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Influence of technological capability, management teams and access to finance on sustainable entrepreneurship over time

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Abstract

Driven by their growing impact on countries' economic development, research on management teams in new technology-based firms (NTBFs) has intensified in recent years, aiming to identify the success and failure factors of these companies, given their high mortality rates. This study investigates the influence of human capital, technological capability, and access to finance on the sustainability over time of new technology-based firms (NTBFs). We employed a PLS-SEM model and data from the Global Entrepreneurship Index (2018), the Digital Platform Economy Index (2020), and the Global Innovation Index (2023), integrating information from 106 countries. Our results show a significant and positive relationship between: (a) technological capability and access to finance, indicating that greater financial resources lead to more robust technological development; and (b) both technological capability and human capital, which directly influence the long-term growth and sustainability of NTBFs. Prior work and entrepreneurial experience within the management team emerged as the strongest predictor of firm survival. These findings suggest entrepreneurs should prioritize experienced teams and innovative models based on new technologies, while policymakers should focus on human capital development, technology-based innovation, and broader access to financing to promote sustainable growth over time of NTBFs.

Keywords New technology-based firms · Management teams · Human capital · Technological capability · Financing attraction · Sustainable entrepreneurship over time

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Introduction

New technology-based firms (NTBFs), whose business models are fundamentally rooted in the development and application of new technologies (Litan & Song, 2008), are of significant interest due to their positive impact on economic and social development, their capacity to create high-quality employment, and their role in revitalizing industries through disruptive technologies. However, they are also characterized by significantly high mortality rates (Colombo & Grilli, 2005; Song et al., 2008; Knockaert et al., 2010).

The successful establishment of an NTBF requires a considerable amount of time. Previous research indicates that approximately 20% fail within the first year, 60% by the fifth year, 75% are unsuccessful by the tenth year, and only 10% survive beyond this period (Larroulet & Couyoumdjian, 2009; Van Praag, 2006; Baron, 2008; Li & Chen, 2009; Lussier, 1995; Lai & Lin, 2015; Eliakis et al., 2020). This high failure rate has driven research into the factors determining success or failure, and how to ensure long-term sustainability. Song et al. (2008) identified eight key factors significantly correlated with NTBF performance: vertical integration in the value chain, market scope, firm age, management team size, availability of financial resources, founding team marketing and industry experience, and the existence of an intellectual property protection mechanism. Moreover, this study found that successful firms were founded by venture teams of 2–5 members, rather than individual entrepreneurs.

While literature initially viewed entrepreneurship as an individual endeavor, more recent research emphasizes its team-based nature (Brinckmann & Hoegl, 2011; De Mol et al., 2020). Management teams have been shown to play a critical role in NTBF performance, as high-potential and high-growth firms are typically created and led by teams rather than individuals (Shrader & Siegel, 2007; Klotz et al., 2014). Positive impacts from management team characteristics include relevant experience in the NTBF's field, team size (larger teams often possess more experience and potentially better performance), team heterogeneity (diverse skills generally lead to better performance), and prior entrepreneurial experience among members (Aspelund et al., 2005; Eliakis et al., 2020; Song et al., 2008).

Human capital factors significantly influence NTBF performance (Song et al., 2008; Shane, 2000), enabling the development of competitive strategies and capitalization on emerging opportunities. Core characteristics of human capital include knowledge, education, experience, and skills (Helfat & Martin, 2015). Research by Jin et al. (2016) explored the link between management team composition and NTBF performance, suggesting that greater human capital allows management teams to more effectively navigate the complexities of the business environment, and that knowledge acquisition, management, and skill development are crucial for the survival of new ventures (Bettiol et al., 2016; Chen et al., 2022; Hashai & Zahra, 2021; Oliva & Kotabe, 2019). Management teams in NTBFs must collaboratively make strategic decisions and take ownership of those choices to foster growth (Brinckmann & Hoegl, 2011), requiring the effective management of both financial and non-financial resources to cover expenses, develop products, create marketing strategies, and compensate team members (Chandler & Hanks, 1993; Delmar et al., 2003; Brinckmann & Hoegl, 2011). The successful acquisition of these resources is a strong indicator of success, especially for high-tech startups where patents and team experience are directly linked to technological capabilities (Hoenig & Henkel, 2015).

Despite existing evidence, research on the impact of management teams on performance remains fragmented and incomplete (Birley & Stockley, 2000), highlighting the need for further studies to understand the factors behind their successes and failures (Bolzani et al., 2019). Furthermore, research on the relationship between human capital and business performance has not yielded consistently robust results (Davidsson & Honig, 2003).

Building on this exploratory research, this study proposes and validates a model examining the influence of human capital factors, developed technological capability, and access to finance on long-term sustainable entrepreneurship. Sustainability, in this context, refers to NTBF's ability to ensure the durability and solidity of its business actions (Chaves-Vargas et al., 2024; Moya-Clemente et al., 2019). The model investigates whether these constructs are positively related to sustainability and analyzes their individual contribution to firm survival and long-term success.

To enhance the validity and reliability of our findings, the study database was constructed using three distinct data sources: (1) the Global Entrepreneurship Index 2018; (2) the Digital Platform Economy Index 2020; and (3) the Global Innovation Index 2023, integrating information from 106 countries.

The remainder of this paper is organized as follows: Sect. 2 presents the hypotheses supported by the theoretical foundations of this research. The methodology used and the data are presented in Sect. 3. Section 4 analyzes the results obtained. Section 5 presents the main conclusions, limitations and future research of this study.

Theoretical framework and research hypotheses

The high mortality rate among new technology-based firms (NTBFs) highlights the need to understand the factors that determine their long-term success and sustainability. This theoretical framework examines three key constructs identified in the literature as influential in the growth and survival of these firms: the human capital of the management team, the firm's developed technological capabilities, and its ability to attract financing. The following sections explore the theoretical foundations of each construct, detailing how they will be operationalized in this study to assess their influence on the long-term sustainability of NTBFs. This framework underpins the model subsequently presented and analyzed.

Human capital

Following Becker and Collins (1964), human capital is defined as the knowledge, skills, and experience individuals accumulate through education, training, and work. While the literature distinguishes between general and specific human capital (Dimov, 2010; Hmieleski et al., 2015; Garcia-Cabrera et al., 2021), this study recognizes that these aspects are interconnected and jointly contribute to NTBF success.

General human capital encompasses factors like team size and educational levels, while specific human capital includes prior work experience, industry-specific expertise, and entrepreneurial experience. The core principle of human capital theory, as articulated by Becker (1975), is that increased human capital generally leads to improved performance regardless of firm context. This is supported by research showing that teams with high human capital are more likely to identify and exploit entrepreneurial opportunities and achieve better performance (Errico et al., 2024).

