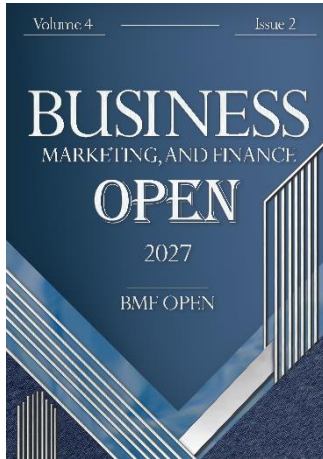




# Estimation and Validation of the Strategic Business Innovation Model Through the Application of Demand Leverage and Supply Chain in Dynamic Ecosystems

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**Abstract:** This study was conducted with the aim of estimating and validating a strategic business innovation model with an emphasis on the role of demand leverage and supply chain within dynamic ecosystems. The statistical population consisted of senior experts, business managers, and specialists from startup companies in the city of Tehran. The sample size was determined as 335 participants based on Cochran's formula. Data analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM) as well as Confirmatory Factor Analysis (CFA). The conceptual model of the research was developed based on the study by Masoumi et al. (2025) and subsequently validated through both quantitative and qualitative analyses. In the first stage, the descriptive statistics of the main variables indicated that the mean values of all variables were above the average level, while skewness and kurtosis values fell within the acceptable range. Therefore, the data demonstrated relative symmetry and normal distribution. The Kolmogorov–Smirnov test was also non-significant for all variables, confirming the normality of the data. Examination of multicollinearity using the Variance Inflation Factor (VIF) revealed that all index values were below 3, indicating the absence of multicollinearity within the model. In the measurement model, reliability and validity indicators, including Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE), were found to be acceptable across all constructs. Accordingly, internal reliability and convergent validity were confirmed. In addition, discriminant validity was assessed using the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT), and was confirmed for all constructs. In the structural model section, the coefficients of determination for the endogenous constructs demonstrated the appropriate explanatory power of the dependent variables, such that the model was able to explain approximately 35% of the variance in the dependent variables, which is considered acceptable and desirable according to the criteria proposed by Chin and Hair. The overall goodness-of-fit index (GOF = 0.624) indicated a strong model fit. Furthermore, effect size analysis demonstrated that causal, contextual, and intervening variables exerted a strong influence on the core phenomenon and strategic actions. Moreover, predictive relevance indices indicated the strong predictive capability of the model for the endogenous constructs. The final results revealed that causal, contextual, and intervening factors play a significant and decisive role in shaping strategic business innovation strategies, and the implementation of these strategies leads to improved organizational outcomes within dynamic ecosystems.

**Keywords:** Strategic Business Innovation, Demand Leverage, Supply Chain, Dynamic Ecosystems

## 1. Introduction

In the contemporary business environment, organizations operate within highly dynamic and uncertain ecosystems characterized by rapid technological change, evolving customer expectations, intensified competition, and increasing disruptions in supply chain structures. Under such conditions, traditional business models and conventional innovation approaches are no longer sufficient to ensure sustainable growth and long-term competitiveness. Consequently, strategic business innovation has emerged as one of the most significant mechanisms through which organizations can adapt to environmental turbulence, create competitive advantages, and sustain organizational performance [1, 2]. Strategic innovation is not limited to the development of new products or services; rather, it encompasses comprehensive transformations in organizational structures, processes, technologies, managerial approaches, and value creation mechanisms. In this regard, organizations that are capable of aligning innovation with strategic objectives are more likely to achieve resilience and sustainable development within dynamic ecosystems [3, 4].

The increasing complexity of global markets has significantly intensified the importance of demand-driven innovation and agile supply chain management. Modern organizations are required to simultaneously respond to fluctuating customer demands, digital transformation pressures, and sustainability requirements while maintaining operational efficiency and strategic flexibility. Demand leverage has therefore become a critical factor influencing organizational innovation strategies because it enables firms to better understand market dynamics, anticipate customer preferences, and redesign their operational and strategic capabilities accordingly [5, 6]. Demand-oriented innovation allows organizations to transform market intelligence into strategic decisions that improve competitiveness and organizational responsiveness. Moreover, supply chains are no longer perceived merely as operational systems for procurement and distribution; they are increasingly viewed as strategic ecosystems capable of facilitating innovation, collaboration, and value co-creation across organizational boundaries [3, 7].

The evolution of digital technologies has further transformed the nature of strategic innovation in organizations. Emerging technologies such as big data analytics, artificial intelligence, blockchain, Internet of Things (IoT), and digital platforms have reshaped the interactions between organizations, suppliers, and consumers. These technologies have enabled firms to improve forecasting capabilities, optimize supply chain performance, and create data-driven business models capable of adapting to environmental uncertainties [8, 9]. Digital transformation is therefore considered one of the primary drivers of strategic business innovation because it enables organizations to redesign traditional processes and create new forms of customer value. According to Ancillai et al. [8], digital technologies significantly contribute to business model innovation by facilitating flexibility, connectivity, and organizational responsiveness. Similarly, Delpasand and Nasiri emphasized that digital transformation functions as a critical enabler of innovative business models in modern competitive environments [9].

Business model innovation has gained substantial attention in recent years because organizations increasingly recognize that competitive advantage depends not only on technological advancement but also on the ability to redesign organizational value propositions and operational architectures. Business model innovation involves changes in the mechanisms through which organizations create, deliver, and capture value [2]. This process enables organizations to respond effectively to environmental complexity, technological disruptions, and changing consumer expectations. Ahmadi et al. demonstrated that innovation in business models and digital marketing capabilities can accelerate the internationalization of small and medium-sized enterprises by enhancing

organizational adaptability and strategic positioning [6]. Similarly, Haghparast et al. reported that business innovation positively influences the relationship between entrepreneurial orientation and new product development performance in technology-oriented firms [4]. These findings highlight the strategic significance of innovation capabilities in improving organizational performance and competitiveness.

