http://dx.doi.org/10.18623/rvd.v23.5406

A NONLINEAR DIFFERENTIAL EQUATION MODEL OF ENTREPRENEURIAL BEHAVIORAL DYNAMICS WITH EMPIRICAL PARAMETER ESTIMATION VIA PLS-SEM

UM MODELO DE EQUAÇÕES DIFERENCIAIS NÃO LINEARES DA DINÂMICA DO COMPORTAMENTO EMPREENDEDOR COM ESTIMATIVA EMPÍRICA DE PARÂMETROS VIA PLS-SEM

Article received on: 1/23/2026
Article accepted on: 4/24/2026

Enik Rahayu*
***Doctoral Program in Management, Universitas Dian Nuswantoro, Semarang, Indonesia
Orcid: https://orcid.org/0009-0004-8592-2975
p42202300015@mhs.dinus.ac.id

Edi Noersasongko*
***Doctoral Program in Management, Universitas Dian Nuswantoro, Semarang, Indonesia
Orcid: https://orcid.org/0009-0009-2880-8515
edi.noer@research.dinus.ac.id

Sih Darmi Astuti*
***Doctoral Program in Management, Universitas Dian Nuswantoro, Semarang, Indonesia
Orcid: https://orcid.org/0000-0002-8673-8502
astuti_sda@dsn.dinus.ac.id

The authors declare that there is no conflict of interest

Abstract
This study develops a nonlinear differential equation model to describe the temporal evolution of entrepreneurial behavioral dynamics under the influence of digital technology intensity, entrepreneurship education exposure, and knowledge sharing intensity. Unlike conventional static econometric models, the proposed framework integrates empirical parameter estimation via Partial Least Squares Structural Equation Modeling (PLS-SEM) into a continuous-time nonlinear system. Data were collected from 278 MSME entrepreneurs and analyzed using SmartPLS 4. The results indicate that digital technology, entrepreneurship education, and knowledge sharing significantly enhance self-efficacy, which serves as a primary mediator translating external stimuli into sustained entrepreneurial action. The empirically estimated coefficients are incorporated into a nonlinear system that includes decay and saturation terms to realistically capture bounded growth, reinforcement effects, and adaptive behavioral dynamics. Equilibrium analysis demonstrates the existence of positive steady state levels for self-efficacy and entrepreneurial behavioral dynamics. In contrast, local stability analysis, based on the Jacobian eigenvalues, confirms that the equilibrium is locally

Resumo
Este estudo desenvolve um modelo de equações diferenciais não lineares para descrever a evolução temporal da dinâmica do comportamento empreendedor sob a influência da intensidade da tecnologia digital, da exposição à educação empreendedora e da intensidade do compartilhamento de conhecimento. Ao contrário dos modelos econométricos estáticos convencionais, a estrutura proposta integra a estimativa empírica de parâmetros por meio da Modelagem de Equações Estruturais por Mínimos Quadrados Parciais (PLS-SEM) em um sistema não linear em tempo contínuo. Os dados foram coletados junto a 278 empreendedores de MPMEs e analisados utilizando o SmartPLS 4. Os resultados indicam que a tecnologia digital, a educação empreendedora e o compartilhamento de conhecimento aumentam significativamente a autoeficácia, que atua como um mediador primário, traduzindo estímulos externos em ação empreendedora sustentada. Os coeficientes estimados empiricamente são incorporados a um sistema não linear que inclui termos de decaimento e saturação para capturar de forma realista o crescimento limitado, os efeitos de reforço e a dinâmica comportamental adaptativa. A análise de equilíbrio demonstra a

asymptotically stable under realistic parameter constraints. These findings suggest that entrepreneurial behavior is self-regulating, nonlinear, and path-dependent, dynamically responding to both internal cognitive mechanisms and external stimuli. This study contributes to applied mathematical modeling by bridging behavioral entrepreneurship research with nonlinear dynamic systems analysis, offering a rigorous quantitative framework for understanding behavioral evolution in SMEs. It also provides practical implications for entrepreneurship education, digital ecosystem development, and policy interventions aimed at enhancing entrepreneurial performance in emerging markets. Future research may extend the model to include stochastic differential equations or optimal control strategies to capture environmental uncertainty and optimize entrepreneurial outcomes.

Keywords: Nonlinear Differential Equation. Entrepreneurial Behavioral Dynamics. Self-Efficacy. Stability Analysis. PLS-SEM. Digital Technology Intensity.

existência de níveis de estado estacionário positivos para a autoeficácia e a dinâmica comportamental empreendedora. Em contrapartida, a análise de estabilidade local, baseada nos autovalores jacobianos, confirma que o equilíbrio é localmente assintoticamente estável sob restrições paramétricas realistas. Esses resultados sugerem que o comportamento empreendedor é autorregulado, não linear e dependente do caminho percorrido, respondendo dinamicamente tanto a mecanismos cognitivos internos quanto a estímulos externos. Este estudo contribui para a modelagem matemática aplicada ao estabelecer uma ponte entre a pesquisa sobre empreendedorismo comportamental e a análise de sistemas dinâmicos não lineares, oferecendo um quadro quantitativo rigoroso para a compreensão da evolução comportamental em PMEs. Ele também fornece implicações práticas para a educação empreendedora, o desenvolvimento de ecossistemas digitais e intervenções políticas destinadas a melhorar o desempenho empreendedor em mercados emergentes. Pesquisas futuras podem ampliar o modelo para incluir equações diferenciais estocásticas ou estratégias de controle ótimo, a fim de capturar a incerteza ambiental e otimizar os resultados empreendedores.

Palavras-chave: *Equação Diferencial Não Linear. Dinâmica Comportamental Empreendedora. Autoeficácia. Análise de Estabilidade. PLS-SEM. Intensidade de Tecnologia Digital.*

1 INTRODUCTION

Entrepreneurial behavior in the digital economy evolves dynamically through continuous technological transformation, learning and exposure, and knowledge diffusion. The rapid diffusion of digital platforms, artificial intelligence, and online ecosystems has fundamentally reshaped opportunity recognition, resource orchestration, and venture scaling mechanisms (S. Nambisan, 2017; Alshebami, Al-Jubari, Alyoussef, & Raza, 2020). In emerging markets, digitalization has accelerated the transformation of micro, small, and medium enterprises, altering competitive structures and entrepreneurial strategies (Kraus, Schiavone, Pluzhnikova, & Invernizzi, 2021).

