



Data-driven corporate growth: A dynamic financial modelling framework for strategic agility

Hengki Tamando Sihotang¹, Desi Vinsensia², Fristi Riandari³ and Suherman Chandra⁴

^{1,4} Sistem Informasi, Universitas Putra Abadi Langkat, Medan, Indonesia

² Manajemen Informatika, STMIK Pelita Nusantara, Medan, Indonesia

³ Manajemen Informatika, Politeknik Negeri Medan, Medan, Indonesia

Article Info

Article history:

Received May 09, 2024

Revised Jun 20, 2024

Accepted Aug 22, 2024

Keywords:

Data-Driven Corporate Growth;
Dynamic Financial Modelling;
Real-Time Data Integration;
Scenario Analysis and Risk
Management;
Strategic Agility.

ABSTRACT

This research aimed to develop a Dynamic Financial Growth Model (DFGM) to enhance corporate growth by promoting strategic agility through data-driven decision-making. The main objective was to optimize corporate value by integrating real-time data, dynamic decision-making, risk management, and scenario analysis. The research employed a mathematical modelling framework that combined predictive analytics, real options theory, and scenario-based optimization to represent dynamic corporate financial decisions. The numerical example demonstrated how the model adjusts strategic decisions in response to changes in market data and evaluates corporate value under optimistic, pessimistic, and baseline scenarios. The main results indicated that the DFGM is effective in optimizing corporate value by allowing for continuous adjustments and strategic flexibility, distinguishing itself from traditional static financial models that lack real-time adaptability. The findings highlighted the value of incorporating risk constraints and scenario analysis, resulting in a balanced approach that manages both growth and uncertainty. However, the study identified limitations, including the need for empirical validation, more complex predictive analytics, and accounting for behavioral factors affecting decision-making. The conclusion emphasizes that the DFGM provides an adaptable and data-driven framework that enhances corporate strategic agility, making it a valuable tool for managing growth in rapidly changing environments, while also suggesting future research to refine the model's practical application.

This is an open access article under the CC BY-NC license.



Corresponding Author:

Hengki Tamando Sihotang,
Sistem Informasi,
Universitas Putra Abadi Langkat,
Jl. Letjen R. Soeprapto No.10, Kwala Bingai, Kec. Stabat, Kabupaten Langkat, Sumatera Utara 20814, Indonesia
Email: hengkitamando26@gmail.com

1. INTRODUCTION

The rapidly evolving business landscape has significantly increased the need for agility in corporate strategy and financial planning[1]. Organizations face the dual challenges of sustaining growth while navigating an unpredictable environment shaped by technological disruptions, global competition, and evolving customer expectations[2]. As a result, there is a pressing demand for new approaches to corporate growth that leverage data analytics and dynamic modelling to foster adaptability[3], [4], [5]. This study aims to develop a data-driven financial modelling framework that enhances strategic agility, helping organizations respond proactively to emerging opportunities and challenges[3], [6].

Traditionally, corporate growth has been driven by long-term planning that relies on static financial models and historical data[7]. However, in today's dynamic environment, static models are often insufficient to address the rapidly changing market conditions [8]. Businesses are now increasingly turning to data-driven decision-making to adapt to new challenges [9], [10]. Data analytics and dynamic financial models can provide deeper insights, facilitate proactive decision-making, and drive strategic agility[11], [12], [13]. Strategic agility is essential for ensuring that businesses can adjust their operations, allocate resources effectively, and capture growth opportunities amidst change[14].

The central issue addressed by this research is the lack of adaptability in current corporate growth frameworks due to static financial models and limited use of real-time data[15], [16], [17], [18]. Many organizations struggle to bridge the gap between data collection and strategic action, often failing to incorporate dynamic financial modelling to keep pace with market shifts[19]. The inability to use data-driven models for scenario analysis and predictive forecasting hampers organizations' ability to respond swiftly to disruptions, leading to missed opportunities and strategic misalignment[20].

Previous research has highlighted the potential of data-driven decision-making to enhance corporate growth. For instance, Brynjolfsson, Hitt, and Kim (2011) demonstrated the positive impact of data analytics on firm productivity[21]. Similarly, Wamba et al. (2017) found that the use of big data analytics positively influences decision-making, ultimately leading to better business performance[22], [23], [24], [25]. However, these studies did not provide a comprehensive framework that integrates financial modelling with strategic agility, nor did they address the specific challenges of real-time adaptability in financial planning.

Despite the growing body of research on data-driven decision-making, there are significant gaps in how dynamic financial modelling can be systematically integrated into corporate growth strategies[9][26]. Prior studies have focused primarily on data collection and analysis but have not fully explored the integration of these insights into adaptive financial models that support strategic agility [3], [9], [27]. Therefore, this research aims to fill this gap by developing a framework that links data-driven insights with dynamic financial modelling, enabling real-time adjustments to corporate strategy and financial planning[28][29].

The research is grounded in several theories. The Resource-Based View (RBV) in Barney, (1991) suggests that a firm's resources, including data and analytical capabilities, are critical to gaining a competitive advantage[30], [31], [32], [33]. The Dynamic Capabilities Theory in Teece, Pisano, & Shuen, (1997)[34] highlights the need for firms to continuously adapt to changing environments. In addition, Systems Theory in Von Bertalanffy, (1968) supports the integration of various organizational functions—such as data analytics, financial modelling, and strategic planning—into a cohesive, adaptive system that enhances corporate growth[35].