Supply chain management has also undergone substantial conceptual transformation in response to environmental challenges and sustainability concerns. Contemporary supply chains are increasingly expected to support circular economy principles, waste reduction strategies, and sustainable production systems. Circular economy frameworks emphasize resource efficiency, waste minimization, recycling, and regenerative business practices, all of which require innovative supply chain structures and collaborative organizational ecosystems [10, 11]. The integration of circular economy principles into supply chain systems has become particularly important in industries characterized by resource scarcity and environmental pressures. Research by Perdana et al. demonstrated that circular supply chain governance significantly contributes to reducing food loss and agricultural waste while improving sustainability outcomes [12]. Likewise, Haque et al. emphasized the importance of waste recovery systems in transforming agricultural waste into economic value within circular economy models [13].

The application of advanced technologies within supply chains has further accelerated the transition toward intelligent and data-driven ecosystems. Smart packaging technologies, blockchain systems, and IoT-based infrastructures have improved traceability, transparency, and operational efficiency across supply chain networks [14, 15]. Kabadurmus et al. highlighted the role of smart packaging and data-driven decision support systems in enhancing supply chain responsiveness during crises and outbreaks [14]. Similarly, Pakseresht et al. demonstrated that blockchain technology can significantly improve sustainability and transparency in agri-food supply chains by supporting circular economy practices [15]. These technological advancements indicate that strategic innovation increasingly depends on the integration of digital capabilities with operational and supply chain infrastructures.

Another important dimension influencing strategic business innovation is organizational learning and knowledge management. Strategic learning enables organizations to adapt to environmental changes, develop innovation capabilities, and improve sustainable performance outcomes [16]. Organizations that possess effective learning mechanisms are more capable of recognizing emerging opportunities, managing uncertainties, and implementing innovative strategies. Aeni identified strategic learning as a mediating mechanism linking green innovation to sustainable organizational performance [16]. Similarly, Sabri Moghadam and Arabshahi reported that innovation performance mediates the relationship between knowledge management alignment and business performance, emphasizing the strategic role of organizational knowledge in fostering innovation-driven competitiveness [17]. These findings suggest that innovation is strongly dependent on organizational capabilities related to knowledge acquisition, learning, and strategic alignment.

Human resource management and organizational culture also play critical roles in facilitating strategic innovation. Innovation-oriented organizations require creative human capital, collaborative leadership structures, and flexible organizational cultures capable of supporting experimentation and adaptation. Strategic human resource management contributes to innovation by improving employee motivation, creativity, and organizational commitment [18]. Najari and Salehi Dolatabad argued that strategic human resource practices significantly enhance innovation and creativity within small and medium-sized enterprises through reciprocal and supportive organizational relationships [18]. In addition, organizational culture significantly influences the willingness of employees and managers to adopt innovative technologies and participate in transformational processes.

Resistance to change and structural rigidity can therefore function as major barriers to strategic innovation within dynamic ecosystems.

Environmental turbulence and global crises have further intensified the need for strategic innovation and adaptive business models. The COVID-19 pandemic demonstrated that organizations with flexible and innovative operational structures were more capable of surviving economic disruptions and maintaining organizational performance. Rahmani Firouzi et al. found that innovation-oriented approaches significantly improved the performance of small and medium-sized enterprises during the COVID-19 crisis, particularly within food industries [19]. These findings illustrate that strategic innovation not only supports long-term competitiveness but also enhances organizational resilience during periods of environmental uncertainty and disruption. Similarly, Kapoor and Wilde emphasized the strategic importance of forecasting capabilities and industry foresight in helping organizations anticipate future changes and respond proactively to environmental shifts [20].

Sustainability concerns have also become central to contemporary strategic innovation frameworks. Organizations are increasingly expected to align economic objectives with environmental and social responsibilities. Circular economy principles, sustainable production systems, and waste reduction strategies have therefore become integral components of modern business innovation models [10, 11]. Research by Sharma et al. demonstrated that digital technologies can help organizations overcome barriers to sustainable production and consumption by enabling circular economy practices within the food sector [21]. Likewise, Jayalath et al. emphasized the role of circular economy paradigms in reducing waste and improving sustainability across vegetable supply chains [22]. These studies collectively indicate that strategic innovation is increasingly interconnected with sustainability-oriented transformations and environmentally responsible organizational practices.

The agricultural and food industries have become particularly important contexts for studying the intersection between innovation, digitalization, and supply chain transformation. The integration of IoT technologies, waste management systems, and circular economy frameworks within agricultural ecosystems has created new opportunities for operational efficiency and value creation [23, 24]. Jarial highlighted the transformative effects of IoT applications on agricultural advisory systems and supply chain management [23], while Bonfiglio proposed data-driven frameworks for identifying regional innovation priorities in agriculture [24]. Furthermore, Croad et al. emphasized the importance of understanding systemic and social dynamics associated with waste generation and food loss within production ecosystems [25]. Such findings reinforce the argument that strategic innovation must be understood as a multidimensional phenomenon influenced by technological, social, environmental, and organizational factors.

Despite the growing body of literature on strategic innovation, business model transformation, and supply chain management, several conceptual and empirical gaps remain unresolved. First, many previous studies have focused on isolated dimensions of innovation, such as digital transformation, entrepreneurial orientation, or supply chain efficiency, without examining the integrated interactions among demand leverage, supply chain dynamics, contextual conditions, and organizational strategies [3, 5]. Second, limited attention has been devoted to developing comprehensive models capable of explaining how causal, contextual, and intervening factors collectively shape strategic innovation processes within dynamic ecosystems. Third, although digital transformation and circular economy principles have received increasing scholarly attention, empirical research examining their combined influence on strategic business innovation remains relatively limited, particularly in emerging economies and startup-oriented ecosystems [8, 9].