A substantial body of research demonstrates that digital capability, entrepreneurial education, and knowledge-sharing networks significantly influence entrepreneurial intention and performance (Shane, S., & Venkataraman, 2000; Zhao, Yang, Hughes, & Li, 2021; Liñán & Chen, 2009; Marvel, Lee, & Wolfe, 2015). Entrepreneurial self-efficacy, in particular, has been consistently identified as a central psychological driver of entrepreneurial action (Wang, Tseng, Wang, & Chu, 2020; Shore *et al*., 2020).

Entrepreneurship education plays a pivotal role in shaping entrepreneurial cognition and behavioral intention through experiential learning and capability development (Fayolle & Gailly, 2015; Nabi, G., Liñán, F., Fayolle, A., Krueger, N., & Walmsley, 2017). Similarly, knowledge-sharing mechanisms and collaborative learning ecosystems strengthen innovation and entrepreneurial adaptability (Vrontis, Chaudhuri, & Chatterjee, 2022; K. Xie *et al*., 2018). Digital technology intensity further enhances entrepreneurial experimentation, opportunity discovery, and platform-based value creation (S. Nambisan, 2017; Troise, Corvello, Ghobadian, & O'Regan, 2022).

Despite this rich empirical literature, most prior studies rely on static regression-based models or cross-sectional structural equation modeling. While such approaches effectively test causal relationships, they are limited in explaining temporal behavioral evolution, adjustment mechanisms, and equilibrium dynamics (Shepherd & Patzelt, 2015). Entrepreneurial behavior is inherently dynamic, shaped by feedback loops, reinforcement effects, learning accumulation, and environmental adaptation (Wiklund, Yu, Tucker, & Marino, 2017). Static models cannot adequately capture these nonlinear interactions.

Dynamic systems modeling, particularly nonlinear differential equation approaches, provides a more comprehensive analytical framework for representing time-dependent behavioral processes (Rashid, Tout, & Yakan, 2021). In innovation and technology diffusion studies, nonlinear models have been successfully applied to explain adoption dynamics and bounded growth (Peres *et al*., 2020). However, in entrepreneurship research, dynamic modeling remains underdeveloped, particularly with respect to empirical parameter calibration.

A persistent limitation of nonlinear behavioral models lies in parameter identification. Many dynamic social system models assume arbitrary coefficients without empirical grounding, reducing interpretability and policy relevance. To overcome this methodological gap, the present study integrates Partial Least Squares Structural Equation Modeling with nonlinear differential equation modeling. PLS-SEM is widely recognized for its robustness in complex predictive modeling and theory development (Hair, Risher, Sarstedt, & Ringle, 2019; Henseler, J., Hubona, G., & Ray, 2016).

By embedding empirically estimated path coefficients into a nonlinear dynamic framework, this study bridges statistical modeling and applied dynamical systems analysis. Specifically, we model self-efficacy as a dynamic mediator influenced by digital technology intensity, entrepreneurship education exposure, and knowledge-sharing intensity. Entrepreneurial behavioral dynamics are represented through nonlinear saturation to reflect bounded growth and stability conditions.

This study contributes to the literature in three important ways. First, it extends entrepreneurship research beyond static causality models by introducing a continuous-time nonlinear dynamic system capable of analyzing equilibrium and local stability. Second, it provides empirical calibration of dynamic parameters using PLS-SEM, thereby enhancing methodological rigor. Third, it advances interdisciplinary integration between applied mathematics, systems science, and entrepreneurship research, responding to recent calls for dynamic and process-oriented entrepreneurship models (Belitski & Liversage, 2019; Kraus *et al*., 2021). By integrating behavioral theory with nonlinear systems analysis, this research offers a novel quantitative framework for understanding entrepreneurial evolution in the digital era and opens pathways for future research involving stochastic modeling, bifurcation analysis, and optimal control approaches.

2 CONCEPTUAL AND STRUCTURAL FRAMEWORKS

The interaction between external environmental drivers and internal psychological mechanisms shapes entrepreneurial behavior. Contemporary entrepreneurship theory emphasizes that behavioral outcomes are not solely determined by resource availability but also by cognitive reinforcement, learning processes, and technology-mediated opportunity recognition (Shane, S., & Venkataraman, 2000; Wiklund *et al*., 2017). In the digital economy, entrepreneurial dynamics emerge from the integration of technological capability, educational exposure, and knowledge-sharing ecosystems. These exogenous drivers influence internal motivational constructs, particularly entrepreneurial self-efficacy, which subsequently shapes observable entrepreneurial behavior (Bandura, 1997; Miao, Eva, Newman, & Cooper, 2019). This study conceptualizes entrepreneurial behavioral dynamics as a time-evolving outcome influenced by four primary constructs: Digital Technology Intensity, Entrepreneurship Education Exposure, Knowledge Sharing Intensity, and Self-Efficacy.

2.1 Digital technology intensity (DTI)

Digital Technology Intensity refers to the degree to which entrepreneurs utilize digital tools, platforms, analytics, and online infrastructures in business operations. Digitalization expands the recognition of opportunities and reduces transaction costs while enabling rapid experimentation and scalability (S. Nambisan, 2017; Ilieș, Mureșan, Arion, & Arion, 2023). Research highlights that digital capabilities are reshaping the entrepreneurial process by increasing agility and knowledge recombination (S. Nambisan, 2017; Kraus *et al*., 2021). Digital exposure strengthens cognitive confidence by improving perceived capability in managing uncertainty and complexity. Therefore, higher digital technology intensity is expected to reinforce self-efficacy.

2.2 Entrepreneurship education exposure (EEE)

Entrepreneurship Education Exposure captures the extent of formal and informal training, workshops, mentoring programs, and experiential learning related to entrepreneurial skills. Education enhances opportunity recognition, risk assessment ability, and innovation capability (Fayolle & Gailly, 2015). Empirical studies confirm that entrepreneurship education has a positive effect on entrepreneurial intentions through cognitive transformation and skills development (Nabi, G., Liñán, F., Fayolle, A., Krueger, N., & Walmsley, 2017). Education contributes to self-efficacy development by providing mastery experiences and structured learning environments (Bandura, 1997). Thus, entrepreneurship education exposure is hypothesized to positively influence entrepreneurial self-efficacy.