The primary objective of this research is to develop a data-driven financial modeling framework aimed at enhancing strategic agility in corporate growth. To achieve this, the research will first identify the factors that hinder the adaptability of traditional financial models, addressing their limitations in dynamic business environments. It will then focus on developing a framework that integrates real-time data into financial modeling, enabling more proactive and informed decision-making. Finally, the framework will be validated through empirical case studies, demonstrating its effectiveness in driving corporate growth and ensuring its practical applicability.

The outcomes of this research will have significant implications for both academic and business communities. For academia, it will contribute to the growing literature on data-driven decision-making, dynamic financial modelling, and strategic agility. For businesses, the proposed framework will provide a practical tool to enhance responsiveness to market changes, optimize resource allocation, and achieve sustainable growth. By enabling real-time adaptability, the research aims to equip organizations with the capabilities needed to thrive in an uncertain and competitive environment.

2. RESEARCH METHOD

This research will follow a mixed-methods approach, beginning with a literature review to understand the current state of dynamic financial modelling and data-driven corporate growth. This will be followed by qualitative interviews with industry experts to identify key factors contributing to strategic agility. Based on the findings, a dynamic financial modelling framework will be developed and validated through case studies and quantitative simulations to assess its effectiveness in enhancing corporate growth.

2.1 Theoretical Basis

The research on "Data-Driven Corporate Growth: A Dynamic Financial Modelling Framework for Strategic Agility" is rooted in several foundational theories and mathematical frameworks that collectively support the concept of using data to drive strategic adaptability and enhance corporate growth. Below are the theoretical bases, supported by relevant formulas and models:

a. Resource-Based View (RBV) Theory

The Resource-Based View (RBV) posits that organizations achieve a competitive advantage by effectively utilizing unique resources and capabilities in Barney, 1991[30], [36], [37], [38]. In the context of this research, data and analytics capabilities are viewed as critical resources that can drive corporate growth when integrated with financial modelling and strategic decision-making[39].

The value of data as a resource can be quantified by evaluating its contribution to financial outcomes through regression analysis:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \epsilon \quad (1)$$

Where:

Y is the financial performance metric (e.g., revenue growth or profitability).

$X_1, X_2, \dots, X_n$ represent data-driven variables (e.g., market trends, customer behavior).

$\beta_1, \beta_2, \dots, \beta_n$ are coefficients indicating the contribution of each variable.

ϵ represents the error term.

b. Dynamic Capabilities Theory

The Dynamic Capabilities Theory in Teece, Pisano, & Shuen, (1997) emphasizes the importance of organizations developing capabilities to respond quickly to environmental changes[34]. In this research, dynamic financial modelling serves as a capability that allows firms to adapt their strategies in real-time[40], [41]. The agility of a firm's strategy can be represented by continuously optimizing financial performance based on changing conditions[42].

This dynamic adjustment can be represented using an optimization function:

$$\max_{x(t)} \int_0^T [R(x(t), t) - C(x(t), t)] dt \quad (2)$$

Where:

$x(t)$ represents the strategic variables controlled by the organization (e.g., investment levels, operational adjustments).

$R(x(t), t)$ is the revenue function as a function of time.

$C(x(t), t)$ is the cost function as a function of time.

T represents the time horizon.

The objective is to maximize net financial performance $R - C$ over the period T

c. Systems Theory

Systems Theory in Von Bertalanffy, (1968) provides a framework for understanding organizations as systems composed of interconnected elements[35]. For data-driven corporate growth, the key components include data sources, financial models, and strategic decision-making processes[9], [43], [44]. This theory underpins the integration of data into financial models to improve agility and performance.

The interaction among the elements in the system can be modeled using differential equations to capture the evolution of financial outcomes in response to internal and external stimuli:

$$\frac{dS(t)}{dt} = f(S(t), D(t), M(t)) \quad (3)$$

Where:

$S(t)$ represents the corporate strategy at time t

$D(t)$ represents the data input at time t

$M(t)$ represents the financial model at time t

$f(\cdot)$ is a function that captures how changes in data and modelling affect strategic decisions.

d. Financial Modelling and Scenario Analysis

Dynamic Financial Modelling is a crucial component of this research[45], [46], [47], [48]. Financial models that are responsive to changes in external and internal data help firms adapt their strategies dynamically[40], [49][50]. Scenario analysis, which helps assess potential outcomes under different conditions, is an essential tool in this context.

A basic financial model for corporate growth can be represented as:

$$V_t = V_{t-1} + \sum_i^n (\Delta R_i - \Delta C_i) \cdot P_i \quad (4)$$

Where:

V_t is the corporate value at time t

V_{t-1} is the corporate value at the previous time period.

ΔR_i represents changes in revenue for scenario i .

ΔC_i represents changes in costs for scenario i

P_i represents the probability of scenario i occurring.

e. Predictive Analytics

Predictive Analytics involves using historical data to predict future outcomes, helping organizations identify opportunities for growth[51], [52], [53]. Predictive models can take the form of linear or non-linear regression, time-series forecasting, or machine learning models. A simple linear predictive model can be represented as:

$$\hat{Y}_t = \alpha + \beta X_t + \epsilon_t \quad (5)$$

Where:

$\hat{Y}_t$ represents the predicted financial performance at time t

X_t is the independent variable (e.g., sales, customer demand).

α and β are coefficients determined by fitting the model.

ϵ_t represents the error term.

f. Real Options Theory

Real Options Theory provides a financial framework to evaluate strategic decisions under uncertainty, which is relevant to assessing the value of flexibility in corporate strategy[54], [55], [56]. It treats each strategic decision as an "option" that can be exercised based on market conditions, similar to financial options[57].

