Effects of Knowledge Management and Financial Attraction on New Technology-based Firm Performance

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Abstract

Purpose: This study examines how knowledge management (KM) within new technology-based firms (NTBFs) affects venture teams' financial attraction (FA) and performance (P), contributing to NTBFs' survival in highly competitive environments. The large socio-economic impact of NTBFs contrasts with high mortality rates, prompting interest in factors influencing long-term success.

Design/Methodology/Approach: We employed a PLS-SEM model using data from the Global Accelerator Learning Initiative (GALI) of Emory University (2013–2019) to analyze 103 NTBFs from Australia, Canada, France, Germany, and the United States.

Findings: The results confirm significant relationships between KM, FA, and NTBF performance, underscoring social capital as a key aspect of KM.

Originality/Value: The findings extend the understanding of these relationships by focusing on venture teams within NTBFs, demonstrating the signaling role of debt financing in attracting investment. The study highlights the crucial role of social capital in KM while indicating that debt may be a stronger signal of viability in specific contexts.

Practical Implications: NTBF venture teams should prioritize building strong networks while acquiring business debt to enhance KM and attract funding. Policymakers must promote KM, encourage collaboration, and facilitate access to business credit lines for these firms.

Keywords: New technology-based firms; venture teams; knowledge management; financial attraction; performance; PLS

Paper Type: Research paper

1. Introduction

New technology-based firms (NTBFs) are essential to economic dynamization, promoting innovation, high-quality employment, and knowledge development (Litan and Song, 2008;

Rannikko et al., 2019). Due to their ability to adopt disruptive technologies, these firms can potentially transform existing industries and spur new market opportunities; nevertheless, they face high mortality rates. Research estimates that approximately 20% fail within their first year, 60% do not survive beyond the fifth year, and only about 10% endure after a decade (Eliakis et al., 2020; Lai and Lin, 2015; Li and Chen, 2009).

High mortality rates among firms underscore the urgent need to understand the factors that contribute to NTBF survival in today's landscape (Slávik and Bednárová, 2024; Ajah, 2023). Research illustrates the effective management of venture teams, particularly in managing knowledge (Rustiarini et al., 2022; García-Cabrera et al., 2021; Gifford et al., 2021; de Mol et al., 2019; Brinckmann and Hoegl, 2011). Amid high uncertainty, knowledge management (KM) and entrepreneurial orientation are essential in determining NTBF survival while strengthening resilience (Karar et al., 2025; Arabiun et al., 2024; Chen et al., 2022; Hashai and Zahra, 2021; Oliva and Kotabe, 2019; Bettiol et al., 2016).

Effective KM can enable NTBFs to improve financial performance while ensuring economic sustainability (Alfiero et al., 2025). Despite their widely recognized importance, research gaps remain regarding the specific linkages between KM practices and different dimensions of NTBF performance (Bolzani et al., 2019; Centobelli et al., 2017). Furthermore, empirical evidence connecting KM practices to improved business performance and to the hindrances in attracting funding is limited (Kianto et al., 2017). This study extends the understanding of this relationship and provides insights into the factors that enhance NTBF performance. The study developed and validated a model that captures the influence of venture team KM factors on NTBFs' ability to access financing. This model can be used to analyze how these factors impact the performance of NTBFs, measured by their capacity to generate income and sustain over time.

Data were sourced from Emory University's Global Accelerator Learning Initiative (GALI). From this dataset, 103 NTBFs that were accelerated in Australia, Canada, France, Germany, and the United States were selected to form the study sample.

The rest of this paper is organized as follows. Section Two presents the theoretical framework and hypotheses. Section Three details the methodology and data. Section Four presents the results. Section Five discusses the findings. Section Six presents the conclusions, theoretical contributions, managerial implications, limitations, and future research directions.

2. Theoretical Framework and Research Hypotheses

This section provides the theoretical foundation for understanding how KM and FA influence NTBF performance. It explores the key constructs, interrelationships, and variables that inform a theoretical model, explaining them. The study evaluates the performance (P) of NTBFs based on two leading indicators: the ability to generate income (their capacity to turn innovation and business models into tangible economic outcomes) and long-term sustainability (their resilience and capacity to adapt within dynamic, competitive environments) (Hejazi et al., 2024; Prokop et al., 2019).

2.1 Knowledge Management (KM)

KM involves the systematic creation, acquisition, sharing, transformation, storage, and evaluation of information within an organization (Mohaghegh et al., 2024). For NTBFs operating in dynamic and competitive environments, KM is not merely a theoretical concept but a crucial mechanism for transforming raw information into actionable insights that fuel innovation, enhance operational efficiency, and improve strategic decision-making (Ahmed et al., 2021; López-Nicolás and Meroño-Cerdán, 2011).