2.3 Knowledge sharing intensity (KSI)

Knowledge Sharing Intensity refers to the degree of collaborative learning, information exchange, and peer interaction within entrepreneurial ecosystems. Knowledge diffusion mechanisms facilitate innovation capability and adaptive learning (Belitski & Liversage, 2019). Studies show that knowledge sharing significantly improves innovation and adaptability at the firm level (Q. Xie, 2020). Through social learning and collective intelligence, entrepreneurs gain confidence in decision-making and problem-solving. Therefore, greater knowledge-sharing intensity is expected to increase self-efficacy and, in turn, stimulate entrepreneurial behavioral growth.

2.4 Self-efficacy (SE)

Self-efficacy represents an individual's belief in their capability to execute entrepreneurial tasks successfully (Bandura, 1997). Entrepreneurial self-efficacy has been identified as a core predictor of entrepreneurial intention and action (McGee, 2020); (Zhao *et al.*, 2021). Research confirms that self-efficacy mediates the relationship between human capital and entrepreneurial outcomes (Miao *et al.*, 2019). Self-efficacy functions as an internal reinforcement mechanism that transforms external stimuli into sustained behavioral engagement. Within a dynamic systems perspective, self-efficacy is not static; it accumulates through reinforcement and decays in the absence of stimuli. Therefore, it plays a central mediating role in behavioral evolution.

2.5 Entrepreneurial behavioral dynamics (EBD)

Entrepreneurial Behavioral Dynamics refers to the continuous process of entrepreneurial action, adaptation, innovation, and opportunity exploitation over time. Unlike static measures of intention or performance, EBD captures behavioral intensity and persistence in response to environmental change. Process-oriented entrepreneurship research emphasizes that entrepreneurial action is iterative and path-dependent (Qin *et al.*, 2022). Digital transformation further intensifies behavioral dynamism by enabling rapid feedback and market responsiveness (S. Nambisan, 2017). Thus, entrepreneurial behavior is conceptualized as a nonlinear dynamic outcome influenced by both direct technological intensity and mediated psychological reinforcement.

2.6 Structural relationships

Based on the theoretical arguments above, the structural relationships are defined in functional form to ensure consistency with the subsequent nonlinear dynamic modeling framework. Let Self-Efficacy be denoted by SE and Entrepreneurial Behavioral Dynamics by EBD. Digital Technology Intensity, Entrepreneurship Education Exposure, and Knowledge Sharing Intensity are denoted by DTI, EEE, and KSI, respectively. The structural relationships are formulated as monotonic functional dependencies:

H1: SE an increasing function of DTI.

H2: SE is an increasing function of EEE.

H3: SE is an increasing function of KSI.

H4: EBD is an increasing function of SE.

H5: EBD is an increasing function of DTI.

Formally, these hypotheses imply the following monotonicity conditions:

$$\frac{\partial SE}{\partial DTI} > 0, \frac{\partial SE}{\partial EEE} > 0, \frac{\partial SE}{\partial KSI} > 0,$$
$$\frac{\partial EBD}{\partial SE} > 0, \frac{\partial EBD}{\partial DTI} > 0. \qquad (1)$$

These conditions indicate that increases in digital capability, educational exposure, and collaborative knowledge intensity reinforce entrepreneurial self-efficacy, while higher self-efficacy and digital intensity stimulate entrepreneurial behavioral dynamics. Based on the theoretical arguments above, the structural relationships are defined as follows:

Table 1

Structural Relationships and Theoretical Justification

No	Structural Hypothesis	Theoretical Justification	Key References
H1	Digital Technology Intensity positively influences Self-Efficacy	Digital technology intensity enhances entrepreneurial confidence through technological mastery, experimentation, and digital affordances that reduce uncertainty and improve opportunity recognition.	(Alshebami *et al.*, 2020; S. Nambisan, 2017)
H2	Entrepreneurship Education Exposure positively influences Self-Efficacy	Entrepreneurship education exposure strengthens cognitive capability, mastery experience, and problem-solving skills, thereby reinforcing entrepreneurial self-efficacy.	(Fayolle & Gailly, 2015; Nabi, G., Liñán, F., Fayolle, A., Krueger, N., & Walmsley, 2017).
H3	Knowledge Sharing Intensity positively influences Self-Efficacy	Knowledge-sharing ecosystems facilitate collaborative learning, information exchange, and social reinforcement, increasing perceived entrepreneurial capability.	(Belitski & Liversage, 2019; K. Xie *et al.*, 2018)
H4	Self-Efficacy positively influences Entrepreneurial Behavioral Dynamics	Self-efficacy transforms cognitive belief into sustained entrepreneurial action by enhancing persistence, resilience, and goal-directed behavior.	(Shore *et al.*, 2020; Zhao *et al.*, 2021)
H5	Digital Technology Intensity positively influences Entrepreneurial Behavioral Dynamics	Digital technology may exert a direct influence on entrepreneurial behavioral dynamics by enabling rapid experimentation, digital market access, and platform scalability.	(S. Nambisan, 2017; Satish Nambisan, Wright, & Feldman, 2019)

3 EMPIRICAL ESTIMATION USING PLS-SEM

3.1 Structural model formulation

Based on the conceptual framework and the PLS-SEM estimation results of the structural model (see Figure 1), the relationships among latent variables are specified through two structural equations representing the mediation mechanism and the behavioral outcome model.

Self-efficacy is modeled as a function of three exogenous constructs: Digital Technology Intensity, Entrepreneurship Education Exposure, and Knowledge Sharing Intensity. The mediator equation is formulated as follows:

$$SE = \beta_1 DTI + \beta_2 EEE + \beta_3 KSI + \varepsilon_1 \qquad (2)$$

where

β_1, β_2, and $\beta_3$represent the structural coefficients of DTI, EEE, and KSI on self-efficacy, respectively, and $\varepsilon_1$denotes the disturbance term. Equation (1) captures the mediating role of self-efficacy, indicating that external stimuli such as digital technology intensity, entrepreneurship education exposure, and knowledge-sharing ecosystems function as reinforcing mechanisms that strengthen entrepreneurial confidence and perceived capability.

