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**An Empirical Model for Forecasting Technology  
Commercialization Performance of Software Products in  
Universities Using Genetic Programming**

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**An Empirical Model for Forecasting Technology Commercialization Performance of Software Products in Universities Using Genetic Programming**

**Abstract**

**Purpose** - This research aimed to develop a predictive model using genetic programming (GP) to assess the technology commercialization performance (TCP) of software products in university settings.

**Methodology** – The prediction model was developed using historical technology commercialization data from Nigerian university commercialization centers through the application of GP. Comparative analyses were conducted to assess the results of the GP model against Artificial Neural Network and Support Vector Machine models. Evaluation metrics such as relative root mean squared error, root mean absolute error, mean absolute percentage error, and coefficient of determination were employed to gauge the accuracy of the models.

**Findings** - The GP model exhibited a coefficient of determination of 0.9854 and 0.9564 for the training and testing data, respectively. The comparison of the models using the evaluation metrics demonstrated that the GP model is superior in its accuracy for forecasting the TCP of software products in university commercialization centers.

**Originality** - This research has developed a new mathematical equation that depicts the relationship between TCP and its influential factors. This aspect has not been explored in previous research. Professionals can use the GP model to strategically allocate resources and improve the commercialization of software products.

**Keywords** Prediction, Technology commercialization, Performance, Genetic programming, Innovation, Universities

**1. Introduction**

Enabling the growth and competitiveness of organizations relies on the vital components of technology development and commercialization. Organizations foster their advancement and enhance their competitive advantage by introducing new products that fulfill market demands and meet future customer needs (Kaczmarska *et al.*, 2021). Organizations rely on various resources, including human and financial capital, along with valuable expertise, to drive developmental activities (Pujotomo *et al.*, 2023). Universities are recognized as pivotal players in the innovation cycle, but they face significant hurdles in attaining their goals of promoting innovation and fostering economic growth by transforming new ideas into innovative products or technologies (Memon *et al.*, 2022).

In African developing countries, funding for emerging organizations falls significantly short of global benchmarks in capital availability, implementation rigor, and the criteria employed to identify suitable candidates for financial assistance (Afful-Dadzie *et al.*, 2017). Despite the obstacles faced by entities such as Nigerian universities, industries, and research centers, the government is actively taking measures to incentivize universities to transform their research outcomes into commercial value. This initiative aims to generate revenue, enhance the knowledge-based economy, and stimulate technological and economic growth (Binuyo and Alimi, 2017). The technologies being assessed for development and commercialization in Nigerian universities within the scope of this study are software products. The development and commercialization of these products have garnered significant attention from the Nigerian government. The government aims to utilize various organizations to tackle the challenges of inadequate infrastructure, soaring unemployment rates, and a struggling economy prevalent in the information technology sector (Ajibo *et al.*, 2019).

The process of commercialization commences with the emergence of an innovative concept within an organization and culminates with the successful introduction of the new product to the market (Min *et al.*, 2019). [Technology commercialization performance \(TCP\) refers to the measurement and evaluation of how effectively and successfully a technology or innovation is brought from the research and development \(R&D\) stage to the market as a viable and profitable product.](#) This evaluation is crucial for understanding the effectiveness of efforts to transform scientific or technological advancements into tangible economic and societal benefits (Nugent and Chan, 2023). [TCP is essential for universities to maximize the impact of their research, generate economic value, and strengthen their role as innovation hubs. By enhancing TCP, universities can accelerate the translation of research into real-world applications, fostering sustainable development and technological progress. Also, effective TCP strengthens university-industry collaborations \(Pujotomo \*et al.\*, 2023\). A TCP model assists policymakers and governments in determining which organizations to support and the extent to which they should be supported. Additionally, it serves as a tool to evaluate an organization's potential for future competitiveness and economic growth \(Altuntas and Dereli, 2012\).](#)

However, decision-makers find it challenging to measure the economic worth of products developed by universities due to the improper allocation of resources linked to the successful commercialization of products. Additionally, the assessment of TCP in any organization mostly depends on expert intuition (Kim *et al.*, 2021). Nevertheless, such approaches are time-consuming, inaccurate, and labor-intensive as the number of products and the intricacy of innovations expand. A valid model for the evaluation of technology commercialization is needed to forecast future outcomes vis-à-vis the results obtained from the evaluation of the factors or criteria that impact TCP (Noh *et al.*, 2018). The relationships between these criteria (input variables) and their impacts on the commercialization process are crucial. [Genetic programming](#)

(GP) as a machine learning method is an integral part of evolutionary computing that generates computer expressions for problem-solving and prediction purposes. GP also offers the additional advantage of higher accuracy (Fallahpour *et al.*, 2021).

Existing models for evaluating and predicting TCP in universities often rely on traditional statistical techniques (Abdul Razak and Murray, 2017; Kang *et al.*, 2013), expert-driven assessments (Afful-Dadzie *et al.*, 2017; Altuntas and Dereli, 2012; Cho and Lee, 2013; Shu *et al.*, 2023; Yazdimoghaddam *et al.*, 2018), and other techniques (Bhatnagar *et al.*, 2020; Kim *et al.*, 2021; Wang *et al.*, 2025), which may lack adaptability and predictive accuracy in dynamic market environments. Additionally, these models do not formulate a mathematical expression that captures complex and nonlinear relationships between commercialization success and its influencing factors. To overcome the limitations of the previous methods, GP will be proposed in this research to develop a more accurate mathematical model that portrays the correlation between the input variables (criteria affecting technology commercialization) and the output variable (TCP).

As far as the authors are aware, there is a scarcity of studies that have applied GP to develop a predictive model for evaluating the TCP of software products in a university commercialization center. Hence, the research question of this study is how such a model can be developed using GP and what is its accuracy as compared to other machine learning models. Having said this, the objectives of this research are to develop a predictive model for assessing the TCP of software products in university settings using GP and to validate the accuracy of the model through comparative analysis with artificial neural network (ANN) and support vector machine (SVM). The absence of a mathematical model in the literature to predict TCP based on a set of input variables has motivated the authors to conduct this research. The significant novelty or contribution of this research is the introduction of the GP approach to evaluate the TCP of software products in universities. This study utilized GP to create a mathematical predictive model that provides a tangible platform for decision-makers to make informed choices based on data rather than relying only on gut feeling.

**2. Literature Review**

Assessing TCP involves collecting data, analyzing key metrics, and comparing the outcomes against predefined success criteria. This process enhances decision-making, resource allocation, and future strategies to improve the commercialization process and achieve the desired outcomes (Afful-Dadzie *et al.*, 2017; Binuyo and Alimi, 2017). The indicators for assessing TCP include financial returns, market penetration, time to market, economic impact, partnerships, and social and environmental impact (Fadeyi *et al.*, 2019). Various models for technology

commercialization have been suggested by prior studies according to their goals and directions. Numerous qualitative and quantitative methods have been proposed for assessing TCP.

Kim *et al.* (2021) suggested using a random forest method to evaluate the economic worth of products developed by universities and used quantitative criteria as the independent variables. The model was validated as an important supplementary tool for appraising products originating from universities based on its statistical results. Shu *et al.* (2023) developed an evaluation model using the VIKOR method to analyze the commercial viability of energy storage technologies. This model proved instrumental in facilitating informed decisions regarding the optimal selection of energy storage technologies. An evaluation index system was developed by Altuntas and Dereli (2012) for the prediction of technology commercialization in investment projects. They applied fuzzy DEMATEL and fuzzy analytic network process to assess the interrelationships among the factors and the weights of each factor, respectively. Moreover, the index value was obtained by applying beta distribution to find the average value of individual factor based on the experts' opinions. The findings of the illustrative case showed that the suggested index system could forecast the commercialization prospects of an investment project based on expert assessment.

Abdul Razak and Murray (2017) determined the significance of innovation strategies in predicting successful commercialization in a public university using hierarchical multiple regression analysis. The findings indicated that effective strategic leadership and the adoption of open innovation strategies emerged as robust indicators of successful commercialization. However, according to this study, collaborative advantage had little impact on commercialization success. A logistic regression model was applied by Kang *et al.* (2013) to evaluate the TCP of large and small firms in Korea. The model's dependent variable was determined by the quantity of products launched by the firms into the market within the preceding 3 years. The outcomes of the logistic regression in the study revealed that some government initiatives considerably improve the success of technology commercialization. Sutopo *et al.* (2022) developed a data envelopment analysis model to estimate the efficacy of technology transfer offices and expedite the transition of research outcomes from universities into market-ready innovations. Yazdimoghaddam *et al.* (2018) designed a fuzzy expert system for early-stage prediction of technology commercialization success before implementation. The model's accuracy was assessed at 73% through the hold-out validation method and it was determined to be highly accurate in forecasting commercialization success.

Also, Yazdimoghaddam *et al.* (2019) studied the factors that contribute to successful technology commercialization and ranked them based on their relative importance. They further developed a scoring model to evaluate TCP. The relationships among technology commercialization success factors were determined using interpretive structural modeling (ISM). ANN with a cascade network was applied by Bhatnagar *et al.* (2020) to forecast the number of

successful new products to be introduced in manufacturing industries. The ANN exhibited great performance outcomes, and the cascading approach improved accuracy and convergence capability. Cho and Lee (2013) developed a scoring model for evaluating the commercial opportunities of new technology products utilizing the Delphi approach and fuzzy AHP. Afful-Dadzie *et al.* (2017) analyzed the commercial viability of start-up enterprises in a government technology venture capital initiative by adopting a modified Strategic Technology Evaluation Program (STEP) model. They employed a robust intuitionistic fuzzy TOPSIS model to assess the modified STEP parameters at the preliminary stage of evaluation. The results revealed that the decision-making framework might be beneficial in other government priority sectors.

A framework was developed by Wang *et al.* (2025) through the integration of absorptive capacity theory and “ladder-like” technological structure to determine the technology transfer and innovation efficiency of a large emerging economy. The study's findings revealed that both domestic and imported technologies collaboratively enhance the efficiency of domestic innovation, while the interplay between domestic and foreign direct investment technologies does not yield positive results. Also, Kruger and Steyn (2024) examined the role of innovation mechanisms in enhancing innovation capabilities within university ecosystems, with a specific focus on the African context. Their study found that initiatives such as makerspaces within universities serve as vital enablers for fostering innovation during the design phase and promoting collaborative efforts.

Table I. Methods used by previous studies for the prediction or evaluation of TCP

Source: Authors own work

| Authors                             | Methods used for predicting or evaluating TCP                                                   |
|-------------------------------------|-------------------------------------------------------------------------------------------------|
| Kim <i>et al.</i> (2021)            | Random forest                                                                                   |
| Shu <i>et al.</i> (2023)            | VIKOR                                                                                           |
| Altuntas and Dereli (2012)          | Fuzzy DEMATEL and fuzzy analytic network process                                                |
| Abdul Razak and Murray (2017)       | Hierarchical multiple regression analysis.                                                      |
| Kang <i>et al.</i> (2013)           | Logistic regression model                                                                       |
| Sutopo <i>et al.</i> (2022)         | Data envelopment analysis                                                                       |
| Yazdimoghaddam <i>et al.</i> (2018) | Fuzzy expert system                                                                             |
| Yazdimoghaddam <i>et al.</i> (2019) | ISM                                                                                             |
| Bhatnagar <i>et al.</i> (2020)      | ANN                                                                                             |
| Cho and Lee (2013)                  | Scoring model                                                                                   |
| Afful-Dadzie <i>et al.</i> (2017)   | Intuitionistic fuzzy TOPSIS                                                                     |
| Wang <i>et al.</i> (2025)           | Framework (integration of absorptive capacity theory and “ladder-like” technological structure) |
| Kruger and Steyn (2024)             | Conceptual framework                                                                            |
| This study                          | GP                                                                                              |

Various techniques have been used to predict or evaluate TCP, as summarized in Table I. Random forest and ANN can model complex nonlinear relationships between variables. However, they lack interpretability, making it difficult to derive explicit mathematical relationships (Öztürk and Başar, 2022; Zema *et al.*, 2024). TOPSIS, VIKOR, and ISM are useful in prioritizing commercialization factors when multiple conflicting criteria exist, but they require

expert judgment, which may introduce bias into the decision-making process. These techniques are less effective in handling large, complex datasets compared to machine learning models (Shu *et al.*, 2023; Thakkar, 2021). The integration of Fuzzy DEMATEL and fuzzy analytic network process effectively captures interdependence and causal relationships among decision factors. However, this method is not meant for performance prediction (Thakkar, 2021).

Furthermore, multiple regression analyzes the influence of several independent variables on a dependent variable but has limitations in handling complex, nonlinear commercialization scenarios due to its assumption of linear relationships (Zema *et al.*, 2024). Likewise, a logistic regression model may not effectively capture highly nonlinear relationships in TCP forecasting. Data envelopment analysis compares and measures the performances of multiple decision-making units in commercialization, but falls short in performance prediction when there is only one decision-making unit in place (Sutopo *et al.*, 2022). Scoring models assign weights to predefined factors and generate a final score, making them straightforward to implement and interpret but they have limited ability to capture complex relationships. Although conceptual frameworks provide a theoretical foundation and systematic approach to TCP analysis, they are not designed for quantitative forecasting (Kruger and Steyn, 2024).

Generally, the limitation of these techniques is that the relationship between the variables is unclear, making it difficult for decision-makers to examine the impact of individual input variable on the resulting output. GP is a data-driven forecasting approach that can generate an equation or mathematical model linking the output and input variables (Jamei and Ahmadianfar, 2020). However, there is a dearth of research applying GP to predict the technology commercialization performance of software products in university commercialization centers. To address this limitation, this research proposes the application of GP to build a mathematical model that elucidates the correlation between input and output variables. It is also necessary to assess the robustness and accuracy of the proposed model.

### 3. Methodology

This section explains the data collection and analysis process. It also presents an overview of the proposed GP, ANN, and SVM models along with the parameters used to evaluate their performance.

#### 3.1. Data collection

The factors or criteria influencing technology commercialization performance, as outlined by Olawore *et al.* (2023), were adopted in this study. Based on literature reviews, they identified and streamlined a set of influential factors influencing the process of commercializing software

products within university commercialization centers. These factors include funding, marketing, intellectual property (IP) protection, R&D capability, knowledge-sharing culture, networking, entrepreneurial capability, and distinctive features. Subsequently, the Delphi method was employed to examine and evaluate these factors. A set of questionnaires was distributed to a panel of 12 experts, which included 7 from academia and 5 from industry. Furthermore, the experts assessed the suitability of the evaluation parameters linked to these factors. The experts were given a new questionnaire for further assessment after being informed about the responses of other experts. The experts refined the factors under consideration until a consensus was reached among them.

Data collection involved visiting 11 university commercialization centers in Nigeria and conducting interviews with their representatives. The selection of centers was based on consultations with commercialization centers to ensure that only actively engaged institutions were included. The interviews were focused on getting the required software commercialization data and records. Confidentiality and anonymity were prioritized to foster openness in responses. The data provided by the representatives were based on the recommended factors or criteria and evaluation parameters that were established from the Delphi study (as provided in Table II). The input variables ( $x$ ) are the factors that influence the TCP of a software product, and the output variable ( $y$ ) is the total income generated from licensing fees and sales of a software product. A total of 75 datasets were collected from the university commercialization centers for these input and output variables, which were considered sufficient for predictive modeling using GP (Shen *et al.*, 2021).

Table II. The evaluation parameter of each criterion and technology commercialization performance

Source: Authors own work

| Criteria                            | Evaluation parameter                                                                                                                                                                                       |
|-------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Funding ( $x_1$ )                   | The funding allocated by an organization to support the development and commercialization of a software product. It is expressed in US dollar (\$) equivalent.                                             |
| Marketing ( $x_2$ )                 | The marketing expenditure of an organization for promoting and selling a software product. It is expressed in US dollar (\$) equivalent.                                                                   |
| Motivational aids ( $x_3$ )         | The monetary rewards or incentives given by an organization to the employees who are engaged in the development and commercialization of a software product. It is expressed in US dollar (\$) equivalent. |
| IP protection ( $x_4$ )             | The number of intellectual property rights obtained for a software product.                                                                                                                                |
| R&D capability ( $x_5$ )            | The number of competent R&D employees that are engaged in the development of a software product.                                                                                                           |
| Knowledge-sharing culture ( $x_6$ ) | The total number of intellectual discourses, conferences, workshops, and training on R&D and entrepreneurship that is coordinated or funded by an                                                          |

|                                                  |                                                                                                                                                                                                                                   |
|--------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                                                  | organization for its personnel in developing and commercializing a software product.                                                                                                                                              |
| Networking ( $x_7$ )                             | The number of active industrial collaborations with an organization for the development and commercialization of a software product.                                                                                              |
| Entrepreneurial capability ( $x_8$ )             | A 5-point Likert scale is applied to evaluate the extent of the entrepreneurial capability of an organization in developing and commercializing a software product (1 = very low, 2 = low, 3 = average, 4 = high, 5 = very high). |
| Distinctive features ( $x_9$ )                   | A 5-point Likert scale is applied to evaluate the level of uniqueness of the features of a software product in supporting its commercialization (1 = very low, 2 = low, 3 = average, 4 = high, 5 = very high).                    |
| Technology commercialization performance ( $y$ ) | The total income generated from licensing fees and sales of a software product. It is expressed in US dollar (\$) equivalent.                                                                                                     |

Note: The term “organization” in Table II implies a university.

The data were collected from Nigerian universities due to the government’s efforts to diversify Nigeria's economy from a commerce-focused type to a flourishing high-tech knowledge economy (Binuyo and Alimi, 2017). Thus, collecting data on TCP in Nigerian universities was a fundamental step in enhancing their contribution to innovation, economic development, and the knowledge-based economy. Table III provides an overview of the statistical analysis conducted on the collected data, highlighting parameters like mean, standard deviation, skewness, kurtosis, and coefficient of variation. The dataset was partitioned into training (or learning) and testing sets, with 80% used for learning and the remaining 20% for testing based on the recommendation of Shen *et al.* (2021) and Zhou *et al.* (2020) to avoid overfitting problems in the analysis.

