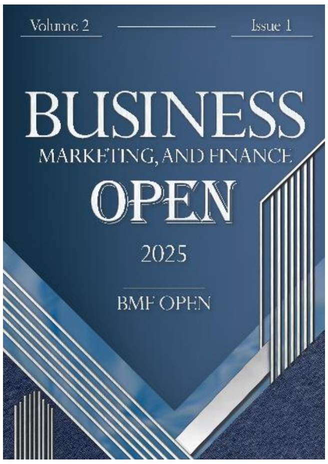
Providing a Smart Startup Model Based on Business Intelligence Capacity, Network Learning, and Innovation

Milad Semnani[1], MohammadAli Keramati[2,*], Safieh Mehrinejad[3] and Azadeh Mehrani[4]

[1] Department of Information Technology Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran;
[2] Department of Industrial Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran;
[3] Department of Financial Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran;
[4] Department of Financial Management, Nowshahr Branch, Islamic Azad University, Nowshahr, Iran;
* Correspondence: mohammadalikeramati@yahoo.com



Citation: Semnani, M., Keramati, M. A., Mehrinejad, S., & Mehrani, A. (2025). Providing a Smart Startup Model Based on Business Intelligence Capacity, Network Learning, and Innovation. *Business, Marketing, and Finance Open*, 1(2), 12-24.

Received: 21 November 2023
Revised: 13 January 2024
Accepted: 22 December 2024
Published: 01 March 2024

Abstract: The aim of this study is to develop a smart startup model based on business intelligence capacity, network learning, and innovation. It is assumed that smart startups are influenced by these factors, and in the present study, the importance of these components has been determined based on their weighting according to startup productivity. The weighting of business intelligence system components and the indices of network learning and innovation was conducted using the Grey Relational Analysis (GRA) method with interval fuzzy numbers. In the next step of the study, a multi-level mathematical model incorporating smart startup components was designed as a multi-objective model based on the weights determined in the previous step. To solve this model, a multi-objective metaheuristic algorithm based on the Pareto archive was implemented. After determining the set of optimal solutions, the obtained solutions were analyzed, and the final solution was selected for optimizing the startup model. The objective function of the problem is to minimize the completion time of the scheduling program. This problem belongs to the class of NP-Hard problems in MATLAB software. In the proposed metaheuristic methods, a column generation technique was combined with the Genetic Algorithm (GA), the Biogeography-Based Optimization (BBO) algorithm, and a hybrid algorithm combining GA and BBO (Hybrid Heuristic Algorithm - HH). Computational results related to algorithm performance analysis indicate that the three metaheuristic algorithms GA, BBO, and Hybridize exhibit significant differences. Consequently, from a statistical perspective and with a 95% confidence level, the algorithm performances in terms of effectiveness rank as follows: GA in the first position, BBO in the second, and Hybridize in the third. The findings of the study suggest that GA is recognized as the superior modeling method in this context. This is valuable for the industry and management as it demonstrates that among the available tools for modeling smart startups, GA can deliver the best performance.

Keywords: Smart Startup, Business Intelligence, Network Learning, Innovation, Metaheuristic Algorithm.

1. Introduction

In recent years, startups have emerged as new concepts in the world of technology and have been designed as temporary organizations aimed at finding a repeatable and scalable business model while offering a novel solution to a problem [1]. The key to startup success lies in proper and rational goal-setting [2]. This aspect is often overlooked by a significant percentage of such businesses, leading to their failure in a short period. The development of a product or the provision of a new service is not feasible without strategic planning [3, 4]. A smart startup system utilizes mathematical models and algorithms to extract information and knowledge from data and present it to decision-makers. In some cases, this activity may be reduced to basic calculations and percentages, which can be represented graphically through simple histograms. However, more involved studies necessitate the development of complex optimization and learning models [5, 6].

The performance of a startup refers to its ability to achieve corporate objectives [7]. There are various perspectives on startup performance, including temporal dimensions (short-term versus long-term) and evaluative criteria (employees versus shareholders, profit versus market share), among others. Previous studies have proposed three different approaches to measuring organizational performance: (1) financial performance, (2) operational and financial performance dimensions, and (3) organizational effectiveness. The first approach, financial performance, serves as an outcome-based performance indicator. However, assessing startup performance remains a constrained concept [8, 9]. In this regard, the level of success of a smart startup can be understood by analyzing its performance based on available resources. Therefore, each startup seeks to analyze its performance, derived from internal business processes, and optimize its performance accordingly [10].

Startups work hard to establish their place in the market and must perform well to survive and grow. It is important to recognize that a small company is not merely a scaled-down version of larger enterprises. There are differences in terms of structure, available resources, management practices, environmental responsiveness, and competitive strategies. In a highly competitive, dynamic, and unstable environment, companies must strive to gather information to enhance their decision-making processes [11]. This challenge is even more significant for startups struggling to secure a position in the market. Such a process can assist managers in aligning effectively with their environment and improving the performance of their firms [12].

Among the various strategies for optimizing the performance of a smart startup, business intelligence has garnered significant attention. The availability of information through electronic tools for acquisition, processing, and communication, which can serve as the foundation for informed decision-making, has increased. Moreover, the backdrop of substantial political and social changes worldwide, intensifying global competition resulting from new or more aggressive market players, and rapid technological advancements necessitate improved information utilization [13].