The value of a real option can be represented using the Black-Scholes formula:

$$C = S_0 N(d_1) - X e^{-rT} N(d_2) \quad (6)$$

Where:

C is the value of the option (e.g., an investment or strategic pivot).

S_0 is the current value of the underlying asset (e.g., an investment opportunity).

X is the exercise price (e.g., cost of the investment).

r is the risk-free rate.

T is the time to maturity of the option.

$N(d_1)$ and $N(d_2)$ are the cumulative normal distribution functions of d_1 and d_2 .

To address the problem of Data-Driven Corporate Growth: A Dynamic Financial Modelling Framework for Strategic Agility, we can develop a new mathematical formulation that incorporates elements from the previous theoretical bases. The formulation will integrate data-driven insights, dynamic decision-making, financial performance optimization, and risk assessment. Below is a developed mathematical model to represent the core of the dynamic financial modelling framework.

2.2. Overview of the Mathematical Formulation

The proposed model will be constructed in a way that:

- Integrates Real-Time Data: Combines data from multiple sources to drive strategic decision-making.
- Adapts to Changing Conditions: Uses dynamic optimization to adjust corporate strategy over time.
- Incorporates Financial Modelling: Uses scenario-based predictions to optimize growth.
- Includes Risk Assessment: Factors in uncertainties to evaluate strategic decisions.

a. Dynamic Financial Growth Model (DFGM)

Consider a corporate entity making strategic decisions at multiple time intervals to maximize its growth in value. Let us denote the growth of corporate value as $V(t)$, which is determined by revenue, costs, investments, and external data sources at any time t .

Objective Function: The goal is to maximize the corporate value $V(t)$ over the planning horizon $[0, T]$:

$$\max_{x(t), I(t)} \int_0^T [R(x(t), I(t), D(t)) - C(x(t), I(t), D(t))] e^{-rt} dt \quad (7)$$

Where:

$x(t)$ represents strategic decisions made by the company (e.g., marketing budget allocation, operational capacity).

$I(t)$ is the investment in strategic growth initiatives (e.g., R&D, market expansion).

$D(t)$ represents external data inputs at time t (e.g., customer behavior, market trends, competitor activities).

$R(x(t), I(t), D(t))$ represents the revenue as a function of strategic decisions, investments, and data.

$C(x(t), I(t), D(t))$ represents the costs incurred as a function of strategic decisions, investments, and data.

r is the discount rate.

Constraints: To ensure practical solutions, we include various constraints:

- Budget Constraint:** Investments cannot exceed the available budget:

$$I(t) \leq B(t)$$

Where $B(t)$ is the available budget at time t .

- Risk Constraint:** To account for the risk associated with different scenarios:

$$\sigma(x(t), D(t)) \leq \sigma_{\max}$$

Where $(x(t), D(t))$ is the risk (e.g., variance in outcomes) of a strategic decision at time t and $\sigma_{\max}$.

- Capacity Constraint:** The operational capacity constraint ensures decisions are feasible within the company's resources:

$$x(t) \leq C_{\max}(t)$$

Where $C_{\max}(t)$ represents the maximum operational capacity at time t .

b. Real-Time Data Integration and Adjustment

To ensure strategic agility, the model incorporates real-time data inputs to adjust financial models. We use a **feedback control mechanism** that updates the strategic decisions $x(t)$ based on the latest data $D(t)$.

$$x(t + \Delta t) = x(t) + \alpha (D(t) - D_{\text{target}}) - \beta \frac{dC(x(t), I(t), D(t))}{dx} \quad (8)$$

Where:

Δt is the time interval for adjustment.

α and β are adjustment coefficients.

D_{target} represents the desired data outcomes (e.g., target market share).

c. Scenario Analysis

To handle uncertainties, we incorporate scenario analysis into the model. Let S_i denote different scenarios (e.g., optimistic, pessimistic, and baseline scenarios) with a probability p_i . The value function $V(t)$ under different scenarios can be expressed as:

$$V(t) = \sum_{i=1}^n p_i [R_i(x(t), I(t)) - C_i(x(t), I(t))] \quad (10)$$

Where:

R_i and C_i represent the revenue and cost functions under scenario S_i .

p_i represents the probability of scenario S_i .

d. Predictive and Optimization Models

We use predictive analytics to estimate future financial outcomes based on current and historical data. The prediction of revenue $\hat{R}(t)$ can be expressed as:

$$\hat{R}(t) = \gamma_0 + \sum_{j=1}^m \gamma_j D_j(t) + \epsilon_t \quad (11)$$

Where:

$D_j(t)$ represents different data variables (e.g., market demand, competitor activities).

γ_j are the coefficients estimated through regression or machine learning models.

ϵ_t represents the prediction error.

The optimization model aims to select $x(t)$ and $I(t)$ to maximize $V(t)$ while minimizing the risk $\sigma(x(t), D(t))$:

$$\min_{x(t), I(t)} [-V(t) + \lambda \sigma(x(t), D(t))] \quad (12)$$

Where:

λ is the risk-aversion parameter that balances corporate growth and risk.

e. Real Options Valuation for Strategic Flexibility

The model also incorporates Real Options Theory to evaluate flexibility in decision-making. Let $C_{\text{option}}(t)$ represent the value of an option to invest or delay a decision, expressed using a variant of the Black-Scholes formula adapted to corporate investments:

$$C_{\text{option}}(t) = S(t)N(d_1) - Ie^{-r(T-t)}N(d_2) \quad (13)$$

Where:

$S(t)$ is the current expected value of the investment opportunity.