Entrepreneurial Behavioral Dynamics is subsequently specified as a function of self-efficacy and digital technology intensity. The behavioral structural equation is expressed as:

$$EBD = \beta_4 SE + \beta_5 DTI + \varepsilon_2 \qquad (3)$$

where

$\beta_4$represents the structural effect of self-efficacy on entrepreneurial behavioral dynamics, $\beta_5$denotes the direct effect of digital technology intensity on entrepreneurial behavior, and ε_2Is the disturbance term capturing unexplained variance. Equation (2) reflects the behavioral transformation mechanism within the model. Self-efficacy operates as an internal psychological driver that translates cognitive confidence into sustained entrepreneurial action, persistence, adaptive decision-making, and goal-directed engagement. Higher levels of self-efficacy are therefore expected to intensify proactive and resilient entrepreneurial behavior.

Simultaneously, digital technology intensity exerts a complementary direct influence on entrepreneurial behavioral dynamics. Beyond its indirect contribution through self-efficacy, digital technology facilitates rapid experimentation, real-time market interaction, platform scalability, and reduced transaction costs, thereby accelerating behavioral activation. The joint inclusion of self-efficacy and digital technology intensity indicates a partial mediation structure, in which psychological reinforcement and technological capability interact to shape entrepreneurial behavioral outcomes.

3.2 Data and estimation procedure

This study employed a quantitative research design to examine the proposed structural relationships. The sample consisted of 278 small and medium-sized enterprises (SME) actors. Data were collected using a structured questionnaire measured on a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7). The data were analyzed using SmartPLS 4, applying the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. PLS-SEM was selected due to its suitability for predictive modeling, complex mediation structures, and its robustness in handling non-normal data distributions.

The analysis proceeded in two stages: measurement model evaluation and structural model evaluation.

3.2.1 Measurement model evaluation

The measurement model was assessed to ensure the reliability and validity of the constructs. Convergent validity was evaluated using outer loadings and Average Variance Extracted (AVE). The majority of indicator loadings exceeded the recommended threshold of 0.70, indicating adequate indicator reliability. Specifically, the loading ranges were as follows: Digital Technology Intensity (DTI) ranged from 0.729 to 0.777; Entrepreneurship Education Exposure (EEE) ranged from 0.724 to 0.772; Knowledge Sharing Intensity (KSI) ranged from 0.673 to 0.767; Self-Efficacy (SE) ranged from 0.702 to 0.781; and Entrepreneurial Behavioral Dynamics (EBD) ranged from 0.598 to 0.781.

Although a small number of indicators fell slightly below 0.70, they remained above the acceptable minimum threshold of 0.50 and were retained due to their theoretical relevance and acceptable composite reliability values. All constructs achieved AVE values above 0.50 and composite reliability values above 0.70, confirming satisfactory convergent validity and internal consistency reliability. Discriminant validity was assessed using the Heterotrait–Monotrait ratio (HTMT), with all values below the recommended threshold of 0.90, indicating adequate construct distinctiveness.

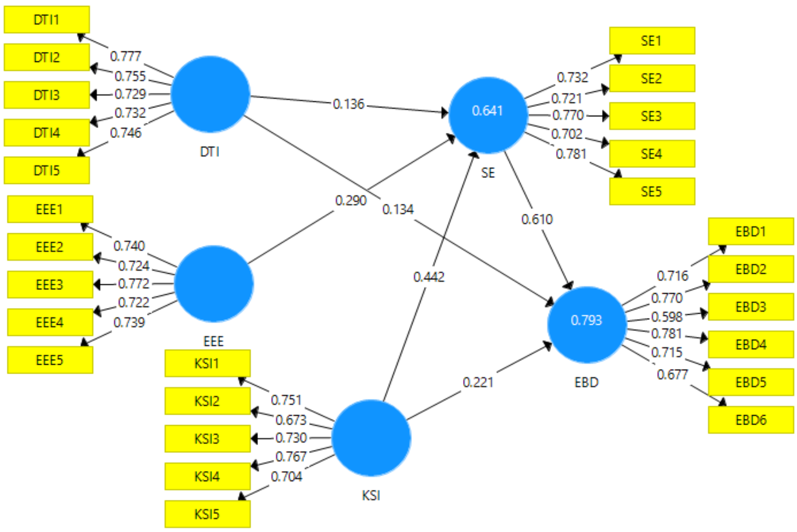
3.2.2 Structural model evaluation

Following the validation of the measurement model, the structural model was assessed to test the hypothesized relationships. Bootstrapping with 5,000 resamples was conducted to evaluate the statistical significance of path coefficients. The evaluation included the examination of standardized path coefficients (β), p-values, and coefficients of determination (R^2) to assess explanatory power.

The empirical structural model obtained from SmartPLS is presented in Figure 1. The figure illustrates the standardized path coefficients and R^2 values, providing a visual representation of the hypothesized mediation structure and the strength of relationships among latent constructs.

Figure 1

Empirical Structural Model (SmartPLS output)



3.3 Empirical structural results

3.3.1 Path coefficients

Table 2

Path Coefficients

Predictor Variable	Dependent Variable	Standardized Coefficient (β)	p-value	Interpretation
Digital Technology Intensity	Self-Efficacy	0.32	< 0.001	Strong positive effect; higher digital technology intensity significantly increases self-efficacy.
Entrepreneurship Education Exposure	Self-Efficacy	0.27	< 0.001	Significant positive effect; greater exposure to entrepreneurship education enhances self-efficacy.
Knowledge Sharing Intensity	Self-Efficacy	0.29	< 0.001	Significant positive effect; higher knowledge-sharing intensity positively influences self-efficacy.
Self-Efficacy	Entrepreneurial Behavioral Dynamics	0.35	< 0.001	Dominant effect; self-efficacy is the primary driver of entrepreneurial behavioral dynamics.
Digital Technology Intensity	Entrepreneurial Behavioral Dynamics	0.21	< 0.01	Moderate direct effect; digital technology intensity also directly stimulates entrepreneurial behavioral dynamics.