In general, implementing a business intelligence system within a startup fosters an intelligent and logical approach to managing complex businesses and organizations [14]. Decision-makers are compelled to develop a mental model of financial flow processes, even while using a spreadsheet to assess the impact of interest rate fluctuations on the budget [15]. The resource-based view theory asserts that to develop and sustain competitive advantages, companies must leverage their physical, human, and organizational assets—both tangible and intangible. Complementing this, the knowledge-based view highlights knowledge as the most valuable resource within a company [16, 17]. Given that knowledge serves as a primary production factor from which a company can derive competitive advantage, it is rooted in resource-based theory. Business intelligence is one such asset, as it facilitates the acquisition of information while simultaneously expanding the knowledge base available to managers. This is made possible through the processes involved in knowledge generation, enabling search and recombination [18].

Learning occurs when individuals share data, information, and knowledge. Knowledge can be understood as meaningful information acquired through comprehension, awareness, and familiarity gained over time through study, research, observation, or experience [10]. Through learning and the acquisition of new capabilities, companies can compete effectively, ensure their survival, and achieve growth. As knowledge evolves and requires reconstruction based on study and experience, continuous change necessitates ongoing learning. Thus, knowledge is neither absolute nor universal [19].

Typically, smart startups possess internal tools for developing much of the knowledge used in innovation. However, traditional startups lack all the necessary inputs for continuous and successful technological development and are compelled to seek external knowledge [20]. They face a unique type of organizational learning challenge that differentiates them from smart startups. Most new ventures have limited and often specialized knowledge bases and encounter unique challenges in accessing external knowledge resources to drive innovation [21, 22].

The innovation of smart startups is conceptualized from two perspectives. The first views it as a behavioral variable, representing the degree to which a company adopts innovations [23]. The second defines it as the willingness to change [24]. This capacity can enhance the utilization of available resources, improve efficiency and potential value, and introduce new intangible assets into the startup [25]. Innovation capability is recognized as a key determinant of organizational survival and success [26, 27]. Greater innovation can serve as a crucial factor in value creation and facilitate responsiveness to customer needs, the development of new capabilities, and the attainment and maintenance of superior performance or profitability in an increasingly complex, competitive, and rapidly changing environment [12].

The literature highlights the significance of business intelligence capacity, network learning, and innovation in the development and performance of startups. Sadeghi et al. (2022) designed a framework for utilizing business intelligence to enhance university-industry relations, identifying multiple layers, including data collection, extraction, transformation, loading, and metadata management. Mohammadi et al. (2022) examined the effect of investor control on startup performance, finding that startup characteristics influence this relationship and that investor experience and expertise moderate it [28]. Sabour (2022) explored the role of entrepreneurial strategies in improving the performance of innovative startups, revealing a positive and significant relationship between administrative, opportunity-driven, imitative, and acquisitive strategies with startup performance [15]. Danayi Fard and Aligholi (2022) identified five key business intelligence components—data sources, extraction, data warehousing, metadata, and analytical tools—showing that business intelligence enhances decision-making processes, strategic modeling, and evaluation [29]. Amiri et al. (2021) developed a fuzzy artificial intelligence model for portfolio optimization, demonstrating that their approach outperforms market indices and previous strategies [30]. Lee et al. (2023) emphasized that business intelligence capabilities and network learning enhance data mining and provide startups with a competitive advantage, allowing them to better adapt to market demands and increase market share [2]. Huang et al. (2023) confirmed that business intelligence influences financial performance through the mediating role of innovation and network learning, indicating that these factors are crucial for financial improvement [22]. Kumburu (2023) discussed the challenges in knowledge management frameworks in commercial organizations, advocating for significant investment in knowledge management systems to improve business efficiency [31]. Lubishtani et al. (2023) explored the impact of knowledge management and transfer on business incubation, showing how knowledge spillovers from incubators and accelerators contribute to startup success [32]. Huang et al. (2022) investigated the effect of business intelligence on marketing, highlighting its role in collaborative learning, financial performance, and customer behavior [21]. Peterson et al. (2022) developed a strategic workforce planning model for business intelligence, demonstrating its potential to help organizations predict workforce gaps and implement appropriate solutions [9]. Godoy et al. (2021) used mathematical modeling to assess business competitiveness, showing that mathematical variables can optimize transportation costs and productivity for small and medium-sized enterprises [19]. Based on this review, implementing a smart startup model that integrates business intelligence, network learning, and innovation is crucial for improving strategic decision-making. Business intelligence enables startups to analyze market trends and patterns effectively, leading to more informed and intelligent decision-making processes.

To develop an optimal smart startup model based on the components of business intelligence, network learning, and innovation, this study employs a mathematical programming model. Mathematical models have traditionally been used in classical scientific disciplines such as physics to describe abstract representations of real-world systems. In studying artificial systems, such as public and commercial organizations, other disciplines—including operations research—have instead applied scientific techniques and mathematical models.