Moreover, many organizations continue to face significant barriers related to technological uncertainty, resource constraints, organizational resistance, and environmental volatility, which complicate the implementation of innovation-oriented strategies. The increasing complexity of global supply chains and competitive environments requires organizations to develop integrated strategic frameworks capable of balancing flexibility, sustainability, technological adaptation, and customer responsiveness [7, 21]. Consequently, there is a clear need for empirical studies that simultaneously examine the structural relationships among strategic innovation components, demand leverage mechanisms, supply chain dynamics, and organizational outcomes within dynamic ecosystems.

Therefore, the present study aims to estimate and validate the strategic business innovation model through the application of demand leverage and supply chain dynamics within dynamic ecosystems.

## 2. Methodology

This study aimed to estimate and validate a strategic business innovation model through the application of demand leverage and supply chain dynamics within dynamic ecosystems. The statistical population consisted of senior experts, business managers, and specialists employed in startup companies in Tehran. A sample size of 335 participants was determined using Cochran’s formula and was subsequently employed in the study. The model was estimated using Structural Equation Modeling (SEM). The research model was developed based on the study conducted by Masoumi et al. (2025), and the estimation and validation of the model were subsequently performed.

## 3. Findings and Results

The following figure illustrates the paradigm coding framework, or in other words, the qualitative process model of the study.

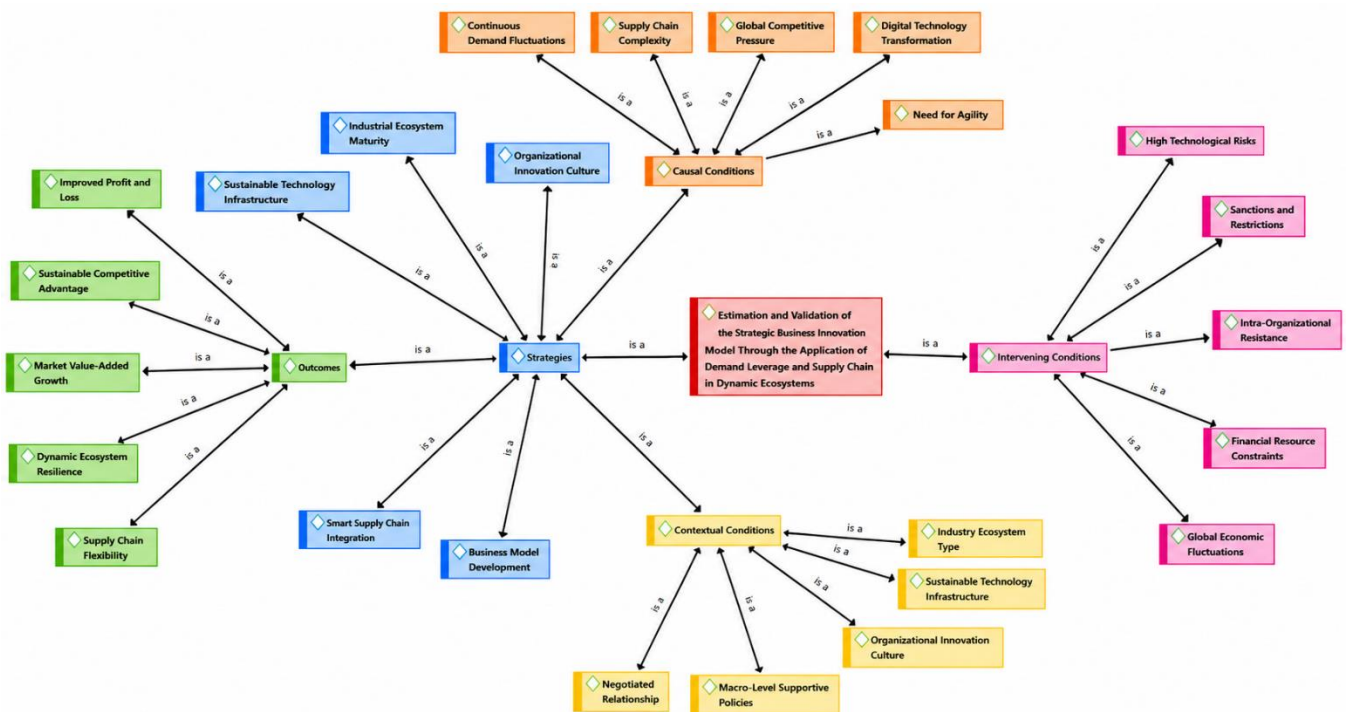


Figure 1. Graphical Output of the ATLAS.ti Software

To describe the main research variables, indices such as mean, standard deviation, and other descriptive statistics were utilized. These indices are presented in the following table.

**Table 1. Descriptive Statistics of the Research Variables**

Variables	Mean	Skewness	Kurtosis	Variance
Causal Factors	3.567	0.745	0.134	0.585
Contextual Factors	3.230	1.112	0.498	0.440
Intervening Factors	3.414	0.117	0.276	0.387
Strategies	3.600	0.330	0.604	0.487
Outcomes	3.547	-0.438	0.365	0.320

To examine the status of the research variables, descriptive statistics including mean, variance, skewness, and kurtosis were employed. Based on the obtained mean values, it is evident that the response option “high” was dominant among the respondents. The mean value associated with causal conditions was higher than that of the other variables. Furthermore, according to the skewness and kurtosis values, all obtained values fell within the acceptable range of (-2, +2), indicating that the data were relatively symmetric and normally distributed. In order to conduct inferential data analysis, Confirmatory Factor Analysis (CFA) and subsequently Structural Equation Modeling (SEM) techniques were employed.

In this study, the Kolmogorov–Smirnov test was used to assess the normality of the data distribution. If the data distribution is normal, inferential statistical tests can be appropriately applied. The null hypothesis assumes that the data are normally distributed. This test was conducted at a 5% significance level. If the significance value is greater than or equal to 0.05, there is insufficient evidence to reject the null hypothesis; therefore, the data distribution is considered normal. The statistical hypotheses were formulated as follows:

H0: The distribution of the variable data is normal.

H1: The distribution of the variable data is not normal.

The results of the normality test are presented in Table 2.

