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Startup typologies in an emerging economy: Financial barriers, ecosystem support, and financing behavior

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Abstract

***PURPOSE**: This study examines whether ICT startups operating within a single emerging-economy ecosystem form distinct typologies based on perceived financial barriers and ecosystem support, and how these typologies relate to financing behavior, financing source composition, and firm characteristics. The study is framed as an exploratory, cross-sectional typology analysis of within-ecosystem heterogeneity. **METHODOLOGY**: The analysis is based on survey data collected from 111 ICT startups in Albania during March–May 2025. K-means clustering was applied using standardized scores of perceived financial barriers and ecosystem support. Differences across typologies were examined using ANOVA, Tukey post-hoc tests, Monte Carlo p-values for sparse financing-source tables, Cramer's V and financing-diversification checks. A parsimonious multinomial logistic regression model was used to profile typology membership. **FINDINGS**: Three typologies are identified: financially constrained, ecosystem-enabled, and ecosystem-disconnected startups. The typologies differ significantly in access to finance and startup performance. They also differ in selected financing sources, especially bootstrapping and crowdfunding. The total number of financing sources used does not differ significantly across groups, indicating differences in financing-source composition rather than overall diversification. Typology membership is profiled by prior startup experience, firm size, and lifecycle stage. **IMPLICATIONS:** The findings show that ecosystem support is not experienced uniformly by startups operating in the same setting. The study contributes to entrepreneurial ecosystem research by highlighting structured heterogeneity within a single ecosystem, and to entrepreneurial finance research by linking financing behavior to startups' perceived support-and-constraint profiles. For practice, the results suggest that startup support policies should be differentiated across financially constrained, ecosystem-enabled and ecosystem-disconnected firms. **ORIGINALITY & VALUE**: The study advances a typology-oriented perspective by showing that ICT startups within the same emerging-economy ecosystem may experience financial barriers and ecosystem support in different combinations. It also distinguishes financing-source composition from financing diversification, showing that startup groups may differ in the types of financing sources used even when the number of sources does not differ significantly. The study provides evidence from Albania, an underexplored small startup ecosystem where structural differentiation among startups is especially relevant.*

***Keywords:** entrepreneurial ecosystems, startup typologies, startup finance, financial constraints, ecosystem support, financing behavior, financing-source composition, digital entrepreneurship, ICT startups, emerging economies*

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INTRODUCTION

Entrepreneurial ecosystems are widely used to explain how startups access resources and develop over time, especially in settings marked by resource scarcity and institutional gaps (Spigel, 2017; Stam, 2015; Stam & van de Ven, 2021). Entrepreneurial activity depends both on firm-level capabilities and on the wider set of actors, institutions and support structures through which opportunities are identified and resources are accessed. Most of this evidence comes from advanced economies, where financing systems, support organizations and entrepreneurial infrastructures are more developed. Although this literature has advanced understanding of how ecosystem-level conditions are associated with entrepreneurial activity, it has also been criticized for treating ecosystems as relatively coherent environments and for paying insufficient attention to differences among firms operating within the same ecosystem (Wurth et al., 2022, 2023). This limitation is important because startups located in the same national or city-level ecosystem may not experience the same degree of support, network access or financing opportunity. In emerging economies, entrepreneurial ecosystems often operate under very different conditions. Startups in these contexts face institutional gaps, weak coordination, fragmented support structures and limited access to specialized finance, all of which can restrict their ability to scale and commercialize new ideas (Bruton et al., 2018; Qoriawan & Apriliyanti, 2023; Wurth et al., 2023). These challenges are particularly relevant for information and communication technology (ICT) startups, which depend on rapid scaling, specialized knowledge and financing arrangements suited to intangible assets and high uncertainty (Hall & Lerner, 2010; Ngoasong, 2018). ICT startups often need financing beyond conventional small-business credit because their assets are intangible, their revenues are uncertain, and their growth prospects are difficult to assess. Their financing conditions therefore depend not only on credit availability, but also on the suitability of seed capital, equity finance and ecosystem intermediation.

Albania provides a relevant setting because its startup ecosystem is expanding but remains structurally young. Recent assessments describe it as being in the early Activation Phase, with limited startup experience, resource constraints, and activity concentrated mainly in Tirana, while also noting stronger local connectedness, founder quality and growing international support through programs such as EU4Innovation and EBRD-backed initiatives (Startup Genome, 2025; StartupBlink, 2026).