Although the primary goal of decision-making process improvement is effectiveness, the use of mathematical models provides additional long-term benefits. Secondly, constructing an abstract model compels decision-makers to focus on the key aspects of the subject under study, leading to a deeper understanding of the phenomenon being examined. Moreover, compared to empirical decision-making methods, the knowledge gained from constructing a mathematical model can be more easily transferred to others within the same organization over time, enabling more precise knowledge retention. Lastly, but importantly, a mathematical model developed for a specific decision-making task is typically universal and adaptable, making it applicable to similar problems in future scenarios [31].

Given the broad scope of optimization in smart startups—where key criteria include company survival, reputation, perceived overall performance, and goal achievement—this research seeks to answer the following question: Based on mathematical modeling, how can a smart startup model be developed using business intelligence capacity, network learning, and innovation?

2. Methodology

This study consists of five stages: identifying the research domain, defining the problem under investigation, presenting the research model, designing the structure of solution algorithms, and generating data for testing and parameter tuning of the model and algorithms. Initially, the scope of the problem was identified, followed by an examination of the parameters required for developing a smart startup model based on business intelligence capacity, network learning, and innovation. To review the theoretical foundations of the study and analyze existing models, library research and a review of articles published in international journals such as *Elsevier* and *Springer*, as well as related books, dissertations, and online databases, were conducted.

It is assumed that smart startups are influenced by these components, and in this study, their significance was determined based on the weighting of these factors concerning startup productivity. The weighting of business intelligence system components and the indices of network learning and innovation was conducted using the Grey Relational Analysis (GRA) method with interval fuzzy numbers. In the next step of the study, a multi-level mathematical model incorporating smart startup components was developed as a multi-objective model based on the weights determined in the previous step. To solve this model, a multi-objective metaheuristic algorithm based on the Pareto archive was implemented. After determining the set of optimal solutions, the obtained solutions were analyzed, and the final solution was selected for optimizing the startup model.

To evaluate the performance of the examined metaheuristic methods, experimental tests were required. To address this, multiple evaluation methods were applied to derive a comprehensive result from their findings. In this section, standard problem instances were first created, and all algorithms were executed to solve them. The conditions and parameters for executing these algorithms were standardized across all methods to ensure fair competition. The Genetic Algorithm (GA), Biogeography-Based Optimization (BBO) algorithm, and a hybrid combination of GA and BBO (Hybrid) were employed to determine a sequence of partial schedules, minimizing the maximum completion time in the startup scheduling problem. The final scheduling solution was derived from two phases: the first phase was solved using GA, BBO, or the Hybrid algorithm in MATLAB, while the second phase was determined based on the completion times from the first phase and the processing times of tasks in the second phase.

The mathematical formulation of the problem in the first stage is as follows:

$$C_1^* = \min \sum_{BEB} \Delta\beta \qquad (1)$$

$$Subject \quad to$$

$$\sum_{BEB} \Delta_\beta \sum_{isi}^{m} \frac{xij^\beta}{Pij} = 1 \quad , \quad j = 1,\ldots,n \qquad (2)$$

$$\sum_{j=1}^{n} v_{ij}^\beta \quad \leq 1 \qquad , i = 1,\ldots,m, \beta \in B \qquad (3)$$

$$\sum_{i=i}^{m} \quad v_{ij}^\beta \leq 1 \qquad , j = 1,\ldots,n, \beta \in B \qquad (4)$$

$$\sum_{j=1}^{n} \quad \sum_{i=1}^{m} \alpha ijr \quad Vij^\beta \quad \leq Wr \qquad , r = 1,\ldots,e \quad , \beta \in B \qquad (5)$$

$$\Delta_\beta \geq \circ \qquad \beta \in B \qquad (6)$$

$$V_{ij}^\beta \in \{0,1\} \qquad , j = 1,\ldots,n \qquad , i = 1,\ldots,m, \qquad , \beta \in B \qquad (7)$$

Subject to the following constraints:

1. Decision variables are binary values, either *0* or *1*.
2. Each task must be completed within the first stage of the startup scheduling process.
3. Each business process in any partial schedule can execute at most one task at a time.
4. Each task can only be processed by one business process at any given moment.
5. Resource utilization in each partial schedule cannot exceed the available resource capacity at any given moment.

This problem is optimally solved using the column generation algorithm, where the optimal maximum completion time is denoted as *T_opt*.

The column generation algorithm is an iterative method that starts with an initial set of columns and, in subsequent iterations, solves the linear programming (LP) problem with all columns generated up to that point, subsequently introducing new columns. At each iteration of the column generation (CG) algorithm, the master problem is solved as an LP model:

$$\underline{Master - \Pr oblem}$$

$$\min \sum_{\beta EB} \Delta\beta \qquad (8)$$

$$Subject \quad to$$

$$\sum_{\beta \in B} \Delta_{\beta} \sum_{i=1}^{m} \frac{vij^{\beta}}{\alpha ij} = 1 \qquad j = 1,\ldots,n \qquad (9)$$

$$\Delta_{\beta} \geq \circ \qquad \beta \in \tilde{\mathrm{B}} \qquad (10)$$

Subject to:

1. Decision variable constraints: *X* values are binary.
2. Fixed values *C* are precomputed based on problem data before the first iteration and are updated in subsequent iterations through the subproblem solution.
3. The subset *B* includes the set of indices (columns) generated so far, which expands with a new index *B+1* in the next iteration.