KM is essential for NTBFs. Operating in highly dynamic, competitive environments, these firms face continual pressure to innovate and adapt rapidly (Madanchian and Taherdoost, 2025). Effective KM practices enable NTBFs to overcome related challenges by fostering the timely capture and integration of market intelligence, promoting a culture of experimentation and learning while enhancing internal resource coordination (Alo et al., 2025; Oliva and Kotabe, 2019; West and Noel, 2009). KM directly contributes to improved performance and long-term sustainability by strengthening its ability to innovate, respond to market changes, and resolve strategic challenges (Migdadi, 2022; Cabrilo and Dahms, 2018).

Furthermore, effective KM practices enhance an NTBF's ability to attract external financing directly. NTBFs can develop compelling business plans and investor pitches that clearly articulate their value proposition and growth potential by systematically gathering, organizing, and communicating relevant information (Rubin et al., 2015). KM can enable NTBFs to identify and pursue relevant funding opportunities, prepare persuasive proposals, and negotiate favorable terms with investors (Lerro et al., 2024; Hmieleski et al., 2015). Effective KM practices, e.g., the efficient transfer and application of knowledge, contribute to improved financial performance, increased revenue and profitability, and reduced operational costs (Alfiero et al., 2025), ultimately making the NTBF a more attractive investment opportunity.

Nevertheless, NTBFs face challenges in conveying their potential to investors amid information asymmetry (Landström, 2023; Glücksman, 2020). Against this backdrop, strong KM practices, particularly those related to the founding team's experience, education, and social networks, can serve as credible signals that demonstrate the venture team's ability to gather, process, and apply market information (Hmieleski et al., 2015). Research indicates that investors consider readily available signals, such as founders' education, work experience, property rights, alliances, and company size, to assess the potential of NTBFs to secure first-round funding (Passavanti et al., 2024). Investors prioritize NTBFs with structured quantitative data. Thus, efficient KM practices help reduce cognitive overload for potential investors, making these NTBFs more appealing (Yang et al., 2025). However, past studies have focused on the isolated effects of specific signals, overlooking their interconnections and joint impact on investment decisions (Passavanti et al., 2024). Therefore, the objective of this study is to explore this framework.

To determine how KM affects NTBF capabilities, it is essential to analyze the factors that facilitate the adoption and development of effective KM practices. Among factors, the education level of the venture team is critical in shaping its ability to implement KM processes (Ahmed et al., 2021). Higher levels of education equip team members with improved cognitive skills, analytical capacity, and a greater ability to absorb and process complex information (Centobelli et al., 2017; Clercq and Arenius, 2006). This enables them to identify, evaluate, and integrate relevant knowledge from internal and external sources more effectively, thereby promoting innovation and strategic decision-making (Errico et al., 2024). Furthermore, formal education can strengthen critical thinking, competence, and informed judgment (Hmieleski et al., 2015), which are essential for navigating the complexities of dynamic environments and attracting investors who value well-informed strategic leadership.

Past work experience and the entrepreneurial experiences of venture team members are invaluable assets that significantly enhance an NTBF's KM capabilities. Such experience provides a wealth of tacit knowledge, practical skills, and established networks that can improve access to external resources, the absorption of relevant information, and the implementation of KM practices (Lim and Busenitz, 2020; Debrulle et al., 2014). For instance, having entrepreneurial experience equips team members with a deeper understanding of market dynamics, competition, and consumer demands, enabling them to identify and evaluate relevant knowledge for more effective strategic decision-making (Song et al., 2024). Having combined formal education and experience helps venture team members to develop unique skills and knowledge; when integrated into an organizational context, these attributes comprise valuable, inimitable, and hard-to-replace resources that promote a sustainable competitive advantage (Alzate-Alvarado et al., 2025; Patzel, 2010).

Social capital acts as a key catalyst for knowledge acquisition and exchange in NTBFs. By connecting them with mentors, investors, and industry experts, it strengthens their capacity to access external resources, gain specialized expertise, and build strategic partnerships (Oliva and Kotabe, 2019; Debrulle et al., 2014; Lotti-Oliva, 2014). Active participation in industry events, networking activities, and mentorship programs facilitates the exchange of experiences, ideas, and best practices, strengthening knowledge acquisition and fostering a culture of continuous learning (Rubin et al., 2015). Social capital facilitates information and knowledge flows by promoting trust-based relationships that strengthen collaboration and knowledge exchange, connecting individuals to diverse information sources and innovative ideas (Pirolo and Presutti, 2010). Thus, NTBFs with strong social capital networks strengthen their KM capabilities, adapt faster to market changes, seize emerging opportunities, and attract the financial resources needed to convert knowledge into innovation and measurable progress (Debrulle et al., 2014). Additionally, recent studies emphasize the importance of social networks and organizational knowledge ecosystems in promoting information diffusion, collaboration, and access among institutions, contributing to organizational readiness for innovation and entrepreneurship (Shatila et al., 2025).