I is the cost of the investment.

T is the time horizon.

$N(d_1)$ and $N(d_2)$ are the cumulative distribution functions of standard normal variables.

The proposed Dynamic Financial Growth Model (DFGM) for corporate growth integrates real-time data, dynamic decision-making, risk assessment, and optimization. By leveraging feedback mechanisms, scenario analysis, predictive analytics, and real options valuation, the model provides a comprehensive framework that supports strategic agility and optimizes corporate value. This formulation offers a quantitative tool for businesses to adapt quickly to changing conditions, optimize financial performance, and make strategic decisions with a clear understanding of risks and rewards.

3. RESULTS AND DISCUSSIONS

To illustrate the application of the Dynamic Financial Growth Model (DFGM), we will create a numerical example using simplified data to demonstrate the key aspects of the model. In this example,

we'll simulate the decision-making process of a company that aims to maximize corporate value through strategic investment and financial decision-making.

3.1. Scenario Setup

Consider a company that is making strategic decisions over a time horizon $T=3$ years. We assume the company has a budget for strategic investments and needs to adjust its decisions based on real-time data inputs and different economic scenarios.

Revenue Function:

$$R(x(t), I(t), D(t)) = 10x(t) + 20I(t) + 5D(t)$$

Cost Function:

$$C(x(t), I(t), D(t)) = 5x(t) + 10I(t) + 3D(t)$$

Investment Budget Constraint:

$$I(t) \leq 50 \forall t \in [0, T]$$

Risk Constraint:

$$\sigma(x(t), D(t)) = 0.2x(t) + 0.1D(t) \leq 10$$

Capacity Constraint:

$$x(t) \leq 100$$

Discount Rate:

$$r = 0.05$$

Adjustment Coefficients:

$$\alpha = 0.3, \beta = 0.2$$

Data Input:

Assume that $D(t)$ is a real-time external variable representing customer demand, varying each year as $D(0) = 30, D(1) = 50$, and $D(2) = 40$.

Scenario Probabilities:

Assume two scenarios with equal probabilities ($p_1 = 0.5$ and $p_2 = 0.5$): **Optimistic Scenario:** Higher revenue growth (R_1), lower costs (C_1). **Pessimistic Scenario:** Lower revenue growth (R_2), lower costs (C_2).

3.2. Step-by-Step Solution

Step 1: Real-Time Data Integration and Adjustment

The company starts with initial values for strategic decisions $x(0)$ and investment $I(0)$. Let's assume:

$$x(0) = 50$$

$$I(0) = 30$$

The initial real-time data input $D(0) = 30$.

The next decision, $x(1)$, will be adjusted based on the difference between $D(t)$ and a target value $D_{\text{target}} = 40$:

$$x(1) = x(0) + \alpha(D(0) - D_{\text{target}}) - \beta \frac{dC(x(0), I(0), D(0))}{dx}$$

First, calculate the derivative of the cost function with respect to x

$$\frac{dC(x(t), I(t), D(t))}{dx} = 5$$

Now substitute the values:

$$x(1) = 50 + 0.3(30 - 40) - 0.2 \times 5$$

$$x(1) = 50 - 3 - 1 = 46$$

Step 2: Revenue and Cost Calculation for $t = 1$

Using the adjusted value $x(1) = 46$ and $I(1) = 30$, and $D(1) = 50$:

Revenue:

$$R(1) = 10x(1) + 20I(1) + 5D(1)$$

$$R(1) = 10 \times 46 + 20 \times 30 + 5 \times 50 = 460 + 600 + 250 = 1310$$

Cost:

$$C(1) = 5x(1) + 10I(1) + 3D(1)$$

$$C(1) = 5 \times 46 + 10 \times 30 + 3 \times 50 = 230 + 300 + 150 = 680$$

Step 3: Value Function Calculation

The corporate value $V(1)$ at $t = 1$, considering discounting:

$$V(1) = (R(1) - C(1))e^{-et}$$

$$V(1) = (1310 - 680)e^{-0.05 \times 1} = 630 \times 0.9512 = 599.26$$

Step 4: Scenario Analysis

For each scenario, calculate $V(t)$:

Optimistic Scenario (S_1): Assume revenue increases by 10% and cost decreases by 5%.

$$R_1(1) = 1.1 \times 1310 = 1441$$

$$C_1(1) = 0.95 \times 680 = 646$$

Value under scenario S_1 :

$$V_1(1) = (R_1(1) - C_1(1))e^{-rt} = (1441 - 646) \times 0.9512 = 755.24$$

Pessimistic Scenario (S_2): Assume revenue decreases by 10% and cost increases by 5%.

$$R_2(1) = 0.9 \times 1310 = 1179$$

$$C_2(1) = 1.05 \times 680 = 714$$

Value under scenario (S_2):

$$V_2(1) = (R_2(1) - C_2(1))e^{-rt} = (1179 - 714) \times 0.9512 = 442.57$$

Expected Value:

$$V(1) = p_1 V_1(1) + p_2 V_2(1) = 0.5 \times 755.24 + 0.5 \times 442.57 = 598.91$$

Step 5: Optimization

To maximize the corporate value while considering risk, we minimize:

$$\min_{x(1), I(t)} [-V(1) + \lambda \sigma(x(1), D(1))]$$

Assuming $\lambda = 1$

Risk:

$$\sigma(x(1), D(1)) = 0.2x(1) + 0.1D(1) = 0.2 \times 46 + 0.1 \times 50 = 9.2 + 5 = 14.2$$

Objective Function:

$$\min [-598.91 + 1 \times 14.2] = -584.71$$

The numerical example illustrates the application of the Dynamic Financial Growth Model (DFGM) in a real-world decision-making scenario. In this example, a company sought to maximize its corporate value by making strategic investment decisions while adapting dynamically to changes in market data. The initial adjustment of strategic decisions in response to real-time data inputs resulted in a reduction of decision variables, showing a reactive approach to maintain financial stability. The calculation of revenue and costs, based on new data and adjusted decisions, provided a corporate value of approximately 599.26 at year one, accounting for the discount factor.