To determine the allocation of tasks to processes in the new column with index *B+1*, the subproblem is solved:

$\underline{Sub - \mathrm{Pr}oblem}$

$$man \qquad \sum_{i=1}^{m} \sum_{j=1}^{n} \pi_{j}^{x} v_{ij}^{\beta'}$$

$$subject \quad to$$

$$\sum_{j=1}^{n^{st}} v_{ij}^{\beta'} \leq 1 \qquad , \quad i = 1,\ldots,m$$

$$\sum_{i=1}^{m} v_{ij}^{\beta'} \leq 1 \qquad , j = 1,\ldots,n$$

$$\sum_{j=1}^{n} \sum_{i=1}^{m} \alpha ijr \quad v_{ij}^{\beta'} \leq wr \qquad r = 1,\ldots,\ell$$

$$v_{ij}^{\beta'} \in \{0,1\} \qquad j = 1,\ldots,n \qquad , i = 1,\ldots,m$$

Subject to:

1. The optimal solution to the dual of the master problem provides the dual variables.
2. The first step in the column generation algorithm involves solving the master problem, yielding the optimal values of *X_opt*.
3. The optimal dual solution of the master problem provides π, the dual variables.
4. The second step in the column generation algorithm involves solving the subproblem to determine the optimal values *Y_opt*, which represent the assignment of tasks to machines in the new column with index *B+1*.

A new iteration of the column generation (CG) algorithm begins if the condition $\pi \geq 0$ holds. Otherwise, the optimal solution has been obtained, and the algorithm terminates.

The initial solution for obtaining the values of *X_opt* in the first stage of the CG algorithm (solving the master problem) is determined by assigning tasks to machines that require the shortest completion time. Additionally, in each partial schedule, only one business process is executed at a time.

3. Findings

After presenting the numerical example and explaining the convergence diagram and the results obtained from running the algorithms, this section compares the three developed algorithms in terms of effectiveness and efficiency. Each algorithm was executed 10 times on 15 different problem instances. After each execution, the results related to the best objective function value (minimum completion time of tasks) and the first time the algorithm reached the best objective function value were recorded. For this purpose, each algorithm was coded in MATLAB 7. All problem instances were executed on a computer with an Intel Core 2 Duo 2.80 GHz processor, 4.00 GB of RAM, and the Windows 10 Ultimate operating system. After executing the metaheuristic algorithms on the selected problem instances, statistical analyses were conducted using one-way analysis of variance (ANOVA) in MATLAB.

In this section, the performance of the three developed metaheuristic algorithms is analyzed in terms of efficiency and effectiveness. The results from running the algorithms on the given problem instances relate to the best objective function value in the two-stage smart startup scheduling problem, specifically the maximum completion time of tasks and the time to reach the best objective function value, which is used as a measure of efficiency. The process of problem generation for the metaheuristic algorithms is then explained. A numerical example is used to examine algorithm performance in terms of efficiency and effectiveness, and finally, the algorithms' statistical performance is compared and evaluated.

Among the key parameters affecting the metaheuristic algorithms are population size and the maximum number of iterations. In this study, these values were set at 40 and 100, respectively. Other key parameters in the Genetic Algorithm (GA) include crossover probability, mutation probability, elitism probability, and the number of best solutions retained from the current population to prevent premature convergence. In the Biogeography-Based Optimization (BBO) algorithm, important parameters include migration probability, mutation probability, and the number of best solutions retained from the population, as shown in Table 1.

Table 1: Required Parameters for Genetic Algorithm and Biogeography-Based Optimization Algorithm

Algorithm	Population	Iterations	Crossover/Migration Probability	Mutation Probability	Percentage of Best Population Retained
GA	40	100	0.8	0.05	0.28
BBO	40	100	0.8	0.04	0.2

Based on the specified parameters, the problem was executed using the three developed metaheuristic algorithms: the Genetic Algorithm (GA), the Biogeography-Based Optimization (BBO), and the hybrid combination of GA and BBO (Hybrid). After each execution, the results obtained from each algorithm, in terms of the best objective function value and the first time to reach the best objective function value (in seconds), were recorded, as presented in Table 2.

Table 2: Results from Algorithm Execution on a Problem with 60 Tasks and 2 Machines

Algorithm	Best Cost (Cmax)	CPU Time (seconds)
GA	229.273	79.4455
BBO	227.8	141.83
Hybrid	227.5	110.82

The best cost refers to the optimal objective function value, i.e., the maximum completion time of tasks, which serves as the effectiveness criterion for the algorithms. The CPU time indicates the first time the algorithm reached the best objective function value in seconds, which is used as the efficiency measure. Therefore, in this example, the performance of the three algorithms can be compared in terms of effectiveness and efficiency. The convergence curves of each algorithm are shown in Figure 1.