Moreover, Capizzi et al. (2025) observe that general and specific human capital is a key factor in the likelihood of securing financing from business angels, which positively impacts company growth. Additionally, signals of human capital, such as educational background and prior experience, play a crucial role in shaping investment decisions (Topaler & Adar, 2025; Naiki & Ogane, 2022), underscoring the critical role of entrepreneurs' human capital in driving both funding acquisition and performance.

This study considers both general and specific human capital components critical for NTBF success, and operationalizes this construct using educational level, prior work and entrepreneurial experience, and developed skills within the management team.

Education is a critical component of human capital and is strongly linked to a company's performance. The level of formal education attained by management team members serves as a key indicator of the knowledge and skills they bring to the organization (Bates, 1990; Errico et al., 2024). This variable captures the highest degree achieved by members of the management team, regardless of their field of study (Hmieleski et al., 2015). Higher levels of formal education are associated with: (1) a stronger understanding of standard business practices and procedures; (2) improved peer competence; (3) enhanced analytical skills; and (4) superior capabilities in judgment and decision-making (Schilhab, 2007; Hmieleski et al., 2015).

While undeniably an important component of human capital and strongly correlated with company performance, the impact of education can vary depending on team size (Patzel, 2010). Larger teams, despite potentially greater collective human capital, may experience communication problems and conflicts that negatively affect overall performance and long-term sustainability. The presence of a specialized team, often including members with formal education, can positively moderate the effect of funding on a NTBF's innovative performance (Ensley et al., 2006; Errico et al., 2024).

In this study, human capital factors are measured by: (1) Prior work and entrepreneurial experience accumulated by the management team, (2) Educational level and (3) Developed Skills.

i) Prior work and entrepreneurial experience

Prior experience significantly impacts NTBF performance, encompassing both prior work experience and prior entrepreneurial experience. While these are distinct, they are deeply interconnected and complementary, synergistically driving firm success. Song et al. (2024) highlight the significant and differentiated impact of founders' prior experiences on their perceptions and the potential performance of their ventures. Human capital theory emphasizes the importance of tacit knowledge, often gained through experience, for navigating the complexities of the startup environment (Helfat & Martin, 2015; Lim & Busenitz, 2020).

Prior entrepreneurial experience fosters this tacit knowledge, enhancing productivity, improving information processing, and strengthening risk management within the team (Hmieleski et al., 2015). This is associated with a more effectual approach to opportunity identification (Song et al., 2024), characterized by greater optimism and a focus on creatively leveraging available resources. Prior work experience, particularly within the relevant industry, provides valuable, firm-specific knowledge and skills that mitigate uncertainty and improve decision-making (Colombo & Grilli, 2005). This is associated with a more causal approach, emphasizing externally validated opportunities and the achievement of competitive advantage through detailed planning (Song et al., 2024). The positive correlation between prior entrepreneurial experience and various firm-level outcomes, such as size, growth, profitability, and access to external financing, has been demonstrated by Dimov (2010); however, further research is needed to fully understand its impact on firm survival (Helfat & Martin, 2015). Jiao et al. (2021) highlight the positive correlation between prior entrepreneurial team experience and team performance. Finally, the knowledge dependence inherent in NTBFs (Dencker & Gruber, 2015) underscores the critical role of prior knowledge within entrepreneurial teams (frequently rooted in founders' prior work experience) in shaping firm strategies, routines, and organizational culture, driving growth (Hashai & Zahra, 2021).

Prior experience contributes specialized knowledge and skills and provides valuable management and organizational capabilities.

ii) Skills

The complementarity of human capital between members of the management team can have a positive impact on the performance of the NTBF (Helfat & Martin, 2015). Education and prior experiences allow people to accumulate an inventory of skills and knowledge that, when integrated into an organizational context, can constitute valuable, non-imitable, and irreplaceable resources that are a source of competitive advantage for a firm (Patzel, 2010). Botella-Carrubi et al. (2025) further emphasize that a team with an adequate skill profile is crucial for managing uncertainty inherent in the operations of NTBFs. The greater the skills and competencies of an organization's members, the more likely it is to achieve its strategic goals, outperform its competitors in the future, and generate high returns (Hitt et al., 1994).

Based on the preceding discussion of the theoretical underpinnings of human capital and its operationalization within this study, we propose our first hypothesis:

H1: Human capital factors have a positive influence on the growth and long-term sustainability of NTBFs.

Technological capability

Technological innovation, driven by the commercial exploitation of new knowledge, is a primary driver of wealth creation which can manifest through the establishment of new business units or entirely new companies (Hindle & Yencken, 2004). The most significant strategic differentiator for TBFs lies in the degree of technical innovation embedded within their core technologies (Eisenhardt & Schoonhoven, 1990). Technological capability, therefore, is a critical factor influencing the growth and long-term sustainability of new technology-based firms (NTBFs). Parida and Örtqvist (2015) found a positive correlation between technological capability (alongside networking and financial resources) and innovation performance in NTBFs. Ahn et al. (2022) further emphasize that technological capabilities form the basis for creating a sustainable competitive advantage, enabling firms to absorb and utilize external technical knowledge or generate new knowledge internally. These capabilities encompass the ability to acquire and utilize technology, solve technical problems, and manage technical personnel.

This study operationalizes the technological capability construct using three key variables that capture different facets of this crucial capability: (1) Development of technology-based business models, (2) Creation of new technological products, and (3) Development of innovation Processes.

Technology-based business models

Business model innovation is essential for firms to maintain competitiveness in the face of technological disruption and changing market dynamics (Tetteh et al., 2025). The creation of successful technology-based business models (defined by their effective leverage of technological capabilities and innovation to meet market demands and generate sustainable competitive advantage) is a crucial indicator of a firm's technological prowess. This is not merely about possessing advanced technologies; it demands a dynamic, adaptive approach. Firms must constantly evolve their business models to integrate existing capabilities with new technological advances and seize emerging opportunities (Brink & Holmén, 2009). Successful firms don't passively hold technology; they actively manage and adapt its use within evolving technological and market landscapes (Eurico Soares de Noronha et al., 2024).

Technological products

The creation of new technological products is a critical dimension of technological capability, particularly for achieving high growth and establishing barriers to entry for competitors. High-growth firms need strategies that allow them to compete effectively with larger, more established firms (Aspelund et al., 2005). Patent registration is frequently cited as a crucial tool for obtaining a competitive advantage, preventing imitation, attracting investment, and increasing the likelihood of acquisition (Souza et al., 2020; Dias & Mazieri, 2020). NTBFs often create and utilize technologies not possessed by established firms (Hindle & Yencken, 2004), leveraging intellectual property to protect innovations. This not only signals the quality and strength of the new firm (Hoenig & Henkel, 2015) but also generates interest from potential investors and increases the likelihood of securing financial resources by showcasing innovation capabilities, reducing uncertainty, and demonstrating added value (Abakah et al., 2024; Troise et al., 2022; Ahlers et al., 2015).

