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Role of Alumni Program in the Prediction of Career Success in an Ecuadorian Public University

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Abstract: Alumni tracking studies at the local, regional and global levels provide quality and efficiency measurement parameters in higher education institutions and project improvements in the quality of professionals. However, there is a gap between alumni tracking and the measurement of career success, influencing the academic offer of careers relevant to labor demands. This article aims to propose a model for predicting career success through the analysis, extraction and evolutionary optimization of objective and subjective variables to determine the role of alumni tracking in a higher education institution. The methodology establishes (i) an analysis of information on the alumni program and career success, (ii) prediction models of career success using genetic algorithms, (iii) validation of prediction models and (iv) the relationship between alumni tracking and career success. The results show models for predicting career success using a genetic algorithm with high certainty percentages, where the objective variables' weight significantly influences the predictive model. However, subjective variables show importance depending on individual characteristics and their value schemes or goals of graduates. As a recommendation, universities could include a monitoring system for their graduates, which is crucial in adapting to the curriculum, especially in strategic technical and human ethical issues.

Keywords: objective career success; subjective career success; alumni tracking; prediction; genetic algorithm

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1. Introduction

Universities are transforming agents in the process of student training. They prepare future professionals who understand global challenges and are active players in a prosperous society [1,2]. The current university proposes a higher education based on training and skills development. It incorporates new learning methods, research on current and global issues, adaptation to existing technologies and intelligent and sustainable infrastructure [3–5]. In addition, it links sustainability projects that drive higher education in the 21st century [6–9].

One of the quality indicators of higher education relates to its graduates' satisfaction and professional performance [10]. Higher education institutions manage these quality standards by evaluating the academic performance of teachers, curricular relevance and infrastructure through graduate monitoring programs (alumni) [11]. Sometimes, the implementation of these programs requires graduate surveys [12,13], qualitative interviews [14], questionnaires [15], professional performance self-assessment forms and alumni networks [16]. These programs determine the graduate's general situation and measure the graduate's successful performance in their professional life [17,18].

Career success is the achievement of desired results from a person's work experiences over time [19]. Career success can be both objective and subjective. Objective career success (OCS) is tangible professional achievements related to variables or indicators such as salary, job position, promotions [20,21], occupational prestige [22], political will [23], labor mobility [24], hierarchy, gender, age and working hours [25]. In contrast, subjective career success (SCS) refers to the individual's judgment regarding their career, professional satisfaction, self-perceived evaluation of professional well-being [26,27], professional orientation [28] and vocation and work commitment [29].

OCS is the cause of SCS; they are positively related and are interdependent. For example, people who have a higher salary feel subjectively more successful [30]. In addition, increased job satisfaction does not necessarily raise SCS when other factors are involved, such as health, family relationships and other personal values [31].

There are different studies by authors who proposed the measurement of professional success through the analysis of objective and subjective variables. That is the case with [32], who correlated human resources and the career success of knowledge workers, using a professional success measurement tool that measures human resources with a high-reliability and -validity scale. The results show that the variables education, work experience, learning ability, internal and external competitiveness and job satisfaction predict career success.

Study [33] analyzed professional crises in the relationship between professional skills, employability and professional success, using data from 704 young Dutch professionals aged 21 to 35. They reported that people with high levels of professional competence have a high degree of perceived employability. They concluded that professional crises, professional competencies and career success are essential factors in professional development.

Another study of 654 Chinese employees examined the effects of perceived organizational career management and career adaptability on indicators of career success (e.g., salary and job satisfaction). They demonstrated a robust positive relationship between perceived corporate career management and professional fulfillment, reflected in employees with higher professional adaptability [34].

On the other hand, educational trajectories, the labor market, age and social classes defined the degree of professional success of British graduates. This study showed that graduates from low social strata have variability and instability in their educational trajectories, which causes a low probability of access to high-level jobs and a greater probability that graduates remain in low social strata [35].

Study [36] reflected the professional success perceived by entrepreneurs through the analysis of five indicators of business success, such as professional achievements, social reputation, personal capabilities, business happiness and financial satisfaction. The results determine that entrepreneurial creativity and opportunity recognition positively relate to entrepreneurial career success.

On the other hand, they analyzed the impact and significance of attitudes such as trust and work behavior in OCS and SCS and their impact on Chinese workers' physical and mental health, through the analysis of a mediated moderation model using multilevel linear regression. The results illustrate important relationships between work and life attitudes at an organizational level [37].

The research by [38] analyzed the validity of the Career Adaptation Abilities Scale (CAAS) through the effect of variables of SCS (satisfaction and professional performance). They reported that professional adaptability predicted professional satisfaction and performance. In addition, the variables worry and trust predicted the two indicators of SCS.

Reference [39] related the development of competencies, leadership, psychological flexibility and career success through a survey of hotel industry employees. The results show that leadership significantly affects the development of competencies. The relationship between the employee and the organization significantly improves the professional success of the workers.

Reference [40] analyzed the variables that promote or limit the career success of graduates, employability and professional development through the analysis of psychosocial processes that drive career success. They highlighted their research on the socioeconomic context, the institution and the curricular strategies that determine graduates' employability and professional development.

Machine learning techniques use computational intelligence to analyze correlations between input and output variables through mathematical and statistical models in different applications [41]. The analysis and selection of variables are essential in constructing prediction models [42]. For example, the genetic algorithm (GA), simple linear regression, multiple regression and logistic regression are techniques that select representative and optimal variables to build a prediction model [43,44].

The genetic algorithm represents an exact or approximate stochastic solution based on the population [45]. It simulates the survival of the fittest individuals and their genes, where a key and a parameter represent a chromosome and a gene, respectively. It evaluates the aptitude of an individual through the fitness function or objective function [46]. It maintains the best solutions in each generation to improve other solutions. The recombination of two leading solutions generates a crossover [47,48]. In addition, the mutation changes the genes on the chromosomes, causing the diversity of individuals in the population, which increases the exploratory behavior of the GA and leads to more optimal solutions [49].

