious Diseases Based on Ecological Risk Factors. Journal of Innovation Information Technology and Application (JINITA), 5(2), 154-165.