Finally, team size presents a complex, potentially contradictory relationship with KM in NTBFs. On the one hand, research suggests that smaller teams often foster more informal, flexible KM practices, promoting rapid innovation and agile decision-making (Hu et al., 2021; Alvarez et al., 2016). Yet, smaller teams also risk knowledge loss if a key member departs (Choi et al., 2021). On the other hand, larger teams might possess a broader range of expertise and experience relevant to KM, potentially leading to a more diverse and comprehensive knowledge base. Nevertheless, larger teams can suffer from communication breakdowns, coordination challenges, and internal conflicts that negatively impact performance while threatening long-term sustainability (Gan et al., 2025; Bernerth et al., 2023; Patzel, 2010). This complex relationship underscores the need for additional research to understand the optimal team size for KM in NTBFs.

This study measures KM as follows: (1) education level, (2) past entrepreneurial experiences accumulated by the venture team, (3) roles held in prior work experience, (4) social capital gained through the acceleration program, and (5) venture team size.

2.2 Attracting Financing

Access to financial resources is critical to NTBFs' success and long-term viability. Inadequate funding—particularly in the early stages—restricts their growth, weakens competitive advantages, and limits innovation capacity (Singh and Mungila-Hillemane, 2023). Conversely, the availability of sufficient funds provides operational flexibility (Schütz and König, 2024), enabling capacity expansion (Li and Lin, 2024), strategic investments in technological development (Liu and Zhao, 2024), and exploitation of market opportunities (Thai and Mai, 2023); these factors directly contribute to enhanced performance and long-term survival. Accordingly, several studies have found that by facilitating the implementation of innovative projects and adaptation to dynamic environments, efficient financial management and a diversified funding portfolio significantly increase an NTBF's probability of success (Alzate-Alvarado et al., 2025).

The ability to attract equity and debt financing reflects an NTBF's perceived potential and risk profile, signaling the market's perception of its viability and attractiveness (Cumming et al., 2019). Particularly through venture capital (VC), equity financing is often associated with high-growth potential due to the strategic guidance, industry expertise, and enhanced credibility that VC investors provide (Fu et al., 2024). Equity financing also involves the dilution of ownership and control, which may not be desirable for all entrepreneurs. On the other hand, debt financing provides immediate capital without diluting ownership, making it an essential resource for meeting short-term operational needs while managing cash flow (Honjo et al., 2025). Nevertheless, due to ongoing payment obligations and reduced decision-making flexibility, excessive reliance on debt financing, particularly long-term debt, can impose strategic restrictions, potentially hindering long-term growth and innovation (Honjo, 2021). Therefore, an NTBF's optimal capital structure is a complex decision that depends on factors such as its development stage, industry dynamics, and risk appetite.

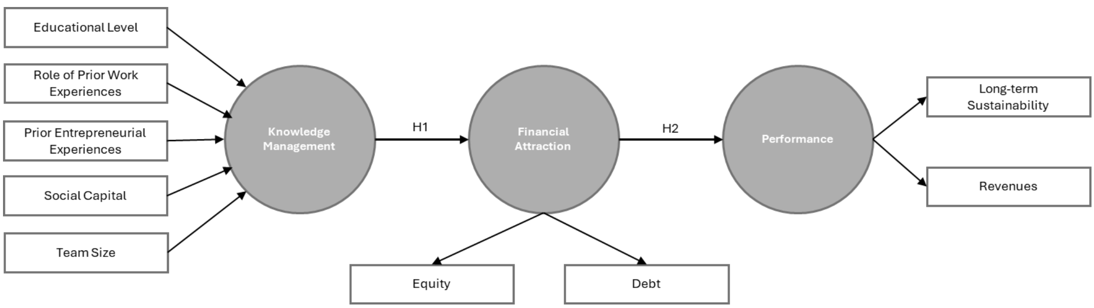
This study measures FA based on the amount of an NTBF's equity financing obtained and total debt acquired, reflecting the relative importance of these two funding sources in shaping their financial capacity and growth trajectory.

Based on the above theoretical elements, we propose a model that analyzes how KM factors influence NTBFs' ability to attract financing and how FA impacts performance. The proposed model is graphically presented in Figure 1 while positing the following:

H1: KM has a positive, direct effect on NTBFs' capacity to attract external financing. This hypothesis is grounded in the notion that the venture team's education level, experience, social capital, and effective KM practices enhance their ability to build credibility with investors and secure equity and debt financing, increasing the NTBF's attractiveness as an investment opportunity.

H2: The ability of venture teams to obtain financing has a positive and direct effect on NTBF performance, as measured by revenue and sustainability over time. This hypothesis posits that access to financial resources enables NTBFs to invest in innovation, expand operations, and weather economic downturns, thereby improving financial performance and long-term viability.