This does not mean that finance is generally inaccessible across the Albanian economy. General access-to-finance conditions have improved in Albania (OECD, 2024). The constraint examined here is narrower: startup-oriented finance. Albanian startups still rely heavily on grants and bootstrapping, while angel investment and domestic venture-capital infrastructure remain limited, creating early-stage funding gaps between accelerator participation and follow-on investment (Startup Genome, 2025). This pattern is consistent with broader evidence from the Western Balkans, where startups' access to external finance remains constrained by weaker credit conditions, shallower venture capital markets, and less developed investor protection mechanisms (Kruja & Irimia-Diéguez, 2025). This makes Albania useful for examining how ICT startups in the same compact ecosystem occupy different perceived support-and-constraint positions.

Financial barriers remain a central challenge in these environments, including limited seed funding, weak venture capital markets, and restricted access to formal credit (Beck & Demirguc-Kunt, 2006; Samara & Terzian, 2021). In this study, financial barriers are examined as perceived financial barriers: founders' subjective assessments of the difficulty, suitability and accessibility of finance for their ventures, rather than direct measures of the objective supply of credit or investment. Recent studies on digital and ICT startup ecosystems in emerging regions consistently identify funding scarcity and uneven support as key obstacles, often compounded by regulatory frictions and weak coordination among ecosystem actors (Lee & Kim, 2025; Qoriawan & Apriliyanti, 2023). Moreover, ecosystem intermediaries such as incubators and accelerators do not necessarily provide financial resources directly; rather, they may indirectly facilitate startups' access to finance through networks, legitimacy, and brokerage functions (Wurth et al., 2022). Ecosystem support is not equally accessible to all startups and often depends on relationships, networks and intermediaries (Dourado Freire et al., 2023; Spigel & Harrison, 2018).

Most existing studies have analyzed these relationships through variable-centered approaches that estimate average associations between ecosystem conditions and startup outcomes (Stam & van de Ven, 2021). This has generated valuable insights, but it leaves limited room to understand how startups within the same ecosystem combine support and constraints in different ways, especially in relation to their financing behavior. Configurational perspectives offer a useful alternative because they show how different conditions combine to produce distinct organizational patterns rather than average effects (Fiss, 2011; Meyer et al., 1993). Typological and cluster-based approaches have been used in related firm-level research to capture heterogeneity that average-effect models may overlook. This study therefore uses K-means clustering as an

exploratory tool to identify coherent startup groups based on two theoretically central dimensions: perceived financial barriers and perceived ecosystem support. The aim is classification and interpretation, not causal estimation.

This issue is particularly relevant in emerging economies (Klein & Braido, 2024; Quinones et al., 2021). Startups operating in the same ecosystem may differ substantially in how they assemble financing portfolios, rely on different funding sources, and navigate constraints through alternative financing strategies. Such differences matter because financing choices are closely linked to how ventures sustain operations, manage risk and pursue growth under conditions of uncertainty. In this study, financing behavior refers to whether and how startups use particular funding sources, such as personal savings, bootstrapping, grants, bank loans, crowdfunding or investor capital. Financing portfolio composition refers to the overall combination of sources used by each firm. The distinction is important because two startups may both use external finance, yet differ substantially in the mix of informal, public, debt-based and equity-oriented sources that constitute their financing portfolios.

This study examines whether ICT startups operating within a single emerging-economy ecosystem form distinct groups based on different combinations of perceived financial barriers and ecosystem support and assesses how these groups differ in their financing behavior and financing portfolio composition. Typologies are defined here as internally coherent groups of startups that share similar combinations of perceived constraints and support conditions. The study uses a typology-oriented configurational perspective and does not focus on modeling direct or mediating effects among ecosystem conditions and startup outcomes. Here, a configurational perspective means examining how multiple conditions interact to form distinct startup profiles, rather than focusing on the separate effects of individual variables. This approach helps identify internally coherent startup groups and systematically examine differences in financing strategies and funding structures, while using performance only as a secondary validation measure. The practical relevance of this approach is that policies based on average ecosystem conditions may overlook firms that experience the same ecosystem in markedly different ways. Identifying typologies can therefore inform more targeted support instruments for startups that are financially constrained, ecosystem-enabled or weakly connected to formal support structures.