Further analysis using scenario-based evaluation revealed the impact of different economic environments on corporate value. In the optimistic scenario, increased revenue and decreased costs led to a higher value of 755.24, while the pessimistic scenario, with reduced revenue and increased costs, yielded a lower value of 442.57. The expected value, calculated by averaging these scenarios based on equal probabilities, was approximately 598.91, which closely matched the value derived from the initial assumptions, indicating a balanced approach to scenario-based financial forecasting.

The risk-adjusted optimization step demonstrated the importance of incorporating risk management in strategic decision-making. The calculated risk, represented by variance in outcomes, led to a minor reduction in overall corporate value, resulting in an optimal value of -584.71. This outcome emphasizes the necessity of balancing growth and risk to achieve strategic agility in a dynamic environment. By integrating predictive analytics, scenario analysis, and risk assessment, the DFGM provided a comprehensive framework for guiding corporate growth decisions, ensuring the company could remain flexible and responsive to evolving conditions while optimizing financial outcomes. This numerical example demonstrates how DFGM can effectively support strategic financial planning, particularly when dealing with uncertainties and dynamic market environments.

3.3. Discussion

The numerical example provided demonstrates how the Dynamic Financial Growth Model (DFGM) can support strategic decision-making through real-time data integration, dynamic optimization, and risk assessment, offering a clear picture of its potential advantages over traditional financial models. The model's effectiveness is seen in its ability to integrate external data sources into decision-making processes and adjust investments dynamically, which contributes to maximizing corporate value under varying economic conditions. This dynamic adaptability is crucial for ensuring a company's strategic agility, as shown by the adjustments made based on customer demand and scenario analyses. The use of scenario evaluation highlighted the difference in outcomes under optimistic and pessimistic conditions, and the optimization function allowed the company to achieve balanced growth while managing risks. In comparison to previous research, the DFGM distinguishes itself by emphasizing the use of real-time data and predictive analytics in a corporate growth context. Traditional models, such as static financial planning frameworks, primarily focus on optimizing investments and resource allocation based on historical data and fixed assumptions, often ignoring the rapid and unpredictable changes in market conditions. Previous research, such as those by Porter and Millar (1985), focused on competitive forces and cost analysis for strategic planning, which had limitations in handling real-time data and lacked mechanisms for continuous adjustment. Similarly, studies by Ansoff (1965) on corporate strategy provided foundational insights into managing firm growth but were based on relatively static and long-term perspectives, without integrating adaptive feedback loops and predictive analytics. The DFGM also differs from more recent approaches that incorporate machine learning for prediction but lack a cohesive integration of scenario analysis and real options theory for flexibility in strategic decision-making. Previous work by Cui and Li (2015), for instance, utilized machine learning to enhance the accuracy of financial predictions but did not address how to use these predictions in real-time decision-making, especially in uncertain scenarios. Furthermore, other studies focused on financial optimization primarily concentrated on maximizing profit or minimizing costs under fixed scenarios without fully incorporating strategic flexibility through methods like real options theory.

4. CONCLUSION

The study presented a comprehensive Dynamic Financial Growth Model (DFGM) designed to optimize corporate value through strategic agility, driven by real-time data integration, dynamic optimization, risk assessment, and scenario analysis. The numerical example illustrated how the DFGM could adjust strategic decisions in response to changing data, thus maximizing corporate value while accounting for varying market conditions and associated risks. The model's integration of real options theory added significant flexibility to decision-making, enabling companies to dynamically evaluate and adapt investment decisions. Compared to traditional financial models and previous research, the DFGM provided a more adaptable framework by leveraging real-time data and predictive analytics for more effective growth strategy optimization. The implications of this research suggest that adopting a data-driven approach with dynamic adjustments allows firms to enhance their resilience and agility in volatile environments. By incorporating scenario analysis and risk management within the model, companies can make informed decisions that optimize growth potential while managing uncertainties. This framework is particularly beneficial in industries where market dynamics are fast-changing and where responsiveness is key to maintaining competitive advantage. However, the study also had several limitations. The application of the DFGM in the numerical example was limited in scope, relying on simplified revenue and cost functions, which may not fully capture the complexity of real-world corporate environments. Additionally, while the model integrates predictive analytics, the variability and reliability of predictions, especially under uncertain external conditions, pose challenges. Behavioral factors influencing decision-making and managerial biases were not addressed, which could limit the practical implementation of the model in real corporate contexts. Moreover, the practical applicability of real options theory in high-risk investment scenarios requires further empirical validation. Future research should address these limitations by expanding empirical

validation across different industries and integrating more complex, machine learning-based predictive techniques to enhance forecast accuracy. Additionally, incorporating behavioral aspects into the financial decision-making process could further refine the model's applicability and reliability in dynamic settings. Furthermore, exploring real-world case studies involving the implementation of real options in corporate investments could provide valuable insights into the practical use of the model. By bridging these research gaps, the DFGM can be further developed into a robust tool for supporting data-driven corporate growth, helping firms navigate uncertain environments with increased strategic agility and optimized financial performance.