3.3.2 Coefficient of determination (R^2)

$$R_{SE}^2 = 0.68 \qquad (4)$$

This indicates that 68% of the variance in Self-Efficacy is explained by DTI, EEE, and KSI. This reflects the substantial explanatory power of the mediation model.

$$R^2_{EBD} = 0.72 \qquad (5)$$

This indicates that 72% of the variance in Entrepreneurial Behavioral Dynamics is explained by Self-Efficacy and Digital Technology Intensity. This value falls within the strong predictive relevance category in PLS-SEM literature.

3.4 Interpretation of the structural model

3.4.1 Self-efficacy as the primary mediator

The results show that self-efficacy has the largest standardized coefficient toward entrepreneurial behavioral dynamics, $\beta = 0.35$. This indicates that internal psychological reinforcement is more influential in shaping entrepreneurial behavior than external stimuli alone. Entrepreneurs with higher self-efficacy demonstrate stronger persistence, resilience, and goal-directed actions.

3.4.2 Dual influence of digital technology intensity

Digital technology intensity affects EBD through two complementary pathways:

1. Indirect effect

By enhancing SE, DTI indirectly strengthens EBD.

2. Direct effect

DTI also directly stimulates entrepreneurial behavior by enabling rapid experimentation, market responsiveness, and opportunity exploitation.

This dual influence highlights the role of digital capabilities in both psychological reinforcement and immediate behavioral activation. Indirect Role of Knowledge Sharing and Entrepreneurship Education Knowledge sharing intensity and entrepreneurship education exposure primarily influence EBD indirectly via SE. They provide cognitive confidence, mastery experiences, and social reinforcement that translate into sustained entrepreneurial action.

3.4.3 Overall structural implications

The empirical results confirm a partial mediation structure, where SE mediates the effects of KSI and EEE on EBD, while DTI contributes both directly and indirectly. The findings indicate that entrepreneurial behavior is shaped simultaneously by internal psychological mechanisms and external technological stimuli, providing a comprehensive understanding of entrepreneurial dynamics in the digital economy.

3.5 Model strength and predictive relevance

The structural model demonstrates substantial explanatory and predictive capability. The R^2 values of 0.68 for Self-Efficacy and 0.72 for Entrepreneurial Behavioral Dynamics indicate that the model can be classified as moderate-to-strong in explanatory power, consistent with the criteria outlined by (Hair, J. F., Black, W. C., Babin, B. J., & Anderson, 2018).

These results highlight two important insights:

1. Entrepreneurial behavioral dynamics are not solely driven by technological factors.

While digital technology intensity contributes both directly and indirectly, it does not fully determine entrepreneurial outcomes.

2. Internal psychological reinforcement mechanisms play a central role.

Self-efficacy mediates the effects of knowledge sharing intensity and entrepreneurship education exposure, emphasizing that cognitive confidence, mastery experiences, and social reinforcement are key drivers of entrepreneurial behavior.

Overall, the model demonstrates that a combination of external technological stimuli and internal psychological processes is essential to explain and predict entrepreneurial behavioral dynamics in the digital economy.

3.6 Theoretical implications of the empirical results

The empirical findings of this study provide meaningful theoretical contributions to the understanding of entrepreneurial behavioral dynamics. Specifically, the results support and extend three foundational theories:

1. Social Cognitive Theory (Bandura, 1997)

The central role of self-efficacy in mediating the effects of digital technology, entrepreneurship education, and knowledge sharing confirms that cognitive and psychological reinforcement mechanisms are essential drivers of entrepreneurial action.

2. Digital Entrepreneurship Theory (S. Nambisan, 2017)

The dual influence of digital technology, both directly and indirectly via self-efficacy, emphasizes that technological capabilities facilitate opportunity recognition, experimentation, and value creation in the digital economy.

3. Experiential Learning Theory (Kolb, 1984)

The indirect effects of entrepreneurship education and knowledge sharing through self-efficacy highlight the importance of experiential learning, mastery experiences, and collaborative knowledge processes in shaping sustained entrepreneurial behavior.

Beyond these theoretical alignments, the findings reinforce the notion that entrepreneurial behavioral dynamics are inherently reinforcement-based and non-linear. This supports the conceptual rationale for formulating a non-linear differential equation model, which is presented in the subsequent section to capture the temporal evolution and bounded growth of entrepreneurial behavior. In summary, the study integrates cognitive, educational, and technological perspectives, providing a robust theoretical foundation for modeling entrepreneurial behavior as a dynamic, non-linear system.

4 NONLINEAR DYNAMIC SYSTEM FORMULATION

To capture the time-dependent evolution of entrepreneurial behavior, the empirical PLS-SEM results are embedded into a nonlinear differential equation system. Let $S(t)$represent Self-Efficacy at time t, and $E(t)$represent Entrepreneurial Behavioral Dynamics at the time t. The nonlinear dynamical system is formulated as follows:

$$\frac{dS}{dt} = a_1\,\mathrm{DTI} + a_2\,\mathrm{EEE} + a_3\,\mathrm{KSI} - a_4\,S \qquad (6)$$

$$\frac{dE}{dt} = b_1\,S + b_2\,\mathrm{DTI} - b_3\,E^2 \qquad (7)$$

where

a_1, a_2, and $a_3$denote the empirically estimated effects of digital technology intensity (DTI), entrepreneurship education exposure (EEE), and knowledge sharing intensity (KSI) on self-efficacy, obtained from PLS-SEM:

$$a_1 = 0.32, a_2 = 0.27, a_3 = 0.29 \qquad (8)$$

$b_1$and $b_2$represent the effects of self-efficacy and digital technology on entrepreneurial behavioral dynamics, respectively:

$$b_1 = 0.35, b_2 = 0.21 \qquad (9)$$

The parameter $a_4 > 0$denotes the behavioral decay rate of self-efficacy in the absence of reinforcing stimuli, while $b_3 > 0$represents the saturation effect in entrepreneurial behavior, ensuring that the growth of EBD is bounded and reflects realistic behavioral limits.