**Table 2. Kolmogorov–Smirnov Test of Data Normality**

Main Factor	Kolmogorov–Smirnov Statistic	Significance Level
Causal Conditions	0.374	0.088
Contextual Conditions	0.390	0.076
Intervening Conditions	0.465	0.061
Strategy	0.500	0.065
Outcome	0.387	0.066

Based on the results of the Kolmogorov–Smirnov test, the significance values in all cases were greater than the error level of 0.05. Therefore, there was no basis for rejecting the null hypothesis, and the data distribution was confirmed to be normal.

Since PLS analysis is derived from linear regression, the assumptions related to regression data must also be examined in this approach.

Before evaluating structural relationships, multicollinearity must be assessed to ensure that the regression results are unbiased {Hair et al., 2019}. In statistics, the Variance Inflation Factor (VIF) evaluates the severity of multicollinearity in ordinary least squares regression analysis. The degree of multicollinearity can be assessed by examining the magnitude of the VIF values. This index indicates the extent to which the variance of estimated coefficients has increased due to multicollinearity. If the VIF value exceeds 5, the level of inflation is considered critical, whereas an ideal VIF value is 3 or below {Hair et al., 2019}.

**Table 3. Multicollinearity Test (VIF)**

Variable	VIF
Causal Conditions	1.000
Contextual Conditions	1.268
Intervening Conditions	1.245
Strategy	1.000
Outcome	1.000
Core Category	0.335

According to the results presented in Table 3, the VIF values for all research components were below 3. Therefore, the research components do not exhibit multicollinearity.

In the present study, Structural Equation Modeling (SEM) based on the Partial Least Squares (PLS) approach was employed to test the measurement model and the research hypotheses. The PLS software has lower dependency on sample size, does not require data normality, and focuses on maximizing variance. Consequently, unlike LISREL and AMOS software, this method is considered more suitable for practical applications.

Each research hypothesis was separately analyzed using the Partial Least Squares technique. Ultimately, the overall research model was also tested using the same approach. Several key points are of critical importance in the PLS technique:

First, the strength of the relationship between a factor (latent variable) and the observed variable is represented by the factor loading. The factor loading value ranges between zero and one. In the standardized measurement model, if the factor loading between an item and its related dimension is lower than 0.40, that indicator (questionnaire item) should be removed from the model. According to Hair et al. (2013), items with factor loadings between 0.30 and 0.70 should also be reviewed for possible deletion, while the acceptable threshold for factor loading is 0.70 and above.

Second, once the correlations among variables are identified, significance testing should be conducted. To evaluate the significance of observed correlations, bootstrapping or jackknife resampling methods are employed. In the present study, the bootstrapping method was used, which generates the t-statistic. At a 5% significance level, if the bootstrapping t-value exceeds 1.96, the observed correlations are considered statistically significant.

In general, relationships between variables in the PLS technique are classified into two categories:

The outer model, which is equivalent to the measurement model (Confirmatory Factor Analysis) in Structural Equation Modeling, illustrates the relationships between latent variables and observed variables.

The inner model, which is equivalent to the structural model (path analysis) in Structural Equation Modeling, examines the relationships among latent variables themselves.