GA is effective in finding optimal solutions to various types of problems, with application in different areas: operations management, route planning of mobile robots in unstructured environments in real time, convolutional neural networks, processing of images, fields of multimedia, medicine, learning environments, transport optimization and energy management of electric vehicles, real-time systems, production management, precision agriculture and resolution of programming problems in the real world [50–55]. Furthermore, it is used in real-life applications; that is, chromosome representation is related to real-life issues, demonstrating the robustness, efficiency, quality and accuracy of the solution [56].

This paper presents a study carried out at the State Technical University of Quevedo (UTEQ) to monitor its graduates through a survey aimed at professional graduates. The construction of a career success prediction model used a genetic algorithm based on graduate tracking parameters and significant variables of career success. However, it emphasizes the importance of a graduate monitoring system aligned with current technological profiles in such a way that it allows one to obtain helpful information to predict the career success of its graduates. This contributes significantly to decision making and compliance with quality indicators for higher education institutions in the country.

The most relevant parameter to measure graduates' career success is the job performance of the graduate in the face of a limited job demand, which implies continuous monitoring of the professional graduates from higher education institutions [57–59]. Therefore, to carry out this study, the authors proposed the following research question: Is it possible that, through the application of a genetic algorithm prediction model and mathematical tools, an optimal model of the career success of graduates in the UTEQ can be developed?

This study proposes a model for predicting career success through the analysis and optimization of objective and subjective variables to determine the role of the alumni program at UTEQ. The information on parameters or indicators of the alumni program and variables on career success allowed an analysis of the significance of variables for the design of a GA in predicting career success. A total of 500 UTEQ graduates and their follow-up characteristics represented the population and genes in this natural selection. The fitness function and genetic operators (e.g., elitist selection, crossover and mutation) found models of career success of the GA. This approach determined the relationship between career success and the alumni program. The statistics found a goodness of fit of 87.61% for the prediction model. The results of this study present models that estimate the career success of UTEQ graduates through the interaction of variables, generating a significant retrospective in decision making in the alumni program.

2. Materials and Methods

The methodology of this study consisted of the following phases: (1) analysis of information regarding alumni tracking and career success, (2) prediction models of career success based on a genetic algorithm, (3) statistical analysis for validation of the prediction models and (4) relationship between career success and alumni tracking (Figure 1).

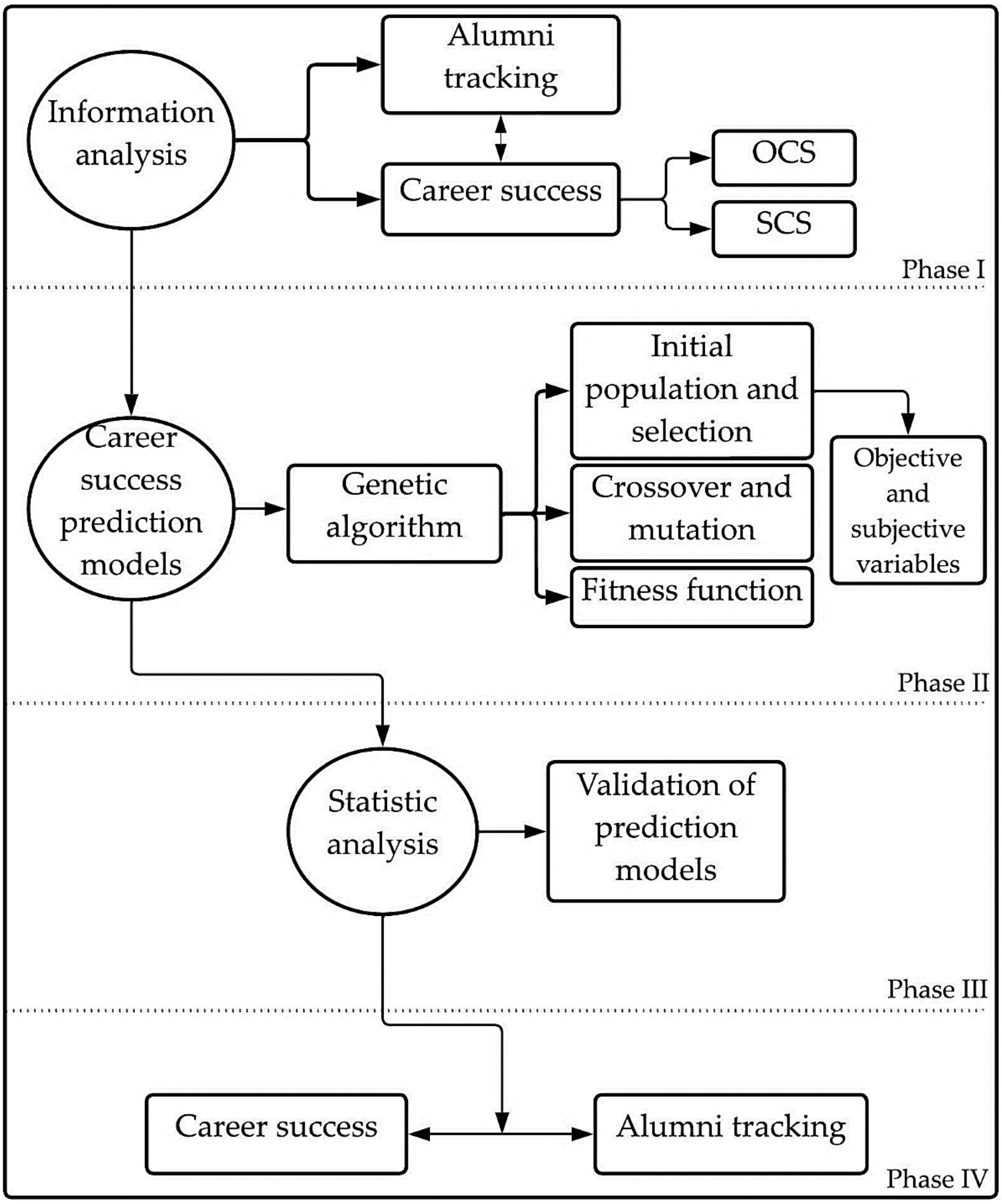


Figure 1. Research methodological design.