Table III. Statistical assessment of the datasets

Source: Authors own work

| Variables                | $x_1$    | $x_2$   | $x_3$    | $x_4$ | $x_5$ | $x_6$ | $x_7$ | $x_8$ | $x_9$ | $y$       |
|--------------------------|----------|---------|----------|-------|-------|-------|-------|-------|-------|-----------|
| Maximum                  | 51846.06 | 9277.54 | 24447.61 | 1.00  | 12.00 | 14.00 | 9.00  | 5.00  | 5.00  | 149024.53 |
| Minimum                  | 8990.70  | 1761.98 | 7682.89  | 0.00  | 4.00  | 4.00  | 2.00  | 3.00  | 2.00  | 22000.27  |
| Range                    | 42855.36 | 7515.55 | 16764.72 | 1.00  | 8.00  | 10.00 | 7.00  | 2.00  | 3.00  | 127024.27 |
| Median                   | 15432.92 | 4855.52 | 12090.71 | 1.00  | 6.00  | 7.00  | 4.00  | 5.00  | 4.00  | 50085.11  |
| Mean                     | 20892.43 | 5158.59 | 13879.63 | 0.79  | 5.67  | 7.43  | 4.15  | 4.53  | 3.69  | 60770.33  |
| Standard deviation       | 11313.49 | 2207.28 | 4919.82  | 0.41  | 1.24  | 2.05  | 1.26  | 0.62  | 0.80  | 31005.45  |
| Skewness                 | 1.05     | 0.25    | 0.77     | -1.40 | 1.96  | 0.96  | 0.50  | -0.97 | 0.29  | 0.92      |
| Kurtosis                 | -0.02    | -0.98   | -0.68    | 0.04  | 8.28  | 0.87  | 1.63  | -0.02 | -0.85 | 0.08      |
| Coefficient of variation | 0.54     | 0.43    | 0.35     | 0.52  | 0.22  | 0.28  | 0.30  | 0.14  | 0.22  | 0.51      |

### 3.2. Genetic programming

GP is an optimal approach used to develop mathematical models for problems. It operates according to the theory of Darwin’s natural selection. GP involves the selection and generation

of computer programs by employing the principles of natural selection (Iqbal *et al.*, 2020). The approach relies on genetic mechanisms like reproduction, crossover, and mutation to iteratively evolve optimal solutions (Abdelkader *et al.*, 2018; Wang *et al.*, 2022). An individual generated randomly in GP requires a set of structured parse trees (as shown in Figure 1) containing functions and terminals (Jamei and Ahmadianfar, 2020). The function set includes arithmetic functions (−, +, ÷, ×), trigonometric functions (cos, sin, tan, cot, sec, csc), logarithmic functions (ln, log), or Boolean functions (AND, OR, NOT). The terminal set consists of constants and independent variables of the model. Thus, the terminals and functions together form the computer programs that are randomly selected (Citakoglu *et al.*, 2020).

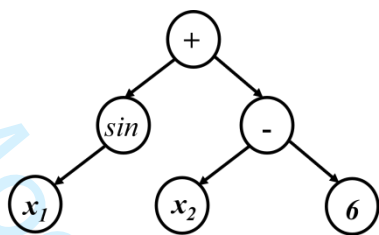


Figure 1. A typical example of a parse tree in the GP model is expressed as:  $\sin x_1 + (x_2 - 6)$   
**Source:** Authors own work

Three initialization methods namely; grow, full, and ramp half-and-half are used to randomly generate computer programs. For a more comprehensive understanding of these initialization techniques, readers can refer to McDermott and O'Reilly (2015). The fitness of computer programs is calculated by employing a fitness function. The fittest computer programs, which have the best RMSE values, are chosen from the initial generation to produce new individuals. The crossover and mutation operators are then successively and repeatedly applied to produce new computer programs for evaluation in the succeeding generation until the termination criterion is met (Jamei and Ahmadianfar, 2020). The steps involved in GP are outlined in Figure 2.

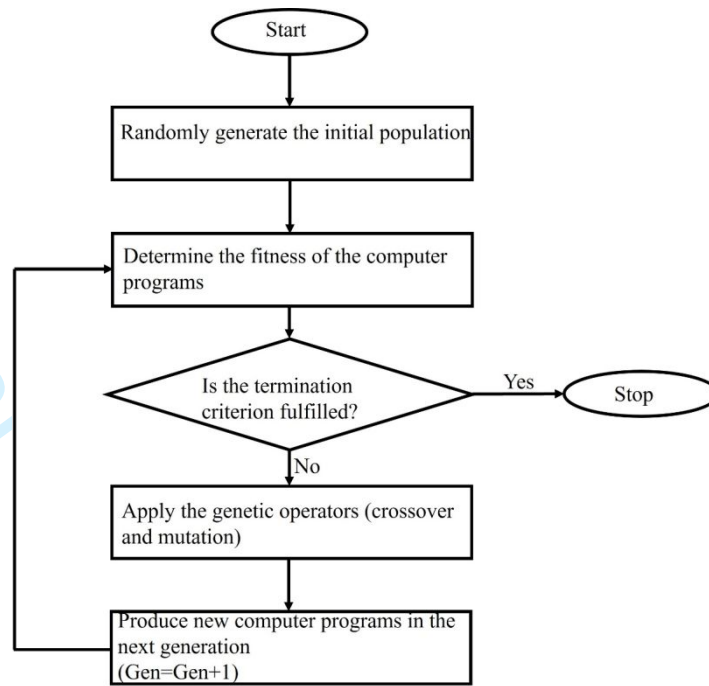


Figure 2. The fundamental framework of GP methodology.

**Source:** Authors own work

In this research, the GP model was developed using GPLAB (a specialized MATLAB toolbox designed for GP research and applications). The GP parameters used in this research are presented in Table IV. Mathematical operators such as multiplication ( $\times$ ), addition ( $+$ ), division ( $\div$ ), subtraction ( $-$ ), and natural logarithm ( $\ln$ ) were applied as the function sets of the model. These functions were selected through an iterative trial-and-error process, where the input variables and random numbers between 0 and 1 were defined as the terminal sets (Silva *et al.*, 2012). The population of computer programs was randomly initialized using the ramp half-and-half technique because the maximum tree depth notably influences the initialization process. Fang *et al.* (2021) recommended a maximum tree depth of 6 to reduce complexity while improving performance quality. The ramp half-and-half initialization approach demonstrated superior performance compared to other initialization approaches (Fang *et al.*, 2021). Therefore, this approach was employed in the current study to build the GP model.

Table IV. Parameters used for GP

**Source:** Authors own work

| Parameters                    | Values                                                                      |
|-------------------------------|-----------------------------------------------------------------------------|
| Function set                  | $\times$ , $+$ , $-$ , $\div$ , $\ln$                                       |
| Terminal set                  | rand, $x_1$ , $x_2$ , $x_3$ , $x_4$ , $x_5$ , $x_6$ , $x_7$ , $x_8$ , $x_9$ |
| Maximum number of generations | 30                                                                          |
| Population size               | 1000                                                                        |
| Initialization method         | Ramp half-and-half                                                          |
| Fitness function              | RMSE                                                                        |
| Selection method              | Lexicographic parsimony pressure                                            |

|                            |     |
|----------------------------|-----|
| Initial maximum tree depth | 6   |
| Crossover rate             | 85% |
| Mutation rate              | 15% |

The population size and number of generations were chosen to be 1000 and 30, respectively. After conducting several trial-and-error efforts, these values were found to perform appropriately in this research. The selection of RMSE as the fitness function was in accordance with the recommendation of Shen *et al.* (2021). It was used to assess fitness values, and the computer programs with the best RMSE were chosen to evolve new computer programs. The lexicographic parsimony pressure method was employed in this research to improve parse tree sizes. Faradonbeh *et al.* (2016) recommended that the method was highly effective in mitigating the bloat phenomenon. A crossover probability of 85% was opted for, in accordance with the recommendation of researchers who proposed that a crossover probability ranging from 80% to 90% can be employed in constructing a GP model to expedite convergence and enhance the exploration of the solution space (Faradonbeh *et al.*, 2016; Yong *et al.*, 2021). A 15% mutation probability was applied to ensure the model maintains diversity and avoids premature convergence. The evolution process stopped when the termination criterion (number of generations) was fulfilled as suggested by Faradonbeh *et al.* (2016).

3.3. Artificial neural network

ANNs are computational algorithms that mimic and process information in a manner similar to the nervous system. As depicted in Figure 3, the fundamental architecture of an ANN consists of an input layer, one or more intermediate hidden layers, and an output layer. The 9 inputs are connected to the hidden layer via the neurons and each input value ( $x_i$ ) is multiplied by a corresponding weight. These weighted products are aggregated, processed by a transfer function, and transformed into an output (Öztürk and Başar, 2022). In this research, a feed-forward backpropagation neural network featuring one hidden layer with an output layer was applied. This choice was made based on the regression features of the research problem. The chosen learning algorithm in this study was Levenberg-Marquardt (*trainlm*), due to its popularity and reliability for ANN training, especially in scenarios where fast convergence and robustness are crucial (Conde-Gutiérrez *et al.*, 2023). The hidden neurons used the hyperbolic tangent activation function (*tansig*), while the output layer used a linear activation function (*purelin*) (Abdullah *et al.*, 2019).

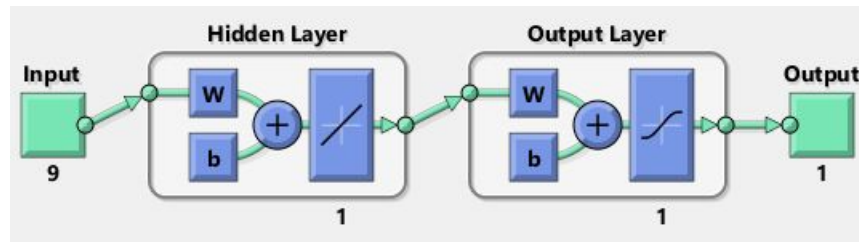


Figure 3. The architecture of the neural network for the prediction of TCP

Source: Authors own work

Fang *et al.* (2021) used a network with  $i$  inputs that required a maximum of  $2i + 1$  hidden nodes in their research to effectively address the overfitting and underfitting of a model. This study applied a trial-and-error process to verify the optimal network architecture from a hidden layer in the potential networks with the number of nodes ranging from 1 to  $2i + 1$ . Hence, several ANN models, ranging from those with 1 to 19 hidden neurons were considered because there were 9 input variables ( $i = 9$ ) in this research. These models underwent a training learning rate of 0.05 with 5000 epochs (Abdullah *et al.*, 2019). The performance during training and testing was assessed using the relative root mean squared error (RRMSE) and coefficient of determination ( $R^2$ ) as the evaluation metrics. Upon completing the training process, the ANN models were evaluated to identify the optimal number of neurons (Rao *et al.*, 2018). Furthermore, a straightforward ranking approach was employed to choose the network that demonstrates the best performance on the training and testing data (Zhou *et al.*, 2020). The models were ranked by their RRMSE values in ascending order, while their  $R^2$  values were prioritized from highest to lowest.

The optimal ANN model, based on the number of hidden neurons, was selected according to its best overall ranking. According to Table V, ANN-1 with an overall rank of 14 outperformed the other ANN networks in terms of performance. Consequently, ANN-1, featuring 1 hidden neuron, was designated as the best model.

Table V. Performance of ANN models with varying numbers of hidden nodes

Source: Authors own work

| Model | Model performance |               |               |               | Ranking  |          |          |          |           |
|-------|-------------------|---------------|---------------|---------------|----------|----------|----------|----------|-----------|
|       | Training          |               | Testing       |               | Training |          | Testing  |          | Total     |
|       | RRMSE             | $R^2$         | RRMSE         | $R^2$         | RRMSE    | $R^2$    | RRMSE    | $R^2$    |           |
| ANN-1 | <b>0.0096</b>     | <b>0.9764</b> | <b>0.0277</b> | <b>0.9430</b> | <b>4</b> | <b>6</b> | <b>1</b> | <b>3</b> | <b>14</b> |
| ANN-2 | 0.0082            | 0.9867        | 0.0361        | 0.9016        | 3        | 1        | 7        | 4        | 15        |
| ANN-3 | 0.0077            | 0.9854        | 0.0390        | 0.8734        | 2        | 3        | 8        | 9        | 22        |
| ANN-4 | 0.0169            | 0.9620        | 0.0323        | 0.9569        | 14       | 9        | 3        | 1        | 27        |
| ANN-5 | 0.0102            | 0.9803        | 0.0347        | 0.8911        | 5        | 5        | 4        | 6        | 20        |
| ANN-6 | 0.0072            | 0.9863        | 0.0589        | 0.6853        | 1        | 2        | 16       | 17       | 36        |
| ANN-7 | 0.0120            | 0.9600        | 0.0292        | 0.9476        | 6        | 10       | 2        | 2        | 20        |
| ANN-8 | 0.0122            | 0.9710        | 0.0396        | 0.8621        | 7        | 7        | 9        | 10       | 33        |
| ANN-9 | 0.0236            | 0.9047        | 0.0507        | 0.8785        | 16       | 19       | 12       | 8        | 55        |

|        |        |        |        |        |    |    |    |    |    |
|--------|--------|--------|--------|--------|----|----|----|----|----|
| ANN-10 | 0.0133 | 0.9512 | 0.0420 | 0.8600 | 8  | 11 | 10 | 11 | 40 |
| ANN-11 | 0.0082 | 0.9831 | 0.0559 | 0.8265 | 3  | 4  | 15 | 13 | 35 |
| ANN-12 | 0.0141 | 0.9486 | 0.0349 | 0.8996 | 10 | 12 | 5  | 5  | 32 |
| ANN-13 | 0.0139 | 0.9465 | 0.0360 | 0.8890 | 9  | 15 | 6  | 7  | 37 |
| ANN-14 | 0.0248 | 0.9077 | 0.0852 | 0.7610 | 17 | 18 | 18 | 16 | 69 |
| ANN-15 | 0.0142 | 0.9482 | 0.0545 | 0.7832 | 11 | 13 | 14 | 15 | 53 |
| ANN-16 | 0.0178 | 0.9132 | 0.0539 | 0.8558 | 15 | 17 | 13 | 12 | 57 |
| ANN-17 | 0.0163 | 0.9340 | 0.0880 | 0.4515 | 13 | 16 | 19 | 19 | 67 |
| ANN-18 | 0.0122 | 0.9631 | 0.0767 | 0.5716 | 7  | 8  | 17 | 18 | 50 |
| ANN-19 | 0.0149 | 0.9481 | 0.0457 | 0.8206 | 12 | 14 | 11 | 14 | 51 |

3.4. Support vector machine

SVM stands as a prominent machine learning approach for classification and regression problems. It is classified as a nonparametric approach based on its dependence on kernel functions. It commonly employs kernel functions such as linear, polynomial, and radial basis functions (Zouzou and Citakoglu, 2022). It is essential to infer a functional relationship between the output variable ( $y_i$ ) and a group of input variables ( $x_i$ ). The link between  $y_i$  and  $x_i$  is defined by a deterministic function (Equation (1)) (Mäkiäho *et al.*, 2023).

$$y_i = f(x_i) = w^T \phi(x_i) + b \tag{1}$$

In this context,  $w^T$  signifies the weight vector,  $\phi(x_i)$  represents a non-linear mapping function, and  $b$  denotes the bias. For a more detailed discussion of SVM and its optimization methods, readers can refer to the work of Zereg and Belouz (2022). The linear kernel function was chosen due to its simplicity, and ability to provide faster training time and lower computational complexity compared to more complex kernel functions like polynomial and radial basis kernels. Improved model performances were observed with the utilization of linear kernel function (Chong *et al.*, 2017). The data for SVM were trained using the ‘*fitrsvm*’ function in MATLAB to evaluate the predicted TCP of a software product in a university.

3.5. Validation and comparison of the models

Validation of the GP model was carried out by comparing its performance with that of ANN and SVM, based on the evaluation metrics. These 2 methods were selected for comparison because they are commonly used by researchers to handle non-linear problems. The performance and accuracy of the models were assessed using the evaluation metrics: relative root mean squared error (RRMSE) (Equation (2)), root mean absolute error (RMAE) (Equation (3)), mean absolute percentage error (MAPE) (Equation (4)), and the coefficient of determination ( $R^2$ ) (Equation (5)).  $R^2$  varies within the range of 0 and 1; a higher value of  $R^2$  suggests a more effective model. Conversely, lower values of RRMSE, RMAE, and MAPE signify superior model performance.

In order to guarantee consistent model performance, input data, and reproducibility, the same datasets were utilized for both the training and testing sets (Olawore *et al.*, 2024). The mean performance and error percentage were determined to account for variability. A Taylor diagram was also employed as a graphical tool to compare the performance of the prediction models (GP, ANN, and SVM models) against the reference data (actual TCP) (Citakoglu and Demir, 2022).

$$RRMSE = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \tilde{y}_i)^2}}{\bar{y}} \quad (2)$$

$$RMAE = \sqrt{\frac{1}{n} \sum_{i=1}^n |y_i - \tilde{y}_i|} \quad (3)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \tilde{y}_i}{y_i} \right| \quad (4)$$

$$R^2 = 1 - \left( \frac{\sum_{i=1}^n (y_i - \tilde{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \right) \quad (5)$$

The actual and predicted TCP values are denoted by  $y_i$  and  $\tilde{y}_i$ , respectively.  $\bar{y}$  is the average of the actual values and  $n$  refers to the overall number of datasets. The distributions of the actual and predicted values were visually summarized using a box plot. It provides a clear depiction of the median, quartiles, and outliers for the actual and predicted values of each model, facilitating their distributional comparison (Citakoglu and Demir, 2022). The Kruskal-Wallis test was utilized as a non-parametric statistical analysis method to ascertain whether there were statistically significant differences between the actual and predicted values. It was used in this study because it does not require data to be normally distributed (Bayram and Çıtakoğlu, 2023).