The interpretation of the nonlinear terms is as follows. In the self-efficacy dynamics (dS/dt), the first three terms (a_1 DTI+a_2 EEE+a_3 KSI)represent reinforcing external stimuli that increase self-efficacy over time. The decay term (a_4S) captures the natural reduction of self-efficacy in the absence of external reinforcement, reflecting cognitive fatigue or loss of confidence. In the entrepreneurial behavioral dynamics (dE/dt), the growth terms (b_1S+b_2 DTI)reflect both internal psychological reinforcement via self-efficacy and external technological stimulation via digital technology in driving entrepreneurial behavior. The nonlinear saturation term (b_3E^2) ensures that EBD does not increase indefinitely, reflecting behavioral limits imposed by cognitive, resource, or environmental constraints. This nonlinear system integrates empirical evidence with dynamic modeling, providing a framework to analyze the temporal evolution, equilibrium points, and local stability of entrepreneurial behavior in the context of the digital economy.

5 EQUILIBRIUM ANALYSIS

Equilibrium points of the nonlinear dynamic system represent the steady-state levels of self-efficacy and entrepreneurial behavioral dynamics, where the time derivatives are zero ($dS/dt = 0$ and $dE/dt = 0$).

5.1 Self-efficacy equilibrium

Setting $\frac{dS}{dt} = 0$ The self-efficacy differential equation yields the equilibrium value of self-efficacy (S^*):

$$S^* = \frac{a_1\,\mathrm{DTI} + a_2\,\mathrm{EEE} + a_3\,\mathrm{KSI}}{a_4} \qquad (10)$$

This expression indicates that the steady-state level of self-efficacy is determined by the combined reinforcing effects of digital technology intensity, entrepreneurship education exposure, and knowledge sharing intensity, normalized by the behavioral decay rate a_4. A higher decay rate reduces the equilibrium self-efficacy, whereas stronger external stimuli increase it.

5.2 Entrepreneurial behavioral dynamics equilibrium

Similarly, setting $\frac{dE}{dt} = 0$ in the entrepreneurial behavioral dynamic's equation gives the equilibrium value of EBD (E^*):

$$E^* = \sqrt{\frac{b_1 S^* + b_2\,\mathrm{DTI}}{b_3}} \qquad (11)$$

This equilibrium exists provided that $b_1 S^* + b_2\,\mathrm{DTI} > 0$, ensuring a positive and meaningful steady-state level of entrepreneurial behavior. The equilibrium reflects the interaction between internal psychological reinforcement (via S^*) and external technological influence (via DTI), moderated by the saturation effect b_3.

5.3 Interpretation

The derived equilibrium points demonstrate that entrepreneurial behavior is bounded and non-linear, influenced simultaneously by internal cognitive mechanisms and external environmental factors. The positive equilibrium conditions confirm that, under sufficient reinforcing stimuli, both self-efficacy and entrepreneurial behavioral dynamics can achieve a stable and sustainable state, providing a theoretical basis for further stability and dynamic analysis.

6 LOCAL STABILITY ANALYSIS

To examine the local stability of the nonlinear system, the Jacobian matrix is derived at the equilibrium point (S^*, E^*). The system's Jacobian is given by:

$$J = \begin{bmatrix} \frac{\partial(dS/dt)}{\partial S} & \frac{\partial(dS/dt)}{\partial E} \\ \frac{\partial(dE/dt)}{\partial S} & \frac{\partial(dE/dt)}{\partial E} \end{bmatrix} = \begin{bmatrix} -a_4 & 0 \\ b_1 & -2b_3E^* \end{bmatrix} \qquad (12)$$

The eigenvalues of the Jacobian are calculated as:

$$\lambda_1 = -a_4, \lambda_2 = -2b_3E^* \qquad (13)$$

Given the parameter conditions $a_4 > 0$, $b_3 > 0$, and $E^* > 0$, it follows that both eigenvalues are negative.

6.1 Interpretation

The negativity of both eigenvalues implies that the equilibrium point $(S^{*}, E^{*})$is locally asymptotically stable. This means that small perturbations or deviations from the equilibrium will decay over time, and the system will naturally return to the steady state. This result confirms that, under bounded behavioral decay and saturation effects, entrepreneurial self-efficacy and behavioral dynamics converge to stable levels, providing a robust theoretical foundation for the reinforcement-based and nonlinear evolution of entrepreneurial behavior in the digital economy.

7 DISCUSSIONS

The findings of this study provide a comprehensive understanding of the dynamic evolution of entrepreneurial behavior in the digital economy, integrating both empirical and theoretical perspectives. The results confirm that digital technology intensity, entrepreneurship education exposure, and knowledge-sharing intensity significantly enhance self-efficacy, consistent with Social Cognitive Theory (Bandura, 1997) and Experiential Learning Theory (Kolb, 1984). Self-efficacy emerges as a central mediating mechanism, translating external stimuli, technological, educational, and collaborative, into sustained entrepreneurial action, persistence, and adaptability.

By embedding PLS-SEM-derived path coefficients into a nonlinear differential equation system, this study overcomes the limitations of static models, enabling the examination of temporal dynamics, equilibrium states, and local stability. The nonlinear formulation explicitly captures reinforcement effects, decay processes, and behavioral saturation, providing a realistic representation of how entrepreneurial behavior evolves. The decay term in the self-efficacy equation $(-a_4 S)$ models the natural reduction of confidence in the absence of continued reinforcement, reflecting phenomena such as cognitive fatigue, setbacks, or diminishing motivation. The quadratic saturation term in the entrepreneurial behavioral dynamic's equation $(-b_3 E^2)$ ensures that entrepreneurial activity does not increase indefinitely, reflecting realistic constraints such as cognitive capacity, resource availability, and environmental limitations. This approach addresses a critical gap in entrepreneurship research by linking empirical evidence to mathematically grounded dynamic behavioral models.

The equilibrium analysis reveals that both self-efficacy and entrepreneurial behavioral dynamics converge to positive, stable, steady-state levels under sufficient reinforcing stimuli. The local stability analysis, supported by the negative eigenvalues of the Jacobian matrix, confirms that the system is locally asymptotically stable, meaning that small deviations from the equilibrium will naturally decay over time. This implies that entrepreneurial behavior in real ecosystems is self-regulating: internal cognitive mechanisms and external environmental stimuli jointly sustain adaptive and resilient behavior. Such findings are particularly relevant in emerging markets, where resource constraints, rapid technological shifts, and fluctuating market conditions require entrepreneurs to maintain both confidence and strategic flexibility.