Using survey data from 111 ICT startups in Albania, an emerging economy, this study addresses the following research questions:

RQ1. What exploratory typologies can be identified among ICT startups operating within the same emerging-economy ecosystem based on perceived financial barriers and ecosystem support?
RQ2. How do these typologies differ in financing behavior and financing-source composition, and do they also differ in overall financing diversification?
RQ3. Which founder and firm-level characteristics are associated with typology membership?

The findings identify three startup typologies: financially constrained, ecosystem-enabled, and ecosystem-disconnected. Differences among these groups are most evident in access to finance, startup performance, and financing-source composition, rather than in the number of funding sources they use. Selected founder and firm characteristics, including prior startup experience, access to finance, firm size and lifecycle stage, are also associated with typology membership.

The study contributes to the literature in four ways. First, it advances entrepreneurial ecosystem research by showing that startups in the same ecosystem may access and use support conditions differently. Second, it brings a configurational perspective to the study of ICT startups in emerging economies by showing how distinct combinations of support and constraints correspond to distinct financing patterns. Third, it contributes to entrepreneurial finance research by showing that financing behavior and financing source composition are associated with startups' ecosystem position, not just firm-level financial choices. Fourth, it provides empirical evidence from an underexplored emerging economy, where ecosystem fragmentation and limited financial depth make such differentiation visible. The findings are not universally generalizable, but may be relevant to other small, concentrated and institutionally developing startup ecosystems. The remainder of the paper is organized as follows. The next section reviews the relevant literature and develops the hypotheses. The methodology section presents the research context, sample, measurement revision and analytical strategy. The results and discussion section reports and interprets the findings. The final section concludes by outlining contributions, implications, limitations, and directions for future research.

LITERATURE REVIEW

Ecosystem support in emerging economies

Entrepreneurial ecosystems are commonly conceptualized as interconnected constellations of actors, institutions, and resource associated with entrepreneurial activity and firm development (Autio et al., 2018; Stam, 2015). While this view has been largely developed in advanced economies, research increasingly shows that ecosystems in emerging economies operate under distinct structural and institutional constraints. Cao and Shi (2021) show that such ecosystems are often marked by resource scarcity, institutional voids, and fragmented support structures, which weaken coordination among actors and limit the development of specialized financial and innovation infrastructure. As result, ecosystem support tends to be less predictable and less evenly accessible than in more mature contexts. At the same time, the entrepreneurial ecosystem concept has been criticized for overstating coherence and underplaying variation among firms located in the same environment. Startups differ in visibility, legitimacy, founder networks, prior experience, and ability to use intermediaries. Ecosystem support should therefore be treated as unevenly perceived and unevenly accessed, especially where formal institutions and private finance markets remain incomplete. These conditions are especially relevant for ICT startups, which rely on rapid scaling, specialized knowledge and external networks to mobilize resources under uncertainty (Hall and Lerner, 2010; Ngoasong, 2018; Klein et al., 2019; Janeway, Nanda and Rhodes-Kropf, 2021). Their assets are often intangible, their early revenues are uncertain, and their growth prospects are difficult for conventional financiers to evaluate.

Evidence from startup financing and digital entrepreneurship research in emerging economies points to recurring funding gaps, regulatory frictions, weak investor networks,and infrastructural limitations (Ngoasong, 2018; Qoriawan & Apriliyanti, 2023; Samara & Terzian, 2021). Ecosystem support mechanisms such as incubators, accelerators, mentoring schemes, universities and public programs function less as direct funding providers. They function as intermediaries that may indirectly improve resource access by enhancing legitimacy, reducing information asymmetries, and connecting startups to investors and other institutional actors (Davalas & Angelaki, 2025; Dourado Freire et al., 2023; Kayser et al., 2023). Because support structures are often unevenly coordinated and used differently across firms, startups operating within the same ecosystem may still face different opportunities to access information, networks, and funding channels. Ecosystem support is therefore understood here not as a uniformly shared condition, but as a perceived and relational resource that shapes how startups engage with available financial resources.