Given that innovations involving high technology allow greater growth potential, the ability to develop technological products should be considered a valuable resource of NTBFs, which can increase the probability of survival and generate greater profitability in a new company (Aspelund et al., 2005).

Innovation processes

Robust innovation processes are essential for technological capability, particularly for NTBFs navigating dynamic and competitive markets. Ahn et al. (2022) emphasize that technological capabilities are fundamental to creating a sustainable competitive advantage, enabling firms to absorb and utilize external technical knowledge or generate new knowledge internally. This underscores the critical role of effective innovation processes in achieving and sustaining this competitive advantage.

Innovation processes - such as R&D, patent acquisition and management, and the absorption and utilization of external technical knowledge - are critical firm-specific resources for NTBFs (Ahn et al., 2022; Zahra, 2021; Kogut & Zander, 1996). The dynamic capabilities framework (Teece et al., 1997) highlights the importance of a firm's ability to sense, seize, and reconfigure opportunities to create value. Innovation processes are key elements of this dynamic capability, enabling firms to adapt to market changes and maintain competitiveness.

Moreover, Kask and Linton (2025) highlight the necessity of an effective innovation system that supports NTBFs by providing access to human capital and resources for innovation, which is essential for enhancing the overall effectiveness of their innovation processes.

This study hypothesizes that technological capability is critical to the growth and long-term sustainability of NTBFs. This involves developing innovative technology-based business models, creating new technological products, and establishing robust innovation processes. Therefore, our second hypothesis is:

H2: Technological capability has a direct and positive influence on the growth and sustainability over time of NTBFs.

Attracting financing

Access to sufficient financing is a critical factor influencing the growth and long-term sustainability of NTBFs, especially those pursuing innovation in high-technology sectors (Singh & Mungila-Hillemane, 2023). The resource-intensive nature of technological innovation means that substantial financial resources are necessary for development and market entry (Bruton & Rubanik, 2002). Adequate funding provides operational flexibility, supporting adaptation to changing market conditions and strategic investment in R&D, ultimately leading to a sustainable competitive advantage and improved performance (Singh & Mungila-Hillemane, 2023; Kumar & Singh, 2019). This section details the theoretical underpinnings of the "Attracting Financing" construct, examining its constituent variables: financial facilitation, access to credit, and access to risk capital.

This study examines the impact of attracting financing on the development of technological capabilities within NTBFs, recognizing that more innovative technologies require greater financial resources for development and market entry. Financial attraction is measured as the availability of (1) Venture capital, (2) Access to credit, and (3) Financial facilitation, which incorporates aspects of finance that drive startups.

Risk capital

Securing risk capital, such as venture capital, is particularly crucial for NTBFs, providing not only crucial financial resources but also a range of value-added services that significantly enhance the probability of success (Knockaert et al., 2010). Venture capital investment plays a pivotal role in enabling rapid growth and scaling operations, often accompanied by strategic guidance and access to extensive networks that facilitate market entry and expansion (Fu et al., 2024). While venture capitalists actively seek investment opportunities in promising technology ventures, their rigorous evaluation process emphasizes identifying ventures with high growth potential and those who can effectively leverage risk capital to maximize returns (Wright et al., 2006). This selection process underscores the importance of a well-defined business model, robust technological capabilities, and a strong management team capable of executing a well-developed strategic plan.

Credit

Access to traditional debt financing presents significant challenges for NTBFs. The lack of collateral and established operational history often hinders their ability to secure bank loans (Frimanslund & Nath, 2024). However, the financial landscape is evolving, with banks increasingly leveraging online lending platforms, open banking initiatives, and fintech solutions to optimize their loan portfolios and provide greater access to credit for entrepreneurs (Anton et al., 2024). This expansion of available funding sources and the development of innovative financial services are contributing to a more diverse range of financing options for NTBFs.

Financial facilitation

A supportive ecosystem is crucial for the success of NTBFs, particularly in addressing the challenges of accessing initial funding and navigating the complexities of early-stage development. Entrepreneurial teams often face difficulties accessing readily available resources and information, making access to initial financing and value-added services essential (Frimanslund & Nath, 2024). The funding landscape has become significantly more diverse, with new investor types (including incubators, accelerators, family offices, impact investors, and grant programs) emerging to cater to the specific funding needs of early-stage technology ventures (Manigart & Khosravi, 2024). The presence of strong human capital within the team can also significantly ease initial financial constraints (Colombo & Grilli, 2005).

Based on these affirmations, we propose our third hypothesis:

H3: Financial attraction has a direct and positive relationship with the technological capability of NTBFs.

Considering these theoretical elements, a model is proposed that collects the impact of the factors of human capital of the management teams, the developed technological capacity, and the ability to attract financing, on the sustainability of NTBFs over time. This model can be observed in Fig. 1.

Methodology

Data collection, sample and measures

Three different data sources used to build the study's database and increase the validity and reliability of the findings:

1. The Global Entrepreneurship Index 2018. This index measures both the quality of entrepreneurship and the scope and depth of the entrepreneurial ecosystem in 137 countries. The methodology of this study collects data on the entrepreneurial attitudes, abilities, and aspirations of the local population and then compares them with the prevailing social and economic infrastructure. This process creates 14 pillars that are used to measure the health of the regional entrepreneurial ecosystem of the participating countries (Ács et al., 2017). For this study, the following pillars were considered: startup skills, human capital, product innovation, innovation process, venture capital, and high growth.

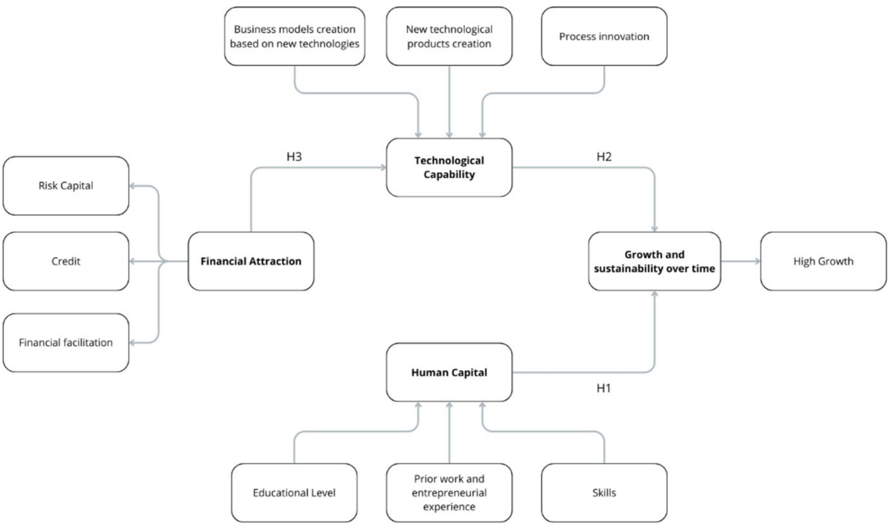

Fig. 1 Theoretical Model of the Factors Influencing the Growth and Sustainability of New Technology-Based Firms (NTBFs) over Time, (Source: the authors, 2025)

2. The Digital Platform Economy Index 2020. This index measures the state of the digital platform economy at the country level in 116 countries. The study uses a composite index that is based on four sub-indices: (a) the development of digital infrastructure, (b) the development of the business platform, (c) the development of the entrepreneurial ecosystem, and (d) the development of digital capabilities (Ács et al., 2020). For this study, the digital technology absorption pillar associated with the digital capabilities development sub-index and the financial ease pillar associated with the entrepreneurial ecosystem development sub-index were considered.
3. The Global Innovation Index 2023. This index aims to provide a comprehensive picture of the world's innovation systems. It reveals the ranking of the most innovative countries out of a total of 132, taking measures on each country's political environment, education, infrastructure, and knowledge creation. For this study, the indicators that have been considered are tertiary education and credit.