## 4. Results

### 4.1. GP model

The developed GP model for forecasting the TCP of a software product in a university setting is presented in Equation (7). Specifically, Equation (6), as initially derived from the parse tree, is rearranged and regrouped to form Equation (7). The parse tree for the best obtained GP model is depicted in Figure 4.

$$y = x_2 + x_3 + \left(\frac{x_4 + x_6}{0.017515} + x_1\right) \ln x_6 - \frac{0.37894}{x_5 x_8} \\ ((x_1 + x_1 + x_9 - x_2 - x_3 - x_6 - x_7 - x_8 - \ln x_8) x_8 + 0.37894) ((\ln(x_1 + x_1 + x_9 - x_2 - x_3 - x_3 - x_8$$

(6)

$$y = x_2 + x_3 + \left(\frac{x_4 + x_6}{0.017515} + x_1\right) \ln x_6 - \frac{0.37894}{x_5 x_8} \\ ((2x_1 + x_9 - x_2 - x_3 - x_6 - x_7 - x_8 - \ln x_8)x_8 + 0.37894((\ln(x_9 - x_2 - 2x_3 - x_8 - x_6 + 2x_1))(x_9 -$$

$$(7)$$

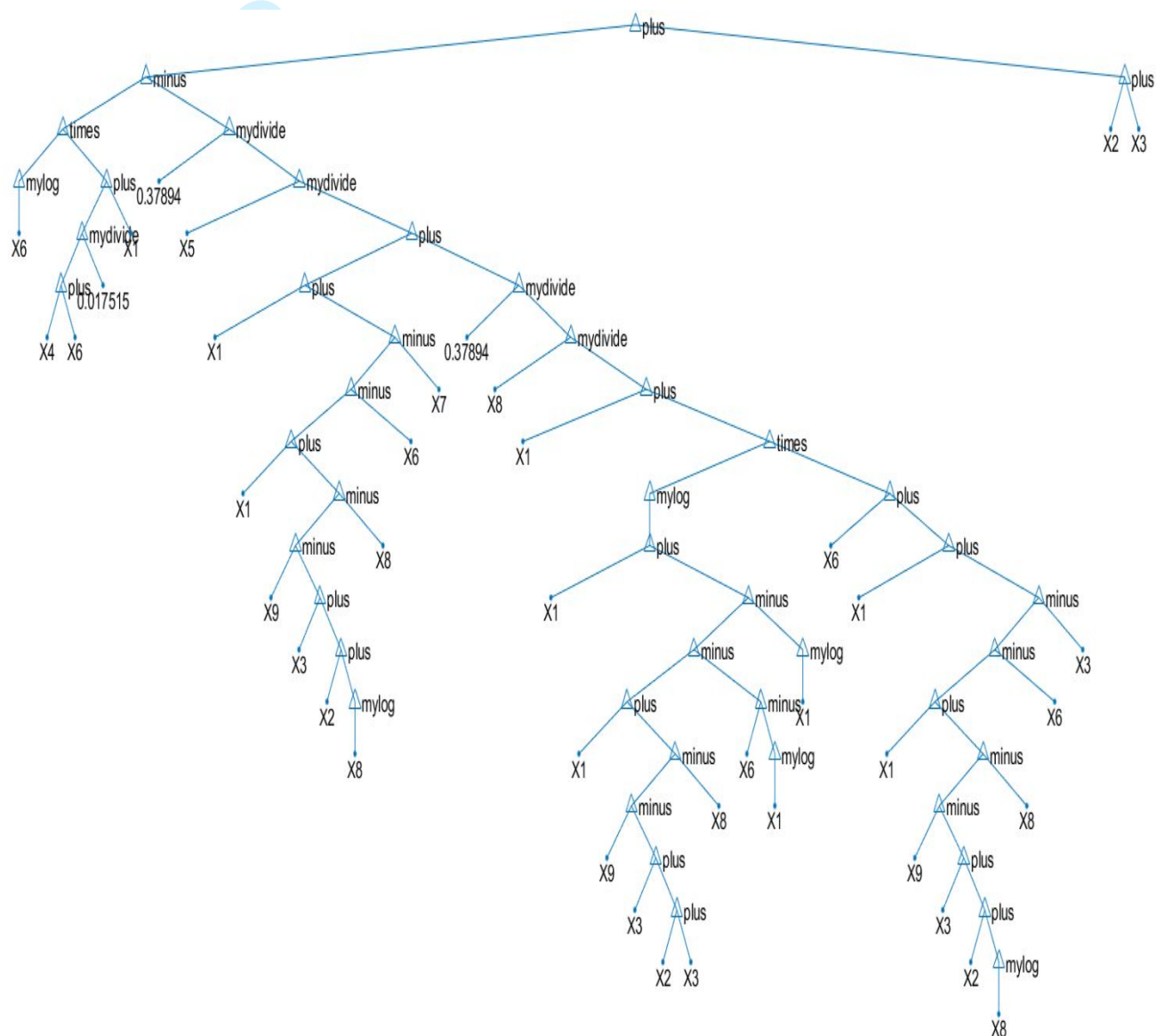


Figure 4. The parse tree for the obtained GP model

#### 4.2. Model evaluation

The effectiveness of the predictive models assessed in this research is shown in Table VI, which includes RRMSE, RMAE, MAPE, and  $R^2$  for the training and testing sets. The  $R^2$  values of GP, ANN, and SVM for the training datasets are 0.9854, 0.9764, and 0.9582, respectively (Figure 5), whereas the  $R^2$  values of GP, ANN, and SVM for the testing datasets are 0.9564, 0.9430, and 0.9421, respectively (Figure 6). The MAPE values for the training and testing sets are as follows: 4.0% - 8.0% for the GP model, 6.0% - 9.0% for the ANN model, and 7.0% - 10.0% for the SVM model. Basically, the corresponding values of RRMSE, RMAE, and MAPE of the training and testing datasets for the GP model are lower than those of the ANN and SVM models (as shown in Figure 7). All these results indicate that the GP model is capable of providing a more accurate TCP prediction of software products in Nigerian universities, as compared to the ANN and SVM models.

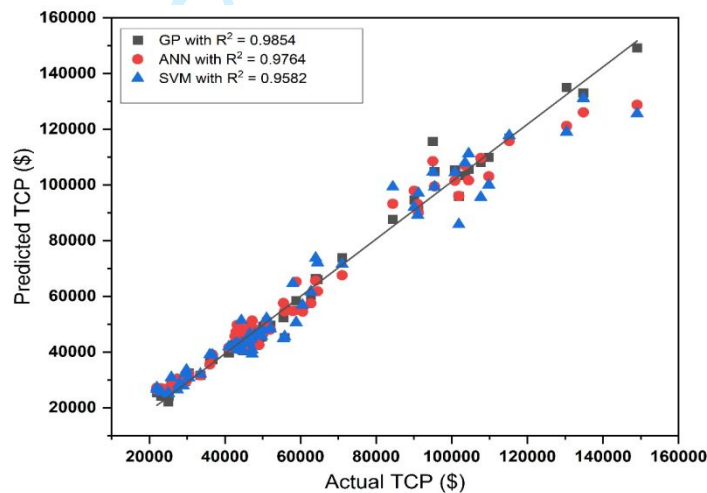


Figure 5.  $R^2$  plot comparing the GP, ANN, and SVM models using the training datasets.  
Source: Authors own work

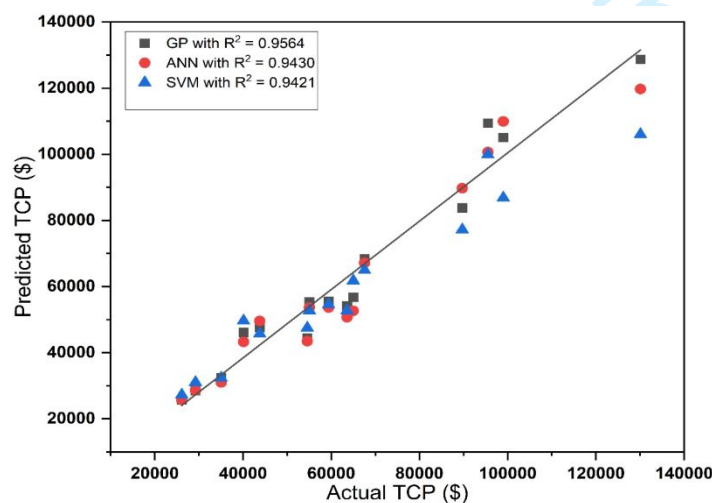


Figure 6.  $R^2$  plot comparing the GP, ANN, and SVM models using the testing datasets.  
Source: Authors own work

Table VI. Evaluation metric outcomes for the three models

Source: Authors own work

| Predictive Model | Training set |         |          |                | Testing set |         |          |                |
|------------------|--------------|---------|----------|----------------|-------------|---------|----------|----------------|
|                  | RRMSE        | RMAE    | MAPE (%) | R <sup>2</sup> | RRMSE       | RMAE    | MAPE (%) | R <sup>2</sup> |
| GP               | 0.0076       | 49.7864 | 4.5896   | 0.9854         | 0.0235      | 70.0660 | 7.8441   | 0.9564         |
| ANN              | 0.0096       | 60.7076 | 6.6241   | 0.9764         | 0.0277      | 75.0064 | 8.8742   | 0.9430         |
| SVM              | 0.0125       | 68.2168 | 7.7904   | 0.9582         | 0.0367      | 82.1718 | 9.8139   | 0.9421         |

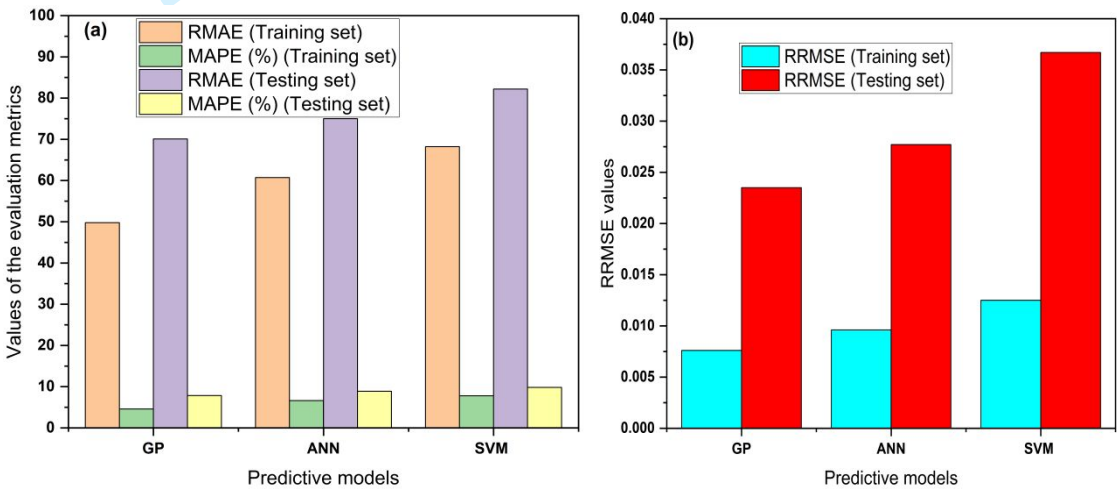


Figure 7. The training and testing set of different predictive models with (a) RMAE and MAPE values and (b) RRMSE values.

Source: Authors own work

As depicted in Figures 8(a) and 8(b), the Taylor diagram reveals that these predictive models have high correlation coefficients in both the training and testing sets. However, the GP model's predicted values of TCP are closer to the actual values compared to the other 2 models. Therefore, the Taylor diagram demonstrates that the GP model has superior performance over ANN and SVM models in predicting TCP.

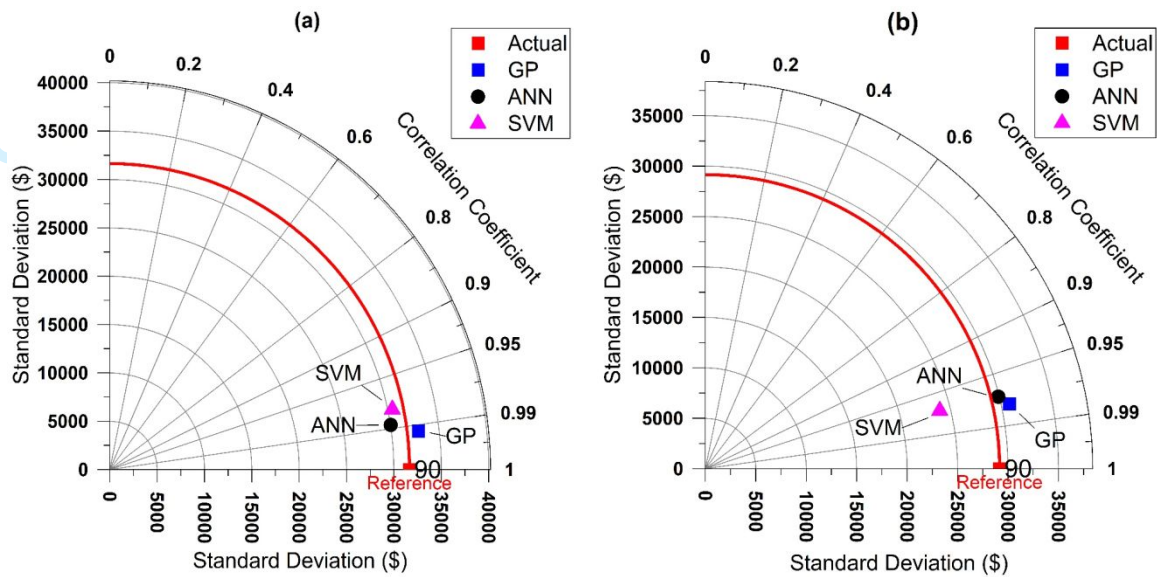


Figure 8. Taylor diagram comparing the performance of the models on the (a) training dataset and (b) testing dataset.

**Source:** Authors own work

The absence of outliers in the box plots shown in Figures 9(a) and 9(b) suggests that the actual and predicted values are relatively homogeneous and do not have extreme values that deviate substantially from their central tendency. This indicates that their distributions are comparatively consistent. The results in Table VII clearly demonstrate that the hypothesis ( $H_0$ ), concerning the comparison between actual and predicted values across the three models for both training and testing datasets, has been accepted. This implies that there is no significant difference between the actual and predicted values based on their ranks.

Table VII. Results of Kruskal–Wallis tests with P-Values at 95% significance level

**Source:** Authors own work

| Training dataset |         |        | Testing dataset |         |        |
|------------------|---------|--------|-----------------|---------|--------|
| Model            | P-Value | $H_0$  | Model           | P-Value | $H_0$  |
| GP               | 0.79299 | Accept | GP              | 0.85193 | Accept |
| ANN              | 0.77283 | Accept | ANN             | 0.60413 | Accept |
| SVM              | 0.75282 | Accept | SVM             | 0.66319 | Accept |

Null Hypothesis ( $H_0$ ): There is no significant difference between the actual and predicted values.

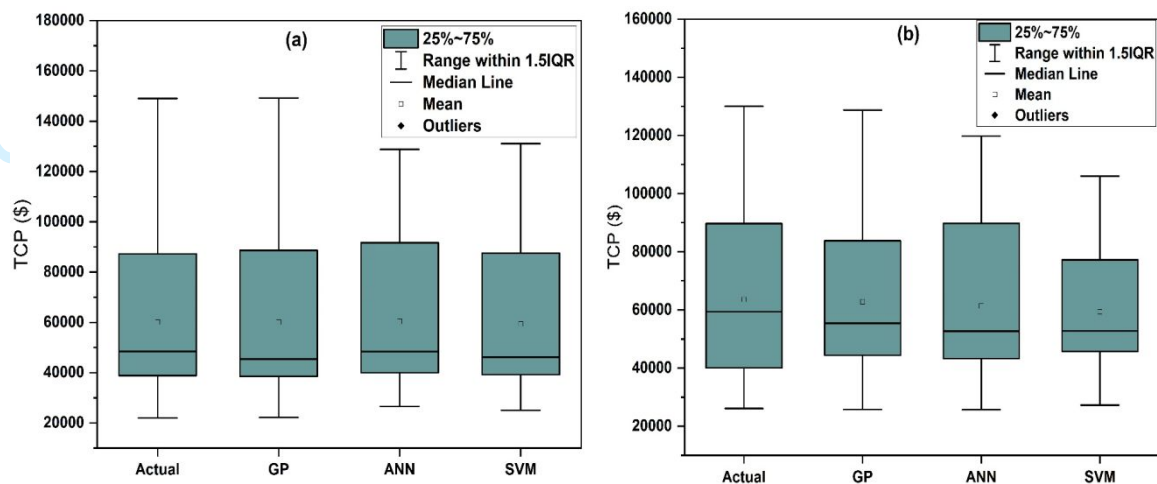


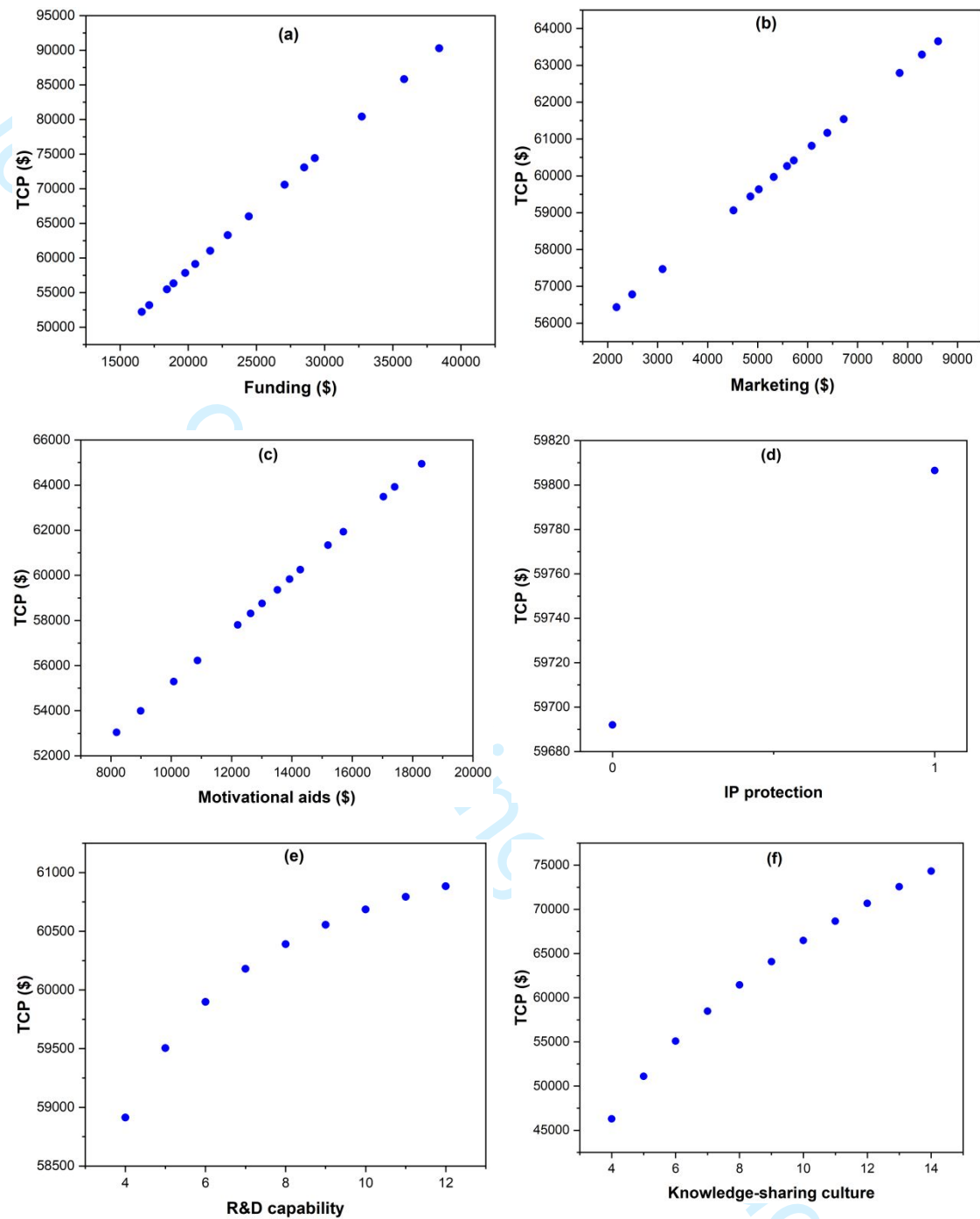
Figure 9. Box-plot diagram of the 3 models for (a) training dataset, and (b) testing dataset.