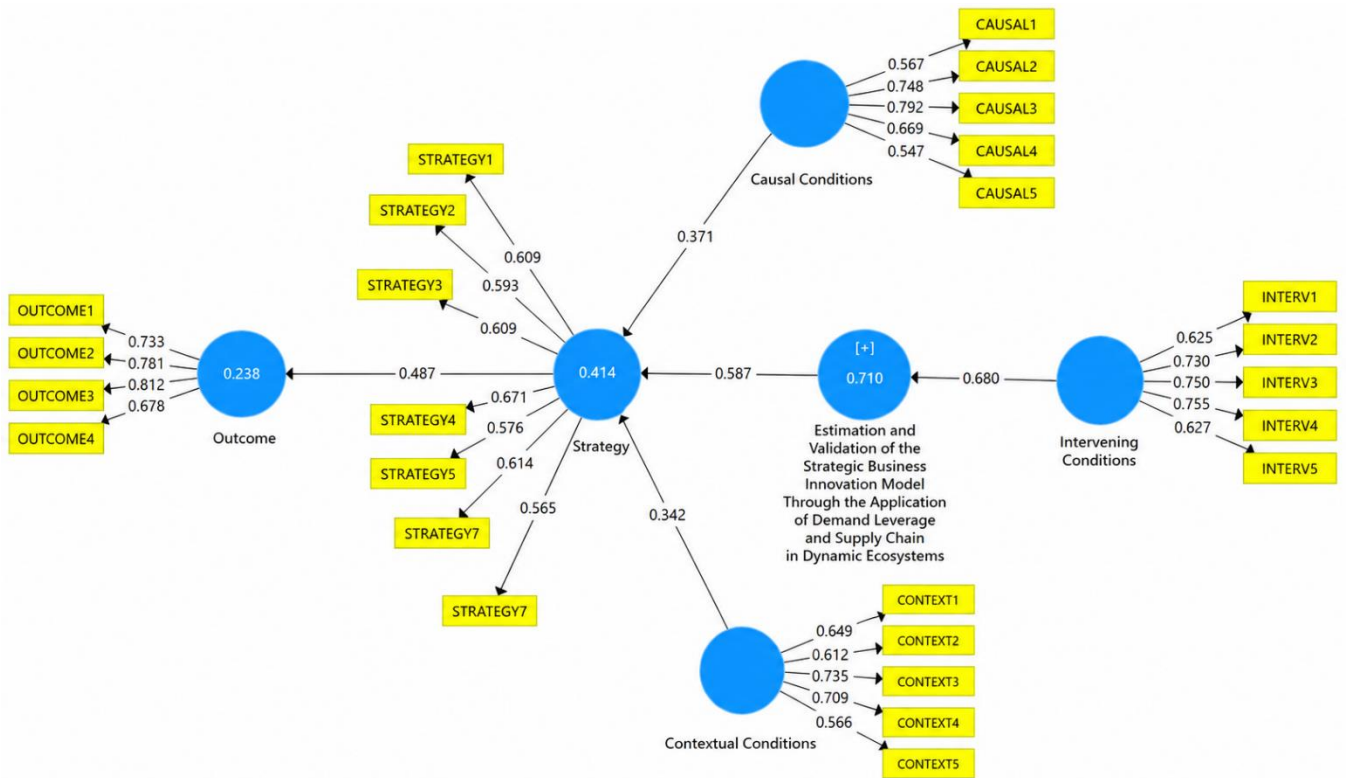


Figure 2. Overall Factor Loadings of the Research Model

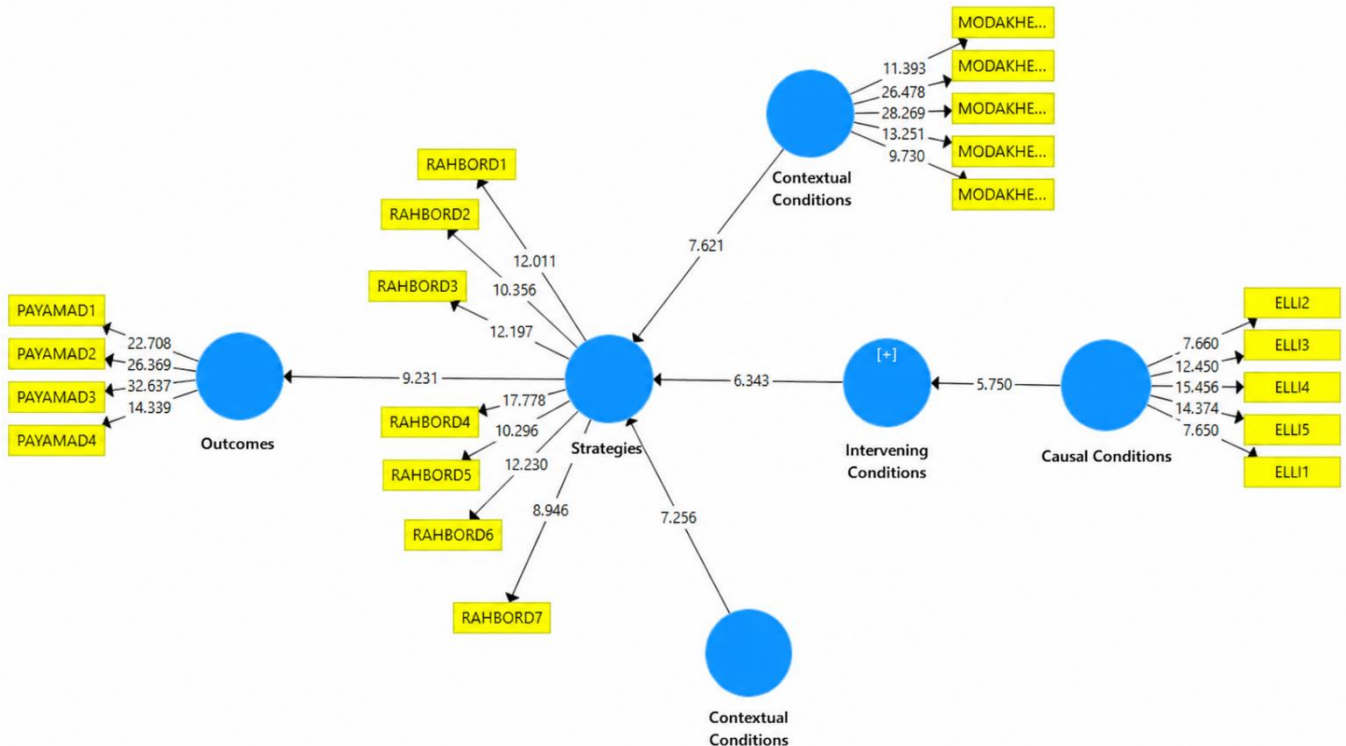


Figure 3. Bootstrapping t-Statistics of the Research Model

To evaluate the validity and reliability of the constructs in PLS measurement models, factor loading coefficients, Cronbach's alpha, Composite Reliability (CR), convergent validity (AVE), and discriminant validity (Fornell-Larcker criterion) were calculated and reported.

To assess the reliability of variables, another key factor used in evaluating the internal consistency reliability of the model is Cronbach's alpha. This coefficient ranges from 0 to 1, where values above 0.70 are considered acceptable and values below 0.70 are regarded as undesirable {Cronbach, 1951}.

Composite Reliability is considered a more accurate and valid criterion than Cronbach's alpha in structural models. In Cronbach's alpha, all indicators of a construct are assigned equal importance, whereas in Composite Reliability, indicators with higher factor loadings contribute more substantially to the calculation. Consequently, CR values provide a more realistic and precise estimate of construct reliability compared to Cronbach's alpha. Similar to Cronbach's alpha, CR values range from 0 to 1, where values above 0.70 are acceptable and values below 0.60 are considered undesirable {Werts et al., 1974}.

Convergent validity was also assessed. When one or more characteristics are measured using two or more methods, the correlation among these measurements provides important evidence regarding validity. If the correlations among tests measuring the same characteristic are high, the questionnaire demonstrates convergent validity. Such correlations are essential to ensure that the instrument measures what it is intended to measure. The Average Variance Extracted (AVE) criterion was used to assess convergent validity. AVE values range from 0 to 1, and values above 0.50 are considered acceptable {Hair et al., 2019}.

The following conditions must be satisfied:

$CR > 0.70$

$CR > AVE$

$AVE > 0.50$

**Table 4. Convergent Validity and Reliability of Research Variables**

Variable	Cronbach's Alpha	AVE	CR
Causal Factors	0.761	0.600	0.833
Contextual Factors	0.736	0.687	0.825
Intervening Factors	0.769	0.651	0.828
Strategies	0.793	0.678	0.734
Outcomes	0.774	0.659	0.833
Core Phenomenon	0.736	0.682	0.845

According to the results presented in Table 4, Cronbach's alpha values for all variables exceeded 0.70; therefore, the reliability of all variables was confirmed. The Average Variance Extracted (AVE) values were consistently greater than 0.50, confirming convergent validity. In addition, Composite Reliability (CR) values were greater than both AVE and 0.70, indicating that all constructs possessed adequate reliability and validity.