Figure 1 Theoretical model of factors influencing NTBF performance



Source: Compiled by the author, 2025

3. Methodology

3.1 Data Collection, Sample, and Measures

Data were sourced from the GALI of Emory University. The database comprises information from 23,241 early-stage ventures. GALI collected standardized data from 2013 to 2019 during the application processes for acceleration programs worldwide and conducted annual performance follow-ups. From this database, 103 NTBFs in Australia, Canada, France, Germany, and the United States were selected based on their participation in acceleration programs and completion of longitudinal studies. The study's constructs are presented in Table 1.

3.2 SEM-PLS for Statistical Analysis

This study employs partial least squares structural equation modeling (PLS-SEM), which is well-suited to achieving the research objectives. Due to the complexity of the relationships among the constructs of KM, FA, and P in NTBFs, PLS-SEM provides significant advantages in terms of flexibility and the capacity to validate causal relationships (Hair et al., 2012). PLS-SEM can validate causal relationships in complex theoretical models (Haenlein and Kaplan, 2004), particularly regarding entrepreneurship (Aparisi-Torrijo et al., 2023). It enables working with moderate sample sizes, which is relevant given the characteristics of the database used (Russo and Stol, 2021; Bayonne et al., 2020; Hair et al., 2019; Richter et al., 2016; Reinartz et al., 2009). The analysis was conducted using SmartPLS software version 4.1.1.4.

A nomological network was constructed that integrates the constructs of KM, FA, and P, and their respective indicators (Gefen et al., 2000). Model evaluation was performed across three stages to validate the hypotheses: measurement model assessment, goodness-of-fit evaluation, and structural model analysis (Hair et al., 2017).

3.2.1 Measurement Model Assessment

This study modeled KM as a formative construct (B Mode) using indicators to define it. FA and P were modeled as reflective constructs (A Mode), where the constructs define the indicators (Jarvis et al., 2003)—assessing the formative constructs involved evaluating multicollinearity, indicator weights, and discriminant validity. Individual indicator reliability, construct reliability, convergent validity, and discriminant validity were considered for reflective constructs (Hair et al., 2021).

3.2.2 Measuring Goodness-of-Fit

Goodness-of-fit was evaluated to determine the extent to which the proposed theoretical model fits the empirical data. The following indices were analyzed: SRMR (standardized root mean square residual), d_ULS (unweighted least squares discrepancy), and d_G (geodesic discrepancy) (Henseler et al., 2016). Evaluating these indices determines whether the model meets established criteria for good fit.

3.2.3 Structural Model Assessment

After confirming model fit, the structural model was analyzed to test the hypotheses. The analysis examined the direction, magnitude, and statistical significance of path coefficients, as well as potential collinearity issues. The coefficient of determination (R^2) and the effect size (f^2) were examined to determine the influence of each predictor construct (Hair et al., 2021; Cepeda-Carrión and Cepeda-Carrion, 2018).

Table 1: Study variable composition

Construct	**Indicator (observable variables)**	**Abreviation**	**Indicator description (given data)**
Knowledge Management (KM)	Education level	EducLevel	Represents the average educational level of the venture team. Constructed from responses to the GALI-administered survey, each founder reported their highest level of education. Each level was assigned a score from 1 to 12 (12 corresponds to a PhD/Doctorate and 1 corresponds to primary education). For each NTBF, the arithmetic mean of the education scores of principal founders with available data was calculated. This average was normalized by dividing it by the maximum possible score (12), allowing observations to be on a comparable scale from 0 to 1. This indicator reflects the average academic qualification of the venture team, regardless of the number of members; it serves as a proxy for their capacity to manage, absorb, and transfer knowledge within the organization.
	Prior entrepreneurial experiences	PrevEntrepExp	Calculated based on the number of new organizations each founder started before launching the current NTBF, it reflects the founders' past entrepreneurial experience. Survey responses were used to obtain the number of ventures founded by each of the three principal founders. Total experience was estimated by multiplying the average number of ventures of the three founders by the total number of partners for firms with more than three partners, assuming that the ventures of additional partners are proportionally similar. The value was normalized using the min–max technique, scaling the score to 0–1 to make comparisons and analysis within the study framework.
	Role of prior work experiences	JobRol	Quantifies the importance of the role played by each founder in their previous jobs; coded on a scale from 1 to 4: 4 for CEO, 3 for senior management, 2 for professional or support staff, and 1 for other operational roles. The average score for each NTBF was calculated from the founders' two most recent jobs with available information. The average was normalized by dividing it by 4, placing the final value in the 0–1 range, allowing comparisons between teams with different numbers of founders or work experience.