Source: Authors own work

As a further evaluation, a more targeted case study was conducted in a privately owned university in Nigeria. The name of the university was not disclosed for anonymity purposes. It manages a commercialization center that oversees intellectual properties, technology transfer and commercialization. The university has developed and commercialized healthcare administration management software, supported by USD 17,062.52 in funding. Marketing expenses totaled USD 4,829.63, while USD 13,217.82 was allocated for employee incentives. The project secured one intellectual property right, involved five R&D employees, and was backed by five industrial collaborations and five university-sponsored training sessions. The university's entrepreneurial capability was rated 4 (high), and the software's uniqueness was 3 (average). The actual TCP (total income from licensing and sales) was USD 44,351.71. The formulated GP model estimated USD 44,556.57 as the predicted TCP, resulting in an error of USD 204.86 and a percentage error of 0.46% when compared with the actual TCP. This showed the applicability of the GP model in predicting TCP due to a low percentage error.

#### 4.3. Parametric analysis

Parametric analysis indicates the capacity of the GP model to adjust to modifications of individual input variables. The ranges of the varied input variables fall within the limits of their respective lowest and highest values (Chu *et al.*, 2021). A parametric analysis of the GP model was conducted by assessing its prediction outcomes for individual model's input, whereas the remaining eight input parameters were held constant at their corresponding average values. Figure 10 illustrates the findings from the parametric analysis performed using the GP model.



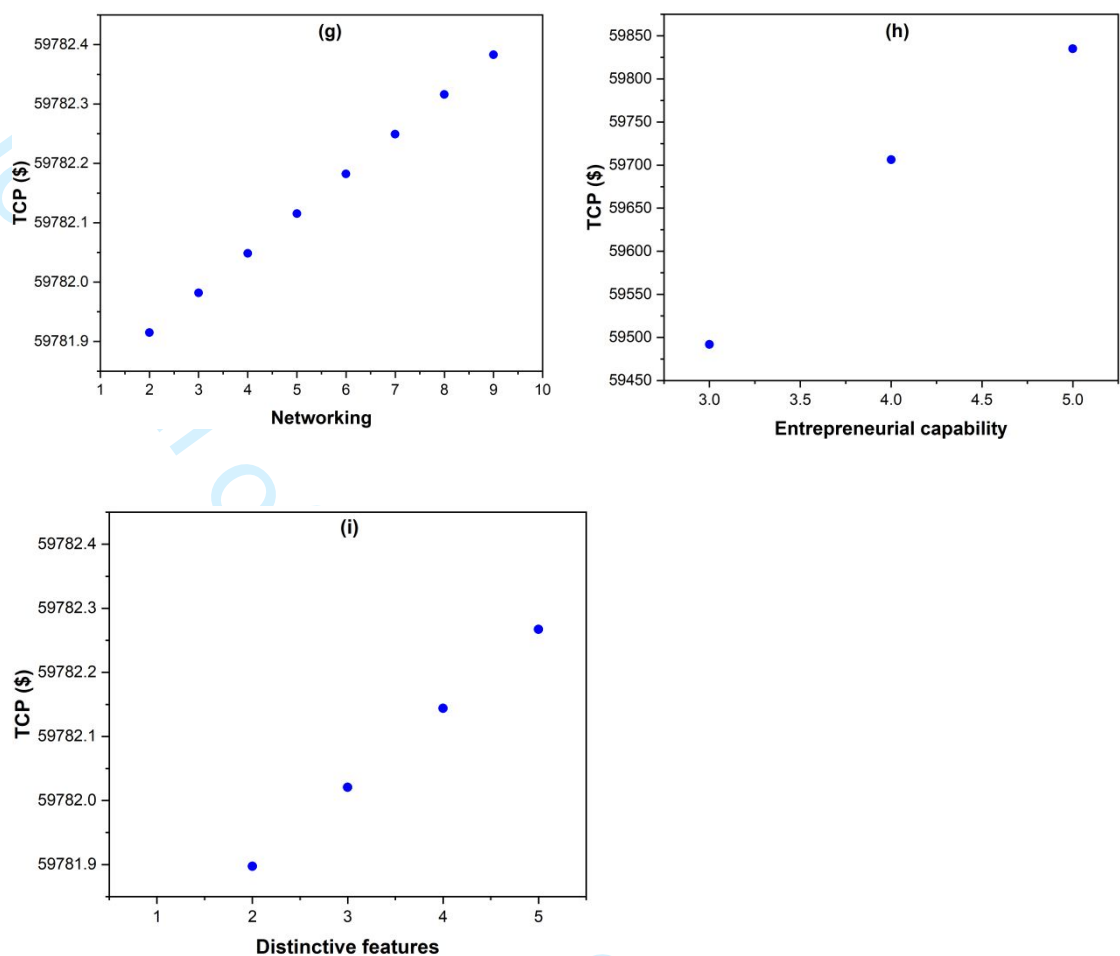


Figure 10. Variation of TCP with regard to 9 input variables ((a) Funding (b) Marketing (c) Motivational aids (d) IP protection (e) R&D capability (f) Knowledge-sharing culture (g) Networking (h) Entrepreneurial capability (i) Distinctive features) via parametric analysis of the GP model

**Source:** Authors own work

5. Discussion

The outcomes derived from the GP analysis furnish an evaluation model for the commercialization of developed software products in university commercialization centers. Professionals can readily use this new model to allocate resources for commercializing software products successfully in university commercialization centers. The developed mathematical model also uncovers the interrelationship between technology commercialization factors and the economic value derived from developing and commercializing software products within a university setting. As mentioned earlier, the  $R^2$  values for the training datasets are 0.9854, 0.9764, and 0.9582 for the GP, ANN, and SVM models, respectively. Based on the testing datasets, the  $R^2$  values are 0.9564, 0.9430, and 0.9421 for the GP, ANN, and SVM models, respectively. Thus, the GP model exhibits superior accuracy, with its  $R^2$  values surpassing those of the other models.

Furthermore, the respective values (for both training and testing datasets) of RRMSE, RMAE, and MAPE for the GP model are lower than those of the ANN and SVM models. A lower value of RRMSE, RMAE, and MAPE signifies better model performance (Fallahpour *et al.*, 2021). Therefore, the comparative analysis of the models based on RRMSE, RMAE, MAPE, and  $R^2$  values indicates that GP is a more effective and accurate model for forecasting the TCP of a software product in universities.

This study's results were compared with previous research, despite the limited studies on TCP prediction of software products in university commercialization centers using machine learning. A comparison with Abdul Razak and Murray (2017) showed that their hierarchical multiple regression model achieved an  $R^2$  of 0.21, whereas the GP, ANN, and SVM models in this study yielded  $R^2$  values closer to 1, demonstrating superior accuracy. This superior accuracy of GP, ANN, and SVM models over multiple linear regression is due to their ability to solve complex and non-linear problems. Similarly, this study's results were compared with Bhatnagar *et al.* (2020), which used ANN to predict product commercialization in the electronics industry. The obtained MAPE values for the training and testing datasets in their research were 5.9715 and 6.2392, respectively. The MAPE values were comparable to this study, with differences attributed to variations in sectors, input variables, and output measures.

The GP model stands out as a more intelligent approach by virtue of its capacity to solve the black box problem which is one of the drawbacks of the other methods used in this research. This enhanced intelligence stems from GP's superior search capabilities and its ability to achieve higher accuracy, particularly when dealing with immensely intricate, non-linear, and chaotic problems. This flexibility, along with GP's capacity to search globally, enables it to avoid local minima, a drawback that ANN and SVM frequently face (Ekmekcioğlu *et al.*, 2023). However, the limitation of GP in this study was its high computational time during the training of the model.

The TCP of a university increases as the amount of funds allocated for developing and commercializing a software product increases (as shown in Figure 10(a)). This corroborates with the findings from Hsu *et al.* (2015) that mentioned that the chances of developing and introducing high-quality products into the market increase, provided there is adequate funding. Additionally, the TCP of universities is observed to increase with improvements in marketing, motivational aids, IP protection, R&D capability, knowledge-sharing culture, networking, entrepreneurial capability, and distinctive features. This is aligned with some previous studies that found a positive relationship between TCP and marketing (Yazdimoghaddam *et al.*, 2019), between TCP and motivational aids (Sharma, 2022), between TCP and IP protection (Chiş and Crişan, 2020), between TCP and R&D capability (Park and Shin, 2017), between TCP and knowledge-sharing culture (Kumar *et al.*, 2015), between TCP and networking (Mafu, 2023), between TCP and entrepreneurial capability (Crudu, 2019), and between TCP and distinctive features (Chiş and Crişan, 2020).

Funding is essential for the advancement and market introduction of software products within university commercialization centers. It supports various aspects of the technology commercialization process, from R&D to the introduction of a software product into the market. Nigerian universities secure funding through grants, donations, and endowments contributed by individuals, organizations, international agencies, and government parastatals, all aimed at fostering the advancement and economic exploitation of software products (M'Chirgui *et al.*, 2018). Marketing is an integral part of the technology commercialization process for software products in university commercialization centers. It bridges the gap between innovation and market demand, ensuring that the developed software products reach their intended customers and achieve commercial success (Yazdimoghaddam *et al.*, 2019). Increasing the marketing expenditure can be an effective strategy to enhance the TCP of a university by boosting the visibility and sales of a software product. Most university commercialization centers in Nigeria introduce developed software products into the markets via online platforms, trade fairs, media, industry events, and partnerships with distributors or spin-off firms.

Motivational aids for personnel in a university commercialization center have a multifaceted impact on TCP. Monetary incentives can serve as powerful motivators for faculties, researchers, and developers. When individuals see the potential for financial rewards, they may be more inclined to actively engage in technology commercialization efforts (Sharma, 2022). Many Nigerian universities have implemented systems to acknowledge and incentivize researchers and developers when their research outcomes are commercialized and made public. The prominent approaches are the allocation of a portion of licensing royalties to the researchers and the promotion of personnel. This factor contributes to increased productivity, innovation, quality, and improved teamwork.

IP protection is a cornerstone of successful technology commercialization in university settings. It provides a competitive edge by preventing competitors from replicating a developed software product with unique features (Chiş and Crişan, 2020). A copyright discourages others from copying a software product and its programming codes, as they might face legal consequences for copyright infringement. In 2006, the National Office for Technology Acquisition and Promotion initiated the creation of Intellectual Property and Technology Transfer Offices in tertiary institutions, which has significantly boosted the number of inventions emerging from Nigerian universities (Fadeyi *et al.*, 2019). These offices are tasked with the protection and administration of intellectual property produced by scientific organizations, such as universities and research institutions. This has helped university commercialization centers to create an avenue for long-term revenue generation from a developed software product. In contrast, it is challenging to monetize a software product without IP protection because potential revenue streams, such as licensing fees, royalties, or sales, may be limited or lost entirely.

The R&D capability of a university is the foundation upon which successful technology commercialization is built. It ensures that a software product is not only technically sound but also aligned with market demands and has the potential to create significant value in the industry (Park and Shin, 2017). Increasing the number of competent personnel involved in the advancement and economic exploitation of a software product can lead to improved TCP for a university by fostering innovation, accelerating development, enhancing product quality, and expanding market reach. A knowledge-sharing culture within a university enhances the TCP of a software product by promoting information exchange, facilitating collaboration, providing access to resources, and creating an environment conducive to knowledge transfer (Hsu *et al.*, 2015). The implementation of academic discourses, seminars, workshops, and training on R&D and entrepreneurship helps to inculcate this culture in a university commercialization center. The Nigerian government has allocated substantial resources to train academics both domestically and internationally using various avenues to acquire knowledge and cultivate a pool of highly skilled researchers and developers. This investment has facilitated the exchange of knowledge and enabled university-based researchers and developers to tap into the collective expertise of the academic community. As a result, software development cycles have accelerated, leading to faster time-to-market for their products and improved TCP.

Networking fosters collaboration between university commercialization centers and industrial organizations or other agencies (Pujotomo *et al.*, 2023). The Nigerian government has established a few science and technology parks near universities to facilitate collaboration between academia and industry. These parks provide a conducive environment for research and innovation. Collaborative projects with industries can accelerate the development and commercialization of software products by combining resources, expertise, and market access. University researchers and students involved in such projects gain practical experience and skill development via government agencies like the Industrial Trust Fund. This can enhance their ability to contribute to the software development process and subsequently, improve the TCP of university commercialization centers.

Entrepreneurial capability empowers universities to analyze and harness the commercial viability of software products, turning them into tangible fiscal value by seizing available market opportunities. Some Nigerian universities have established entrepreneurship centers, technology incubators, and innovation hubs to nurture entrepreneurial talent and facilitate the development of software products and other technologies. The unique role of these established centers is to motivate academics to partake in entrepreneurial pursuits and risk-taking akin to their industry counterparts. This inculcates academics in Nigerian universities to imbibe a culture characterized by risk-taking, effective problem-solving, and the successful introduction of software products for market adoption. A university commercialization center endowed with robust entrepreneurial

capability not only stimulates economic growth but also elevates a university's prosperity and productivity.

Finally, the distinctive features of a software product play a crucial role in its TCP. These features refer to unique characteristics or attributes that differentiate a software product from others in the market. These features give a software product a competitive edge (Chiş and Crişan, 2020). When a software product offers something unique or better than existing solutions, it becomes more attractive to potential customers, which can lead to higher sales and market share. However, it is essential to balance innovation with market research to ensure that distinctive features align with customer needs and preferences.

6. Conclusions

In this research, a GP model was formulated using historical data related to technology commercialization, which were sourced from Nigerian university commercialization centers. Comparative analyses were conducted with ANN and SVM models by utilizing similar datasets. The effectiveness of the models was evaluated using RRMSE, RMAE, MAPE, and  $R^2$ . Also, the Kruskal–Wallis test was used to assess whether there were statistically significant differences between the actual and predicted values based on their ranks. Parametric analysis was also conducted for the GP model.

The GP model achieved  $R^2$  values of 0.9854 for the training set and 0.9564 for the testing set. In comparison, the ANN model showed  $R^2$  values of 0.9764 and 0.9430 for the training and testing sets, respectively, while the SVM model obtained  $R^2$  values of 0.9582 for the training set and 0.9421 for the testing set. According to the evaluation criteria, the GP model surpassed both the ANN and SVM models in forecasting the TCP of university software products with superior accuracy. The Kruskal–Wallis test indicated that there was no significant disparity between the actual and forecast values, based on their ranks, at a 95% significance level. Parametric analysis showed the relationship between each input variable and TCP separately. The developed GP mathematical model also revealed the interrelationship between technology commercialization factors and the economic value derived from developing and commercializing software products within a university setting. This new model can be readily employed by professionals to allocate resources for the successful commercialization of software products.

From an academic viewpoint, this research has made an important contribution by introducing the GP approach to evaluate TCP in universities. It has extended the boundaries of research by introducing a new approach to predict commercialization performance, which can serve as a foundation for further exploration and innovation. From a policy perspective, the GP model equips Nigerian government agencies such as the Tertiary Education Trust Fund (TETFund), National Information Technology Development Agency (NITDA), and National

Office for Technology Acquisition and Promotion (NOTAP) with an objective framework to prioritize funding for universities with strong commercialization potential. Institutions demonstrating strong commercialization success, as predicted by the model, could receive increased research grants and infrastructure support. Furthermore, the model can be integrated into the National Digital Economy Policy and Strategy (NDEPS) to support the establishment of innovation hubs and university-industry linkages, aligning research outputs with market needs. By facilitating data-driven decision-making, the GP model helps policymakers to optimize funding distribution, strengthen commercialization strategies, and drive national technological advancement.