The resulting database, compiled from data on 106 countries, is detailed in Table 1. Figure 2 provides a visual representation of how the data from these sources were integrated to form the constructs used in this study.

Use of PLS-SEM for statistical analysis

This study utilizes Partial Least Squares Structural Equation Modeling (PLS-SEM) due to its alignment with the research objectives. The study's aim (exploring the complex interplay of human capital, technological capability, attracting financing, and NTBF sustainability over time) operates within a relatively under-researched domain demanding hypothesis testing and iterative model refinement. PLS-SEM's suitability for exploratory research, its emphasis on prediction, and its capacity to accommodate both formative and reflective measurement models render it the optimal methodology.

Moreover, PLS-SEM is recognized as a valuable analytical tool within the context of social sciences, particularly in fields such as entrepreneurship. As highlighted by Aparisi-Torrijo et al. (2023), recent literature has demonstrated its efficacy in addressing complex theoretical models and reinforcing studies in family business, entrepreneurship, and human resources (Hair et al., 2012; Manley et al., 2021). The method's ability to simultaneously assess explanation and prediction is particularly relevant in entrepreneurial research, where understanding and forecasting outcomes based on varying predictors is essential for theory development and practical application (Criado-Gomis et al., 2018; Hair, 2021).

This choice is further supported by the likelihood of non-normal data distributions within the employed databases and by the robustness of PLS-SEM to smaller sample sizes (Reinartz et al., 2009; Bayonne et al., 2020), particularly considering the limitations inherent in the aggregated data from 106 countries. The sample size surpasses the minimum threshold established by Reinartz et al. (2009), facilitating iterative model refinement and enabling rigorous causal-predictive analysis while maintaining necessary flexibility. The emphasis on prediction is crucial for this study, enabling data-driven improvements in model accuracy.

Table 1 Study variables composition

Constructs	Indicator (Observable variables)	Abbreviation	Pillar / indicator (given data)	Pillar / indicator Description (given data)	Source
Human Capital (HC)	Skills to start and grow a NTBF	Skills	Startup Skills	Assess the perception of startup skills among the population and weigh this aspect against the quality of education. Include entrepreneur characteristics that determine the growth potential of the new firm, as well as motivation based on opportunity and the potential for technological intensity of the new firm	Global Entrepreneurship Index 2018
	Prior work and entrepreneurial experience	PrevExp	Human Capital	Assess the quality of entrepreneurs by considering the percentage of new businesses founded by individuals with higher education beyond secondary school and the freedom of the labor market.	Global Entrepreneurship Index 2018
	Educational level	Educ	Tertiary education	The tertiary education sub-pillar of the economy encompasses two key aspects: the percentage of the population with a tertiary education, regardless of whether it's focused on advanced research, and the proportion of graduates in STEM fields (science, engineering, mathematics, statistics, information and technology) and manufacturing, engineering, and construction.	Global Innovation Index 2023
Technological Capability (TC)	New technology-based business models creation	NewBMTech	Digital absorption	Involves the capabilities of entrepreneurs to build new business models and/or digital products/services, based on the opportunities provided by digital technology.	Digital Platform Economy Index 2020
	New technological products creation	NewTechProd	Product Innovation	Capture the trend of companies creating new products and integrating new technologies.	Global Entrepreneurship Index 2018

Table 1 (continued)

Constructs	Indicator (Observable variables)	Abbreviation	Pillar / indicator (given data)	Pillar / indicator Description (given data)	Source
	Process Innovation	ProcessInnov	Process Innovation	Captures the use of new technologies by emerging companies, with access to high-quality human capital in STEM fields to conduct applied research.	Global Entrepreneurship Index 2018
Financial Attraction (FA)	Available Risk Capital	RiskCap	Risk Capital	Measures the availability of risk capital to meet growth aspirations. Two types of financing are combined: informal investment and the institutional depth of the capital market.	Global Entrepreneurship Index 2018
	Credit	Credit	Credit	Measures an economy's capacity to provide the financial resources that innovative companies need to develop and commercialize their products and services, through bank loans and government investment in innovation.	Global Innovation Index 2023
	Financial Facilitation	FinancFacil	Financial Facilitation	Reflects various financial aspects that drive startups, enables financial transactions over the internet, and provides platforms for providers and users of financial sources.	Digital Platform Economy Index 2020
Growth and Sustainability over Time (HighGrowth)	High Growth	High Growth	High Growth	Assesses businesses' growth intentions and their strategic capabilities to achieve that growth. It is a composite measure of the percentage of high-growth firms that intend to hire at least ten people and plan to grow by more than 50% in five years, the availability of venture capital, and the sophistication of business strategy.	Global Entrepreneurship Index 2018

The starting point is the theoretical justification that supports the dependency relationships, examining each proposed relationship from a theoretical perspective to ensure that the results are conceptually valid (Hair et al., 2007). The SEM method is used to test theoretical assumptions with empirical data (Haenlein & Kaplan, 2004).

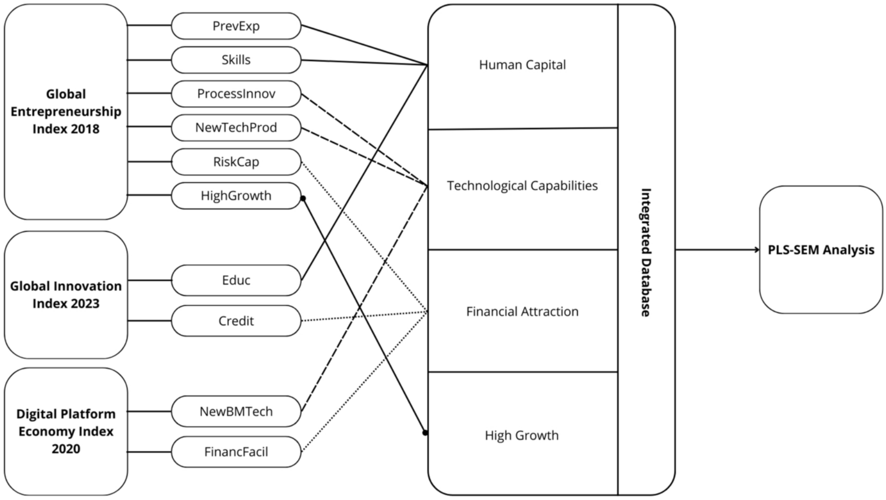

Fig. 2 Data Integration for Construct Development, (Source: the authors, 2025)

Structural equation models assess in a single, systematic and integrative analysis, the measurement model, understood as the relationships between the latent variables and their indicators; and the structural model, which corresponds to the part of the complete model that proposes relationships between the latent variables. Such relationships reflect substantive hypotheses based on theoretical considerations (Gefen et al., 2000).