REFERENCES

- [1] W. Elali, "The importance of strategic agility to business survival during corona crisis and beyond," *Int. J. Bus. Ethics Gov.*, vol. 4, no. 2, pp. 1–8, 2021, doi: <https://doi.org/10.51325/ijbeg.v4i2.64>.
- [2] J. R. L. Kaivo-oja and I. T. Lauraeus, "The VUCA approach as a solution concept to corporate foresight challenges and global technological disruption," *foresight*, vol. 20, no. 1, pp. 27–49, 2018, doi: <https://doi.org/10.1108/FS-06-2017-0022>.
- [3] Y. Barlette and P. Baillette, "Big data analytics in turbulent contexts: towards organizational change for enhanced agility," *Prod. Plan. Control*, vol. 33, no. 2–3, pp. 105–122, 2022, doi: <https://doi.org/10.1080/09537287.2020.1810755>.
- [4] M. Zollo, E. L. M. Bettinazzi, K. Neumann, and P. Snoeren, "Toward a comprehensive model of organizational evolution: Dynamic capabilities for innovation and adaptation of the enterprise model," *Glob. Strateg. J.*, vol. 6, no. 3, pp. 225–244, 2016, doi: <https://doi.org/10.1002/gsj.1122>.
- [5] F. Cosenz and E. Bivona, "Fostering growth patterns of SMEs through business model innovation. A tailored dynamic business modelling approach," *J. Bus. Res.*, vol. 130, no. 6, pp. 658–669, 2021, doi: <https://doi.org/10.1016/j.jbusres.2020.03.003>.
- [6] S. Kolasani, "Innovations in digital, enterprise, cloud, data transformation, and organizational change management using agile, lean, and data-driven methodologies," *Int. J. Mach. Learn. Artif. Intell.*, vol. 4, no. 4, pp. 1–18, 2023, [Online]. Available: <https://ijmlai.in/index.php/ijmlai/article/view/35>
- [7] D. Kumar, "Enterprise growth strategy: vision, planning and execution," in *Enterprise Growth Strategy*, Routledge, 2016, p. 418. doi: <https://doi.org/10.4324/9781315579870>.
- [8] H. Chen, R. H. L. Chiang, and V. C. Storey, "Business intelligence and analytics: From big data to big impact," *MIS Q.*, vol. 36, no. 4, pp. 1165–1188, 2012, doi: <https://doi.org/10.2307/41703503>.
- [9] F. Provost and T. Fawcett, "Data science and its relationship to big data and data-driven decision making," *Big data*, vol. 1, no. 1, pp. 51–59, 2013, doi: <https://doi.org/10.1089/big.2013.1508>.
- [10] F. Provost, *Data Science for Business: What you need to know about data mining and data-analytic thinking*, vol. 355. O'Reilly Media, Inc, 2013.
- [11] N. Stylos, J. Zwiendelaar, and D. Buhalis, "Big data empowered agility for dynamic, volatile, and time-sensitive service industries: the case of tourism sector," *Int. J. Contemp. Hosp. Manag.*, vol. 33, no. 3, pp. 1015–1036, 2021, doi: <https://doi.org/10.1108/IJCHM-07-2020-0644>.
- [12] K. S. Al-Omouh, F. Garcia-Monleon, and J. M. M. Iglesias, "Exploring the interaction between big data analytics, frugal innovation, and competitive agility: The mediating role of organizational learning," *Technol. Forecast. Soc. Change*, vol. 200, no. 3, p. 123188, 2024, doi: <https://doi.org/10.1016/j.techfore.2023.123188>.
- [13] T. Clauss, M. Abebe, C. Tangpong, and M. Hock, "Strategic agility, business model innovation, and firm performance: an empirical investigation," *IEEE Trans. Eng. Manag.*, vol. 68, no. 3, pp. 767–784, 2019, doi: <https://doi.org/10.1109/TEM.2019.2910381>.
- [14] Y. Doz and M. Kosonen, "The dynamics of strategic agility: Nokia's rollercoaster experience," *Calif. Manage. Rev.*, vol. 50, no. 3, pp. 95–118, 2008, doi: <https://doi.org/10.2307/41166447>.
- [15] B. Azvine, Z. Cui, D. D. Nauck, and B. Majeed, "Real time business intelligence for the adaptive enterprise," in *The 8th IEEE International Conference on E-Commerce Technology and The 3rd IEEE International Conference on Enterprise Computing, E-Commerce, and E-Services (CEC/EEE'06)*, IEEE, 2006, p. 29. doi: <https://doi.org/10.1109/CEC-EEE.2006.73>.
- [16] G. Weichhart, A. Molina, D. Chen, L. E. Whitman, and F. Vernadat, "Challenges and current developments for sensing, smart and sustainable enterprise systems," *Comput. Ind.*, vol. 79, no. 6, pp. 34–46, 2016, doi: <https://doi.org/10.1016/j.compind.2015.07.002>.
- [17] F. D. Macías-Escrivá, R. Haber, R. Del Toro, and V. Hernandez, "Self-adaptive systems: A survey of current approaches, research challenges and applications," *Expert Syst. Appl.*, vol. 40, no. 18, pp. 7267–7279, 2013.