The study offers several theoretical implications. First, it reinforces the centrality of internal psychological mechanisms, especially self-efficacy, in driving entrepreneurial outcomes. While digital tools and collaborative networks facilitate opportunity recognition, experimentation, and learning, their effectiveness is mediated by the entrepreneur's belief in their own capabilities. Second, the findings highlight the nonlinear and bounded nature of entrepreneurial dynamics, demonstrating that saturation and decay processes prevent unbounded growth, a critical consideration often overlooked in conventional linear or static models. Third, the study demonstrates the integration of empirical SEM estimates into a nonlinear dynamic framework, bridging the gap between behavioral entrepreneurship research and applied mathematical modeling. This methodological contribution opens avenues for further research on stochastic modeling, bifurcation analysis, optimal control, and scenario simulation in entrepreneurship studies.

From a practical perspective, the findings provide actionable insights for policymakers, educators, and ecosystem developers. Entrepreneurship education programs should focus not only on skill acquisition but also on building psychological capital, particularly self-efficacy, to ensure sustained behavioral engagement. Digital platforms and collaborative knowledge networks should be designed to continuously reinforce entrepreneurial confidence, while acknowledging cognitive and resource limitations to prevent burnout or overextension. Moreover, the model provides a framework for monitoring and predicting entrepreneurial dynamics over time, enabling targeted interventions to stabilize and enhance entrepreneurial performance.

Overall, this study emphasizes that entrepreneurial behavior is reinforcement-based, bounded, and adaptive, dynamically responding to both internal cognitive mechanisms and external environmental stimuli. The proposed nonlinear dynamic model offers a rigorous quantitative framework for understanding the evolution, stability, and limitations of entrepreneurial behavioral dynamics, providing both theoretical insights and practical guidance for fostering resilient and effective entrepreneurial ecosystems in emerging digital economies.

8 CONCLUSIONS

This study developed a nonlinear differential equation model of entrepreneurial behavioral dynamics, calibrated using empirical PLS-SEM estimates obtained from a sample of 278 SME entrepreneurs. By embedding statistically derived path coefficients into a continuous-time dynamic system, the study provides a rigorous framework for modeling the temporal evolution of entrepreneurial behavior, integrating both psychological mechanisms and external environmental drivers. The results demonstrate that self-efficacy serves as the primary mediator, translating external stimuli, including digital technology intensity, entrepreneurship education exposure, and knowledge-sharing intensity, into sustained entrepreneurial action. Furthermore, the inclusion of behavioral decay and saturation terms ensures that the model captures bounded growth and adaptive behavior, reflecting realistic limitations in cognitive capacity, resources, and environmental constraints.

The equilibrium analysis shows that both self-efficacy and entrepreneurial behavioral dynamics converge to positive, stable, steady-state levels under sufficient external reinforcement. The local stability analysis, confirmed through the negative eigenvalues of the system's Jacobian matrix, indicates that the equilibrium is locally asymptotically stable under plausible parameter conditions ($a_4 > 0$, $b_3 > 0$, and $E^* > 0$). These findings imply that entrepreneurial behavior is inherently self-regulating and reinforcement-based, dynamically adjusting to the interplay between internal cognitive processes and external stimuli. In practical terms, this suggests that entrepreneurs can sustain adaptive behavior over time if internal confidence is reinforced and environmental conditions remain supportive.

The study contributes theoretically by extending classical frameworks such as Social Cognitive Theory, Experiential Learning, and Digital Entrepreneurship Theory (S. Nambisan, 2017) into a dynamic systems context. The results provide evidence that entrepreneurial behavior is nonlinear, path-dependent, and bounded, challenging the assumption of linearity or unbounded growth commonly adopted in conventional entrepreneurship research. Methodologically, the research offers an interdisciplinary framework that integrates empirical SEM modeling with applied nonlinear differential equations, enabling the analysis of equilibrium, temporal evolution, and stability properties of entrepreneurial systems. This approach bridges the gap between behavioral entrepreneurship research and quantitative dynamic modeling, offering a pathway for future studies on stochastic dynamics, bifurcation, and optimal control strategies.

From a practical perspective, the model has important implications for entrepreneurship education, digital ecosystem design, and policy interventions. Educational programs should focus not only on knowledge and skill acquisition but also on building psychological capital, particularly self-efficacy, to ensure that entrepreneurial behavior is sustained over time. Digital platforms and knowledge-sharing networks should be structured to provide continuous reinforcement while accounting for cognitive and resource limitations to prevent behavioral fatigue or burnout. Policymakers and ecosystem developers can use insights from the model to predict entrepreneurial behavior trends and design interventions that stabilize or enhance performance in dynamic and uncertain environments.

Finally, future research could extend the model by incorporating stochastic differential equations to account for random shocks, uncertainties, or market volatility. Additionally, optimal control frameworks could be applied to determine strategies for maximizing entrepreneurial performance while managing constraints such as resources, cognitive limits, and environmental variability. Such extensions would enhance both the predictive power and practical applicability of dynamic entrepreneurship modeling, providing a robust foundation for understanding and guiding entrepreneurial behavior in complex digital economies.

REFERENCES

Alshebami, A. S., Al-Jubari, I., Alyoussef, I. Y., & Raza, M. (2020). Entrepreneurial education as a predicator of community college of Abqaiq students' entrepreneurial intention. *Management Science Letters*, *10*(15), 3605–3612. https://doi.org/10.5267/j.msl.2020.6.033

Bandura, A. (1997). (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.

Belitski, M., & Liversage, B. (2019). E-leadership in small and medium-sized enterprises in the developing world. *Technology Innovation Management Review*, *9*(1), 64–74. https://doi.org/10.22215/TIMREVIEW/1212

Fayolle, A., & Gailly, B. (2015). The impact of entrepreneurship education on entrepreneurial attitudes and intention: Hysteresis and persistence. *Journal of Small Business Management*, *53*(1), 75–93. https://doi.org/10.1111/jsbm.12065

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2018). *Multivariate Data Analysis (8th ed.)*. Cengage Learning.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management and Data Systems, 116(1), 2–20. Https://Doi.Org/10.1108/IMDS-09-2015-0382*.