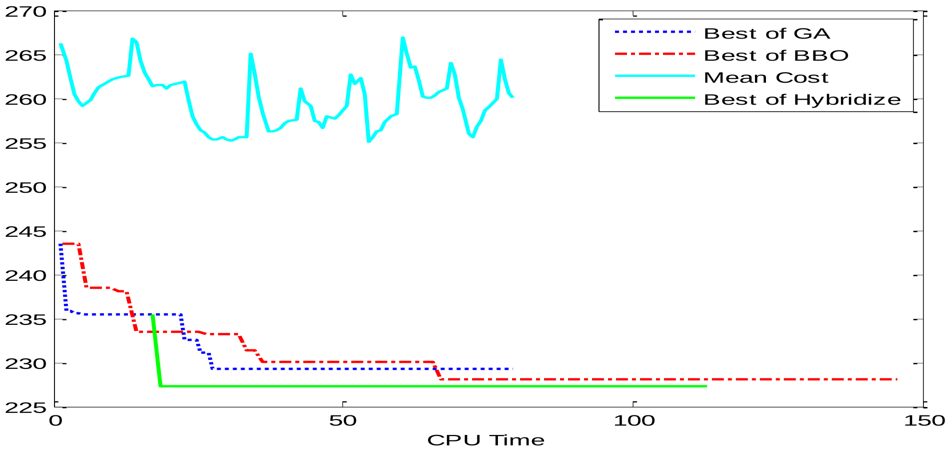


Figure 1: Convergence Curves from Algorithm Execution on a Sample Problem with 60 Tasks and 2 Machines

In this example, with the goal of minimizing the objective function in the shortest possible time, the best to worst performance ranking of the algorithms is as follows:

1. The hybrid combination of GA and BBO (Hybrid) performed best.
2. The Biogeography-Based Optimization (BBO) algorithm ranked second.
3. The Genetic Algorithm (GA) had the lowest performance.

To evaluate the performance of the metaheuristic algorithms across different problem instances, the Relative Distance Index (RDI) was used. The calculation of RDI is given in Equation (1). In this equation, C represents the solution obtained by the developed algorithms, C_min is the smallest target value, and C_max is the largest target value from each execution across the 15 different problem instances. The RDI value indicates how far each algorithm's solutions deviate from the best-obtained solution. A higher RDI suggests that an algorithm generates more outlier solutions, whereas a lower RDI indicates that an algorithm produces more optimal solutions and is thus more reliable.

$$RDI = \mathrm{Alg}_{sol} \_ Min_{sol} \; Max_{sol} \_ Min_{sol}$$

Table 3: Comparison of Algorithm Performance Based on Best Objective Function Value and CPU Time Across Sample Problems

n*m	GA Cmax	BBO Cmax	Hybrid Cmax	GA CPU Time	BBO CPU Time	Hybrid CPU Time
50*2	202.3	201.56	198.4	62.9	114.933	93.75
60*2	231.05	229.2	227.1	77.929	141.627	109.832
70*2	265.3	262.0735	261.3	90.716	181.918	140.355
80*2	314.25	310.5	308	131.76	221.65	187.58
90*2	349.4	347.9	346.9	143.7	241.3	189.112

Based on the RDI equation, the best objective function values obtained from each algorithm execution were normalized across all 15 problem instances. The RDI results for each algorithm's best objective function value across sample problems are shown in Table 4.

Table 4: Comparison of RDI Results for Best Objective Function Value Across Sample Problems

n*m	GA RDI	BBO RDI	Hybrid RDI
50*2	0.92975	0.71901	0
60*2	1	0.69624	0.218013
70*2	0.84457	0.5	0.071429
80*2	0.58865	0.37455	0.090618
90*2	0.54644	0.4406	0.153464

In addition to evaluating the best objective function value as a measure of algorithm effectiveness, the algorithms were also assessed and compared in terms of their time to reach the best objective function value, serving as a measure of efficiency. The Tukey test was performed to compare the performance of the three developed algorithms at a 95% confidence level. The test initially compared GA with BBO and Hybridize.

```
Individual 95% CIs For Mean Based on
                                        Pooled StDev
Level          N   Mean   StDev  -------+---------+---------+---------+--
Cmax of GA      150  0,7100   0,2129                          (-*)
Cmax of BBO      150  0,4231   0,1700               (*)
Cmax of HYBRID   150  0,0952   0,0910  (-*)
                      -------+---------+---------+---------+--
                           0,20      0,40      0,60      0,80

Pooled StDev = 0,1658

Tukey 95% Simultaneous Confidence Intervals
All Pairwise Comparisons

Individual confidence level = 98,03%

Cmax of GA subtracted from:

         Lower   Center   Upper
Cmax of BBO     -0,3317  -0,2869  -0,2421
Cmax of HYBRID  -0,6596  -0,6148  -0,5700

         --+---------+---------+---------+-------
Cmax of BBO              (*-)
Cmax of HYBRID   (-*)
         --+---------+---------+---------+-------
         -0,60     -0,30      0,00      0,30

Cmax of BBO subtracted from:

         Lower   Center   Upper
Cmax of HYBRID  -0,3727  -0,3279  -0,2831
         --+---------+---------+---------+-------
Cmax of HYBRID          (*-)
         --+---------+---------+---------+-------
         -0,60     -0,30      0,00      0,30
```

Figure 2: Tukey Test Results for Best Objective Function Value

The results indicate that all three metaheuristic algorithms, GA, BBO, and Hybridize, exhibit significant differences. Statistically, at a 95% confidence level, the ranking of algorithm effectiveness from best to worst is as follows:

1. GA ranks first.
2. BBO ranks second.
3. Hybridize ranks third.

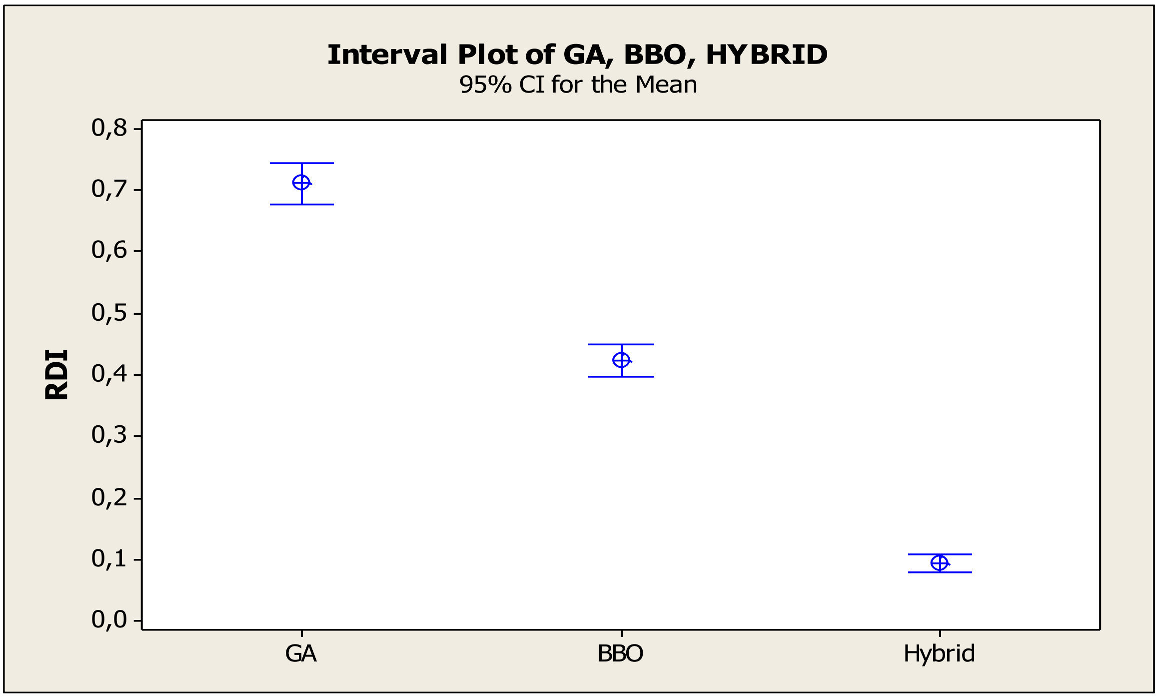


Figure 3: Mean and 95% Confidence Interval Chart for Best Objective Function Value

The findings indicate that in terms of effectiveness, GA ranks highest. This result suggests that among the evaluated methods, GA provides the best performance for modeling smart startups.

4. Discussion and Conclusion

The objective of this study was to develop a smart startup model based on business intelligence capacity, network learning, and innovation. The startup productivity problem, when simplified with assumptions, is classified as a complex problem. As a result, the computational time for exact solution methods increases to an impractical level, making it necessary to utilize metaheuristic methods for solving these problems. Moreover, given the constraints on additional resources and the necessity of intelligent decision-making in the problem examined in this study, standalone metaheuristic methods are insufficient. Therefore, metaheuristic methods must be integrated with the column generation technique to create a hybrid solution approach. After obtaining the results from each hybrid method, they were analyzed and compared to determine the most effective approach.

In this study, three metaheuristic algorithms—Genetic Algorithm (GA), Biogeography-Based Optimization (BBO), and Hybridize—were applied to solve the two-stage smart startup problem. The column generation technique was combined with GA (a metaheuristic algorithm), BBO (a metaheuristic algorithm based on biogeography optimization), and a hybrid combination of GA and BBO (Hybridize). The goal of this research was to minimize the maximum completion time of tasks.

Computational results assessing the performance of these algorithms indicate that GA exhibits superior performance in solving various instances of the two-stage smart startup problem and in achieving the best objective function value compared to BBO and Hybridize. This study, which originates from the field of smart startup modeling, focused on criteria such as business intelligence capacity, network learning, and innovation. The three methods—GA, BBO, and Hybridize—were evaluated for modeling purposes. According to the findings, BBO ranks second, demonstrating moderate effectiveness in comparison to GA. This suggests that BBO is also a viable method for modeling smart startups, although it falls slightly short compared to GA. Finally, the Hybridize method ranks third, indicating that its performance is lower than that of the other two methods and that it may be less efficient for modeling smart startups. Overall, the results of this study demonstrate that GA provides the highest effectiveness in modeling smart startups, whereas Hybridize performs the weakest.

Therefore, this study examined three different approaches for modeling smart startups. The key evaluation criteria included business intelligence capacity, network learning, and innovation—factors that are highly significant from industrial and managerial perspectives. The findings indicate that GA is recognized as the superior modeling method in this domain. This is particularly valuable for industry and management, as it shows that among the available tools for modeling smart startups, GA delivers the best performance.

Furthermore, the study results suggest that BBO also holds industrial and managerial value and can be considered a reasonable alternative for smart startup modeling. These findings can assist managers and business owners in selecting the most effective approach for modeling and developing smart startups. From an industrial perspective, this can enhance business operations and performance. Finally, Hybridize was also evaluated, but the results suggest that it is less effective than the other two methods. These findings can help managers and business owners choose the best strategies for developing smart startups and, from an industrial viewpoint, contribute to improving market competitiveness and overall efficiency.