This study was limited to data from Nigerian university commercialization centers. Future research could extend the model to other countries to compare TCP dynamics across various innovation ecosystems. This study did not incorporate probabilistic modeling, limiting its ability to capture uncertainties and temporal variations in TCP forecasting. Future research could explore stochastic modeling approaches, such as Monte Carlo simulation and Markov models, to incorporate probabilistic elements in TCP forecasting. Finally, the utilization of other evolutionary-based soft computing techniques to enhance the accuracy of the developed model can be considered in future studies.

#### **Data Availability**

The data supporting this research are available upon request from the first author.

#### **Declaration of Interest statement**

The authors state that they have no competing interests to disclose concerning this research paper.

#### **Ethical Statement**

Not applicable

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## Dear Professor/ Editor-in-Chief/ Reviewers

Thank you very much for the valuable comments. We have revised the paper carefully and accordingly. All the revisions made are highlighted in blue color in the paper. Below are our responses on how the revisions have been made.

### Reviewer #1

**Comment:** Strengthen the introduction by providing a more comprehensive background on the importance of technology commercialization performance (TCP) in universities. Consider defining key terms and framing the problem statement more clearly to outline the study's relevance and context.

**Response:** Thanks. We have provided the importance of TCP in universities. The key terms have been defined and highlighted in the manuscript. Please refer to pages 2-3. Also, the problem statement has been clearly included to outline the study's relevance and context. Please refer to page 3 as highlighted.

**Comment:** Incorporate a broader range of literature to highlight various approaches, methodologies, and frameworks in assessing TCP. Discuss the strengths and weaknesses of existing models in greater detail, as this will provide a clearer rationale for the introduction of the Genetic Programming (GP) model.

**Response:** Thanks. A broader range of literature that highlights various approaches, methodologies, and frameworks in assessing TCP has been included. Four additional studies have been included in the literature review and highlighted. Please refer to page 5. The strengths and weaknesses of the existing models are provided and highlighted on pages 5-6.

**Comment:** Elaborate on the methodology section by detailing the data collection processes, the selection criteria for input variables, and the specifics of the GP model implementation. Clear descriptions of how parameters were tuned and validated will help ensure transparency and reproducibility.

**Response:** Thank you for your valuable feedback and for highlighting the need for further elaboration in the methodology section. In response to your comment, we have expanded the methodology section by providing detailed explanations on the data collection processes and the selection criteria for input variables as highlighted on page 7. Tuning of the parameters was minimized because the suggested parametric values used in developing the GP model were obtained from previous studies. Please refer to pages 10-11 for the specifics of the GP model implementation.

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**Comment:** Present the results in a more structured manner, utilizing graphs or tables for visual representation, which can enhance reader comprehension. Include a discussion about the implications of metrics like RRMSE, RMAE, and MAPE, especially in relation to how they compare to existing models.

**Response:** Thanks for the comment. The RRMSE, RMAE, and MAPE plots have been included as Figure 7 with discussion. There are currently Table VI and Figures 7a and 7b in the manuscript that present the results. Please refer to pages 16-17. Also, in-depth discussion about the implications of metrics, especially in relation to how they compare them to existing models, are provided and highlighted on pages 21-22.

**Comment:** Expand the discussion section to connect findings more directly to previous literature and potential real-world applications. Address how the GP model might evolve over time or under varying conditions, and identify possible limitations encountered during the analysis.

**Response:** Thank you for your insightful feedback. In response to your suggestion, we have expanded the Discussion section to strengthen the connection between our findings and existing literature, as well as to highlight their real-world applications. Please refer to page 22. Also, in response to your comment, we acknowledge that the current study did not explicitly consider the evolution of the GP model over time. The research focused on developing a predictive model based on historical data to develop a mathematical model without incorporating temporal variations. Time is not a variable or factor in the GP model. Please refer to page 26 for this explanation. The limitation encountered during the analysis has been included in the manuscript. Please refer to Page 22.

**Comment:** Provide a more thorough exploration of the policy implications of your findings. Discuss how policymakers can utilize the GP model to make informed decisions regarding funding and support for university software product commercialization.

**Response:** Thanks. We have expanded the discussion in the manuscript on how policymakers can leverage the GP model to enhance decision-making regarding funding and support for university software product commercialization. Please refer to pages 25-26.

**Comment:** Clearly articulate directions for future research. While the paper mentions limitations, it could benefit from specific suggestions for other methodologies (like stochastic models) and potential areas of application beyond the Nigerian context.

**Response:** Thanks. We have clearly articulated the directions for future research. Please refer to page 26.

**Comment:** Conduct a thorough proofreading for grammatical correctness, coherence, and adherence to formatting guidelines. Ensure that figures, tables, and references follow a consistent style as per the publication standards, such as APA or MLA.

**Response:** Thanks. We have engaged a native English expert to check and proofread the entire article. All grammatical errors, coherence, and adherence to formatting guidelines have been carefully checked and corrected.

**Comment:** Review and potentially expand the references to include more recent studies or seminal works that might have been overlooked. This would reinforce the paper's academic rigor and situate the research within the broader academic discourse.

**Response:** Thanks. The references have been reviewed and expanded to include additional recent studies. Please refer to pages 26-31.

## **Reviewer #2**

### **Comment:**

Dear Authors,

The topic of the paper is interesting and current, being suitable for the Journal of Modelling in Management. The article has an appropriate layout and format, clearly describing its objectives and working methodology. The abstract positively reflects the content of the article and the title is well connected. The subject is relevant, bringing important contributions to assess the technology commercialization performance of software products in university settings. This research are used genetic programming (GP) which allowed the development a predictive model for forecasting technology commercialization performance of software products in Universities. By collecting data and developing mathematical models using genetic programming, artificial neural networks and machine learning, the research solves concrete problems regarding the measurement of technology commercialization performance of software products in universities in developing countries. The paper identifies implications for research, academia, and society, bridging the gap between theory and practice. Through the study conducted and the results presented, the paper makes an important contribution to the field of development teh Universities and offers new development perspectives. The authors demonstrate through comparative analysis of the presented models that GP is a more efficient and accurate model for forecasting the TCP of a software product in universities. However, I recommend that you develop the application part, as much as possible, in the results paragraph, analyzed through a case study, within the limits of available data that can be made public. I recommend that the paper be accepted for publication with minor revision.

Best regards,

**Response:** Thanks for the comment. A case study has been included and analyzed on page 19.

## **Reviewer #3.**

**Comment:** The introduction requires revision. While it provides some context, it needs to clearly articulate the research gap, objectives, and novelty of this review paper. A more focused literature review leading to a well-defined research question is needed. The authors should explicitly state how this work advances the field beyond existing research.

**Response:** Thanks. The introduction has been revised, and the research gap, objectives, and novelty has been included. The research questions based on a more focused review and how this work advances the field have also been clearly explained. Please kindly refer to page 3 as highlighted.

**Comment:** The literature review section is inadequate. It lacks a critical analysis of previous works and does not effectively synthesize the current state of knowledge. Also add the following works:

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3 10.1016/j.energy.2018.08.135  
4 10.1016/j.tsep.2024.102471  
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6 10.1016/j.est.2022.104314  
7 10.1016/j.tsep.2024.102938.  
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9 **Response:** Thanks. The literature review has been expanded with more previous studies and  
10 their critical analysis. Four additional studies have been included in the literature review and  
11 highlighted. Also, the current state of knowledge has been effectively synthesized. Please refer  
12 to pages 5-6 as highlighted. Also, the works of 10.1016/j.energy.2018.08.135 and  
13 10.1016/j.est.2022.104314 have been added to the manuscript as highlighted on page 9.  
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16 **Comment:** The overall structure of the paper needs improvement. Some sections are  
17 disproportionately long or short, affecting the balance and flow of the manuscript.

18 **Response:** Thanks. The overall structure and flow of the paper have been improved.  
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21 **Comment:** I don't see much interesting conclusions.  
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23 **Response:** Thanks for the comments. The conclusion section has been improved to be more  
24 interesting and insightful as highlighted on pages 25-26.  
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27 **Comment:** There are numerous grammatical and stylistic issues throughout the text that need  
28 attention. A thorough proofreading and editing process is required.

29 **Response:** Thanks. We have engaged a native English expert to check and proofread the entire  
30 article. All grammatical errors and other issues have been carefully checked and corrected  
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## An Empirical Model for Forecasting Technology Commercialization Performance of Software Products in Universities Using Genetic Programming

### Abstract

**Purpose** - This research aimed to develop a predictive model using genetic programming (GP) to assess the technology commercialization performance of software products in university settings.

**Methodology** - The prediction model was developed using historical TC data from Nigerian university commercialization centers (UCCs) through the application of GP. Comparative analyses were conducted to assess the results of the GP model against Artificial Neural Network and Support Vector machine models. Evaluation metrics such as relative root mean squared error, root mean absolute error, mean absolute percentage error, and coefficient of determination were employed to gauge the accuracy of the models.

**Findings** - The GP model exhibited a coefficient of determination of 0.9854 and 0.9564 for the training and testing data, respectively. The comparison of the models using the evaluation metrics demonstrated that the GP model is superior in its accuracy for forecasting the TCP of software products in UCCs.

**Originality** - This research has developed a new mathematical equation that depicts the relationship between technology commercialization performance and the factors. This aspect has not been explored in previous research. Professionals can use the GP model to strategically allocate resources and improve the commercialization of software products.

**Keywords** Prediction, Technology commercialization, Performance, Genetic programming, Innovation, Universities

### 1. Introduction

Enabling the growth and competitiveness of organizations relies on the vital components of technology development and commercialization. Organizations foster their advancement and enhance their competitive advantage by introducing new products that fulfill market demands and meet future customer needs (Kaczmarek *et al.*, 2021). Organizations rely on various resources, including human and financial capital, along with valuable expertise, to drive developmental activities (Pujotomo *et al.*, 2023). Universities are recognized as pivotal players in the innovation cycle, but they face significant hurdles in attaining their goals of promoting innovation and fostering economic growth by transforming new ideas into innovative products or technologies (Memon *et al.*, 2022).

In African developing countries, funding for emerging organizations falls significantly short of global benchmarks in capital availability, implementation rigor, and the criteria employed

to identify suitable candidates for financial assistance (Afful-Dadzie *et al.*, 2017). Despite the obstacles faced by entities such as Nigerian universities, industries, and research centers, the government is actively taking measures to incentivize universities to transform their research outcomes into commercial value. This initiative aims to generate revenue, enhance the knowledge-based economy, and stimulate technological and economic growth (Binuyo and Alimi, 2017). The technologies being assessed for development and commercialization in Nigerian universities within the scope of this study are software products. The development and commercialization of these products have garnered significant attention from the Nigerian government. The government aims to utilize various organizations to tackle the challenges of inadequate infrastructure, soaring unemployment rates, and a struggling economy prevalent in the information technology sector (Ajibo *et al.*, 2019).

The process of commercialization commences with the emergence of an innovative concept within an organization and culminates with the successful introduction of the new product to the market (Min *et al.*, 2019). Technology commercialization performance (TCP) refers to the measurement and evaluation of how effectively and successfully a technology or innovation is brought from the research and development (R&D) stage to the market as a viable and profitable product. This evaluation is crucial for understanding the effectiveness of efforts to transform scientific or technological advancements into tangible economic and societal benefits (Nugent and Chan, 2023). TCP model assists policymakers and governments in determining which organizations to support and the extent to which they should be supported. Additionally, it serves as a tool to evaluate an organization's potential for future competitiveness and economic growth (Altuntas and Dereli, 2012). However, decision-makers find it challenging to measure the economic worth of products developed by universities due to the improper allocation of resources linked to the successful commercialization of products. Additionally, the assessment of TCP in any organization mostly depends on expert intuition (Kim *et al.*, 2021). Nevertheless, such approaches are time-consuming, inaccurate, and labor-intensive as the number of products and the intricacy of innovations expand. A valid model for the evaluation of technology commercialization is needed to forecast future outcomes vis-à-vis the results obtained from the evaluation of the factors or criteria that impact TCP (Noh *et al.*, 2018).

The relationships between these criteria (input variables) and their impacts on the commercialization process are crucial. Genetic programming (GP) is an integral part of evolutionary computing that employs the theory of genetic algorithms (GA) to generate computer expressions for problem-solving purposes. It also offers the additional advantage of higher accuracy (Fallahpour *et al.*, 2021). To overcome the limitations of the conventional methods, GP will be proposed in this research to develop a more accurate mathematical model that portrays the correlation between the input variables (criteria affecting technology commercialization) and the output variable (TCP).

As far as the authors are aware, there is a scarcity of studies that have applied GP to develop a predictive model for evaluating the TCP of software products in a university commercialization center. The objectives of this research are to develop a predictive model for assessing the TCP of software products in university settings using GP and to validate the accuracy of the model through comparative analysis with artificial neural network (ANN) and support vector machine (SVM). The absence of a mathematical model in the literature to predict TCP based on a set of input variables has motivated the authors to conduct this research. The significant contribution of this research is the introduction of the GP approach to evaluate the TCP of software products in universities. This study utilized GP to create a mathematical predictive model that provides a tangible platform for decision-makers to make informed choices based on data rather than relying only on gut feeling.

## 2. Literature Review

Assessing TCP involves collecting data, analyzing key metrics, and comparing the outcomes against predefined success criteria. This process enhances decision-making, resource allocation, and future strategies to improve the commercialization process and achieve the desired outcomes (Afful-Dadzie *et al.*, 2017; Binuyo and Alimi, 2017). The indicators for assessing TCP include financial returns, market penetration, time to market, economic impact, partnerships, and social and environmental impact (Fadeyi *et al.*, 2019). Various models for technology commercialization have been suggested by prior studies according to their goals and directions. Numerous qualitative and quantitative methods have been proposed for assessing TCP.

Kim *et al.* (2021) suggested using a random forest method to evaluate the economic worth of products developed by universities and used quantitative criteria as the independent variables. The model was validated as an important supplementary tool for appraising products originating from universities based on its statistical results. Shu *et al.* (2023) developed an evaluation model using the VIKOR method to analyze the commercial viability of energy storage technologies. This model proved instrumental in facilitating informed decisions regarding the optimal selection of energy storage technologies. An evaluation index system was developed by Altuntas and Dereli (2012) for the prediction of technology commercialization in investment projects. They applied fuzzy DEMATEL and fuzzy analytic network process to assess the interrelationships among the factors and the weights of each factor, respectively. Moreover, the index value was obtained by applying beta distribution to find the average value of individual factor based on the experts' opinions. The findings of the illustrative case showed that the suggested index system could forecast the commercialization prospects of an investment project based on expert assessment.

Abdul Razak and Murray (2017) determined the significance of innovation strategies in predicting successful commercialization in a public university using hierarchical multiple regression analysis. The findings indicated that effective strategic leadership and the adoption of open innovation strategies emerged as robust indicators of successful commercialization. However, according to this study, collaborative advantage had little impact on commercialization success. A logistic regression model was applied by Kang *et al.* (2013) to evaluate the TCP of large and small firms in Korea. The model's dependent variable was determined by the quantity of products launched by the firms into the market within the preceding 3 years. The outcomes of the logistic regression in the study revealed that some government initiatives considerably improve the success of technology commercialization. Sutopo *et al.* (2022) developed a data envelopment analysis model to estimate the efficacy of technology transfer offices and expedite the transition of research outcomes from universities into market-ready innovations.

Yazdimoghaddam *et al.* (2018) designed a fuzzy expert system for early-stage prediction of technology commercialization success before implementation. The model's accuracy was assessed at 73% through the hold-out validation method and it was determined to be highly accurate in forecasting commercialization success. Also, Yazdimoghaddam *et al.* (2019) studied the factors that contribute to successful technology commercialization and ranked them based on their relative importance. They further developed a scoring model to evaluate TCP. The relationships among technology commercialization success factors were determined using interpretive structural modeling (ISM). ANN with a cascade network was applied by Bhatnagar *et al.* (2020) to forecast the number of successful new products to be introduced in manufacturing industries. The ANN exhibited great performance outcomes, and the cascading approach improved accuracy and convergence capability.

Table 1: Methods used by previous studies for the prediction or evaluation of TCP

| Authors                             | Methods used for predicting or evaluating TCP    |
|-------------------------------------|--------------------------------------------------|
| Kim <i>et al.</i> (2021)            | Random forest                                    |
| Shu <i>et al.</i> (2023)            | VIKOR                                            |
| Altuntas and Dereli (2012)          | Fuzzy DEMATEL and fuzzy analytic network process |
| Abdul Razak and Murray (2017)       | Hierarchical multiple regression analysis.       |
| Kang <i>et al.</i> (2013)           | Logistic regression model                        |
| Sutopo <i>et al.</i> (2022)         | Data envelopment analysis                        |
| Yazdimoghaddam <i>et al.</i> (2018) | Fuzzy expert system                              |
| Yazdimoghaddam <i>et al.</i> (2019) | ISM                                              |
| Bhatnagar <i>et al.</i> (2020)      | ANN                                              |
| <i>This study</i>                   | <i>GP</i>                                        |

Various techniques have been used to predict or evaluate TCP, as summarized in Table 1. However, the limitation of these techniques is that the relationship between the variables is unclear, making it difficult for decision-makers to examine the impact of individual input variable on the resulting output. Overfitting and underfitting are common challenges in ANN modeling,

which also necessitates greater computational resources. It is also disparaged as a black box (Öztürk and Başar, 2022). SVM models rely heavily on the appropriate selection of the kernel function and regularization parameters, which can make the tuning process challenging and often require substantial experimentation to achieve optimal performance. Additionally, SVM is often considered a black-box model (Başakın *et al.*, 2022). GP is a data-driven forecasting approach that can generate an equation or mathematical model linking the output and input variables (Jamei and Ahmadianfar, 2020). However, there is a dearth of research applying GP to predict the technology commercialization performance of software products in university commercialization centers. To address this limitation, this research proposes the application of GP to build a mathematical model that elucidates the correlation between input and output variables. It is also necessary to assess the robustness and accuracy of the proposed model.