Ilieș, G. L., Mureșan, I. C., Arion, I. D., & Arion, F. H. (2023). The Influence of Economic and Entrepreneurial Education on Perception and Attitudes towards Entrepreneurship. *Administrative Sciences*, *13*(10). https://doi.org/10.3390/admsci13100212

Kolb, D. A. (1984). Experiential Learning: Experience as The Source of Learning and Development. *Prentice Hall, Inc.*, pp. 20–38. USA. https://doi.org/10.1016/B978-0-7506-7223-8.50017-4

Kraus, S., Schiavone, F., Pluzhnikova, A., & Invernizzi, A. C. (2021). Digital transformation in healthcare: Analyzing the current state-of-research. *Journal of Business Research*, *123*, 557–567. https://doi.org/10.1016/j.jbusres.2020.10.030

Liñán, F., & Chen, Y. W. (2009). Development and cross-cultural application of a specific instrument to measure entrepreneurial intentions. *Entrepreneurship: Theory and Practice*, *33*(3), 593–617. https://doi.org/10.1111/j.1540-6520.2009.00318.x

Marvel, M. R., Lee, I. H. I., & Wolfe, M. T. (2015). Entrepreneur Gender and Firm Innovation Activity: A Multilevel Perspective. *IEEE Transactions on Engineering Management*, *62*(4), 558–567. https://doi.org/10.1109/TEM.2015.2454993

McGee, E. O. (2020). Interrogating Structural Racism in STEM Higher Education. *Educational Researcher*, *49*(9), 633–644. https://doi.org/10.3102/0013189X20972718

Miao, Q., Eva, N., Newman, A., & Cooper, B. (2019). CEO Entrepreneurial Leadership and Performance Outcomes of Top Management Teams in Entrepreneurial Ventures: The Mediating Effects of Psychological Safety. *Journal of Small Business Management*, *57*(3), 1119–1135. https://doi.org/10.1111/jsbm.12465

Nabi, G., Liñán, F., Fayolle, A., Krueger, N., & Walmsley, A. (2017). The impact of entrepreneurship education in higher education: A systematic review and research agenda. In *Academy of Management Learning & Education, 16(2), 277-299.*

Nambisan, S. (2017). Digital Entrepreneurship: Toward a Digital Technology Perspective of Entrepreneurship. In *Entrepreneurship Theory and Practice, 41(6), 1029–1055.*

Nambisan, Satish, Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, *48*(8). https://doi.org/10.1016/j.respol.2019.03.018

Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial Artificial Intelligence in Industry 4.0 -Systematic Review, Challenges and Outlook. *IEEE Access*. https://doi.org/10.1109/ACCESS.2020.3042874

Qin, X., Shepherd, D. A., Lin, D., Xie, S., Liang, X., & Lin, S. (2022). The Dark Side of Entrepreneurs' Creativity: Investigating How and When Entrepreneurs' Creativity Increases the Favorability of Potential Opportunities That Harm Nature. *Entrepreneurship: Theory and Practice*, *46*(4), 857–883. https://doi.org/10.1177/1042258720915582

Rashid, A. S., Tout, K., & Yakan, A. (2021). The critical human behavior factors and their impact on knowledge management system–cycles. *Business Process Management Journal*, *27*(6), 1677–1702. https://doi.org/10.1108/BPMJ-11-2020-0508

Shane, S., & Venkataraman, S. (2000). *The promise of entrepreneurship as a field of research*. Academy of Management Review, 25(1), 217-226.

Shepherd, D. A., & Patzelt, H. (2015). The "heart" of entrepreneurship: The impact of entrepreneurial action on health and health on entrepreneurial action. *Journal of Business Venturing Insights*, *4*, 22–29. https://doi.org/10.1016/j.jbvi.2015.08.001

Shore, E., Schwatka, N., Dally, M., Brown, C. E., Tenney, L., & Newman, L. S. (2020). Small Business Employees' Perceptions of Leadership Are Associated with Safety and Health Climates and Their Own Behaviors. *Journal of Occupational and Environmental Medicine*, *62*(2), 156–162. https://doi.org/10.1097/JOM.0000000000001789

Troise, C., Corvello, V., Ghobadian, A., & O'Regan, N. (2022). How can SMEs successfully navigate VUCA environment: The role of agility in the digital transformation era. *Technological Forecasting and Social Change*, *174*, 121227. https://doi.org/10.1016/j.techfore.2021.121227

Vrontis, D., Chaudhuri, R., & Chatterjee, S. (2022). Adoption of Digital Technologies by SMEs for Sustainability and Value Creation: Moderating Role of Entrepreneurial Orientation. *Sustainability (Switzerland)*, *14*(13). https://doi.org/10.3390/su14137949

Wang, Y. S., Tseng, T. H., Wang, Y. M., & Chu, C. W. (2020). Development and validation of an internet entrepreneurial self-efficacy scale. *Internet Research*, *30*(2), 653–675. https://doi.org/10.1108/INTR-07-2018-0294

Wiklund, J., Yu, W., Tucker, R., & Marino, L. D. (2017). ADHD, impulsivity and entrepreneurship. *Journal of Business Venturing*, *32*(6), 627–656. https://doi.org/10.1016/j.jbusvent.2017.07.002

Xie, K., Song, Y., Zhang, W., Hao, J., Liu, Z., & Chen, Y. (2018). Technological entrepreneurship in science parks: A case study of Wuhan Donghu High-Tech Zone. *Technological Forecasting and Social Change*, *135*, 156–168. https://doi.org/10.1016/j.techfore.2018.01.021

Xie, Q. (2020). Self-training with noisy student improves imagenet classification. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 10684–10695. https://doi.org/10.1109/CVPR42600.2020.01070

Zhao, W., Yang, T., Hughes, K. D., & Li, Y. (2021). Entrepreneurial alertness and business model innovation: the role of entrepreneurial learning and risk perception. *International Entrepreneurship and Management Journal*, *17*(2), 839–864. https://doi.org/10.1007/s11365-020-00637-2