- [18] S. Ren, Y. Zhang, Y. Liu, T. Sakao, D. Huisin, and C. M. V. B. Almeida, "A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: A framework, challenges and future research directions," *J. Clean. Prod.*, vol. 210, no. 10, pp. 1343–1365, 2019, doi: <https://doi.org/10.1016/j.jclepro.2018.11.025>.
- [19] K. Shimizu and M. A. Hitt, "Strategic flexibility: Organizational preparedness to reverse ineffective strategic decisions," *Acad. Manag. Perspect.*, vol. 18, no. 4, pp. 44–59, 2004, doi: <https://doi.org/10.5465/ame.2004.15268683>.
- [20] B. Sen Gupta, "Supply Chain Disruption & Plausible Solution in the Scenario of COVID-19 Pandemic; Forging a Pandemic Adaptive Supply Chain," Tampere University, 2020. doi: <https://trepo.tuni.fi/handle/10024/123429>.
- [21] E. Brynjolfsson, L. M. Hitt, and H. H. Kim, "Strength in numbers: How does data-driven decisionmaking affect firm performance?," *Available SSRN 1819486*, vol. 1, no. 1, pp. 1–33, 2011, doi: <https://dx.doi.org/10.2139/ssrn.1819486>.
- [22] S. F. Wamba, A. Gunasekaran, S. Akter, S. J. Ren, R. Dubey, and S. J. Childe, "Big data analytics and firm performance: Effects of dynamic capabilities," *J. Bus. Res.*, vol. 70, no. 3, pp. 356–365, 2017, doi: <https://doi.org/10.1016/j.jbusres.2016.08.009>.
- [23] A. Gunasekaran *et al.*, "Big data and predictive analytics for supply chain and organizational performance," *J. Bus. Res.*, vol. 70, no. 2, pp. 308–317, 2017, doi: <https://doi.org/10.1016/j.jbusres.2016.08.004>.
- [24] L. Li, J. Lin, Y. Ouyang, and X. R. Luo, "Evaluating the impact of big data analytics usage on the decision-making quality of organizations," *Technol. Forecast. Soc. Change*, vol. 175, no. 2, p. 121355, 2022, doi: <https://doi.org/10.1016/j.techfore.2021.121355>.
- [25] Q. A. Nisar, N. Nasir, S. Jamshed, S. Naz, M. Ali, and S. Ali, "Big data management and environmental performance: role of big data decision-making capabilities and decision-making quality," *J. Enterp. Inf. Manag.*, vol. 34, no. 4, pp. 1061–1096, 2021, doi: <https://doi.org/10.1108/JEIM-04-2020-0137>.
- [26] S. Singh, S. S. Rajest, S. Hadoussa, A. J. Obaid, and R. Regin, *Data-driven decision making for long-term business success*. IGI Global, 2023.
- [27] A. E. Artene, A. E. Domil, and L. Ivascu, "Unlocking Business Value: Integrating AI-Driven Decision-Making in Financial Reporting Systems," *Electron.*, vol. 13, no. 15, pp. 30–69, 2024, doi: <https://doi.org/10.3390/electronics13153069>.
- [28] M. Al-Okaily and A. Al-Okaily, "Financial data modeling: an analysis of factors influencing big data analytics-driven financial decision quality," Emerald Publishing Limited, 2024. doi: <https://doi.org/10.1108/JM2-08-2023-0183>.
- [29] D. Bechtsis, N. Tsolakis, E. Iakovou, and D. Vlachos, "Data-driven secure, resilient and sustainable supply chains: gaps, opportunities, and a new generalised data sharing and data monetisation framework," *Int. J. Prod. Res.*, vol. 60, no. 14, pp. 4397–4417, 2022, doi: [10.1080/00207543.2021.1957506](https://doi.org/10.1080/00207543.2021.1957506).
- [30] P. M. Madhani, "Resource based view (RBV) of competitive advantage: an overview," *Resour. based view concepts Pract. Pankaj Madhani, ed*, vol. 3, no. 6, pp. 3–22, 2010, doi: <https://ssrn.com/abstract=1578704>.
- [31] R. Dahiya, S. Le, J. K. Ring, and K. Watson, "Big data analytics and competitive advantage: the strategic role of firm-specific knowledge," *J. Strateg. Manag.*, vol. 15, no. 2, pp. 175–193, 2022, doi: <https://doi.org/10.1108/JMA-08-2020-0203>.
- [32] S. Akter, A. Gunasekaran, S. F. Wamba, M. M. Babu, and U. Hani, "Reshaping competitive advantages with analytics capabilities in service systems," *Technol. Forecast. Soc. Change*, vol. 159, no. 10, p. 120180, 2020, doi: <https://doi.org/10.1016/j.techfore.2020.120180>.
- [33] A. Garg and D. P. Goyal, "Sustained business competitive advantage with data analytics," *Int. J. Bus. Data Anal.*, vol. 1, no. 1, pp. 4–15, 2019, doi: <https://doi.org/10.1504/IJBDA.2019.098829>.
- [34] D. J. Teece, G. Pisano, and A. Shuen, "Dynamic capabilities and strategic management," *Strateg. Manag. J.*, vol. 18, no. 7, pp. 509–533, 1997, doi: [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7%3C509::AID-SMJ882%3E3.o.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.o.CO;2-Z).
- [35] L. von Bertalanffy, "General systems theory as integrating factor in contemporary science," *Akten des XIV. Int. Kongresses für Philos.*, vol. 2, no. 1, pp. 335–340, 1968, doi: <https://doi.org/10.5840/wcp1419682120>.
- [36] M. P. Ferreira, F. R. Serra, B. K. Costa, and M. Almeida, "A bibliometric study of the resource-based view (RBV) in international business research using barney (1991) as a key marker," *Innovar*, vol. 26, no. 61, pp. 131–144, 2016.
- [37] J. Barney, "Firm resources and sustained competitive advantage," *J. Manage.*, vol. 17, no. 1, pp. 99–120, 1991, doi: <https://doi.org/10.1177/014920639101700108>.
- [38] J. Barney, "Special theory forum the resource-based model of the firm: origins, implications, and prospects," *J. Manage.*, vol. 17, no. 1, pp. 97–98, 1991, doi: <https://doi.org/10.1177/014920639101700107>.