### 3. Methodology

This section explains the data collection and analysis process. It also presents an overview of the proposed GP, ANN, and SVM models along with the parameters used to evaluate their performance.

#### 3.1. Data collection

The factors or criteria influencing technology commercialization performance, as outlined by Olawore *et al.* (2023), were adopted in this study. Based on literature reviews, they identified and streamlined a set of influential factors influencing the process of commercializing software products within university commercialization centers. These factors include funding, marketing, intellectual property (IP) protection, R&D capability, knowledge-sharing culture, networking, entrepreneurial capability, and distinctive features. Subsequently, the Delphi method was employed to examine and evaluate these factors. A set of questionnaires was distributed to a panel of 12 experts, which included 7 from academia and 5 from industry. Furthermore, the experts assessed the suitability of the evaluation parameters linked to these criteria. The experts were given a new questionnaire for further assessment after being informed about the responses of other experts. The experts refined the factors under consideration until a consensus was reached among them.

The criteria established following the Delphi study are outlined and detailed in Table 2. The data needed to develop the GP model were collected from 11 different commercialization centers in Nigerian universities. The data were collected from Nigerian universities due to the government's efforts to diversify Nigeria's economy from a commerce-focused type to a flourishing high-tech knowledge economy (Binuyo and Alimi, 2017). Thus, collecting data on

TCP in Nigerian universities was a fundamental step in enhancing their contribution to innovation, economic development, and the knowledge-based economy.

Table 2: The evaluation parameter of each criterion and technology commercialization performance

| Criteria                                         | Evaluation parameter                                                                                                                                                                                                                   |
|--------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Funding ( $x_1$ )                                | The funding allocated by an organization to support the development and commercialization of a software product. It is expressed in US dollar (\$) equivalent.                                                                         |
| Marketing ( $x_2$ )                              | The marketing expenditure of an organization for promoting and selling a software product. It is expressed in US dollar (\$) equivalent.                                                                                               |
| Motivational aids ( $x_3$ )                      | The monetary rewards or incentives given by an organization to the employees who are engaged in the development and commercialization of a software product. It is expressed in US dollar (\$) equivalent.                             |
| IP protection ( $x_4$ )                          | The number of intellectual property rights obtained for a software product.                                                                                                                                                            |
| R&D capability ( $x_5$ )                         | The number of competent R&D employees that are engaged in the development of a software product.                                                                                                                                       |
| Knowledge-sharing culture ( $x_6$ )              | The total number of intellectual discourses, conferences, workshops, and training on R&D and entrepreneurship that is coordinated or funded by an organization for its personnel in developing and commercializing a software product. |
| Networking ( $x_7$ )                             | The number of active industrial collaborations with an organization for the development and commercialization of a software product.                                                                                                   |
| Entrepreneurial capability ( $x_8$ )             | A 5-point Likert scale is applied to evaluate the extent of the entrepreneurial capability of an organization in developing and commercializing a software product (1 = very low, 2 = low, 3 = average, 4 = high, 5 = very high).      |
| Distinctive features ( $x_9$ )                   | A 5-point Likert scale is applied to evaluate the level of uniqueness of the features of a software product in supporting its commercialization (1 = very low, 2 = low, 3 = average, 4 = high, 5 = very high).                         |
| Technology commercialization performance ( $y$ ) | The total income generated from licensing fees and sales of a software product. It is expressed in US dollar (\$) equivalent.                                                                                                          |

Note: The term “organization” in Table 2 implies a university.

Table 3 provides an overview of the statistical analysis conducted on the data, highlighting parameters like mean, standard deviation, skewness, kurtosis, and coefficient of variation. Data collection involved 75 datasets sourced from university commercialization centers. The dataset was partitioned into training (or learning) and testing sets, with 80% used for learning and the remaining 20% for testing based on the recommendation of Shen *et al.* (2021) and Zhou *et al.* (2020) to avoid overfitting problems in the analysis.

Table 3: Statistical assessment of the datasets

| Variables                | $x_1$    | $x_2$   | $x_3$    | $x_4$ | $x_5$ | $x_6$ | $x_7$ | $x_8$ | $x_9$ | $y$       |
|--------------------------|----------|---------|----------|-------|-------|-------|-------|-------|-------|-----------|
| Maximum                  | 51846.06 | 9277.54 | 24447.61 | 1.00  | 12.00 | 14.00 | 9.00  | 5.00  | 5.00  | 149024.53 |
| Minimum                  | 8990.70  | 1761.98 | 7682.89  | 0.00  | 4.00  | 4.00  | 2.00  | 3.00  | 2.00  | 22000.27  |
| Range                    | 42855.36 | 7515.55 | 16764.72 | 1.00  | 8.00  | 10.00 | 7.00  | 2.00  | 3.00  | 127024.27 |
| Median                   | 15432.92 | 4855.52 | 12090.71 | 1.00  | 6.00  | 7.00  | 4.00  | 5.00  | 4.00  | 50085.11  |
| Mean                     | 20892.43 | 5158.59 | 13879.63 | 0.79  | 5.67  | 7.43  | 4.15  | 4.53  | 3.69  | 60770.33  |
| Standard deviation       | 11313.49 | 2207.28 | 4919.82  | 0.41  | 1.24  | 2.05  | 1.26  | 0.62  | 0.80  | 31005.45  |
| Skewness                 | 1.05     | 0.25    | 0.77     | -1.40 | 1.96  | 0.96  | 0.50  | -0.97 | 0.29  | 0.92      |
| Kurtosis                 | -0.02    | -0.98   | -0.68    | 0.04  | 8.28  | 0.87  | 1.63  | -0.02 | -0.85 | 0.08      |
| Coefficient of variation | 0.54     | 0.43    | 0.35     | 0.52  | 0.22  | 0.28  | 0.30  | 0.14  | 0.22  | 0.51      |

### 3.2. Genetic programming

GP is an optimal approach used to develop mathematical models for problems. It operates according to the theory of Darwin's natural selection. GP involves the selection and generation of computer programs by employing the principles of natural selection. The approach relies on genetic mechanisms like reproduction, crossover, and mutation to iteratively evolve optimal solutions (Iqbal *et al.*, 2020).

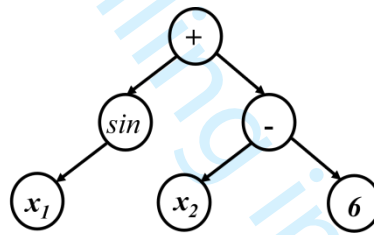


Figure 1: A typical example of a parse tree in GP model, expressed as:  $\sin x_1 + (x_2 - 6)$

An individual generated randomly in GP requires a set of structured parse trees (as shown in Figure 1) containing functions and terminals (Jamei and Ahmadianfar, 2020). The function set includes arithmetic functions ( $-$ ,  $+$ ,  $\div$ ,  $\times$ ), trigonometric functions ( $\cos$ ,  $\sin$ ,  $\tan$ ,  $\cot$ ,  $\sec$ ,  $\csc$ ), logarithmic functions ( $\ln$ ,  $\log$ ), or Boolean functions (AND, OR, NOT). The terminal set consists of constants and independent variables of the model. Thus, the terminals and functions together form the computer programs that are randomly selected (Citakoglu *et al.*, 2020). Three initialization methods namely; grow, full, and ramp half-and-half are used to randomly generate computer programs. For a more comprehensive understanding of these initialization techniques, readers can refer to McDermott and O'Reilly (2015). The fitness of computer programs is calculated by employing a fitness function. The fittest computer programs, which have the best RMSE values, are chosen from the initial generation to produce new individuals. The crossover and mutation operators are then successively and repeatedly applied to produce new computer

programs for evaluation in the succeeding generation until the termination criterion is met (Jamei and Ahmadianfar, 2020). The steps involved in GP are outlined in Figure 2.

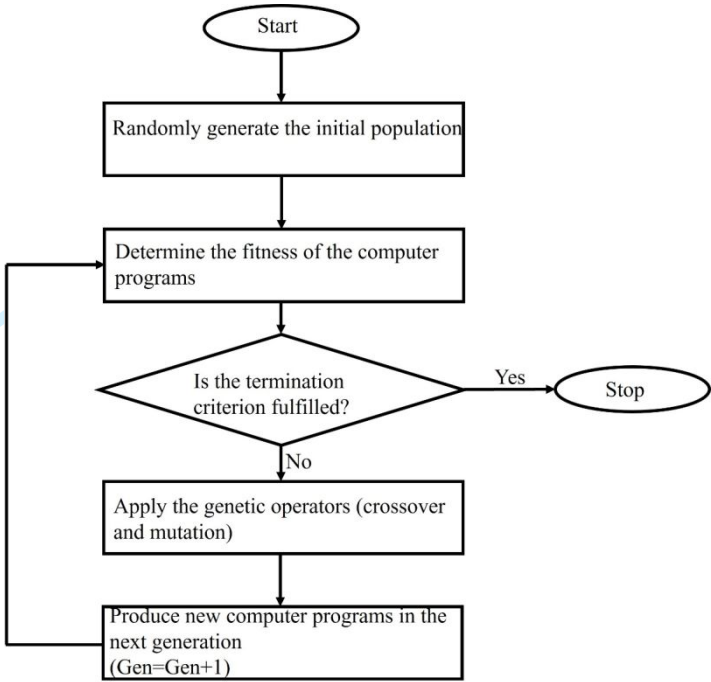


Figure 2: The fundamental framework of GP methodology.

In this research, the GP model was developed using GPLAB (a specialized MATLAB toolbox designed for GP research and applications). The GP parameters used in this research are presented in Table 4. Mathematical operators such as multiplication ( $\times$ ), addition ( $+$ ), division ( $\div$ ), subtraction ( $-$ ), and natural logarithm ( $\ln$ ) were applied as the function sets of the model. These functions were selected through an iterative trial-and-error process, where the input variables and random numbers between 0 and 1 were defined as the terminal sets (Silva *et al.*, 2012). The population of computer programs was randomly initialized using the ramp half-and-half technique because the maximum tree depth notably influences the initialization process. Fang *et al.* (2021) recommended a maximum tree depth of 6 to reduce complexity while improving performance quality. The ramp half-and-half initialization approach demonstrated superior performance compared to other initialization approaches (Fang *et al.*, 2021). Therefore, this approach was employed in the current study to build the GP model.

Table 4: Parameters used for GP

| Parameters                    | Values                                              |
|-------------------------------|-----------------------------------------------------|
| Function set                  | $\times, +, -, \div, \ln$                           |
| Terminal set                  | rand, $x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9$ |
| Maximum number of generations | 30                                                  |

|                            |                                  |
|----------------------------|----------------------------------|
| Population size            | 1000                             |
| Initialization method      | Ramp half-and-half               |
| Fitness function           | RMSE                             |
| Selection method           | Lexicographic parsimony pressure |
| Initial maximum tree depth | 6                                |
| Crossover rate             | 85%                              |
| Mutation rate              | 15%                              |

The population size and number of generations were chosen to be 1000 and 30, respectively. After conducting several trial-and-error efforts, these values were found to perform appropriately in this research. The selection of RMSE as the fitness function was in accordance with the recommendation of Shen *et al.* (2021). It was used to assess fitness values, and the computer programs with the best RMSE were chosen to evolve new computer programs. The lexicographic parsimony pressure method was employed in this research to improve parse tree sizes. Faradonbeh *et al.* (2016) recommended that the method was highly effective in mitigating the bloat phenomenon. A crossover probability of 85% was opted for, in accordance with the recommendation of researchers who proposed that a crossover probability ranging from 80% to 90% can be employed in constructing a GP model to expedite convergence and enhance the exploration of the solution space (Faradonbeh *et al.*, 2016; Yong *et al.*, 2021). A 15% mutation probability was applied to ensure the model maintains diversity and avoids premature convergence. The evolution process stopped when the termination criterion (number of generations) was fulfilled as suggested by Faradonbeh *et al.* (2016).

### 3.3. Artificial neural network

ANNs are computational algorithms that mimic and process information in a manner similar to the nervous system. As depicted in Figure 3, the fundamental architecture of an ANN consists of an input layer, one or more intermediate hidden layers, and an output layer. The 9 inputs are connected to the hidden layer via the neurons and each input value ( $x_i$ ) is multiplied by a corresponding weight. These weighted products are aggregated, processed by a transfer function, and transformed into an output (Öztürk and Başar, 2022).

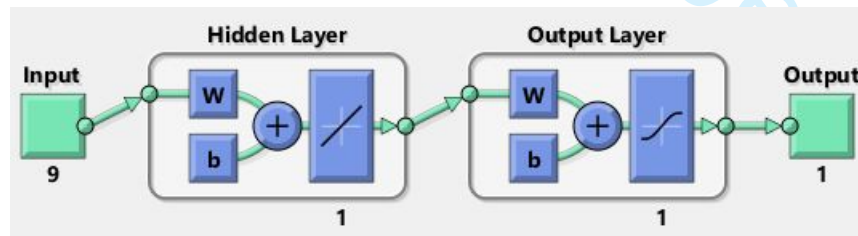


Figure 3: Architecture of the neural network for prediction of TCP

In this research, a feed-forward backpropagation neural network featuring one hidden

layer with an output layer was applied. This choice was made based on the regression features of the research problem. The chosen learning algorithm in this study was Levenberg-Marquardt (*trainlm*), due to its popularity and reliability for ANN training, especially in scenarios where fast convergence and robustness are crucial (Conde-Gutiérrez *et al.*, 2023). The hidden neurons used the hyperbolic tangent activation function (*tansig*), while the output layer used a linear activation function (*purelin*) (Abdullah *et al.*, 2019).

Fang *et al.* (2021) used a network with  $i$  inputs that required a maximum of  $2i + 1$  hidden nodes in their research to effectively address the overfitting and underfitting of a model. This study applied a trial-and-error process to verify the optimal network architecture from hidden layer in the potential networks with number of nodes ranging from 1 to  $2i + 1$ . Hence, several ANN models, ranging from those with 1 to 19 hidden neurons were considered because there were 9 input variables ( $i = 9$ ) in this research. These models underwent a training learning rate of 0.05 with 5000 epochs (Abdullah *et al.*, 2019). The performance during training and testing was assessed using the relative root mean squared error (RRMSE) and coefficient of determination ( $R^2$ ) as the evaluation metrics. Upon completing the training process, the ANN models were evaluated to identify the optimal number of neurons (Rao *et al.*, 2018). Furthermore, a straightforward ranking approach was employed to choose the network that demonstrates the best performance on the training and testing data (Zhou *et al.*, 2020). The models (as shown in Figure 5) were ranked by their RRMSE values in ascending order, while their  $R^2$  values were prioritized from highest to lowest.

The optimal ANN model, based on the number of hidden neurons, was selected according to its best overall ranking. According to Table 5, ANN-1 with an overall rank of 14 outperformed the other ANN networks in terms of performance. Consequently, ANN-1, featuring 1 hidden neuron, was designated as the best model.

Table 5: Performance of ANN models with varying numbers of hidden nodes

| Model | Model performance |               |               |               | Ranking  |          |          |          |           |
|-------|-------------------|---------------|---------------|---------------|----------|----------|----------|----------|-----------|
|       | Training          |               | Testing       |               | Training |          | Testing  |          | Total     |
|       | RRMSE             | $R^2$         | RRMSE         | $R^2$         | RRMSE    | $R^2$    | RRMSE    | $R^2$    |           |
| ANN-1 | <b>0.0096</b>     | <b>0.9764</b> | <b>0.0277</b> | <b>0.9430</b> | <b>4</b> | <b>6</b> | <b>1</b> | <b>3</b> | <b>14</b> |
| ANN-2 | 0.0082            | 0.9867        | 0.0361        | 0.9016        | 3        | 1        | 7        | 4        | 15        |
| ANN-3 | 0.0077            | 0.9854        | 0.0390        | 0.8734        | 2        | 3        | 8        | 9        | 22        |
| ANN-4 | 0.0169            | 0.9620        | 0.0323        | 0.9569        | 14       | 9        | 3        | 1        | 27        |
| ANN-5 | 0.0102            | 0.9803        | 0.0347        | 0.8911        | 5        | 5        | 4        | 6        | 20        |
| ANN-6 | 0.0072            | 0.9863        | 0.0589        | 0.6853        | 1        | 2        | 16       | 17       | 36        |
| ANN-7 | 0.0120            | 0.9600        | 0.0292        | 0.9476        | 6        | 10       | 2        | 2        | 20        |

|        |        |        |        |        |    |    |    |    |    |
|--------|--------|--------|--------|--------|----|----|----|----|----|
| ANN-8  | 0.0122 | 0.9710 | 0.0396 | 0.8621 | 7  | 7  | 9  | 10 | 33 |
| ANN-9  | 0.0236 | 0.9047 | 0.0507 | 0.8785 | 16 | 19 | 12 | 8  | 55 |
| ANN-10 | 0.0133 | 0.9512 | 0.0420 | 0.8600 | 8  | 11 | 10 | 11 | 40 |
| ANN-11 | 0.0082 | 0.9831 | 0.0559 | 0.8265 | 3  | 4  | 15 | 13 | 35 |
| ANN-12 | 0.0141 | 0.9486 | 0.0349 | 0.8996 | 10 | 12 | 5  | 5  | 32 |
| ANN-13 | 0.0139 | 0.9465 | 0.0360 | 0.8890 | 9  | 15 | 6  | 7  | 37 |
| ANN-14 | 0.0248 | 0.9077 | 0.0852 | 0.7610 | 17 | 18 | 18 | 16 | 69 |
| ANN-15 | 0.0142 | 0.9482 | 0.0545 | 0.7832 | 11 | 13 | 14 | 15 | 53 |
| ANN-16 | 0.0178 | 0.9132 | 0.0539 | 0.8558 | 15 | 17 | 13 | 12 | 57 |
| ANN-17 | 0.0163 | 0.9340 | 0.0880 | 0.4515 | 13 | 16 | 19 | 19 | 67 |
| ANN-18 | 0.0122 | 0.9631 | 0.0767 | 0.5716 | 7  | 8  | 17 | 18 | 50 |
| ANN-19 | 0.0149 | 0.9481 | 0.0457 | 0.8206 | 12 | 14 | 11 | 14 | 51 |

### 3.4. Support vector machine

SVM stands as a prominent machine learning approach for classification and regression problems. It is classified as a nonparametric approach based on its dependence on kernel functions. It commonly employs kernel functions such as linear, polynomial, and radial basis functions (Zouzou and Citakoglu, 2022). It is essential to infer a functional relationship between the output variable ( $y_i$ ) and a group of input variables ( $x_i$ ). The link between  $y_i$  and  $x_i$  is defined by a deterministic function (Equation (1)) (Mäkiäho *et al.*, 2023).

$$y_i = f(x_i) = w^T \phi(x_i) + b \quad (1)$$

In this context,  $w^T$  signifies the weight vector,  $\phi(x_i)$  represents a non-linear mapping function, and  $b$  denotes the bias. For a more detailed discussion of SVM and its optimization methods, readers can refer to the work of Zereg and Belouz (2022). The linear kernel function was chosen due to its simplicity, and ability to provide faster training time and lower computational complexity compared to more complex kernel functions like polynomial and radial basis kernels. Improved model performances were observed with the utilization of linear kernel function (Chong *et al.*, 2017). The data for SVM were trained using the 'fitrsvm' function in MATLAB to evaluate the predicted TCP of a software product in a university.