Implementing a smart startup model based on business intelligence capacity, network learning, and innovation is essential, as this model enables companies to make more intelligent decisions using business and marketing data. Business intelligence capacity helps firms analyze and organize their data optimally. Additionally, network learning allows the model to dynamically utilize new data and improve decision-making processes. Innovation, on the other hand, is the most critical factor distinguishing a company from its competitors. Implementing a smart startup model ensures that innovations are systematically and strategically integrated into decision-making processes and product and service development. In general, adopting this model enhances efficiency, improves strategic decision-making, and fosters sustainable development and long-term corporate success.

From an economic perspective, implementing a smart startup model based on these factors can improve a company's financial performance. Since this model optimizes the use of business and marketing data and facilitates more intelligent decision-making, it is expected to enhance financial outcomes. Furthermore, increased efficiency and productivity in decision-making processes and strategy execution can reduce costs and, consequently, boost profitability. Therefore, implementing this model can be regarded as a valuable investment in corporate growth and economic advancement, potentially impacting macroeconomic development as well.

Based on the findings, several practical recommendations can be made:

1. Given that the smart startup model is designed based on business intelligence capacity, network learning, and innovation, it is recommended that this model be considered for the establishment and development of startups.
2. Since GA and BBO ranked first and second in terms of effectiveness, respectively, it is suggested that these algorithms be utilized in optimization and decision-making processes related to startups.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

References

[1] V. Smachylo, O. Dymchenko, O. Rudachenko, I. Bozhydai, and Y. Khailo, *Formation of Strategies for the Development of Startup Ecosystems as a Prerequisite for Sustainable Entrepreneurship In: Semenov, A., Yepifanova, I., Kajanová, J. (eds) Data-Centric Business and Applications*. 2024, pp. 1-1.

[2] X. Li, X. Yi, F. Mustakim, and F. Altoibi, "Investigating the business intelligence capabilities' and network learning effect on the data mining for start-up's function," *Information Processing & Management*, vol. 5, pp. 1-14, 2023.

[3] M. Nuseir, A. Aljumah, and M. Alshurideh, "How the Business Intelligence in the New Startup Performance in UAE During COVID-19: The Mediating Role of Innovativeness," *Business Intelligence, Studies in Systems, Decision and Control*, vol. 4, pp. 63-80, 2021. [Online]. Available: https://doi.org/10.1007/978-3-030-67151-8_4.

[4] N. Seitz, E. E. Lehmann, and P. Haslanger, "Corporate accelerators: design and startup performance," *Small Business Economics*, 2023. [Online]. Available: https://doi.org/10.1007/s11187-023-00817-8.

[5] M. Urbaniec and A. Żur, "Business model innovation in corporate entrepreneurship: Exploratory insights from corporate accelerators," *International Entrepreneurship and Management Journal*, vol. 17, no. 2, pp. 865-888, 2021. [Online]. Available: https://doi.org/10.1007/s11365-020-00646-1.

[6] M. Sánchez-Robles, J. R. Saura, and D. Ribeiro-Soriano, "Overcoming the challenges of cooperative startups businesses: insights from a bibliometric network analysis," *Review of Managerial Science*, 2023. [Online]. Available: https://doi.org/10.1007/s11846-023-00670-9.

[7] E. Yimfor and J. A. Garfinkel, "Predicting success in entrepreneurial finance research," *Journal of Corporate Finance*, vol. 81, 2023. [Online]. Available: https://doi.org/10.1016/j.jcorpfin.2023.102359.

[8] T. Weiblen and H. W. Chesbrough, "Engaging with startups to enhance corporate innovation," *California Management Review*, vol. 57, no. 2, pp. 66-90, 2015. [Online]. Available: https://doi.org/10.1525/cmr.2015.57.2.66.

[9] T. G. Petersen, "Strategic workforce planning model in business intelligence," University of Twente Student Theses, 2022.

[10] A. Borodin, I. Mityushina, E. Streltsova, A. Kulikov, I. Yakovenko, and A. Namitulina, "Mathematical Modeling for Financial Analysis of an Enterprise: Motivating of Not Open Innovation," *J. Open Innov. Technol. Mark. Complex.*, vol. 7, p. 79, 2021. [Online]. Available: https://doi.org/10.3390/joitmc7010079.

[11] R. K. Shankar and D. A. Shepherd, "Accelerating strategic fit or venture emergence: Different paths adopted by corporate accelerators," *Journal of Business Venturing*, vol. 34, no. 5, p. 105886, 2019. [Online]. Available: https://doi.org/10.1016/j.jbusvent.2018.06.004.

[12] I. Savin, K. Chukavina, and A. Pushkarev, "Topic-based classification and identification of global trends for startup companies," *Small Business Economics*, vol. 60, pp. 659-689, 2023. [Online]. Available: https://doi.org/10.1007/s11187-022-00609-6.

[13] X. Chen, D. Zou, G. Cheng, and H. Xie, "Detecting latent topics and trends in educational technologies over four decades using structural topic modeling: A retrospective of all volumes of Computers & Education," *Computers & Education*, vol. 151, p. 103855, 2020. [Online]. Available: https://doi.org/10.1016/j.compedu.2020.103855.