Table 1 (continued)

Construct	Indicator (observable variables)	Abreviation	Indicator description (given data)
Knowledge Management (KM)	Team size	TeamSize	Summing the three principal founders identified in the survey and any additional individuals who are also part of the founding team yields the total number of members in the venture team, as reported in the GALI survey. The total number of members was normalized using min–max scaling to a range of 0–1, based on the minimum and maximum values observed in the sample.
	Social capital	SocialCap	Based on each NTBF's perception, the relative importance of four benefits commonly associated with acceleration programs was assessed as a proxy for social capital. Ranked from 1 (most important) to 7 (least significant), these benefits reflect the extent to which the NTBF perceived the acceleration program as contributing to: (1) entrepreneurial skills development, (2) mentorship from business experts, (3) access to a network of like-minded entrepreneurs, and (4) network development (e.g., with potential partners and clients). Total scores (sum of positions assigned to the four benefits, maximum 28 points) were normalized (divided by 28) to produce a value between 0 and 1; this reflects the relative importance attributed to the social capital benefits received through the program and is considered an indicator of access to valuable knowledge and resources within the entrepreneurial ecosystem. This variable reflects the network-based support received by an NTBF.
Financial Attraction (FA)	Equity	InvOutequity	Measures the amount of external equity financing obtained from sources outside the firm from its founding until the third year of participation in the acceleration program. The reported amounts correspond to funds raised at the time of application and in years 1, 2, and 3 thereafter. The sum of these amounts was transformed using a logarithmic function to reduce the influence of extreme values. It was normalized using min–max scaling, mapping values to the 0–1 range to facilitate comparisons between firms.
	Debt	InvTotaldebt	Reflects the total amount of financing through loans or debts acquired by the firm from its founding until the third year of participation in the acceleration program. The reported amounts correspond to loans obtained at the time of application and in years 1, 2, and 3 thereafter. The sum of these amounts was transformed using a logarithmic function to reduce the impact of extreme values, and normalized using min–max scaling, adjusting the values to a 0–1 range to facilitate comparison between firms.

Table 1 (continued)

Construct	Indicator (observable variables)	Abreviation	Indicator description (given data)
Performance (P)	Long-term sustainability	EBO	Identifies firms considered established according to the GEM definition, which indicates that a firm has paid salaries, wages, or other payments to owners for more than 42 months (approximately 3.5 years). To determine their age, the application date to the program was used, adding the three subsequent years corresponding to responses obtained during three consecutive follow-up years, and comparing this total with the firm's founding date to calculate how many years they had at the time of responding in that final year. Firms with at least 4 years of age at that time were considered established.
	Revenues	Revenue	Measures the total accumulated revenues generated by an NTBF from its founding until three years afterward, excluding any form of philanthropic investment, donations, or personal debt. It was constructed based on the initial response regarding revenues since the founding and the reported annual values for the three subsequent years, in U.S. dollars. The sum of these amounts was transformed using the logarithm ($\log(x + 1)$) to reduce dispersion caused by extreme values. The transformed value was normalized using the min–max technique, mapping all values to the range of 0–1.

4. Results

4.1 Measurement Model

Multicollinearity in the formative measurement model was assessed using the VIF, with acceptable values set at 3.3 or lower for each indicator (Hair et al., 2019). Table 2 confirms that all indicators meet this requirement.

Table 2: VIF collinearity statistic and outer weights of indicators

Construct	Indicator	VIF	Outer weights
KM	EducLevel	1.131*	0.376
	JobRol	1.993*	0.215
	PrevEntrepExp	1.012*	0.346
	SocialCap	1.089*	0.802
	TeamSize	2.168*	−0.099

Note: *Indicates that the corresponding value meets the criterion described.

For the KM construct, results indicate that social capital is the most influential indicator, underscoring the vital role of networks and relationships in knowledge acquisition, sharing, and application within NTBFs. Its significance was confirmed using the two-tailed bootstrap method, with $p < 0.05$ considered statistically significant (Dijkstra and Henseler, 2015). Table 3 shows that social capital is the only significant indicator for KM, suggesting that participation in accelerator programs, mentorship, and networking are key mechanisms for knowledge management, and that these aspects are key to knowledge acquisition in NTBFs (Debrulle et al., 2014; Oliva and Kotabe, 2019; Lotti-Oliva, 2014; Rubin et al., 2015).

Table 3: Significance criterion for weights and loadings

Construct	Indicator	Original sample (O)	Sample mean (M)	p-Value	Confidence interval		External loadings (λ)
					2.5%	97,5%	
KM	EducLevel	0.376	0.292	0.296	−0.395	0.939	0.514
	JobRol	0.098	0.229	0.747	−0.31	0.817	0.132
	PrevEntrepExp	0.346	0.252	0.335	−0.340	0.947	0.295
	SocialCap	0.802	0.580	0.010*	0.454	1.079	0.843*
	TeamSize	−0.33	−0.157	0.44	−0.778	0.794	−0.000

Note: *Indicates that the corresponding value meets the criterion described.