### 3.5. Validation and comparison of the models

Validation of the GP model was carried out by comparing its performance with that of ANN and SVM, based on the evaluation metrics. These 2 methods were selected for comparison because they are commonly used by researchers to handle non-linear problems. The performance and accuracy of the models were assessed using the evaluation metrics: relative root mean squared error (RRMSE) (Equation (2)), root mean absolute error (RMAE) (Equation (3)), mean absolute percentage error (MAPE) (Equation (4)), and the coefficient of determination ( $R^2$ ) (Equation (5)).

$R^2$  varies within the range of 0 and 1; a higher value of  $R^2$  suggests a more effective model. Conversely, lower values of RRMSE, RMAE, and MAPE signify superior model performance. In order to guarantee consistent model performance, input data, and reproducibility, the same datasets were utilized for both the training and testing sets (Olawore *et al.*, 2024). The mean performance and error percentage were determined to account for variability. A Taylor diagram was also employed as a graphical tool to compare the performance of the prediction models (GP, ANN, and SVM models) against the reference data (actual TCP) (Citakoglu and Demir, 2022).

$$RRMSE = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \tilde{y}_i)^2}}{\bar{y}} \quad (2)$$

$$RMAE = \sqrt{\frac{1}{n} \sum_{i=1}^n |y_i - \tilde{y}_i|} \quad (3)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \tilde{y}_i}{y_i} \right| \quad (4)$$

$$R^2 = 1 - \left( \frac{\sum_{i=1}^n (y_i - \tilde{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \right) \quad (5)$$

The actual and predicted TCP values are denoted by  $y_i$  and  $\tilde{y}_i$ , respectively.  $\bar{y}$  is the average of the actual values and  $n$  refers to the overall number of datasets. The distributions of the actual and predicted values were visually summarized using a box plot. It provides a clear depiction of the median, quartiles, and outliers for the actual and predicted values of each model, facilitating their distributional comparison (Citakoglu and Demir, 2022). The Kruskal-Wallis test was utilized as a non-parametric statistical analysis method to ascertain whether there were statistically significant differences between the actual and predicted values. It was used in this study because it does not require data to be normally distributed (Bayram and Çitakoğlu, 2023).

## 4. Results

### 4.1. GP model

The developed GP model for forecasting the TCP of a software product in a university setting is presented in Equation (7). Specifically, Equation (6), as initially derived from the parse tree, is rearranged and regrouped to form Equation (7). The parse tree for the best obtained GP model is

depicted in Figure 4.

$$y = x_2 + x_3 + \left( \frac{x_4 + x_6}{0.017515} + x_1 \right) \ln x_6 - \frac{0.37894}{x_5 x_8} \\ ((x_1 + x_1 + x_9 - x_2 - x_3 - x_6 - x_7 - x_8 - \ln x_8) x_8 + 0.37894(((\ln(x_1 + x_1 + x_9 - x_2 - x_3 - x_3 - x_8$$

(6)

$$y = x_2 + x_3 + \left( \frac{x_4 + x_6}{0.017515} + x_1 \right) \ln x_6 - \frac{0.37894}{x_5 x_8} \\ ((2x_1 + x_9 - x_2 - x_3 - x_6 - x_7 - x_8 - \ln x_8) x_8 + 0.37894(((\ln(x_9 - x_2 - 2x_3 - x_8 - x_6 + 2x_1))(x_9 -$$

(7)

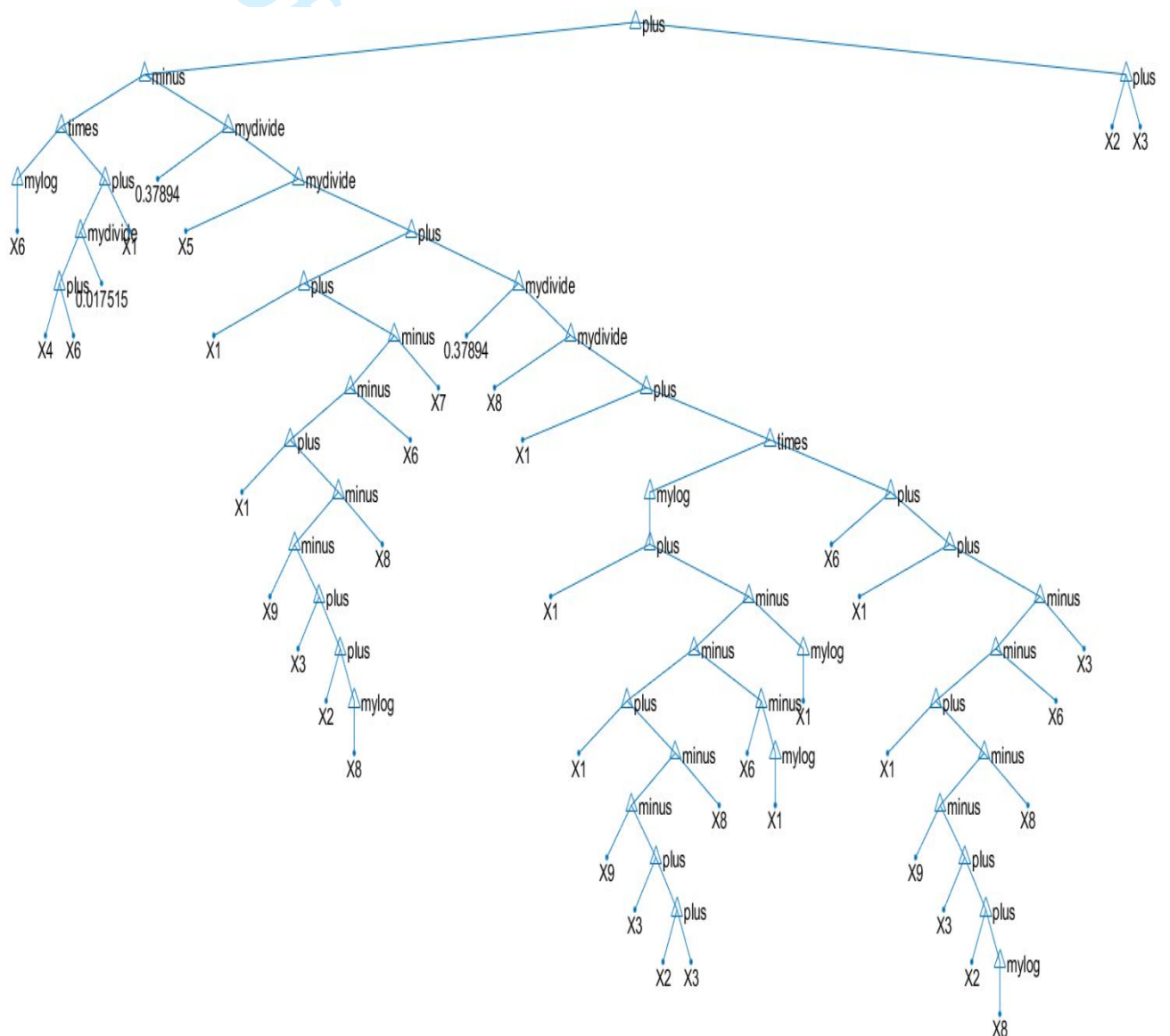


Figure 4: The parse tree for the obtained GP model

4.2. Model evaluation

The performance of these models was assessed and contrasted using metrics such as  $R^2$ , RRMSE, RMAE, and MAPE. The  $R^2$  values of GP, ANN, and SVM for the training datasets are 0.9854, 0.9764, and 0.9582, respectively (Figure 5), whereas the  $R^2$  values of GP, ANN, and SVM for the testing datasets are 0.9564, 0.9430, and 0.9421, respectively (Figure 6). The error percentages for the training and testing sets are as follows: 4.0% - 8.0% for the GP model, 6.5% - 9.0% for the ANN model, and 7.5% - 10.0% for the SVM model. The effectiveness of the predictive models assessed in this research is shown in Table 6, which includes RRMSE, RMAE, MAPE, and  $R^2$  for the training and testing sets. As depicted in Figures 7(a) and 7(b), the Taylor diagram reveals that these predictive models have high correlation coefficients in both the training and testing sets. However, the GP model's predicted values of TCP are closer to the actual values compared to the other 2 models. Therefore, the Taylor diagram demonstrates that the GP model has superior performance over ANN and SVM models in predicting TCP.

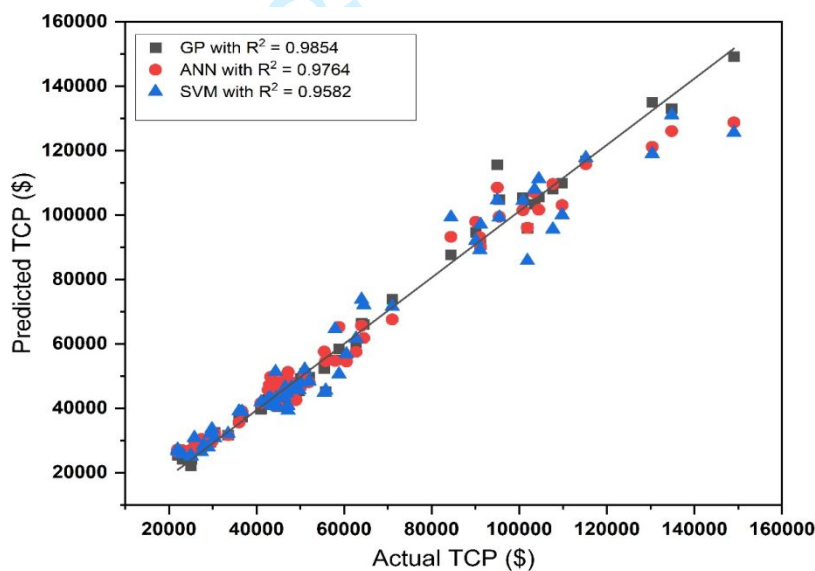


Figure 5:  $R^2$  plot comparing the GP, ANN, and SVM models using the training datasets.

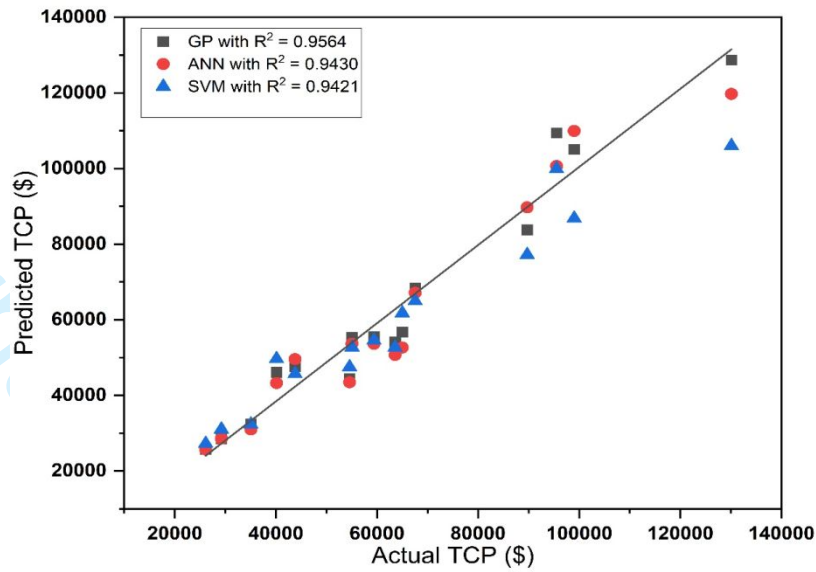


Figure 6:  $R^2$  plot comparing the GP, ANN, and SVM models using the testing datasets.

Table 6: Evaluation metric outcomes for the three models

| Predictive Model | Training set |         |          |        | Testing set |         |          |        |
|------------------|--------------|---------|----------|--------|-------------|---------|----------|--------|
|                  | RRMSE        | RMAE    | MAPE (%) | $R^2$  | RRMSE       | RMAE    | MAPE (%) | $R^2$  |
| GP               | 0.0076       | 49.7864 | 4.5896   | 0.9854 | 0.0235      | 70.0660 | 7.8441   | 0.9564 |
| ANN              | 0.0096       | 60.7076 | 6.6241   | 0.9764 | 0.0277      | 75.0064 | 8.8742   | 0.9430 |
| SVM              | 0.0125       | 68.2168 | 7.7904   | 0.9582 | 0.0367      | 82.1718 | 9.8139   | 0.9421 |

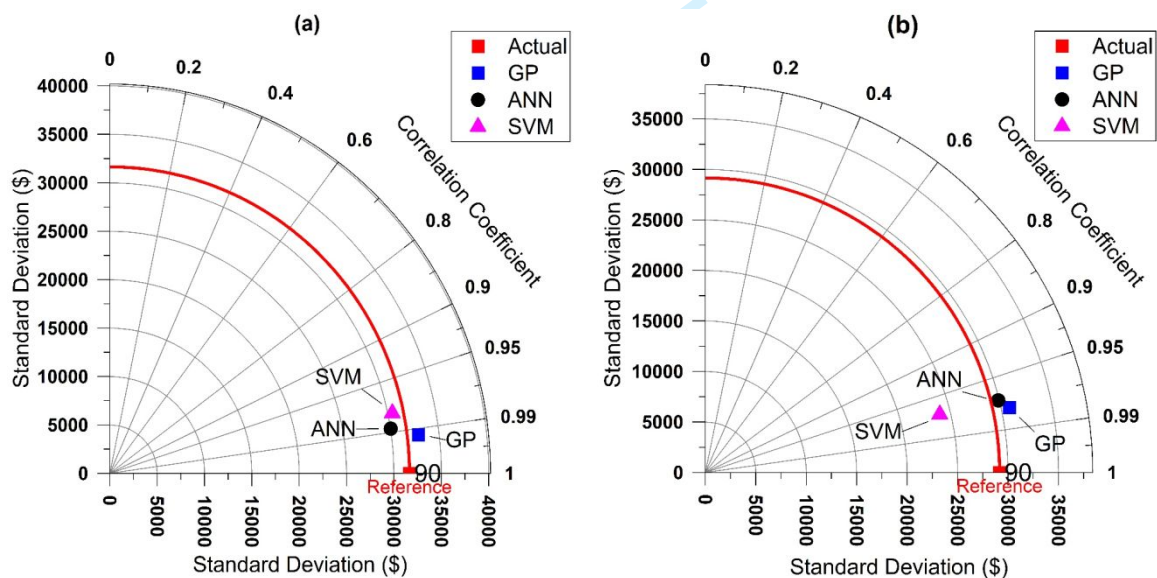


Figure 7: Taylor diagram comparing the performance of the models on the (a) training dataset and (b) testing dataset.

The absence of outliers in the box plots shown in Figures 8(a) and 8(b) suggests that the actual and predicted values are relatively homogeneous and do not have extreme values that deviate substantially from their central tendency. This indicates that their distributions are

comparatively consistent. The results in Table 7 clearly demonstrate that the hypothesis ( $H_0$ ), concerning the comparison between actual and predicted values across the three models for both training and testing datasets, has been accepted. This implies that there is no significant difference between the actual and predicted values based on their ranks.

Table 6: Results of Kruskal–Wallis tests with P-Values at 95% significance level

| Training dataset |         |        | Testing dataset |         |        |
|------------------|---------|--------|-----------------|---------|--------|
| Model            | P-Value | $H_0$  | Model           | P-Value | $H_0$  |
| GP               | 0.79299 | Accept | GP              | 0.85193 | Accept |
| ANN              | 0.77283 | Accept | ANN             | 0.60413 | Accept |
| SVM              | 0.75282 | Accept | SVM             | 0.66319 | Accept |

Null Hypothesis ( $H_0$ ): There is no significant difference between the actual and predicted values.