A nomological network is constructed, incorporating the constructs of Human Capital, Technological Capability, Attraction of Financing, and Growth and Sustainability over Time, along with their respective indicators. Both the structural model (inner model in PLS-SEM) and the relationships (paths) between the indicators and constructs in the measurement models are explicitly represented by the nomogram. The results are interpreted in two stages: in the first, the evaluation of feasibility and validity of the measurement model is analyzed and in the second, the evaluation of the structural model (Hair et al., 2017). The assessment of the measurement model is carried out by evaluating the relationships between the indicators (observable variables) and the constructs. Finally, the assessment of the structural model is carried out, to assess the sign, magnitude and relevance of the relationships between the constructs (Sánchez-Franco et al., 2019). To carry out the different analyses, Smart PLS software version 4.1 is used.

Measurement model assessment

The constructs of Human Capital and Technological Capability have been estimated in mode B, which means they are formative measurement models. The construct of Financial Attraction has been estimated in mode A, which means it is a reflective measurement model. The formative measurement model assumes that the variance of a construct is fully explained by a block of indicators and its error term. The measures or indicators of the construct represent characteristics that collectively explain the concept contained in the construct, then changes in the indicators imply changes in the construct. For its part, the reflective measurement model assumes that the variance of a block of effects indicators is fully explained by an unobserved variable and its random errors. The indicators are competitive with each other and represent manifestations of the construct, in the sense that each measure is determined by the construct itself (Jarvis et al., 2003). Special attention should be paid to model identification in any PLS-SEM (Henseler et al., 2016), so that each construct requires a nomological network to be evaluated (Cepeda-Carrión & Cepeda-Carrion, 2018).

The assessment of a formative measurement model involves examining the following aspects at the indicator level: assessment of multicollinearity, relative contribution of the weights, assessment of the loadings and their significance. The discriminant validity of each construct is also calculated. Conversely, the assessment of the reflective measurement model evaluates the individual reliability of the indicators, construct reliability, convergent validity, and discriminant validity (Hair et al., 2021).

Structural model assessment

An evaluation of the structural model is conducted to verify the validity of the hypotheses and assess the significance and magnitude of the relationships between the different variables. Path coefficients are the most important outcome of this model and indicate the change in a dependent variable resulting from a one-unit change in an independent variable while holding all other independent variables constant. The bootstrap confidence intervals of the path coefficients aid in generalizing the sample to the population (Cepeda-Carrión & Cepeda-Carrion, 2018).

To assess the structural model, it is necessary to review potential multicollinearity problems, evaluate the algebraic sign, magnitude, and statistical significance of the path coefficients, assess the coefficient of determination (R^2) and the effect sizes (f^2) (Hair et al., 2021).

Predictive performance of the model

The predictive power is evaluated to determine the model's ability to predict values of the dependent constructs from the independent constructs in future observations. This is done through a cross-validation process, using holdout samples (Sánchez-Franco et al., 2019).

Results

The PLS-SEM algorithm has been calculated. The results of this model are displayed in Fig. 3, which shows the factor loadings of each indicator, the path coefficients, and the R^2 value.

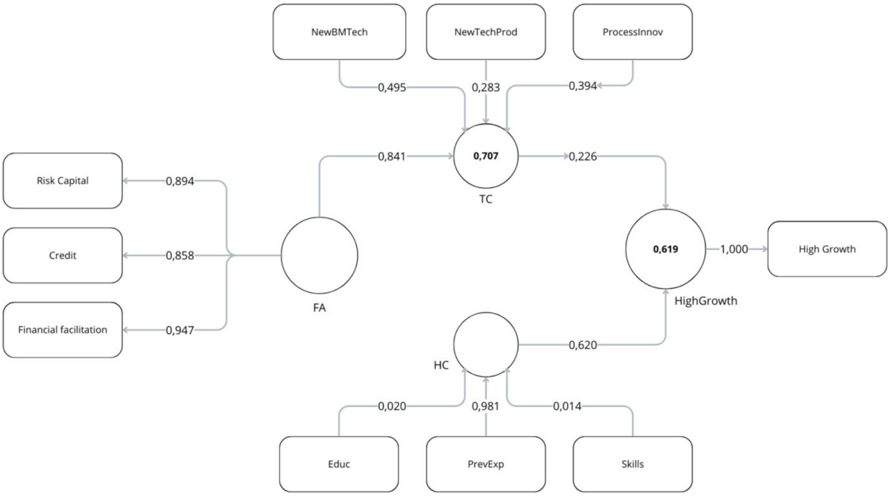

Fig. 3 PLS-SEM Model Results, (Source: the authors, 2025)

Table 2 VIF collinearity statistic and outer weights of indicators

Construct	Indicator	VIF	Outer Weights
HC	Educ	2.304*	0.020
	PrevExp	1.812*	0.981
	Skills	1.483*	0.014
TC	NewBMTech	2.090*	0.495
	NewTechProd	1.390*	0.283
	ProcessInnov	2.064*	0.394

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

Measurement model

An assessment of the formative measurement model is conducted. Multicollinearity is assessed using the variance inflation factor (VIF)$\leq$3.3 for each of the indicators that make up the formative constructs (Hair et al., 2019). In Table 2, we observe that this relationship holds.

Regarding the relative contribution of the indicators for each construct, we have that: for Human Capital, the indicator with the greatest weight is Prior Work and Entrepreneurial Experience, while, for Technological Capacity, the indicator with the greatest weight is the Creation of Business Models based on New Technologies, followed by the Process Innovation.