[14] M. P. Rice and E. Noyes, *Incubators as catalysts in entrepreneurship ecosystems*. Edward Elgar Publishing, 2021.

[15] A. Sabour, "The role of entrepreneurial strategies in improving the performance of innovative startups," in *Proceedings of the Second National Conference on Improvement and Reconstruction of Organizations and Businesses*, 2022: Tehran.

[16] H. Alizadeh, K. Alba, and A. Rahdari, "Assessing the development and sustainability of SMEs based on industry acceptance 4.0," in *1st National Conference on Modern Applied Research in Business and Industrial Development (ARBI2024)*, 2024, pp. 1-16. [Online]. Available: https://civilica.com/doc/2037846.
[17] H. Alizadeh and M. Foroughi, "A Strategic SWOT Analysis of Leading Electronics Companies based on Artificial Intelligence," *International Journal of Business Management and Entrepreneurship (IJBME),* vol. 2, no. 2, pp. 1-16, 2023.
[18] A. Chaubey and C. Sahoo, "Assimilation of business intelligence: The effect of external pressures and top leaders commitment during pandemic crisis," *International Journal of Information Management,* vol. 50, pp. 10-22, 2022.
[19] C. Godoy, A. Cundar, M. Barriga, and N. Vasco, "The business competitiveness of SMEs through mathematical modeling," *Creative Commons Attribution-NonCommercial-NoDerivs 4.0 International,* vol. 13, pp. 1-19, 2021. [Online]. Available: https://doi.org/10.31876/er.v4i32.718.
[20] A. Mehrani, H. Alizadeh, and A. Rasouli, "Evaluation of the Role of Artificial Intelligence Tools in the Development of Financial Services and Marketing," *Journal of Technology in Entrepreneurship and Strategic Management,* vol. 1, no. 1, pp. 71-82, 2022.
[21] Z. Huang, K. Savista, and L. Yi, "The impact of business intelligence on the marketing with emphasis on cooperative learning: Case-study on the insurance companies," *Information Processing and Management,* vol. 59, pp. 10-20, 2022. [Online]. Available: https://doi.org/10.1016/j.ipm.2021.102824.
[22] Z. Huang, K. Savista, and J. Zhong, "The Business Intelligence impact on the financial performance of start-ups," *Information Processing and Management,* vol. 50, pp. 10-23, 2023.
[23] A. P. Lopes and M. M. Carvalho, "Evolution of the open innovation paradigm: Towards a contingent conceptual model," *Technological Forecasting & Social Change,* 2018. [Online]. Available: https://doi.org/10.1016/j.techfore.2018.02.014.
[24] F. Hamad, R. Al-Aamr, S. A. Jabbar, and H. Fakhuri, "Business intelligence in academic libraries in Jordan: Opportunities and challenges," *IFLA Journal,* vol. 47, pp. 37-50, 2021. [Online]. Available: https://doi.org/10.1177/0340035220931882.
[25] M. Jalali Filshour and H. Alizadeh, "Presenting a digital marketing model based on artificial intelligence in the field of financial services with a data foundation approach," in *The First National Conference on Digital Transformation, Banking and Insurance*, 2022. [Online]. Available: https://civilica.com/doc/1578810/.
[26] S. S. A. C. Popa, "Antecedents, moderators, and outcomes of innovation climate and open innovation: An empirical study in SMEs," *Technological Forecasting and Social Change,* vol. 118, pp. 134-142, 2017. [Online]. Available: https://doi.org/10.1016/j.techfore.2017.02.014.
[27] S. Hilbolling, H. Berends, F. Deken, and P. Tuertscher, "Complementors as connectors: managing open innovation around digital product platforms," *Journal of R&D Management,* vol. 50, no. 1, pp. 18-30, 2020. [Online]. Available: https://doi.org/10.1111/radm.12371.
[28] Z. Mohammadi and S. K. Chavoshi, "Investigating the impact of investor control on startup performance with the moderating role of expertise and experience," *Iranian Political Sociology Monthly,* vol. 5, pp. 274-290, 2022.
[29] J. Danayi Fard and M. Aligholi, "The role of business intelligence in organizational decision-making: Analyzing components with a mixed approach," *Resource Management in Law Enforcement,* vol. 37, pp. 67-91, 2022.
[30] M. Amiri, I. Raeisi Vanani, S. H. Razavi Haji Agha, and T. Jafari, "Development of fuzzy artificial intelligence and multi-objective programming model for optimizing investment company portfolios," *Intelligent Business Management Studies,* vol. 10, no. 36, pp. 243-302, 2021.
[31] N. Kumburu, *Ontology-based knowledge management framework in business organizations and water users networks in Tanzania Handbook of Hydroinformatics*. 2023, pp. 333-348.
[32] E. Lubishtani, E. Beka, and A. Jhja, "The Impact of Knowledge Management and Knowledge Transfer in Growth and Innovation: A Study of Business Start-Ups, Business Incubators and Business Accelerators," *IFAC-PapersOnLine,* vol. 55, pp. 54-59, 2023. [Online]. Available: https://doi.org/10.1016/j.ifacol.2022.12.010.