2.1. Information Analysis of the Alumni Tracking and Career Success

The information analysis proposed two review scenarios. The first scenario established variables within the framework of the external evaluation model of universities and polytechnic schools of Ecuador [60,61] and manuals of instruments and recommendations on the follow-up of graduates of studies carried out in higher education institutions of Ecuador, Latin America and Europe [62,63]. This allowed the interpretation of quality indicators related to alumni tracking (AT) (Table 1) [64,65]. The second scenario determined predominant variables in the scientific context associated with the career success of graduates from higher education institutions (Tables 2 and 3). Both methods provided a relevant database for constructing the GA for predicting career success, analyzed from the objective (O) and subjective (S) points of view.

Table 1. Parameters of the alumni tracking.

N°	General Features	Variables	Reference Citation
AT1	Sociodemographic	Age, marital status, gender, place of birth and place of residence	[17,18]
AT2	Formation	Obtained title	[13,64]
AT3		Graduation average	[64]
AT4	First job	Job	[63,64]
AT5		Time elapsed to obtain the first job	
AT6		Relationship with career	
AT7	Relationship with the post-formation labor market	Employment level	[13,64]
AT8		Relationship of employment to career	[12,64]
AT9		Job and salary	[18,64]
AT10		Contract period	[13,64]
AT11		Job satisfaction	[63,64]
AT12		Organization type	[17,64]
AT13	General skills	Domain skills (learning, critical thinking, communication and leadership)	[10,15,66,67]
AT14		Competencies of knowledge acquired in the career	[12,64,66–68]
AT15		Knowledge competencies required on the job	[10,64,66,68]
AT16	Relationship with the institution	Satisfaction with the training received	[64,69]
AT17		Career utility	[64,69]
AT18		Teaching professionalism and curricular relevance	[11,64,69]

Table 2. OCS Variables.

N°	Variables	Reference Citation
O1	Profession	[62,70,71]
O2	Graduation note	
O3	Graduation year	
O4	Year of employment	
O5	Salary	[21,22,31,72–76]
O6	Promotion	[21,31,73,75,77]
O7	Job	[74,78,79]
O8	Age	[25,76,80,81]
O9	The educational level of the parents	[82,83]
O10	Monthly family income	[74,79,84]
O11	Professional prestige	[22,72,85]
O12	Job in a prestigious institution	[86–88]
O13	Leadership	[39,86]
O14	Hierarchical level	[31,74,89]
O15	Years of career	[70,89]

Table 3. SCS Variables.

N°	Variables	Reference Citation
S1	Professional or job satisfaction	[31,72,90–93]
S2	Identification with job	[31,73,94]
S3	Emotional intelligence	[91,95,96]
S4	Fulfillment of goals and professional achievements	[31,97–99]
S5	Satisfaction with the knowledge and skills acquired in the higher education institution	[100,101]
S6	Ethical behavior	[102]
S7	Personality	[103]
S8	Authenticity	[72,90]
S9	Development of basic skills and competencies	[90,92,104,105]
S10	Self-efficacy	[80]

2.2. Career Success Prediction Model

This study considered the surveys of the graduate monitoring program of the State Technical University of Quevedo (UTEQ) in Ecuador. The graduate records generated a database, converted to a text or flat file with comma-separated values (CSVs) [106,107]. The file import allowed the selection of the significantly correlated variables through a correlation matrix (correlation coefficient greater than or equal to 0.7) [108,109]; Tables 1–3 show some of these variables. In addition, the CSV allowed the connection with the genetic algorithm.

The custom development of the genetic algorithm used the open-source programming language Python. This language allowed the coding of the genetic, computational model based on four genetic operators (i.e., selection, evaluation, genetic crossover and mutation) through libraries such as Numpy and Matplotlib [110,111].

2.2.1. Representation of Chromosome

The GA starts with a population, which is a set of individuals [112,113]. Each individual is a possible solution; in this case, an individual represents a graduate. Each individual in the population is a chromosome made up of a set of genes (objective and subjective variables of career success). Figure 2 shows the structure of the chromosome, with its respective genes and possible values. Compared to human genetics, the genotype or DNA is the GA encoding, and an individual's phenotype or physical characteristics are the GA's solution [113,114].

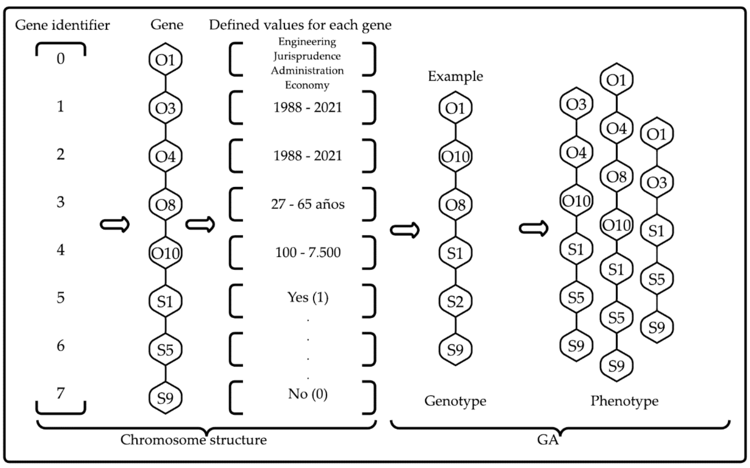


Figure 2. Representation of individuals (chromosome).