To apply the significance criterion for weights and loadings and continue with the validity of the measurement model, the two-tailed bootstrapping method is used, which is based on generating new pseudo-samples of the same size as the original sample, by repeated sampling of the available data. The indicator will be significant if p is less than 0.05 (Dijkstra & Henseler, 2015). Table 3 provides the following insights: (1) The only significant indicator for the Human Capital construct is Prior Work and Entrepreneurial Experience. This suggests that this indicator has a strong and statistically significant relationship with the overall Human Capital construct. (2)

Table 3 Significance criterion for weights and loadings

Construct	Indicator	Original Sample (O)	Sample Mean (M)	p-Value	Confidence Interval 2.5%	Confidence Interval 97.5%	External Loadings (λ)
HC	Educ	0.020	0.020	0.873	−0.239	0.247	0.684
	PrevExp	0.981	0.969	0.000*	0.806	1.110	1.000*
	Skills	0.014	0.021	0.903	−0.184	0.267	0.396
TC	NewBMTech	0.495	0.486	0.000*	0.287	0.665	0.911*
	NewTechProd	0.283	0.281	0.003*	0.102	0.475	0.718*
	ProcessInnov	0.394	0.397	0.000*	0.204	0.595	0.878*

Note. * Indicates that the corresponding value meets the criteria described

Table 4 Heterotrait-Monotrait ratio (HTMT) matrix

	FA	TC	HC	HighGrowth
FA				
TC	0.885*			
HC	0.825*	0.657*		
HighGrowth	0.739*	0.633*	0.768*	

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

Loading of the Educational Level indicator is high, indicating its importance. While not as influential as Prior Work and Entrepreneurial Experience, Educational Level still plays a significant role in the Human Capital construct. (3) All components of the Technological Capability construct have been found to be statistically significant. This implies that each of these indicators contributes meaningfully to the overall Technological Capability construct.

Discriminant validity ensures that a construct is distinct and not redundantly like other constructs within the model. In formative models, this is crucial to ensure that each construct represents a unique concept and is not excessively correlated with other formative or reflective constructs (Urbach & Ahlemann, 2010). To assess discriminant validity in formative models, the HTMT index is calculated as the average of the Heterotrait-heteromethod correlations (correlations between indicators measuring different constructs) divided by the average of the Monotrait-heteromethod correlations (correlations between indicators measuring the same construct). If the Monotrait-heteromethod correlations are greater than the Heterotrait-heteromethod correlations, then there is discriminant validity. The HTMT index should be less than or equal to 0.85 or 0.9 (Henseler et al., 2016). The resulting matrix can be observed in Table 4, which demonstrates the discriminant validity of the variables with formative criteria.

Once the assessment of the formative measurement model is completed, the assessment of the reflective measurement model is carried out. Initially, the individual reliability of the indicators is calculated, for which the outer loading (λ) must be greater than or equal to 0.707 (Hair et al., 2021). As shown in Table 5, this condition is satisfied for every indicator comprising the Financial Attraction and Growth and Sustainability over Time constructs, indicating that the individual reliability of the constructs is adequate.

Table 5 Individual Indicator reliability

Construct	Indicator	External Loadings (λ)
FA	RiskCap	0.894*
	Credit	0.858*
	FinancFacil	0.947*
HighGrowth	High Growth	1.000*

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

Table 6 Reliability and convergent validity of the construct

Construct	Cronbach's Alpha	Composite Reliability (ρc)	Dijkstra Henseler (ρa)	AVE
FA	0.883*	0.928*	0.908*	0.811*

Note. * Indicates that the corresponding value meets the criteria described

Table 7 Discriminant Validity–Fornell-Larcker criterion

	FA	HighGrowth
FA	(0.900)	
HighGrowth	0.699	(1.000)

To evaluate internal consistency, that is, the reliability of the construct, Cronbach's alpha (Hair et al., 2021), composite reliability (ρc) (Ali et al., 2018) and Dijkstra Henseler (ρa) are used (Dijkstra & Schermelleh-Engel, 2014).

All these indicators must be greater than or equal to 0.7. Additionally, to determine convergent validity, which is the degree to which the construct converges to explain the variance of its items, the average variance extracted (AVE) is calculated. The AVE must be greater than or equal to 0.5. This indicates that the construct explains at least 50% of the variance of its items (Hair et al., 2019). Table 6 provides evidence that all these conditions are met for the Financial Attraction construct.

On the other hand, discriminant validity indicates the extent to which a given construct is different from other constructs in the structural model (Hair et al., 2019). To assess discriminant validity, it is necessary to evaluate the Fornell-Larcker criterion and the HTMT index.

The Fornell-Larcker criterion (√AVE) considers the amount of variance that a construct captures from its indicators, which should be greater than the variance that the construct shares with other constructs. Thus, to achieve discriminant validity, the square root of the AVE of a construct must be greater than the correlation it has with any other construct (Fornell & Larcker, 1981). Table 7 shows that discriminant validity is verified for the constructs Financing Attraction and Growth and Sustainability over Time. The square root of the AVE value for each construct is shown on the diagonal in parentheses. The remaining data in the table are correlations between the latent variables.

The HTMT index is a more sensitive measure for detecting weak discriminant validity. For example, the HTMT index between HighGrowth and FA is 0.739, which indicates good discriminant validity for these constructs.

Structural model

Once the formative and reflective measurement models have shown validity and reliability, the structural model is examined to see how well it predicts the formulated hypotheses. Collinearity, sign, magnitude and significance of the path coefficient, coefficients of determination ($R^2$and effect size (f^2) are the key analyzes to perform (Aparisi-Torrijo et al. 2023).

Variance inflation factor (VIF ≤ 3.3) is used to test collinearity (Hair et al., 2019). Table 8 shows that there are no multicollinearity issues among the antecedents of the Finance Attraction variable in influencing the dependent variable Growth and Sustainability over Time through Technological Capability. Additionally, there are no multicollinearity issues among the antecedents of the Human Capital and Technological Capability variables in explaining the same dependent variable.

By evaluating the algebraic sign, magnitude, and statistical significance of the path coefficients, we can understand the relationships between the constructs in the research model. The magnitude of a path coefficient ranges from −1 to 1. Higher values indicate a stronger relationship between the constructs, while values closer to 0 indicate a weaker relationship. If a path coefficient has the opposite sign of what was hypothesized, it suggests that the hypothesis is not supported by the data (Sarstedt et al., 2014). The level of significance is determined from the Student t value derived from the re-sampling or bootstrapping process. The 1-tailed technique is used, where $p<0.05$ to establish a confidence interval between 5% and 95%. Additionally, the signs of the path coefficients at the extremes should be consistent with the hypothesized direction. The coefficient of determination (R^2), which represents a measure of predictive value, should be between 0 and 1 for each construct to be considered acceptable (Hair et al., 2017). The higher the R^2 value, the greater the predictive ability. Chin (1998) considers values above 0.67 to be substantial, between 0.33 and 0.67 to be moderate, and below 0.33 to be weak. The minimum R^2 value according to Falk and Miller (1992) is 0.1. Effect sizes (f^2) are used to assess whether the omitted construct has a substantive impact on the endogenous constructs. Values between 0.02 and 0.15 are considered weak, those between 0.15 and 0.35 are considered moderate, and those above 0.35 indicate strong effects (Hair et al., 2017).