Indicators must not overlap with other constructs in the model (Urbach and Ahlemann, 2010). To assess discriminant validity in formative models, the HTMT index was calculated. Discriminant validity is confirmed when correlations between indicators of the same construct exceed those between indicators of different constructs, and when the HTMT index exceeds 0.85–0.9, depending on the criterion (Henseler et al., 2016). Table 4 indicates that the variables meet the formative criteria for discriminant validity.

Table 4: Heterotrait–Monotrait Ratio (HTMT) matrix

	FA	**KM**	**P**
FA			
KM	0.356*		
P	0.504*	0.193*	

Note: *Indicates that the corresponding value meets the criterion described.

After evaluating the formative model, the individual reliability of the indicators in the reflective model was assessed. Each indicator was required to have an outer loading (λ) equal to or greater than 0.707 (Hair et al., 2021). Table 5 shows that this condition is met for the debt indicator in the FA construct and for revenue and long-term sustainability indicators comprising the P construct. These results indicate that the key indicators are strongly associated with their constructs, reinforcing their relevance for interpreting the model's relationships.

Table 5: Individual indicator reliability

Construct	**Indicator**	**External loading (λ)**
FA	InvOutequity	0.530
	InvTotaldebt	0.955*
P	EBO	0.795*
	Revenue	0.857*

Note: *Indicates that the corresponding value meets the criterion described.

This study assessed reliability to ensure the constructs were internally consistent and valid (Hair et al., 2021; Ali et al., 2018; Dijkstra and Schermelleh-Engel, 2014), as well as the extent to which their indicators converged on a single construct (Hair et al., 2019). Table 6 confirms that the FA construct met all established criteria. While the P construct had a composite reliability below the 0.7 threshold, Dijkstra–Henseler's rho (ρA) exceeded this threshold, indicating that the construct's internal consistency is adequate, though limited.

Table 6: Construct reliability and convergent validity

Construct	Composite reliability (ρc)	Dijkstra–Henseler (ρa)	AVE
FA	0.709*	0.732*	0.597*
P	0.548	0.812*	0.683*

Note: *Indicates that the corresponding value meets the criterion described.

Discriminant validity, which ensures that each construct measures a distinct concept (Hair et al., 2019), was assessed using the Fornell–Larcker criterion (Fornell and Larcker, 1981) and the HTMT index (Hair et al., 2019). Table 7 shows that FA and P met this criterion. The table presents the square root of the AVE on the diagonal (in parentheses), with the off-diagonal values representing correlations between latent variables.

Table 7: Discriminant validity; Fornell–Larcker criterion

	FA	P
FA	(0.773)	
P	0.699	(0.827)

Discriminant validity is more accurately assessed using the HTMT index. The HTMT for the constructs P↔FA is 0.504; therefore, both constructs achieved discriminant validity.

4.2 Goodness-of-Fit Assessment

Model fit was assessed using the Standardized Root Mean Square Residual (SRMR) and exact fit tests based on bootstrapping (Hu and Bentler, 1998; Henseler et al., 2016). The results, presented in Table 8, indicate that all values met the specified thresholds, suggesting that the proposed relationships between KM, FA, and P are well-supported by the data and can be meaningfully interpreted.

Table 8: Goodness-of-fit indices

		Original sample (O)	Sample mean (M)	95%	99%
SRMR	Saturated model	0.061*	0.096	0.204	0.215
	Estimated model	0.07*	0.095	0.201	0.211
d_ULS	Saturated model	0.168*	0.58	1.869	2.086
	Estimated model	0.22*	0.58	1.821	1.997

d_G	Saturated model	0.039*	11.95	32.953	35.614
	Estimated model	0.051*	12.221	32.848	35.326

Note: *Indicates that the corresponding value meets the criterion described.

4.3 Structural Model

With the measurement models confirmed as valid and reliable, the structural model was analyzed to assess support for the proposed relationships (hypotheses). This involved examining the sign, magnitude, and statistical significance of the relationships, as well as the amount of variance explained (AVE) (Alzate-Alvarado et al., 2025; Aparisi-Torrijo et al., 2023).

The VIF was used to assess multicollinearity among the model variables, with a maximum acceptable value of 3.3 (Hair et al., 2019). Table 9 shows that this criterion is met in all cases. The results confirm the absence of multicollinearity in the relationship between FA and P and the influence of KM on P mediated by FA.