Perceived financial barriers

Financial constraints have long been recognized as a major challenge for entrepreneurial ventures, especially in settings marked by underdeveloped capital markets, and institutional weaknesses (Beck & Demirguc-Kunt, 2006; Chundakkadan & Sasidharan, 2020; Hall & Lerner, 2010). In emerging economies, these constraints are often reinforced by limited risk capital, weak investor networks and regulatory uncertainty, which restrict startups' ability to secure external finance (Ferrucci et al., 2021).

These constraints are not only objective but also perceptual. Perceived financial barriers refer to entrepreneurs' subjective assessments of the difficulty, suitability or accessibility of external finance, including expectations of rejection, lack of information and perceived misalignment between financing instruments and business models (Cole & Sokolyk, 2016; Roper & Scott, 2009). Such perceptions may influence financing behavior independently of actual market conditions by affecting whether and how founders' approach external funding sources.

In ICT startup ecosystems, perceived financial barriers may be particularly pronounced due to valuation uncertainty, intangible assets and limited understanding of technology-based business models among investors and lenders (Quinones et al., 2021; Samara & Terzian, 2021). This is also consistent with recent review evidence showing that young and innovative startups often face financing difficulties because they lack historical data, proven performance metrics and transparency, which intensifies information asymmetry with external financiers (Kruja & Irimia-Diéguez, 2024). Under these conditions, founders may rely more heavily on internal or informal financing even when external options formally exist, which may, in turn, constrain growth. This makes perceived financial barriers relevant not only as constraints on resource acquisition, but also as factors that may generate different financing responses across ventures. In this study, perceived financial barriers are therefore treated as founder-level assessments of finance accessibility and suitability, not as direct measures of the objective supply of credit or investment.

Financing portfolios as behavioral expressions of positioning

Financing behavior can be observed through the financing portfolios that startups assemble over time. Financing portfolios provide a useful way to capture how startups navigate the constraints and opportunities of their ecosystem. They refer to the combination of funding sources used by firms, including internal funds, informal finance, public support and, where available, external equity (Block et al., 2018; Cassar, 2004; Berger & Udell, 2006). Prior research shows that these portfolios vary across stages of development and institutional contexts, reflecting not only funding needs, but also the structure of available opportunities.

In emerging economies, financing portfolios often reveal how startups adapt to constrained and uneven support environments. ICT startups may rely heavily on informal finance, bootstrapping, and public programs, particularly in the early stages, where formal capital remains limited. At the same time, ecosystem actors such as accelerators and innovation hubs can help ventures access early-stage support and partially bridge institutional gaps (Ngoasong, 2018; Quinones et al., 2021).

Entrepreneurial-finance theory provides a useful lens for interpreting these patterns. The pecking-order perspective suggests that firms tend to prioritize internal finance before moving toward external sources, largely because external capital is affected by information asymmetry and financing costs (Myers, 1984; Myers & Majluf, 1984). For young ventures, this logic is especially relevant because limited track records, intangible assets and uncertain revenues may increase dependence on founder resources, informal finance, or other accessible sources (Cassar, 2004). The financial-growth-cycle view further suggests that financing options should broaden as firms mature, accumulate credibility and become more visible to lenders or investors (Berger & Udell, 1998).

These pathways are not always stable. Limited investor availability, weak intermediation and scarce follow-on funding may disrupt financing trajectories and keep startups dependent on internal or contingent sources of finance (A. Z. Klein & Braido, 2024; M. Klein et al., 2019; Oladele et al., 2024). In small emerging ecosystems, this progression may be further constrained by thin domestic risk-capital markets and weak intermediation. For this reason, the present study distinguishes financing-source composition from financing diversification. Startups may differ in the types of financing sources they use, such as bootstrapping, grants, trade credit or crowdfunding, without necessarily relying on a larger number of sources. Financing portfolios are better understood not simply as technical funding choices, but as observable patterns reflecting how startups are positioned within their ecosystems and how effectively they mobilize available support and funding channels.