Figure 3; Table 9 present the results obtained after running the model. The hypotheses proposed in the model are positive, and so are the path coefficients for each of the paths. The p-values for each of the proposed relationships between the constructs are less than 0.05. The relationship between the constructs FA → TC is strong (0.841), as is the relationship HC → HighGrowth (0.620). The relationship between TC → HighGrowth (0.226) is weak. All these considerations and their results support hypothesis H1, H2, and H3.

Table 8 Variance inflation factor (VIF) for antecedent variables

	FA	TC	HC	HighGrowth
FA		1.000		
TC				1.759
HC				1.759
HighGrowth				

Table 9 Structural model hypothesis test results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t -Statistics (O/STDEV)	*p*-Value
1. FA → TC	0.841	0.844	0.028	30.259	0.000*
2. TC → HighGrowth	0.226	0.233	0.079	2.853	0.002*
2. HC → HighGrowth	0.620	0.618	0.079	7.854	0.000*

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

Table 10 Effect size

	FA	TC	HC	HighGrowth
FA		2.411*		
TC				0.076
HC				0.574*
HighGrowth				

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

For TC, an R^2 of 0.707 (a substantial value) was obtained, and for HighGrowth, an R^2 of 0.619 (a moderate value) was obtained. This means, on the one hand, that 70.7% of the variance in Technological Capability (TC) is explained by the Financial Attraction Factors (FA), indicating that the latter have a very strong influence on Technological Capability. On the other hand, 61.9% of the variance in Growth and Sustainability over Time (HighGrowth) is explained by Technological Capability (TC) and Human Capital Factors (HC), showing that the fit is adequate and evidencing that TC and HC are reasonably good predictors of the growth and sustainability over time of NTBFs.

Table 10 presents the effect sizes, allowing us to identify the importance of each predictor in the PLS-SEM model. The relationship between the constructs FA → TC = 2.411 is extremely high, indicating that the Financial Attraction Factors (FA) have an extremely strong impact on Technological Capability (TC). The relationship between the constructs TC → HighGrowth = 0.076 indicates that Technological Capability (TC) has a relatively low impact on Growth and Sustainability over Time (HighGrowth). Finally, the relationship between the constructs HC → HighGrowth = 0.574 suggests that Human Capital Factors (HC) have a considerably strong impact on the Growth and Sustainability over Time (HighGrowth) of NTBFs.

Model predictive power

To assess the model's predictive capability and confirm the robustness of the proposed theoretical relationships (Financial Attraction → Technological Capability → High Growth and Human Capital → High Growth), we employed cross-validation (Q^2). We utilized the PLS prediction algorithm developed by Shmueli et al. (2016) implemented in SmartPLS software. Positive Q^2 values indicate the model's predictive relevance, signifying its ability to accurately predict future values of the dependent constructs. The Q^2 value for Technological Capability (TC) was 0.690 and for High Growth it was 0.596. These high Q^2 values demonstrate the model's strong predictive ability, suggesting that the proposed relationships not only explain the observed data effectively but are also valuable for predicting future outcomes. This reinforces the model's practical utility in strategic decision-making and planning the development of NTBFs.

Discussion and conclusions

The purpose of this study is to build and validate a model using PLS-SEM to examine whether the constructs of Human Capital, Technological Capability, and Financing Attraction are positively related to the growth and sustainability over time of NTBFs. Additionally, this study aims to analyze the level of contribution of each construct.

This study provides strong support for Hypothesis 1 (H1), demonstrating a significant positive relationship between human capital and NTBF sustainability over time. The results (see Table 2; Fig. 3) reveal that prior work and entrepreneurial experience were the most influential predictors of high growth, a finding that underscores the critical role of accumulated skills and practical experience in navigating the challenges inherent in the NTBF environment (Helfat & Martin, 2015; Lim & Busenitz, 2020). This emphasis on the importance of practical experience aligns with Garcia-Cabrera et al. (2021), who highlighted the significant influence of knowledge resources derived from the management team and access to external knowledge sources on innovation and firm performance. Our findings, however, present a more nuanced perspective than that presented by Jiao et al. (2021), who reported a smaller, yet significant, correlation between entrepreneurial experience and firm performance. Jiao et al. (2021) also identified several moderating factors—experience type, firm type, and cultural context—that influence this relationship. The absence of such moderating factors in our analysis may account for the stronger relationship observed in this study between prior work experience and high growth.

The impact of educational level, while statistically significant, was less pronounced than that of prior work and entrepreneurial experience. This suggests that practical experience is particularly crucial in the initial stages of an NTBF, a finding that contrasts with Colombo and Grilli (2005), who emphasized the positive effect of industry-specific technical experience on firm performance. Our findings, therefore, highlight the significance of practical, entrepreneurial experience over formal education in the early stages of an NTBF, supporting Garcia-Cabrera et al.'s (2021) emphasis on the role of both internal and external knowledge resources. Further research is needed to explore the complex interplay between various forms of human capital and their influence on NTBF success, potentially investigating the moderating effects identified by Jiao et al. (2021) and the contrasting perspectives of Colombo and Grilli (2005) regarding the relative importance of specific vs. general entrepreneurial experience.

The results strongly support Hypothesis 2 (H2), indicating a significant positive relationship between technological capability and NTBF sustainability over time. The creation of technology-based business models emerged as the most significant predictor of high growth, a finding consistent with the work of Eurico Soares de Noronha et al. (2024) and Ahn et al. (2022), who emphasized the importance of developing effective business models that leverage technological capabilities to gain a competitive advantage. This finding is further supported by the initial analyses, which revealed that the Creation of Business Models Based on New Technologies indicator held the greatest weight within the Technological Capability construct (see Table 2, Fgure 3). This highlights the critical importance of not only technological innovation itself, but also the capacity to effectively translate these innovations into commercially viable and sustainable business models.

While process innovation also contributed significantly to technological capability, its impact proved to be less potent than that of business model based on new technologies development. This aligns with the conclusions of Khaksar et al. (2017) and Hindle and Yencken (2004), who underscored the importance of not only technological innovation but also the successful implementation of these innovations within effective business models to enhance growth and value creation. Management teams must focus not only on technological innovation but also on strategically structuring their business models to maximize the impact of their technological advancements. This integrated approach of combining technological innovation with effective business model based on new technologies design, is key to achieving a sustainable competitive advantage and ensuring that technological innovations translate into commercial success and long-term sustainability.