2.2.2. Genetic Algorithm Parameter Settings

The exploration and stabilization of the results of the proposed algorithm required an adjustment of the appropriate parameters, shown in Table 4 [112,115,116]. The generation chromosomes (graduates) end when the genetic algorithm reaches its maximum iteration [113,117,118]. For optimal results, the population size ranges from 50 to a maximum of 500 graduates. This study used ten samples of 50 individuals. The elitist selection method selected the chromosomes with the best fitness values. The search probability (crossover) in a new solution is 0.8, and the mutation probability that establishes the diversity of the population is 0.05; assigning lower values to the mutation rate allows an early convergence of GA [119–122].

Table 4. Initial parameters of the genetic algorithm.

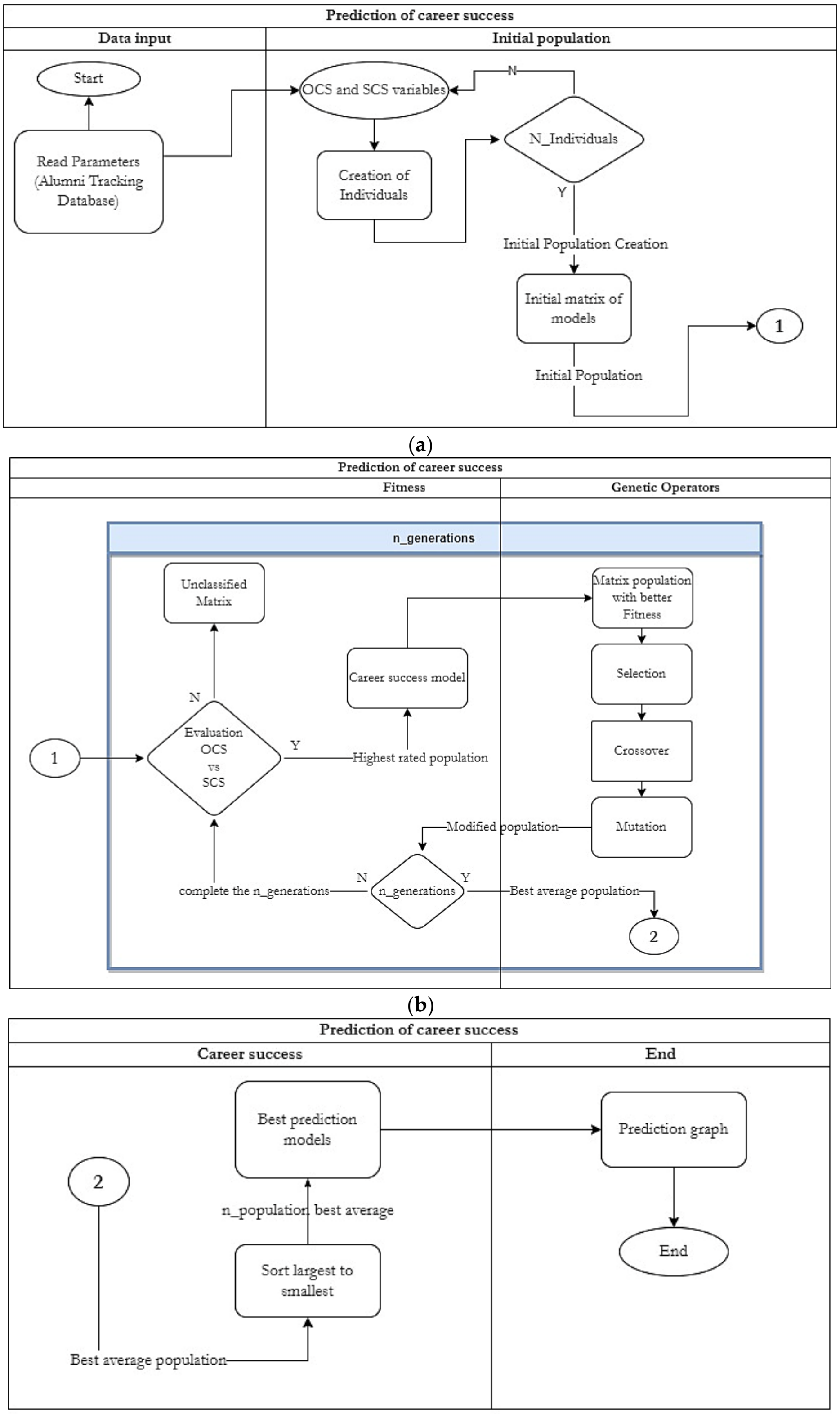
Parameters	Assignment
Population size	500
Maximum generation	100
Crossover probability	0.8
Mutation probability	0.05

2.2.3. Genetic Algorithm Design

The GA was built based on the basic functional structures that characterize it, relating to methodologies proposed by [123–125]. The design of the algorithm proposed the following processes: (1) data reading, according to the parameters of the alumni tracking database, (2) creation of the initial population defining the number of individuals, (3) fitness process, (4) use of genetic operators (e.g., selection, crossover and mutation) and (5) career success prediction models (Figure 3).

The creation of the initial population used the parameters of individuals (graduates) and genes (objective and subjective variables of professional success). That generated an initial array of prediction models (Figure 3a). First, the fitness function assigns a value to all chromosomes in the population [56]. This process comprises multiple variables optimized by the GA; both chromosomes and genes adjust to minimize or maximize the fitness value [126]. Next, the fitness evaluation process defined the fitness function, which identified the degree of goodness of fit for each individual. This function generated two matrices: a matrix of unclassified (i.e., individuals with low scores) and a matrix of the population with better fitness (i.e., individuals with high scores) (Figure 3b). Table 5 presents the fitness functions of the genes involved in the prediction models of professional success. That allowed the choice of better individuals before performing the crossover and mutation operations.