Discriminant validity is one of the criteria used to evaluate the fit of measurement models and encompasses two aspects:

First, comparing the correlation between the indicators of a construct and the construct itself against the correlations of those indicators with other constructs.

Second, comparing the correlation of a construct with its own indicators against its correlations with other constructs.

This criterion evaluates the extent to which a construct is more strongly related to its own indicators than to other constructs. Acceptable discriminant validity indicates that a construct interacts more strongly with its own indicators than with other constructs. Discriminant validity is considered acceptable when the AVE value of each construct exceeds the shared variance between that construct and other constructs in the model. This evaluation is

performed using a matrix containing correlation coefficients between constructs and the square roots of AVE values for each construct. The model demonstrates acceptable discriminant validity if the values on the main diagonal are greater than the values below them.

**Table 5. Fornell–Larcker Criterion**

Variables	Causal Factors	Contextual Factors	Intervening Factors	Strategies	Outcomes	Core Phenomenon
Causal Factors	0.774					
Contextual Factors	0.551	0.828				
Intervening Factors	0.478	0.598	0.806			
Strategies	0.418	0.474	0.536	0.823		
Outcomes	0.513	0.509	0.587	0.470	0.811	
Core Phenomenon	0.613	0.591	0.480	0.401	0.503	0.825

As shown in Table 5, the values on the main diagonal are greater than all values in their corresponding columns, indicating that the model possesses adequate discriminant validity. Recent studies by Henseler et al. (2015) demonstrated that the Fornell–Larcker criterion may not perform adequately when factor loadings among constructs differ only slightly. Therefore, Henseler et al. proposed the HTMT criterion as an alternative. If all HTMT values are below 0.90, the model demonstrates acceptable discriminant validity.

**Table 6. HTMT Criterion Results for Assessing Discriminant Validity**

Variables	Causal Factors	Contextual Factors	Intervening Factors	Strategies	Outcomes	Core Phenomenon
Causal Factors						
Contextual Factors	0.737					
Intervening Factors	0.620	0.797				
Strategies	0.430	0.573	0.711			
Outcomes	0.748	0.684	0.485	0.739		
Core Phenomenon	0.414	0.710	0.638	0.592	0.630	

According to Table 6, all obtained values are below 0.90; therefore, the HTMT discriminant validity criterion is acceptable.

After confirming the measurement models through reliability, convergent validity, and discriminant validity tests, the results of the structural model can be presented. In the structural section of the model, unlike the measurement models, attention is not directed toward the questionnaire items or observed variables; rather, only the latent variables and their interrelationships are examined. To assess model fit, the structural model fit index based on the coefficient of determination ( $R^2$ ) was used.

The coefficient of determination is a criterion used to connect the measurement and structural sections of Structural Equation Modeling. It indicates the extent to which the variance of each dependent variable is explained by the independent variables. A critical point is that  $R^2$  is calculated only for endogenous (dependent) constructs, while its value for exogenous constructs is zero. Higher  $R^2$  values for endogenous constructs indicate better model fit. Chin (1998) proposed the values 0.19, 0.33, and 0.67 as indicators of weak, moderate, and strong explanatory power, respectively. Additionally, Henseler (2009) and Hair et al. (2011) introduced the values 0.25, 0.50, and 0.75 as benchmarks for weak, moderate, and strong structural model fit based on  $R^2$  values.

$$R^2 = \frac{0.376 + 0.494 + 0.178}{3} = 0.349$$

Based on the results, the coefficient of determination ( $R^2$ ) for the endogenous constructs of the research model was satisfactory. The coefficient of determination for the dependent components indicated that 35% of the variance

in the model variables was explained by the combined effects of the independent and dependent variables, which is considered strongly acceptable.

This criterion pertains to the overall structure of Structural Equation Models. Using this criterion, researchers can evaluate the overall fit of the research model after separately assessing the measurement and structural components. The GOF criterion was introduced by Tenenhaus et al. (2005) and is calculated as follows:

$$GOF = \sqrt{Avg(Communalities) \times R^2}$$

Communalities represent the average shared variance of each construct, while  $R^2$  represents the average explained variance of the endogenous constructs. Wetzels et al. (2009) proposed the values 0.01, 0.25, and 0.36 as indicators of weak, moderate, and strong GOF values, respectively.

The GOF value was calculated as follows:

$$Avg(R^2) = 0.44$$

$$GOF = \sqrt{0.887 \times 0.44} = 0.624$$

Therefore, based on the GOF criterion, the model was confirmed.

Effect size is another fit index for the structural model and applies to exogenous independent variables. The  $F^2$  index was introduced by Jacob Cohen (1988). The  $F^2$  index for an independent variable indicates the extent of change in the dependent variable estimation when the effect of that independent variable is removed. According to Cohen, the values 0.02, 0.15, and 0.35 represent weak, moderate, and strong effect sizes, respectively. The effect size is calculated using the coefficient of determination.

$$F^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$

Where:

$R^2_{included}$  = Path coefficient with the predictor variable included

$R^2_{excluded}$  = Path coefficient with the predictor variable excluded

Based on the above equation, the coefficient of determination is first calculated with the independent variable included and then recalculated after removing its effect. The resulting value is subsequently interpreted according to Cohen’s proposed thresholds.

Predictive power or cross-validated redundancy is another criterion for evaluating the structural model. The predictive capability of the model can be assessed using the nonparametric Stone–Geisser test (1974), while  $Q^2$  evaluates the success of this prediction. Hair et al. (2019) proposed the values 0, 0.25, and 0.50 as indicators of weak, moderate, and strong predictive power for endogenous constructs, respectively. In PLS software,  $Q^2$  values are calculated using the blindfolding technique.