Table 9: Variance inflation factor (VIF) for antecedent variables

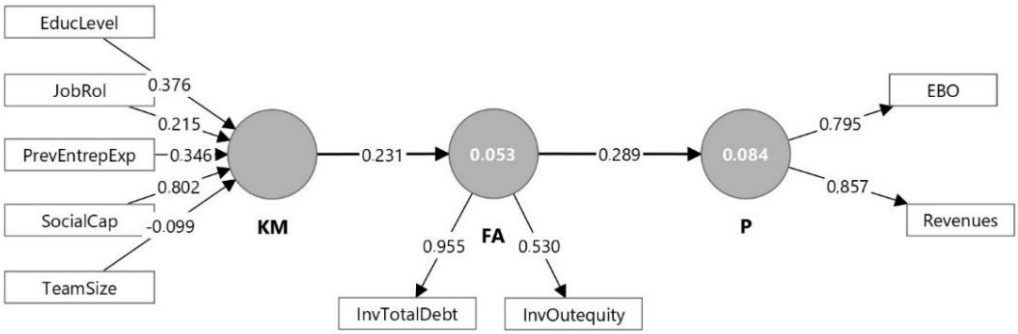
	FA	**KM**	**P**
FA			1.000*
KM	1.000*		
P			

Note: *Indicates that the corresponding value meets the criterion described.

Hypotheses were tested by examining the sign, magnitude, and statistical significance of path coefficients, which reflect the direction and strength of relationships between constructs. Significance was assessed via bootstrapping and Student's t-test ($p < 0.05$) (Sarstedt et al., 2014). The coefficient of determination (R^2) measures variance explained by the model (Hair et al., 2017), while effect size (f^2) evaluates the impact of each construct (Hair et al., 2017).

The results (Figure 2 and Table 10) illustrate empirical support for the proposed hypotheses. The path coefficients show the expected signs, and the p-values for each relationship are below 0.05, indicating that the relationships are statistically significant. However, the relationships between KM → FA and FA → P are relatively weak. This result suggests that the influence of these constructs may be limited or that other factors play a more critical role. The finding suggests that additional research is needed to examine other potential causal relationships.

Figure 2: PLS-SEM Model results



Source: Compiled by the author, 2025

Table 10: Structural model hypothesis results

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	t -Statistics (O/STDEV)	p-Value
1. FA → P	0.289	0.299	0.098	2.954	0.002*
2. KM → FA	0.231	0.313	0.113	2.034	0.021*

Note: * Indicates that the corresponding value meets the criterion described.

While the proposed model confirms the existence of significant relationships among KM, FA, and P in NTBFs, it is essential to note that the obtained R^2 coefficients are relatively low. Thus, the current model explains only a small proportion of the variance in these variables, possibly due to unmeasured contextual or industry-specific factors.

Similarly, the analysis of effect sizes (f^2) (Table 11) shows that the relationships among the constructs in the PLS-SEM model have a limited magnitude. The relationships between FA and P, and the impact of KM on FA, are considered low. This finding suggests that other factors likely play a role. Therefore, future research should examine the effects of contextual factors, venture team characteristics, and specific financing strategies to explain a greater proportion of the variance in performance and in NTBFs' capacity to attract financing.

Table 11: Effect size

	FA	KM	P
FA			0.091
KM	0.056		
P			

5. Discussion

The formative measurement model proposed in this study highlights social capital as the most influential factor in KM. This finding suggests a critical role for it in strengthening KM within NTBFs in the study context. The finding aligns with past research emphasizing the role of social capital as a catalyst for knowledge acquisition, thereby promoting access to resources and collaboration (Debrulle et al., 2014; Oliva and Kotabe, 2019; Lotti-Oliva, 2014). The findings underscore the strategic importance of strengthening social capital to promote effective KM practices in NTBFs; this is particularly evident given the challenges these firms face in conveying their potential to investors amid information asymmetry (Landström, 2023; Glücksman, 2020).

Although team size contributes minimally to the KM construct, its negative coefficient indicates that smaller teams may exhibit higher KM. While this effect requires cautious interpretation, it aligns with literature suggesting that larger teams can encounter communication issues and internal conflicts that hinder KM (Patzel, 2010; Gan et al., 2025; Bernerth et al., 2023), whereas smaller teams may achieve optimal performance through direct supervision and effective collaboration (Backes-Gellner and Mohnen, 2015). This finding implies a trade-off, where coordination challenges balance the benefits of a broader knowledge base.

Regarding FA, debt is a particularly relevant indicator for NTBFs, suggesting that access to debt financing is key to their financial structure and ability to attract investment. This finding aligns with past research indicating that NTBFs often rely more on debt in early stages (Cole and Sokolyk, 2018), while formal debt enables them to overcome financial constraints (Robb and Robinson, 2014). A preference for debt may reflect reluctance to dilute ownership amid low valuations and high early-stage uncertainty. Additionally, debt financing provides immediate capital without diluting ownership, making it essential for meeting short-term operational needs and managing cash flow (Honjo et al., 2025).

Regarding P, the results indicate that revenue and long-term sustainability are relevant indicators. This finding suggests that both the ability to generate income and the capacity to sustain oneself are key dimensions in NTBF performance. Similarly, Prokop et al. (2019) found that the ability to generate revenue and achieve long-term sustainability is a central dimension of P. Reaching a sustainability stage in which the NTBF achieves stable returns is considered an indicator of success and overall P, validating the relevance of these metrics in this study.