Table 6 presents the pseudocode of fitness function evaluation that weighted the best individuals and the best estimate of professional success. The weighting of the mean of the individuals concerning the genes allowed the assessment of the prediction models. In the case of the time of transition to employment, the resulting weighting is inversely proportional. On the other hand, concerning family income (O10), the resulting weight is directly proportional.



(**c**)

Figure 3. Design of the proposed algorithm. (**a**) Entry of monitoring parameters to graduates and creation of the initial population. (**b**) Fitness process and genetic operations such as crossover and mutation. (**c**) Professional success prediction models.

Table 5. GA fitness functions.

Genes	Description	GA Fitness Functions
	OCS Variables	
O1	Frequent professions of UTEQ graduates.	Frequency percentage.
O3 and O4	The difference between these variables determined the transition time to employment.	The longer the transition time, the lower the aptitude assessment. The shorter the transition time, the higher the aptitude assessment.
O8	Age of graduates.	Three weights: - 1: $\geq$51 years. - 0.5: 31 $\leq$ age $\leq$ 50 years. - 0: 24 $\leq$ age $\leq$ 30 years.
O10	Variation in family income.	The higher the family income, the higher the aptitude assessment.
	SCS Variables	
S1, S5 y S9	SCS variables, professional satisfaction and satisfaction with the knowledge and skills acquired at the University.	Value of 1 for satisfaction and 0 for dissatisfaction.

Table 6. Evaluation of the fitness function of the GA.

```
def fitnes (self, O4-O3, O10, PromS, O8, Actual-O3, O1, model):
#the sum of individuals for genes
if(model == "1"):
average_ individuals = ((O4-O3) + O10 + PromS)/3
elif(model == "2"):
average_ individuals = ((O4-O3) + O8 + O10 + PromS)/4
elif(model == "3"):
average_ individuals = (O1 + (A-O3) + PromS)/3
return average_individuals
```

After this, the GA uses the information generated by the fitness function to choose the individuals that pass the crossover and mutation operations to select the best solution according to the fitness values [127]. The GA seeks better solutions through genetic processes such as selection, crossing and mutation [128]. The selection operation considers selecting elite individuals from the population, the crossover is the recombination of selected individuals, and transformation randomly selects a gene and replaces it with a new one [129]. In this study, the genetic operators classified the best chromosomes through (1) selection: choosing the best individuals based on fitness evaluation, (2) crossover: exchange of objective and subjective variables of career success and (3) mutation: random modification of objective and subjective variables of professional success (Figure 3b). At the end of iterations (n_generations), the GA generated the best predictions through reports and graphs (Figure 3c).

2.3. Statistic Analysis

The statistical analysis studied the relationship and behavior of genes (i.e., OCS and SCS variables) through the correlation between variables, choosing the most significant variables [130]. This correlation and the results of the GA allowed the calculation of the standard deviation, confidence intervals and confidence level of prediction models at a significance of 95% [131–133].

These statistical indices determine the probability distributions of the GA in ranges defined by the confidence intervals, obtaining prediction results at 300 iterations [134,135].

2.4. Relationship between Career Success and Alumni Tracking

Figure 4 shows the conceptual framework of the impact of graduate follow-up on professional success through the relationship of objective and subjective variables.

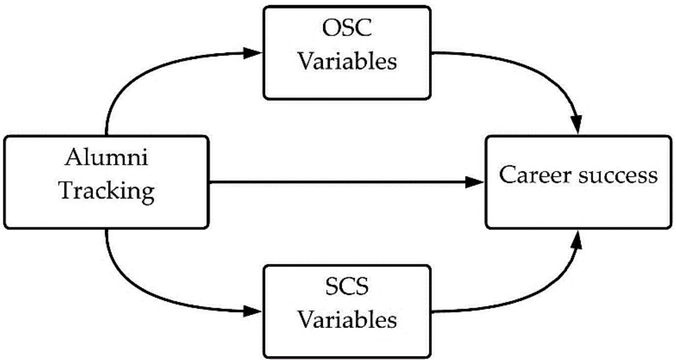


Figure 4. Relationship between alumni tracking and career success.

The prediction models of the genetic algorithm made it possible to analyze and identify the trends in the relationship between the parameters of professional success and the follow-up of graduates [136,137].

3. Results

3.1. Prediction Models

Table 7 shows the career success prediction models obtained through the GA with the data of the 500 individuals (UTEQ graduates). The prediction models considered the most significant genes in the database, OCS and SCS variables (Tables 2 and 3). The three models used the same subjective variables to estimate career success.

The first model estimates graduates' career success through the sum of the mean values of unemployment time, economic income, skills development, professional satisfaction and satisfaction with the knowledge acquired at the university. The mathematical difference between the parameters year of graduation and employment defines the transition to a job or time of unemployment. Furthermore, the subjective variables considered are a crucial determinant in the prediction since the personal perception of professional satisfaction influences the determination of professional success. On the other hand, the second model estimates career success considering all the genes used in the first model. In addition, it analyzes the age variable as a prediction argument that encourages successful graduates. Finally, the third model estimates professional success under a different approach; it uses the parameter of the current year to establish the time that has elapsed after graduation. In addition, it considers the graduate's profession in estimation significant.

Table 7. Career success prediction models.