**Table 7. Effect Size Criterion (Cohen’s Index)**

Variables	$Q^2$	$F^2$
Causal Conditions	0.534	0.465
Contextual Conditions	0.635	0.354
Intervening Conditions	0.500	0.608
Strategy	0.457	0.546
Outcome	0.384	—

As shown in Table 7, the obtained  $Q^2$  values, which indicate the predictive power of the model for endogenous constructs, demonstrate that the predictive capability of the research constructs is estimated to be strong.

#### 4. Discussion and Conclusion

The present study aimed to estimate and validate a strategic business innovation model through the application of demand leverage and supply chain dynamics within dynamic ecosystems. The findings demonstrated that causal, contextual, and intervening conditions exert significant effects on the formation and implementation of strategic innovation strategies, while these strategies substantially contribute to improved organizational outcomes. The statistical results confirmed the adequacy of the proposed structural model, as the values associated with reliability, convergent validity, discriminant validity, predictive relevance, and overall model fit were all within acceptable ranges. Furthermore, the coefficient of determination indicated that approximately 35% of the variance in endogenous variables was explained by the integrated effects of causal, contextual, and intervening conditions. These findings indicate that strategic business innovation is a multidimensional and systemic phenomenon influenced simultaneously by market demand, supply chain structures, organizational capabilities, technological conditions, and environmental dynamics.

One of the major findings of the study was the significant influence of causal conditions on strategic innovation strategies. Variables such as continuous demand fluctuations, supply chain complexity, global competitive pressure, digital transformation, and organizational agility were identified as critical drivers of innovation-oriented strategic actions. This finding aligns with the argument proposed by Jafari et al., who emphasized that demand leverage and strategic innovation significantly improve supply chain management and organizational responsiveness within electronic industries [5]. In dynamic ecosystems, organizations can no longer rely on static operational structures because customer expectations and market conditions continuously evolve. Consequently, firms are increasingly compelled to adopt flexible and innovation-oriented strategies capable of responding to rapid environmental changes. The current findings are also consistent with the work of Kapoor and Wilde, who argued that forecasting behavior and industry foresight capabilities are essential for enabling organizations to anticipate future market disruptions and strategically adapt to environmental uncertainty [20].

The significant effect of digital transformation on strategic business innovation further confirms the growing importance of technology-driven organizational adaptation. The findings revealed that technological transformation acts as a central mechanism facilitating strategic flexibility, operational optimization, and innovation performance. This result is strongly supported by Delpasand and Nasiri, who identified digital transformation as one of the primary drivers of business model innovation in modern organizations [9]. Likewise, Ancillai et al. concluded that digital technologies significantly contribute to the redesign of business models by improving connectivity, organizational learning, and value creation mechanisms [8]. The integration of digital technologies into supply chain systems enables organizations to optimize processes, improve forecasting accuracy, and increase customer responsiveness. Therefore, organizations operating within dynamic ecosystems increasingly depend on digital infrastructures to maintain competitiveness and strategic resilience.

Another important finding of the study concerns the role of contextual conditions in shaping strategic innovation processes. Variables such as sustainable technological infrastructure, innovation-oriented organizational culture, industrial ecosystem maturity, supportive macro-level policies, and creative human capital significantly influenced organizational strategies. These findings suggest that innovation cannot emerge solely from technological investment or market pressure; rather, it requires a supportive organizational and institutional environment. This result is consistent with the findings reported by Najari and Salehi Dolatabad, who emphasized the critical role of strategic human resource management in enhancing innovation and creativity within small and medium-sized

enterprises [18]. Human capital constitutes one of the most important strategic resources for innovation because employees' knowledge, creativity, and adaptability directly affect organizational learning and strategic flexibility.

Similarly, the findings support the perspective proposed by Aeini, who identified strategic learning as a mediating mechanism connecting innovation initiatives to sustainable organizational performance [16]. Organizations possessing stronger learning capabilities are more capable of integrating environmental knowledge into strategic decision-making processes. In dynamic ecosystems characterized by rapid technological and market changes, continuous learning becomes essential for maintaining strategic alignment and organizational adaptability. Furthermore, the significant role of organizational culture in the present study supports the conclusions drawn by Sabri Moghadam and Arabshahi, who demonstrated that strategic alignment in knowledge management positively influences innovation performance and business outcomes [17]. Organizations with innovation-supportive cultures are generally more successful in implementing transformational strategies because they encourage collaboration, experimentation, and adaptive behavior among employees and managers.

The findings related to intervening conditions also provide important insights into the barriers and challenges associated with strategic business innovation. The results indicated that technological risks, financial resource limitations, organizational resistance, sanctions, and global economic fluctuations significantly influence strategic innovation implementation. These findings demonstrate that innovation-oriented strategies are not implemented within stable or risk-free environments. Instead, organizations often face multiple operational, institutional, and environmental obstacles that complicate innovation processes. This finding aligns with the observations of Sharma et al., who reported that organizations encounter numerous barriers when attempting to implement digital technologies and circular economy practices within production and supply chain systems [21]. Resistance to technological change, lack of financial support, and uncertainty regarding technological outcomes often reduce organizational willingness to invest in innovation initiatives.

The present findings are also consistent with Rahmani Firouzi et al., who found that organizations operating during the COVID-19 pandemic faced severe environmental uncertainties and economic disruptions, thereby requiring innovative and adaptive strategies to maintain business performance [19]. Dynamic ecosystems are inherently characterized by volatility and unpredictability, and therefore organizations must continuously develop resilience-oriented strategies to manage environmental risks. In this context, strategic innovation functions not only as a mechanism for growth and competitiveness but also as a survival strategy enabling organizations to maintain operational continuity during crises and disruptions.