The strong positive relationship between Financial Attraction (FA) and Technological Capability (TC), as revealed by the results, provides robust support for Hypothesis 3 (H3). This significant and positive correlation underscores the critical role of funding in driving technological development and innovation within NTBFs. The indicators of Risk Capital, Credit, and Financial Facilitation all significantly contributed to the Finance Attraction construct (see Table 2; Fig. 3), demonstrating that the firm's ability to manage and obtain diverse funding sources is essential for financial success and attracting external investment. This aligns with Bruton and Rubanik (2002), who emphasized the resource-intensive nature of technological innovation, and Knockaert et al. (2010), who highlighted the importance of financial resources for the performance of technology-based firms. Access to sufficient capital enables firms to invest in R&D, acquire necessary technology, and assemble skilled personnel, ultimately leading to enhanced technological capabilities. This finding is further supported by the strong positive and direct relationship observed between FA and TC (see Table 9; Fig. 3), showing how attracting sufficient financing directly fuels technological development. Moreover, Singh & Mungila-Hillemane (2023) showed that adequate resources provide the operational flexibility needed for maintaining a sustainable competitive advantage, and Kumar and Singh (2019) linked this operational flexibility to technological innovation. These findings, coupled with our own, demonstrate the crucial role of attracting financial resources in driving technological advancement and fostering innovation within the NTBF sector. The ability to secure diverse funding sources is, therefore, paramount for achieving both innovation and long-term sustainability.

While both Human Capital (HC) and Technological Capability (TC) significantly and positively influenced NTBF sustainability over time, the effect size of HC was considerably stronger than that of TC (see Table 9; Fig. 3). Although the combined effects of HC and TC explain a substantial 61.9% of the variance in growth and sustainability over time, this leaves 38.1% of the variance unexplained. This suggests the influence of other factors not included in this model. Nevertheless, HC and TC remain reasonably good predictors of long-term growth and sustainability for NTBFs.

The relatively greater impact of HC underscores the crucial role of experienced and skilled management teams in effectively leveraging technological capabilities and navigating the complex challenges inherent in the startup environment. This dominance of human capital may reflect the critical need for strong leadership and managerial expertise, particularly in the early stages of an NTBF, to successfully translate technological innovations into sustainable competitive advantage.

While financial attraction has a significant impact on technological capability, the influence of technological capability on growth and sustainability proved to be comparatively less decisive. This highlights the importance of human resources in driving both technological advancement and long-term business success.

The model's strong predictive power, as evidenced by the high Q^2 values, further supports its practical utility in forecasting the performance of NTBFs based on factors such as human capital, technological capability, and financial attraction.

This study contributes to the understanding of the determinants of NTBFs growth, which can guide both business practice and future academic research. There are not many studies that combine technological factors with human capital and financing attraction in the context of sustainable and long-lasting entrepreneurship. This research is expected to stimulate similar dynamics of knowledge creation, contributing to the growth of the research field on management teams, their influence on NTBFs, and the development of more complete theories on the growth and long-term sustainability of these firms.

Implications, limitations and future research

The findings of this study underscore the fundamental importance of human capital, technological capability, and financing attraction as key determinants of the growth and sustainability of NTBFs over time. Based on the results, it is recommended that entrepreneurs prioritize the composition of management teams consisting of individuals with prior entrepreneurial and work experience, as these experiences have a significantly greater impact on the long-term performance and sustainability of NTBFs.

Considering these findings, it is beneficial for entrepreneurs to foster a diverse management team by actively seeking individuals with varied backgrounds and experiences, which can encourage innovative problem-solving and adaptability within their organizations. Additionally, investing in ongoing training and mentorship is crucial. By emphasizing the development of soft skills and practical knowledge through targeted training programs and mentoring relationships, entrepreneurs can better equip their management teams for the challenges they may face. It is essential to recognize that the empirical knowledge acquired through practical experience may prove to be more significant than the level of formal education attained. Therefore, in the process of team selection, it is imperative to pursue individuals who not only possess complementary skills but also have a solid track record within the business environment.

Moreover, attracting financing is critical for the development of technological capability. Entrepreneurs should ensure they have robust strategies in place to secure investments, as access to financial resources facilitates not only technological innovation but also the implementation of effective business models that can adapt to a dynamic market landscape. Policymakers should enhance access to diverse financing options by promoting financial facilitation, diversifying debt sources, and encouraging venture capital investment. They should also facilitate access to microloans, crowdfunding, and government-backed loans to improve financing alternatives for NTBFs.

To further support sustainable entrepreneurship over time, it is vital for policymakers to create favorable regulatory environments that simplify access to funding for early-stage ventures, ensuring that NTBFs can secure the necessary resources for growth and innovation. Supporting initiatives that enhance collaboration among stakeholders - including educational institutions, industry partners, and financial organizations - can build a stronger ecosystem that fosters the growth of NTBFs.

For policymakers, it is crucial to cultivate an environment that promotes the development of human capital through targeted training and skill development programs for entrepreneurship. This includes implementing policies that incentivize investment in research and development, as well as establishing networks that connect entrepreneurs with financial resources and experienced advisors. By strengthening these dynamics, it is possible to contribute to a more resilient business ecosystem that fosters innovation and sustainable growth for NTBFs.

Despite these valuable insights, this study has several limitations that should be considered when interpreting the results. First, the reliance on cross-sectional data from the Global Entrepreneurship Index (2018), the Digital Platform Economy Index (2020), and the Global Innovation Index (2023) limits our ability to establish definitive causal relationships and understand the temporal dynamics of these relationships. While these indices provide valuable insights into the entrepreneurial ecosystem and innovation capacity at the country level, variations in data quality and availability across countries might affect the generalizability of our findings.

The PLS-SEM methodology, while appropriate for analyzing complex relationships and making predictions, does not allow for definitive conclusions regarding causality. Furthermore, the chosen indicators, while theoretically relevant, do not encompass all factors influencing NTBF sustainability over time, and the use of aggregated country-level data might mask important firm-level variations.

Finally, the diverse economic, social, and cultural contexts in which NTBFs operate could significantly influence the applicability of our findings.

Future research should address these limitations by employing longitudinal studies to track the dynamic interplay of variables over time and using more granular, firm-level data to gain a deeper understanding of the factors influencing individual NTBFs performance. Furthermore, a broader range of indicators reflecting contextual factors, such as industry-specific characteristics and regulatory environments, could improve the scope and accuracy of future analyses.

Investigate whether targeted investments in human capital, such as education and training for management team members, constitute an effective strategy for increasing NTBFs performance. This research should consider the impact of various training and development approaches, examine differences in the impact of general vs. specific human capital, and explore the influence of different types of education and prior experience on firm outcomes. The influence of team size and industry context on these relationships should also be analyzed.

Further exploration is needed to understand the dynamic interplay between technological capabilities, innovation processes, and firm performance. Future studies should analyze the relationship between specific technological investments and firm outcomes, considering different innovation strategies and organizational structures. A deeper analysis of how technological intensity interacts with funding and human capital is also necessary.

Future research should assess the effectiveness of different financing strategies for NTBFs, taking into consideration the advantages and limitations of various funding sources (e.g., venture capital, debt financing or government grants). Investigate the influence of financial facilitation programs and policies on access to finance and the role of fintech solutions in expanding credit availability for NTBFs.

By addressing these limitations and exploring these future research directions, we can gain a more comprehensive understanding of the complex factors driving NTBFs sustainability over time.

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Declarations

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