N°	Prediction Models	Genes
1	$\sum_{i=1}^{500}[(O4-O3)+O10+S1+S5+S9]$	O3, O4, O10, S1, S5, S9
2	$\sum_{i=1}^{500}[(O4-O3)+O8+O10+S1+S5+S9]$	O3, O4, O8, O10, S1, S5, S9
3	$\sum_{i=1}^{500}[O1+(\mathrm{A}-O3)+S1+S5+S9]$; where A represents the current year	O1, O3, S1, S5, S9

3.2. The Elitist Weighting of Graduates

Table S1 (Supplementary Material) presents the best career success weightings obtained using the first GA prediction model. The results show the influence of the OCS and

SCS variables in predicting the career success of UTEQ graduates. The transition time to employment ranges from 0 to 5 years. In total, 66% of graduates found jobs in a shorter transition time after graduation. However, the personal perception of professional satisfaction establishes a slight decrease in the professional success of elite graduates, caused by 60% of professional dissatisfaction. On the other hand, developing skills and satisfaction with the knowledge acquired increases the career success of select graduates. In addition, there is a notorious influence on the weights determined by family income.

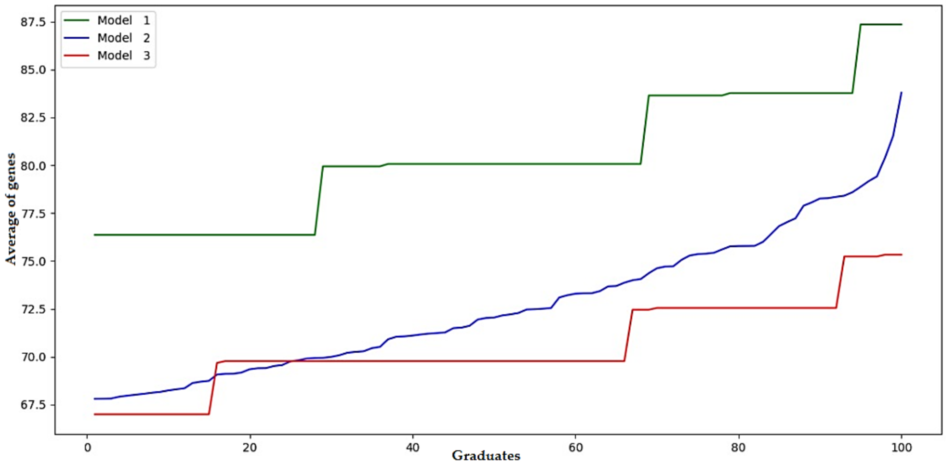
In the second model, 52% of graduates found employment sooner after graduation. The results show a high percentage (68%) in graduates older than 46 years in the prediction of career success and a low rate (14%) in young graduates (25 to 35 years of age). Regarding the subjective variables, they highlight a high percentage of dissatisfaction regarding the knowledge and skills acquired in the higher education institution (64%) (Table S2).

The third prediction model presents lower weights than the previous models. It included the relationship of a career in the prediction of career success. The significant knowledge sciences correspond to engineering (I), administration (A), economics (E) and jurisprudence (J). The results show that 84% of graduates are successful in engineering and management sciences. On the other hand, this model included the current year as the year of graduation to establish the professional's graduation time. In total, 58% of the graduates have a graduation time of fewer than 30 years, which is related to the age of the graduates considered in the second model. The subjective variables found a lower percentage of dissatisfaction regarding the knowledge and skills acquired at the university (Table S3).

3.3. Dynamics of Prediction Models

The three prediction models present dynamism in their behavior according to the genes and the weights of the best-selected individuals. The elite weighting of these models shows an increasing trend according to the variation in the population. The first model with its respective genes presents higher weights than the other models at 100 iterations run in the GA (Figure 5a). As the number of iterations increases, the models show greater significance in their behavior. After 200 iterations, the first model is still more significant (Figure 5b). Therefore, the greater the number of iterations (300), the greater the precision of the models obtained (Figure 5c). Finally, the trend keeps the first professional success prediction model above the others. The significance and correlation of the predictor variables (OCS and SCS) achieved these results.

On the other hand, Figure 6 presents the evolution of the number of chromosomes in each generation based on a set of operated genes for each prediction model. In addition, it shows how the fitness values according to the iterations achieve greater precision in the upper quartile (with 0.05 mutation, 0.8 crossover and 50 generations). The convergence of the GA is maintained in this quartile, with model one being the one with the highest convergence toward the optimal solution concerning the other prediction models. This prediction model finds the best characteristics of successful graduates (with O3, O4, O10, S1, S5 and S9).



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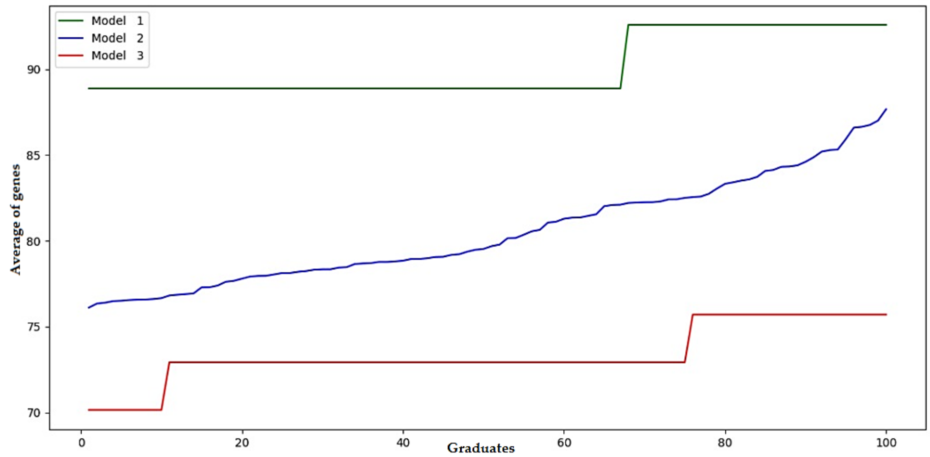