Another significant contribution of the present study lies in the identification of strategic actions capable of improving organizational outcomes within dynamic ecosystems. Strategies such as smart supply chain integration, collaborative inter-organizational innovation, demand–supply alignment, business model development, negotiated relationships, and data-driven optimization were found to positively influence organizational performance. These findings strongly correspond with the work of Ahmadi et al., who demonstrated that innovation in business models and digital marketing capabilities accelerates the internationalization process of small and medium-sized enterprises by improving organizational adaptability and strategic responsiveness [6]. Business model innovation enables firms to redesign their value creation mechanisms in response to changing customer demands and technological developments.

The findings additionally support the conclusions of Tavakoli et al., who identified strategic innovation components as significant determinants of supply chain performance improvement within manufacturing industries [3]. Strategic innovation enhances organizational flexibility and responsiveness by integrating

technological systems, market intelligence, and collaborative networks into operational processes. Furthermore, the positive influence of collaborative innovation strategies observed in the present study supports the arguments proposed by Ashraf et al., who reconceptualized supply chain flows as interconnected systems requiring integrated coordination among organizational actors [7]. Supply chains within dynamic ecosystems increasingly function as collaborative innovation networks rather than isolated operational structures.

The findings regarding organizational outcomes demonstrated that strategic innovation strategies significantly improve competitive advantage, market value-added growth, profitability, ecosystem resilience, and supply chain flexibility. These results align with the findings of Haghparast et al., who reported that business innovation positively contributes to new product development performance and organizational competitiveness [4]. Strategic innovation enables organizations to respond more effectively to market fluctuations and customer expectations while simultaneously improving internal operational efficiency. Similarly, Hosseini et al. highlighted the strategic role of innovation in strengthening brand management and enhancing organizational positioning within competitive markets [1].

The relationship between strategic innovation and sustainability-oriented outcomes also emerged as a significant dimension of the present study. The integration of supply chain flexibility, ecosystem resilience, and value-added growth demonstrates that innovation strategies can contribute simultaneously to economic and sustainability objectives. These findings correspond with the growing body of literature emphasizing the relationship between circular economy principles and sustainable business innovation [10, 11]. Circular economy frameworks encourage organizations to redesign production systems, reduce waste, and improve resource efficiency, all of which require innovative organizational strategies and technological integration.

The present findings are further supported by research conducted by Perdana et al., who demonstrated that circular supply chain governance improves sustainability performance through waste minimization and resource optimization [12]. Similarly, Haque et al. emphasized that waste recovery systems can transform environmental challenges into economic opportunities within agricultural ecosystems [13]. These studies collectively indicate that strategic innovation increasingly functions as a mechanism through which organizations simultaneously pursue competitiveness, sustainability, and resilience.

The findings associated with data-driven optimization and smart supply chain systems also support the growing significance of advanced technologies in innovation-oriented ecosystems. Kabadurmus et al. demonstrated that smart packaging systems and data-driven decision-making technologies improve supply chain performance and responsiveness during environmental disruptions [14]. Likewise, Pakseresht et al. highlighted the role of blockchain technology in enhancing transparency, sustainability, and coordination within circular supply chains [15]. The present study confirms that organizations capable of integrating digital technologies into supply chain systems are more likely to achieve strategic flexibility and operational efficiency within dynamic ecosystems.

Moreover, the findings related to ecosystem resilience and sustainability align with the conclusions of Jayalath et al., who emphasized the importance of circular economy paradigms in reducing waste generation and improving sustainability within supply chain systems [22]. Similarly, Croad et al. demonstrated that understanding systemic and social dynamics associated with waste production is essential for developing sustainable and resilient production ecosystems [25]. These findings collectively reinforce the argument that strategic innovation should be conceptualized as a multidimensional process integrating technological adaptation, sustainability objectives, market responsiveness, and collaborative organizational structures.

The findings of the present study therefore contribute theoretically and practically to the strategic innovation literature by providing an integrated framework explaining how demand leverage, supply chain dynamics, contextual conditions, and intervening factors collectively shape organizational innovation strategies and performance outcomes. The validated model demonstrates that innovation within dynamic ecosystems depends on the interaction between technological capabilities, organizational learning, market responsiveness, collaborative supply chain structures, and sustainability-oriented strategic thinking.

One limitation of the present study is that the statistical population was limited to experts, managers, and startup specialists within a specific geographical context, which may reduce the generalizability of the findings to other industries and national environments. Furthermore, the study relied on cross-sectional data collection, making it difficult to evaluate long-term causal relationships among the research variables. Another limitation concerns the use of self-report questionnaires, which may introduce response bias or subjective interpretation among participants. Additionally, certain contextual variables such as governmental regulations, political instability, and macroeconomic conditions may not have been fully captured within the structural model.

Future studies are recommended to examine the proposed model within different industrial sectors and international contexts in order to improve the external validity of the findings. Longitudinal research designs could also provide deeper insights into the long-term effects of strategic innovation and digital transformation on organizational sustainability and resilience. Researchers may further investigate the moderating roles of organizational size, technological capability, leadership style, and environmental uncertainty in the relationship between innovation strategies and organizational outcomes. In addition, future studies could integrate qualitative approaches such as grounded theory or case-study analysis to explore the behavioral and managerial dimensions of innovation implementation within dynamic ecosystems.

From a practical perspective, organizations should prioritize the integration of digital technologies, data-driven decision systems, and collaborative supply chain structures in order to strengthen strategic flexibility and innovation capability. Managers should also invest in organizational learning systems, innovation-oriented cultures, and strategic human resource practices to improve adaptability and employee creativity. Policymakers can contribute to ecosystem sustainability by developing supportive innovation policies, improving technological infrastructures, and facilitating access to financial and technological resources for startups and small businesses. Finally, organizations operating within dynamic ecosystems should continuously monitor market demand fluctuations and environmental changes in order to proactively redesign business models and maintain sustainable competitive advantages.

#### **Authors' Contributions**

Authors equally contributed to this article.

#### **Ethical Considerations**

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

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## Conflict of Interest

The authors report no conflict of interest.

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