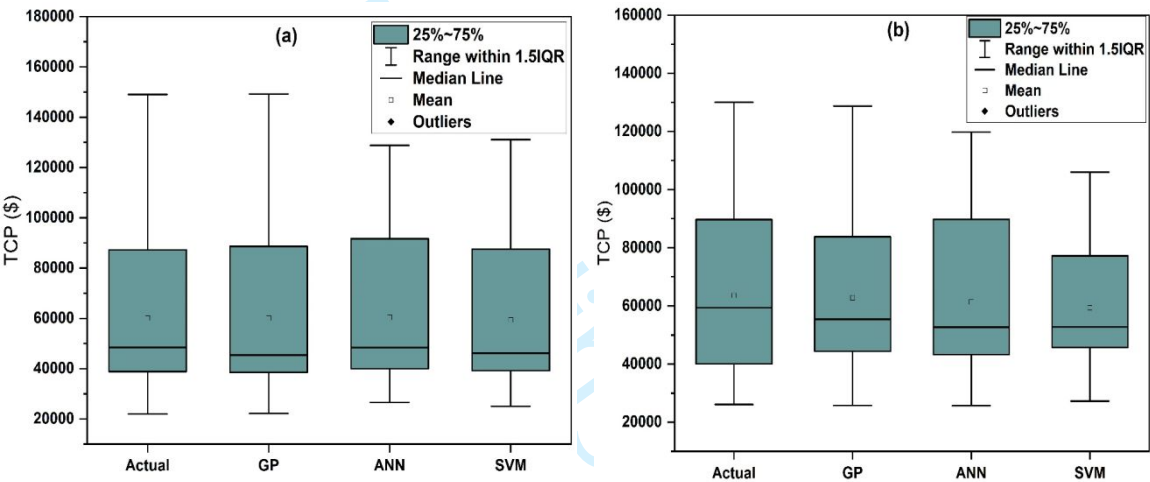
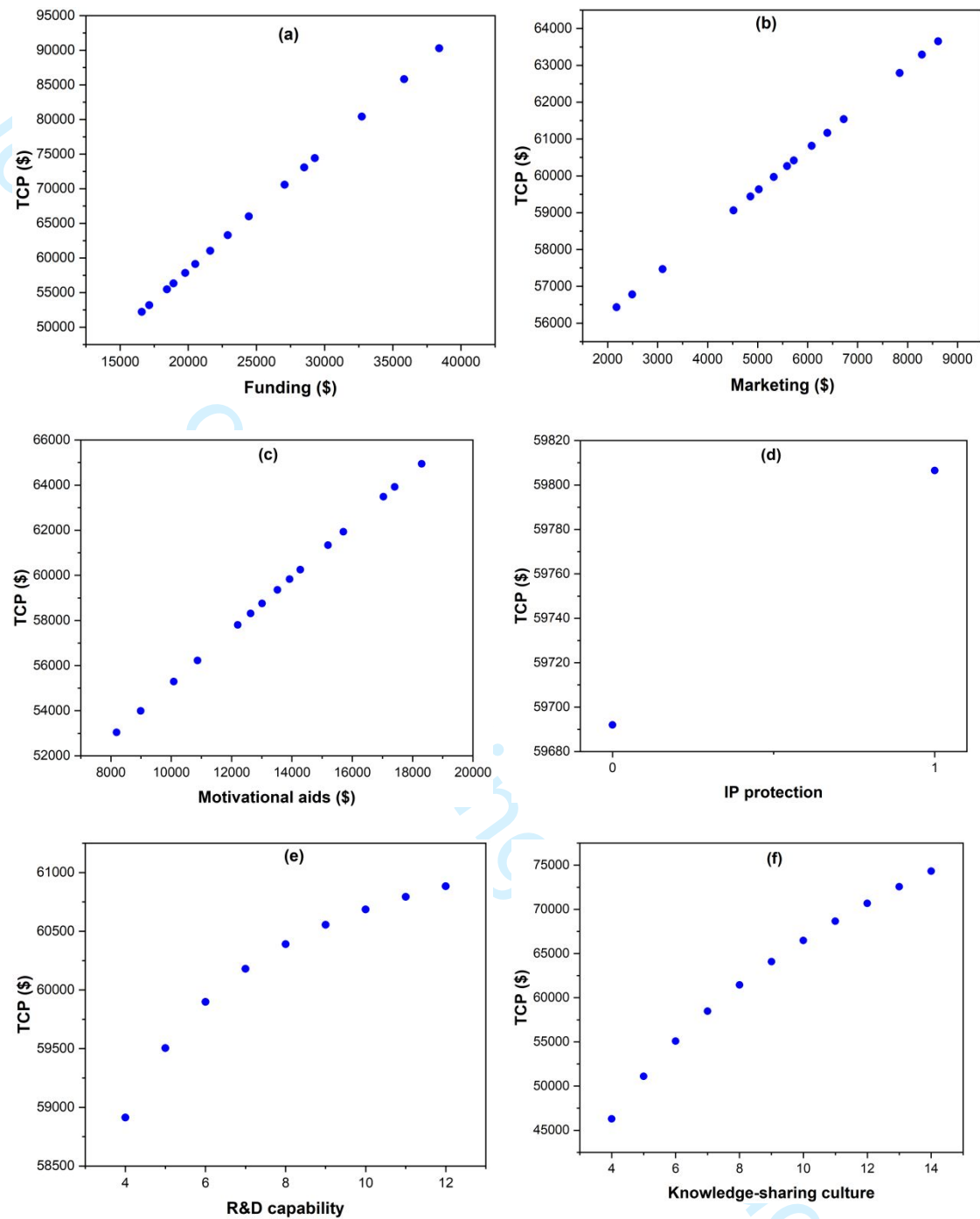


Figure 8: Box-plot diagram of the 3 models for (a) training dataset, and (b) testing dataset.

4.3. Parametric analysis

Parametric analysis indicates the capacity of the GP model to adjust to modifications of individual input variables. The ranges of the varied input variables fall within the limits of their respective lowest and highest values (Chu *et al.*, 2021). A parametric analysis of the GP model was conducted by assessing its prediction outcomes for individual model’s input, whereas the remaining eight input parameters were held constant at their corresponding average values. Figure 9 illustrates the findings from the parametric analysis performed using the GP model.



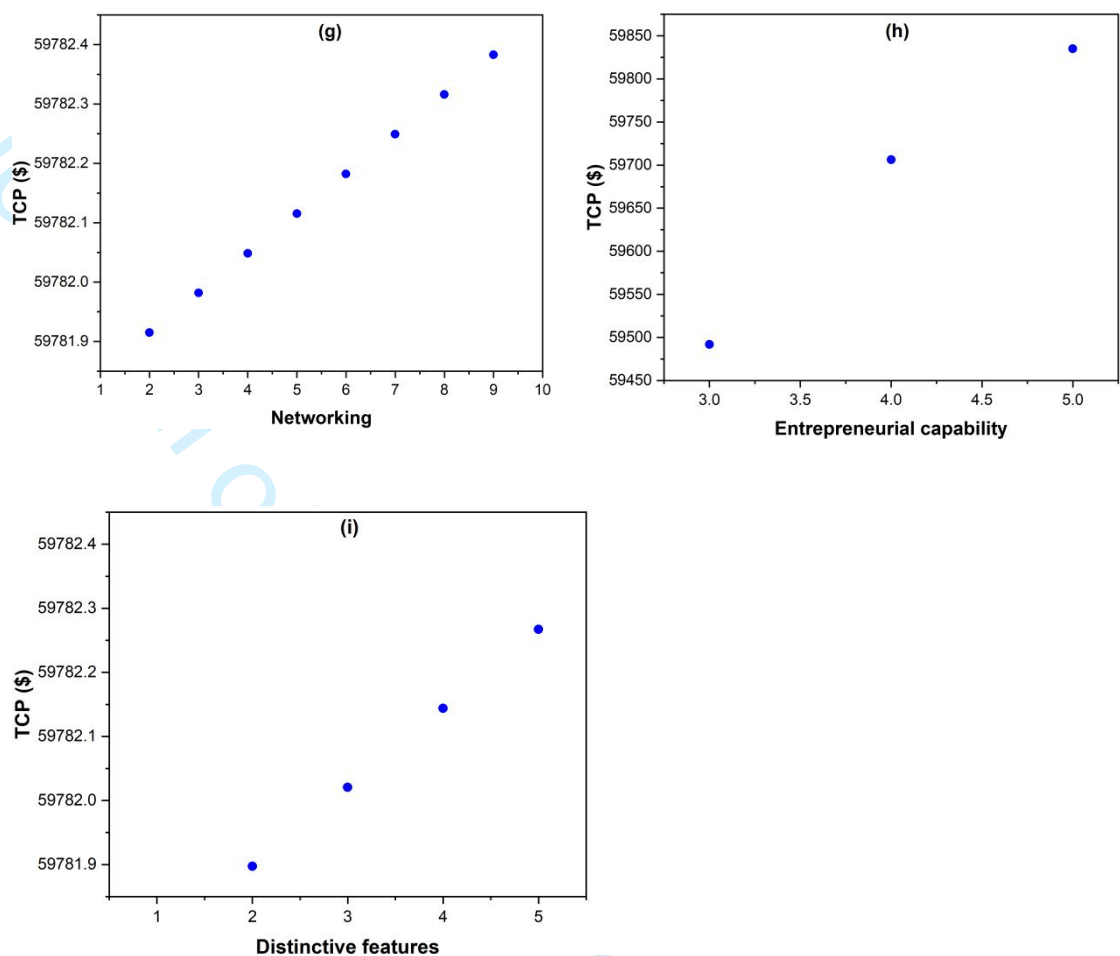


Figure 9: Variation of TCP with regard to 9 input variables ((a) Funding (b) Marketing (c) Motivational aids (d) IP protection (e) R&D capability (f) Knowledge-sharing culture (g) Networking (h) Entrepreneurial capability (i) Distinctive features) via parametric analysis of the GP model

5. Discussion

The outcomes derived from the GP analysis furnish an evaluation model for the commercialization of developed software products in university commercialization centers. Professionals can readily use this new model to allocate resources for commercializing software products successfully in university commercialization centers. The developed mathematical model also uncovers the interrelationship between technology commercialization factors and the economic value derived from developing and commercializing software products within a university setting.

The  $R^2$  values for the training datasets are 0.9854, 0.9764, and 0.9582 for the GP, ANN, and SVM models, respectively. In contrast, for the testing datasets, the  $R^2$  values are 0.9564, 0.9430, and 0.9421 for the GP, ANN, and SVM models, respectively. Thus, the GP model exhibits superior accuracy, with its  $R^2$  values surpassing those of the other models. Furthermore, the

respective values (for both training and testing datasets) of RRMSE, RMAE, and MAPE for the GP model are lower than those of the ANN and SVM models. A lower value of RRMSE, RMAE, and MAPE signifies better model performance (Fallahpour *et al.*, 2021). Therefore, the comparative analysis of the models based on RRMSE, RMAE, MAPE, and  $R^2$  values indicates that GP is a more effective and accurate model for forecasting the TCP of a software product in universities.

The GP model stands out as a more intelligent approach by virtue of its capacity to solve the black box problem which is one of the drawbacks of the other methods used in this research. This enhanced intelligence stems from GP's superior search capabilities and its ability to achieve higher accuracy, particularly when dealing with immensely intricate, non-linear, and chaotic problems. This flexibility, along with GP's capacity to search globally, enables it to avoid local minima, a drawback that ANN and SVM frequently face (Ekmekcioğlu *et al.*, 2023).

The TCP of a university increases as the amount of funds allocated for developing and commercializing a software product increases (as shown in Figure 9(a)). Additionally, the TCP of universities is observed to increase with improvements in marketing, motivational aids, IP protection, R&D capability, knowledge-sharing culture, networking, entrepreneurial capability, and distinctive features.

Funding is essential for the advancement and market introduction of software products within university commercialization centers. It supports various aspects of the technology commercialization process, from R&D to the introduction of a software product into the market. Nigerian universities secure funding through grants, donations, and endowments contributed by individuals, organizations, international agencies, and government parastatals, all aimed at fostering the advancement and economic exploitation of software products (M'Chirgui *et al.*, 2018).

Marketing is an integral part of the technology commercialization process for software products in university commercialization centers. It bridges the gap between innovation and market demand, ensuring that the developed software products reach their intended customers and achieve commercial success (Yazdimoghaddam *et al.*, 2019). Increasing the marketing expenditure can be an effective strategy to enhance the TCP of a university by boosting the visibility and sales of a software product. Most university commercialization centers in Nigeria introduce developed software products into the markets via online platforms, trade fairs, media, industry events, and partnerships with distributors or spin-off firms.

Motivational aids for personnel in a university commercialization center have a multifaceted impact on TCP. Monetary incentives can serve as powerful motivators for faculties, researchers, and developers. When individuals see the potential for financial rewards, they may be more inclined to actively engage in technology commercialization efforts (Sharma, 2022). Many Nigerian universities have implemented systems to acknowledge and incentivize

researchers and developers when their research outcomes are commercialized and made public. The prominent approaches are the allocation of a portion of licensing royalties to the researchers and the promotion of personnel. This factor contributes to increased productivity, innovation, quality, and improved teamwork.

IP protection is a cornerstone of successful technology commercialization in university settings. It provides a competitive edge by preventing competitors from replicating a developed software product with unique features (Chiş and Crişan, 2020). A copyright discourages others from copying a software product and its programming codes, as they might face legal consequences for copyright infringement. In 2006, the National Office for Technology Acquisition and Promotion initiated the creation of Intellectual Property and Technology Transfer Offices in tertiary institutions, which has significantly boosted the number of inventions emerging from Nigerian universities (Fadeyi *et al.*, 2019). These offices are tasked with the protection and administration of intellectual property produced by scientific organizations, such as universities and research institutions. This has helped university commercialization centers to create an avenue for long-term revenue generation from a developed software product. In contrast, it is challenging to monetize a software product without IP protection because potential revenue streams, such as licensing fees, royalties, or sales, may be limited or lost entirely.

The R&D capability of a university is the foundation upon which successful technology commercialization is built. It ensures that a software product is not only technically sound but also aligned with market demands and has the potential to create significant value in the industry (Park and Shin, 2017). Increasing the number of competent personnel involved in the advancement and economic exploitation of a software product can lead to improved TCP for a university by fostering innovation, accelerating development, enhancing product quality, and expanding market reach.

A knowledge-sharing culture within a university enhances the TCP of a software product by promoting information exchange, facilitating collaboration, providing access to resources, and creating an environment conducive to knowledge transfer (Hsu *et al.*, 2015). The implementation of academic discourses, seminars, workshops, and training on R&D and entrepreneurship helps to inculcate this culture in a university commercialization center. The Nigerian government has allocated substantial resources to train academics both domestically and internationally using various avenues to acquire knowledge and cultivate a pool of highly skilled researchers and developers. This investment has facilitated the exchange of knowledge and enabled university-based researchers and developers to tap into the collective expertise of the academic community. As a result, software development cycles have accelerated, leading to faster time-to-market for their products and improved TCP.

Networking fosters collaboration between university commercialization centers and industrial organizations or other agencies (Pujotomo *et al.*, 2023). The Nigerian government has

established a few science and technology parks near universities to facilitate collaboration between academia and industry. These parks provide a conducive environment for research and innovation. Collaborative projects with industries can accelerate the development and commercialization of software products by combining resources, expertise, and market access. University researchers and students involved in such projects gain practical experience and skill development via government agencies like the Industrial Trust Fund. This can enhance their ability to contribute to the software development process and subsequently, improve the TCP of university commercialization centers.

Entrepreneurial capability empowers universities to analyze and harness the commercial viability of software products, turning them into tangible fiscal value by seizing available market opportunities. Some Nigerian universities have established entrepreneurship centers, technology incubators, and innovation hubs to nurture entrepreneurial talent and facilitate the development of software products and other technologies. The unique role of these established centers is to motivate academics to partake in entrepreneurial pursuits and risk-taking akin to their industry counterparts. This inculcates academics in Nigerian universities to imbibe a culture characterized by risk-taking, effective problem-solving, and the successful introduction of software products for market adoption. A university commercialization center endowed with robust entrepreneurial capability not only stimulates economic growth but also elevates a university's prosperity and productivity.

Finally, the distinctive features of a software product play a crucial role in its TCP. These features refer to unique characteristics or attributes that differentiate a software product from others in the market. These features give a software product a competitive edge (Chiş and Crişan, 2020). When a software product offers something unique or better than existing solutions, it becomes more attractive to potential customers, which can lead to higher sales and market share. However, it is essential to balance innovation with market research to ensure that distinctive features align with customer needs and preferences.

## 6. Conclusions

In this research, a GP model was formulated using historical data related to technology commercialization, which were sourced from Nigerian university commercialization centers. Comparative analyses were conducted with ANN and SVM models by utilizing similar datasets. The effectiveness of the models was evaluated using RRMSE, RMAE, MAPE, and  $R^2$ . Also, the Kruskal–Wallis test was used to assess whether there were statistically significant differences between the actual and predicted values based on their ranks. Parametric analysis was also conducted for the GP model.

The GP model achieved  $R^2$  values of 0.9854 for the training set and 0.9564 for the testing set. In comparison, the ANN model showed  $R^2$  values of 0.9764 and 0.9430 for training and testing sets, respectively, while the SVM model obtained  $R^2$  values of 0.9582 for training set and 0.9421 for testing set. According to the evaluation criteria, the GP model surpassed both the ANN and SVM models in forecasting the TCP of university software products with superior accuracy. The Kruskal–Wallis test indicated that there was no significant disparity between the actual and forecast values, based on their ranks, at a 95% significance level.

Parametric analysis showed the relationship between each input variable and TCP separately. The developed GP mathematical model also revealed the interrelationship between technology commercialization factors and the economic value derived from developing and commercializing software products within a university setting. This new model can be readily employed by professionals to allocate resources for the successful commercialization of software products. From an academic viewpoint, this research has made an important contribution by introducing the GP approach to evaluate TCP in universities. It has extended the boundaries of research by introducing a new approach to predict commercialization performance, which can serve as a foundation for further exploration and innovation. In practical terms, this study presents decision-makers with a tangible platform to make informed choices based on data rather than relying solely on intuition. The model assists in making prompt decisions and mitigates inaccuracies throughout the process of developing and commercializing software products in university commercialization centers. Ultimately, the predictive model also serves as a tool for policymakers and government officials to determine which universities or entrepreneurs should receive support and to what extent.

This research has limitations due to its reliance on data acquired from Nigerian university commercialization centers. The scope can be expanded beyond developing countries in future studies. Also, potential research can explore stochastic or probabilistic data to formulate a predictive model for TCP. The utilization of other evolutionary-based soft computing techniques to enhance the accuracy of the developed model can be considered in future studies.

**Data Availability**

The data supporting this research are available upon request from the first author.

**Declaration of Interest statement**

The authors state that they have no competing interests to disclose concerning this research paper.

## Ethical Statement

Not applicable

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