The model confirms significant relationships between KM, FA, and P in NTBFs, providing empirical support for the proposed hypotheses. Specifically, KM positively influences FA (H1), and FA positively influences P (H2). The findings align with the research indicating that KM increases the likelihood of obtaining financial resources (Alfiero et al., 2025; Rubin et al., 2015; Hmieleski et al., 2015), along with the essential role of financing in driving innovation and P in NTBFs (Singh and Mungila-Hillemane, 2023; Jeong et al., 2020; Knockaert et al., 2010). However, the relatively low R^2 values suggest that the model captures only a limited portion of the variance, while other unmeasured factors play a significant role. This underscores the need for future research to examine contextual and industry-specific variables that influence FA and NTBF outcomes.

6. Conclusions

6.1 Theoretical Contributions

This study advances theoretical understanding of KM and its impact on NTBFs in several ways. First, the findings underscore social capital as the most influential factor in enhancing KM, especially under resource constraints and information asymmetry, providing empirical evidence of its role in facilitating knowledge acquisition, sharing, and application within these firms.

Second, the study elucidates the complex relationship between team size and KM, extending past research that has focused on linear relationships. Our findings reveal a nuanced, potentially contradictory dynamic where smaller teams may foster more agile KM practices. Comparatively, larger teams may face communication and coordination challenges.

Finally, the findings confirm the signaling role of FA. This supports the notion that the ability to attract equity and debt financing acts as a credible market signal, reflecting an NTBF's perceived potential and risk profile. Notably, our study nuances the understanding of how investors perceive these signals by showing that debt financing is a particularly relevant indicator for the NTBFs investigated. The findings suggest that debt may be a stronger signal of viability in specific contexts.

6.2 Managerial Implications

For venture teams aiming to leverage KM effectively, this study emphasizes the strategic value of cultivating strong networks. Teams should actively participate in industry events, join relevant organizations, and engage with experienced mentors and advisors. These actions promote knowledge exchange, grant access to valuable resources, and foster a culture of continuous learning within the NTBF. By prioritizing these efforts, venture teams can build a robust KM ecosystem that drives innovation and strengthens organizational capabilities.

Given the importance of debt financing for attracting investment, NTBF venture teams should prioritize securing business debt by developing strong relationships with lenders and demonstrating the ability to generate stable cash flows and manage debt effectively. This should include a strategic shift to prioritize debt financing over equity financing, particularly in the early stages of firm development. Venture teams can enhance their attractiveness to investors by prioritizing debt financing, demonstrating financial stability, and securing the resources necessary for growth and sustainability over time.

Policymakers play a vital role in supporting the success of NTBFs. To foster effective KM practices, they should prioritize initiatives that enable network building and knowledge exchange within the entrepreneurial ecosystem. This includes strategically funding industry-specific incubator and accelerator programs, creating platforms and incentives for experienced entrepreneurs and industry experts to mentor NTBFs, and supporting knowledge-exchange events that encourage collaboration among NTBFs, research institutions, and other stakeholders.

Moreover, policymakers should implement policies that promote competition among financial institutions and reduce entry barriers for NTBFs, enhancing access to debt financing. This should include establishing public–private partnerships (PPPs) to generate guarantee funds that back business debt for NTBFs. This serves to streamline the application process for business debt, reducing administrative burden. It can also incentivize lending to NTBFs by offering tax incentives and other benefits to financial institutions that actively lend to these firms.

6.3 Limitations and Future Research Directions

While advancing understanding of KM and FA in NTBFs, this study has limitations that suggest directions for future research. First, the GALI database's heterogeneity—arising from data collected by different accelerators across countries—may introduce variability in selection criteria and data quality, limiting the generalizability of findings. Second, the relatively small sample size (103 NTBFs) warrants caution. However, PLS-SEM can accommodate small samples through its segmentation process (Reinartz et al., 2009); future studies should strive for larger samples to enhance statistical power. Third, while the model confirms significant relationships among KM, FA, and P, the relatively weak path coefficients suggest that it captures only a limited portion of the variance in these variables. Thus, other unmeasured factors, such as contextual and industry-specific variables, may also play a significant role.

Therefore, future research should consider the following: (1) examine the impact of contextual factors, such as public policies and local ecosystem characteristics; (2) deepen the understanding of venture team characteristics beyond education and experience, considering factors such as diversity of skills and team cohesion; (3) investigate the impact of team size on KM across different NTBF lifecycle stages, extending the analysis to members who join over time; and (4) integrate qualitative methodologies, such as case studies and in-depth interviews, to explore the causal mechanisms underlying these phenomena, revealing the complexities and nuances that quantitative analyses do not capture. Future research could also explore alternative measures for P to strengthen construct reliability and validity. Addressing these limitations could enable future research to develop more comprehensive, robust models to guide strategic decisions and inform public policies that promote innovation and sustainable growth in NTBFs.

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