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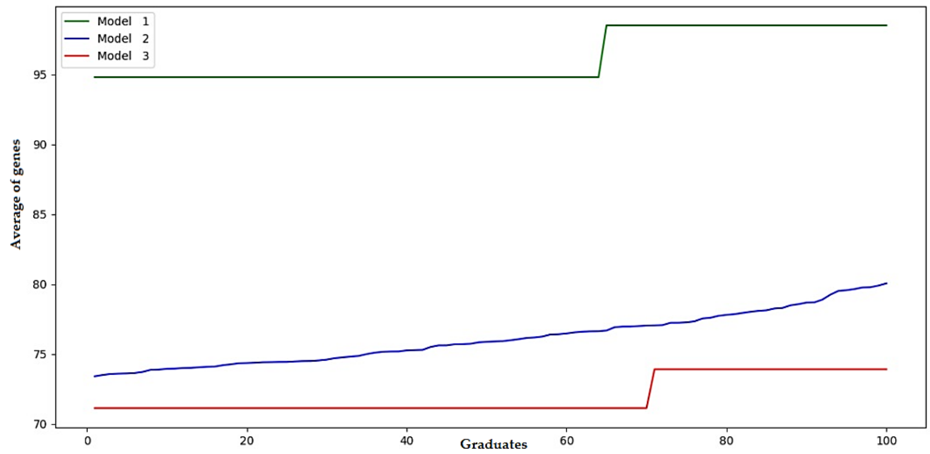

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Figure 5. Prediction of career success according to the number of generations of the GA. (**a**) Prediction models with 100 iterations. (**b**) Prediction models with 200 iterations. (**c**) Prediction models with 300 iterations.

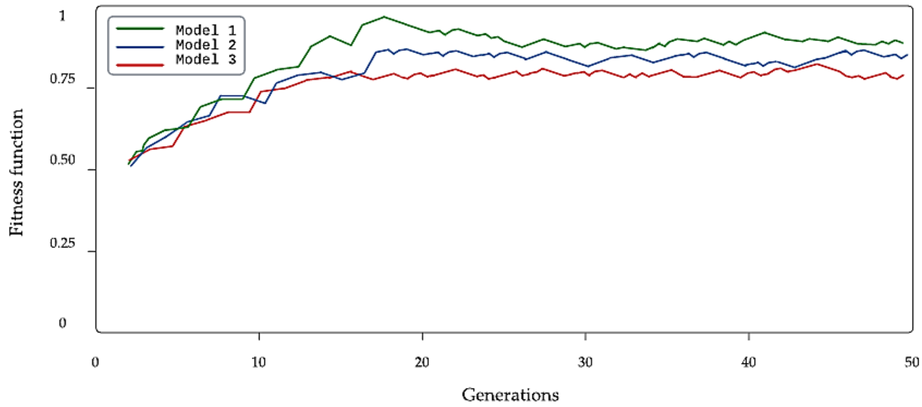

Figure 6. Evolution and convergence of the GA at 50 generations.

3.4. Validation of Prediction Models

In validating the prediction models, the GA considered the results of the successful predictions of the UTEQ graduates at 300 iterations. There is a strong relationship between genes and elitist weights of graduates, relationships measured by correlation coefficients. The results of the GA show acceptable levels of confidence in the models with a significance of 95%. Table 8 presents the statistical parameters that determine each predictive model's standard deviation, confidence intervals and confidence level [131].

Table 8. Confidence estimation of prediction models.

Statistics	Values		
	Model 1	**Model 2**	**Model 3**
Significance level	0.95	0.95	0.95
Standard deviation	0.316	0.375	0.569
Confidence interval	0.062	0.074	0.112
Confidence level	87.61%	85.2%	77.40%

All three models are in the upper quartile of acceptable confidence levels. However, the first model represents the best option for predicting professional success with a confidence level of 87.61% and an interrelation of objective genes (time of transition to employment and family income) and subjective genes (skills development, professional satisfaction and satisfaction with the acquired knowledge). On the other hand, the different models represent a valid alternative depending on the behavior of the variables since they consider other parameters.

3.5. Relationship between Career Success and Alumni Tracking

Table 9 presents the relationship of career success based on the relevance of the alumni program through the parameters that make up the products and results of the graduate follow-up studies. This relationship found significant variables of the GA (e.g., transition to employment, professional career and satisfaction with the knowledge and skills acquired in the university) for the prediction of professional success [62]. In addition, some parameters of the follow-up of graduates are indicators of evaluation and accreditation of the quality of higher education.

Table 9. Relationship of career success with the alumni tracking.

Alumni Tracking	Career Success (Genetic Algorithm Variables)	Relationship
Product (knowledge, skills, career, motivation)	Career Salary	Career success depends on the knowledge acquired during the training process.
	Age	Age is a significant predictor in estimating professional success and a dynamic parameter contributing to alumni's decision making.
	Development of basic skills and competencies	Contributes to the analysis of the professional profile of the graduate.
	Job satisfaction	Subjective metrics for the occupational analysis of graduates.
Results (transition to employment, employment, contribution to society)	Satisfaction with the knowledge and skills acquired in the higher education institution	Satisfaction with the knowledge acquired and skills development are complementary to professional development.
	Employment	Employment measures career success, and it is an indicator of the professional results of universities.
	Transition to employment (the year of getting a job and year of graduation)	The lack of a link between the labor market and the university influences the transition to employment.
	Family income	Contributes to the socioeconomic analysis of graduates.

The relationship between the knowledge acquired and employment leads to the assessment of the use of knowledge acquired by graduates during their academic training. Furthermore, career success is dependent on the results of graduate follow-up studies. In other words, there is a probability that career success will be measured by the employment of graduates, their transition time to the job and their perception of satisfaction with acquired knowledge, which produces indicators of professional results in universities.

The external evaluation model of universities and polytechnic schools determines the legal orientation of the follow-up of graduates within the framework of the quality of education of the universities of Ecuador. Under this regulation, the UTEQ university assigns career commissions to follow up on professionals, obtaining personal and professional data from its graduates through self-administered surveys [60].