- [39] V. Grover, R. H. L. Chiang, T.-P. Liang, and D. Zhang, "Creating strategic business value from big data analytics: A research framework," *J. Manag. Inf. Syst.*, vol. 35, no. 2, pp. 388–423, 2018, doi: <https://doi.org/10.1080/07421222.2018.1451951>.
- [40] H. Makkonen, M. Pohjola, R. Olkkonen, and A. Koponen, "Dynamic capabilities and firm performance in a financial crisis," *J. Bus. Res.*, vol. 67, no. 1, pp. 2707–2719, 2014, doi: <https://doi.org/10.1016/j.jbusres.2013.03.020>.
- [41] C. Vitari and E. Raguseo, "Digital data, dynamic capability and financial performance: an empirical investigation in the era of Big Data," *Systèmes d'information Manag.*, vol. 21, no. 3, pp. 63–92, 2016, [Online]. Available: <https://shs.cairn.info/revue-systemes-d-information-et-management-2016-3-page-63?lang=fr>
- [42] M. L. Santos-Vijande, J. Á. López-Sánchez, and J. A. Trespalacios, "How organizational learning affects a firm's flexibility, competitive strategy, and performance," *J. Bus. Res.*, vol. 65, no. 8, pp. 1079–1089, 2012, doi: <https://doi.org/10.1016/j.jbusres.2011.09.002>.
- [43] O. Troisi, G. Maione, M. Grimaldi, and F. Loia, "Growth hacking: Insights on data-driven decision-making from three firms," *Ind. Mark. Manag.*, vol. 90, no. 10, pp. 538–557, 2020, doi: <https://doi.org/10.1016/j.indmarman.2019.08.005>.
- [44] J. Brownlow, M. Zaki, A. Neely, and F. Urmetzer, "Data and analytics-data-driven business models: A Blueprint for Innovation," *Cambridge Serv. Alliance*, vol. 7, no. February, pp. 1–17, 2015.
- [45] R. Kaufmann, A. Gadmer, and R. Klett, "Introduction to dynamic financial analysis," *ASTIN Bull. J. IAA*, vol. 31, no. 1, pp. 213–249, 2001, doi: <https://doi.org/10.2143/AST.31.1.1003>.
- [46] V. Svatošová, "Proposal and simulation of dynamic financial strategy model," *Futur. Stud. Res. J. Trends Strateg.*, vol. 11, no. 1, pp. 84–101, 2019, doi: <https://doi.org/10.24023/FutureJournal/2175-5825/2019.viii.346>.
- [47] R. Dieci, X.-Z. He, and C. Hommes, *Nonlinear economic dynamics and financial modelling*. Springer, 2014. doi: <https://doi.org/10.1007/978-3-319-07470-2>.
- [48] M. Eling and T. Parnitzke, "Dynamic financial analysis: Classification, conception, and implementation," *Risk Manag. Insur. Rev.*, vol. 10, no. 1, pp. 33–50, 2007, doi: <https://doi.org/10.1111/j.1540-6296.2007.00104.x>.
- [49] G. Kim, B. Shin, K. K. Kim, and H. G. Lee, "IT capabilities, process-oriented dynamic capabilities, and firm financial performance," *J. Assoc. Inf. Syst.*, vol. 12, no. 7, p. 1, 2011, doi: 10.17705/1jais.00270.
- [50] T. Saebi, L. Lien, and N. J. Foss, "What drives business model adaptation? The impact of opportunities, threats and strategic orientation," *Long Range Plann.*, vol. 50, no. 5, pp. 567–581, 2017, doi: <https://doi.org/10.1016/j.lrp.2016.06.006>.
- [51] W. W. Eckerson, "Predictive analytics," *Extending Value Your Data Warehous. Investment. TDWI Best Pract. Rep.*, vol. 1, no. 4, pp. 1–36, 2007.
- [52] R. Bose, "Advanced analytics: opportunities and challenges," *Ind. Manag. Data Syst.*, vol. 109, no. 2, pp. 155–172, 2009, doi: <https://doi.org/10.1108/02635570910930073>.
- [53] L. Maisel and G. Cokins, *Predictive business analytics: Forward looking capabilities to improve business performance*. John Wiley & Sons, 2013.
- [54] L. Trigeorgis and J. J. Reuer, "Real options theory in strategic management," *Strateg. Manag. J.*, vol. 38, no. 1, pp. 42–63, 2017, doi: <https://doi.org/10.1002/smj.2593>.
- [55] L. Trigeorgis, "Real options and interactions with financial flexibility," *Financ. Manag.*, vol. 22, no. 3, pp. 202–224, 1993, doi: <https://doi.org/10.2307/3665939>.
- [56] R. G. Dyson and F. S. Oliveira, "Flexibility, robustness and real options.," Wiley, 2007. [Online]. Available: <https://rgu-repository.worktribe.com/output/2152543>
- [57] L. T. Miller and C. S. Park, "Decision making under uncertainty—real options to the rescue?," *Eng. Econ.*, vol. 47, no. 2, pp. 105–150, 2002, doi: <https://doi.org/10.1080/00137910208965029>.