4. Discussion

The estimation of the career success of UTEQ graduates used a genetic algorithm prediction. This GA generates optimal prediction solutions through graduate tracking variables or parameters and achieves operational efficiency through genetic operators (e.g., elite selection of successful graduates). It has a greater capacity to search for graduates in short execution times. Crossover and mutation of graduates allow for a better diversity of the graduate population with high chances of success. On the other hand, other studies used a GA to diversify the search and solve real-world optimization problems [125], such as dynamic energy-saving optimization [130], volunteer teacher transfer problems [138] and intelligent educational systems [124].

GA of success prediction is adaptive and modifiable in population number, genes, generations and probabilities of genetic operators. That allowed the calculation of optimal graduate weights with different populations and iterations. Similarly to other studies, the GA of temporal network analysis increases individuals and enables the calculation of denser weights, even by reducing the number of generations [139]. Likewise, the GA improves its performance through forwarding rules, where the more significant number of iterations represents better results [140]. In this study, the GA is reproducible and adaptable to the parameters of the UTEQ graduate tracking.

The prediction model with the highest reliability of the GA multidimensionally estimates the career success of graduates (Table 7); that is, it significantly relates objective and subjective variables in the prediction. Where professional satisfaction positively affects the time of transition to work, family income and development of skills of graduates. Similarly, other studies measure subjective career success in a multidimensional way through learning and development, work/life balance, financial security and entrepreneurship, considering these dimensions as significant predictors in estimating career success [90]. They also relate professional skills and employability [33], the quality of internships and the proactive personality [141] in measuring career success. On the contrary, other career success estimates consider a single variable's weight. For example, the dynamics of permanent learning mentality relate to objective and subjective career success [142], whereas age has a significant relationship with success [81]. The GA of this study allows the use of various variables according to the follow-up of UTEQ graduates and determines the significance between them to predict its graduates' success better.

Some studies estimate professional success through different approaches such as multivariate linear regression, logarithmic, multiple standard and hierarchical regression, analyzing objective predictor variables such as compensation, promotion, salary, profession, time dedicated to working, leadership, organizational commitment and gender, and subjective such as perceived success. These studies demonstrated an average influence of 25%, with a maximum of 51%, of predictor variables on objective or subjective career success outcomes [143–147]. The study proposed in this article used a prediction GA that estimated the professional success of 500 UTEQ graduates with 87.61% reliability, so the model's goodness of fit is acceptable with all its significant predictors considering the representative sample in different iterations. Similarly, other GAs make their estimates in various applications (e.g., meteorology, economics and health), reaching optimal results justified by the prediction accuracy. For example, rainfall prediction reported an accuracy of 80% in its estimates [148]. Likewise, a GA applied estimated financial problems in private sanitation companies, which reflected an accuracy of 85.16% [149]. Another study used a GA to optimize route transport for ambulances, where it detected an accuracy of 73.5% [150].

Some studies applied different methodologies to the GA, demonstrating the relationship of the achievement of their graduates through the analysis of parameters of the alumni program. For example, a study from a university in Israel used exploratory factor analysis to relate the development of general and specific skills of 21st-century graduates and students to various teaching and learning methods [15]. Other studies applied descriptive statistics and multiple linear regression to determine the satisfaction of university graduates in Indonesia and the United States through the relationship between the variable infrastructure, teacher professionalism, employment opportunities, social classes and curricular relevance [11,151]. On the other hand, universities in Norway and Turkey conducted studies on the performance analysis of graduates, using descriptive statistics to improve graduates' research skills, study plans, competencies, career development and quality of education [10,12]. In addition, a graduate relationship management model used logistic regression to analyze the demographics, lifestyles, expectations and interests of graduates from a university in Thailand to establish marketing strategies for Alumni associations [18]. So, the GA of the present study is a proposal for measuring career success that includes the use of objective and subjective variables and their interaction with products and results of the alumni program. Furthermore, it contributes to the follow-up of its graduates and establishes improvements in education and educational management in higher education institutions.

The main limitation of this research is the low percentage of responses by graduates in possible predictor variables such as the position of the graduate for the estimation of professional success.

5. Conclusions

The prediction model proposed in this study was developed in the Python programming language through a GA based on the parameters of the alumni program. This model estimated the professional success of UTEQ graduates through the interaction of objective and subjective variables, generating a significant retrospective for decision making in tracking its graduates.

The study used data from 500 graduates and obtained predictive results of the career success of the graduates with an acceptable level of reliability (87.61%). So, it gives guidelines for tracking graduates through the transition to employment, family income, development skills of the graduates, their job satisfaction and the knowledge acquired. These variables represent a high significance when the prediction model reaches its maximum limit of generations.

The GA estimated that the average transition time to employment for successful UTEQ graduates is two years. In total, 70% of these graduates feel professionally satisfied and pleased with the knowledge and skills acquired at the university. A high percentage of graduates (89%) perceive that they developed their basic skills and competencies during their academic training.

Based on the application of a genetic algorithm, this study could be replicated based on the correlated variables. In addition, the reality of other higher education institutions must be considered to complement the analysis, including the increase in the population to a more significant number of generations, to obtain reliable results in predicting professional success. Therefore, the authors recommend that higher education institutions implement a robust monitoring system for their graduates based on the analysis of their realities, their environment and the following policies:

- Continuous training strategies as an opportunity to interact with professionals.
- Follow-up of graduates for the objective and subjective measurement of job satisfaction.
- Improve formal and informal communication policies that promote interaction and benefits with professionals as a digital employment exchange.
- Involve professionals in research projects and link society developed in universities.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app12199892/s1, Table S1: Results of best individuals of prediction model 1. Table S2: Results of best individuals of prediction model 2. Table S3: Results of best individuals of prediction model 3.

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