Toward a configurational and typological perspective

Research on ecosystem support, financial barriers and entrepreneurial finance consistently points to heterogeneity among startups operating within the same institutional context (Mason & Brown, 2014; Spigel & Harrison, 2018). Variable-centered approaches, which focus on average relationships between ecosystem conditions and firm-level outcomes, may obscure this within-ecosystem variation and offer limited insight into how multiple conditions combine within firms (Stam & van de Ven, 2021). Configurational perspectives offer an alternative by emphasizing that different outcomes may result from distinct combinations of conditions, rather than from single factors acting independently (Fiss, 2011; Misangyi et al., 2017). Typology-based approaches translate this logic into empirical analysis by identifying groups of firms with similar profiles that can be systematically compared (Ketchen & Shook, 1996; Meyer et al., 1993). This perspective is especially relevant in emerging-economy ecosystems, where fragmentation, institutional voids and uneven resource distribution are likely to generate diverse startup trajectories (Cao & Shi, 2021; Kayser et al., 2023; Qoriawan & Apriliyanti, 2023). It also aligns with research on digital entrepreneurship, which stresses the importance of context-specific resource mobilization and adaptive strategies in venture development (Klein & Braido, 2024; Ngoasong, 2018).

The literature suggests that startups operating within the same emerging-economy ecosystem are unlikely to experience financial barriers and ecosystem support in uniform ways. Different combinations of these two conditions may give rise to distinct startup typologies. These typologies are expected to differ in financing behavior and financing portfolio composition. Founder and firm level characteristics may also help profile differences in typology membership.

The conceptual argument is that perceived financial barriers capture information opacity and uncertainty surrounding young ICT ventures, while ecosystem support can reduce that opacity through signaling, network brokerage, legitimacy transfer and access to information channels. Where support is stronger, startups should be more visible to financiers and better positioned to use non-bank or investor-facing sources. Where support is weaker, startups are expected to remain

more dependent on internal, informal or transactional sources. These mechanisms link the typological classification to financing behavior without implying causal effects from cross-sectional data.

Accordingly, the following hypotheses are proposed:

H1: ICT startups operating within the same emerging-economy ecosystem can be grouped into exploratory typological profiles based on different combinations of perceived financial barriers and ecosystem support.
H2: The identified startup typologies are associated with systematic differences in financing behavior and financing portfolio composition, but not necessarily with overall financing diversification.
H3: Founder and firm level characteristics are associated with membership in different startup typologies.

METHODOLOGY

Research context

This study was conducted in Albania, a small, emerging economy in Southeast Europe characterized by a geographically concentrated, still-developing startup ecosystem. Recent ecosystem assessments estimate that Albania's broader startup ecosystem comprises approximately 400-420 companies, concentrated mainly in Tirana (Startup Genome, 2025). Building on this ecosystem-level context, the present study focuses more narrowly on independent ICT and ICT-enabled startups operating within this national startup ecosystem. Although the ICT sector has expanded steadily in recent years, early-stage financing channels remain underdeveloped. Entrepreneurial activity is primarily concentrated in Tirana, where incubators, accelerators, and donor-supported innovation programs operate. This setting provides a suitable context for examining within-ecosystem differentiation among ICT startups operating within the same institutional environment.

Research design and sample

This study adopts a cross-sectional survey design to identify structural heterogeneity among ICT startups. The design is exploratory and typology-oriented. It is not intended to estimate causal effects, but to identify whether startups can be grouped into internally coherent profiles based on perceived financial barriers and ecosystem support, and then to examine whether these profiles differ in financing behavior, portfolio composition, and firm characteristics.

The target population consisted exclusively of independent ICT startups operating in Albania. Firms were identified through multiple sources, including the national business registry using ICT-related activity codes, startup and innovation hubs in Tirana, accelerator and incubator participant lists, and professional ICT associations. To be eligible, firms had to be engaged in ICT-related activities and actively operating at the time of data collection. Founders and co-founders were selected as key informants because they are directly involved in financing decisions and strategic positioning. They were also appropriate respondents because the main constructs, perceived financial barriers and perceived ecosystem support, require respondents familiar with the venture's financing attempts and ecosystem interactions.

For this study, a startup was defined as an independent ICT or ICT-enabled venture founded within the previous ten years, actively operating in Albania, and pursuing an innovation-oriented or scalable business model in which digital technologies are central to the product, service delivery, or growth process. The sample excluded subsidiaries, branches of established corporations, public institutions, inactive firms and conventional SMEs that used ICT only for routine administration without a technology-based or scalable value proposition. ICT-enabled startups were included only when digital technology constituted a core element of the business model rather than a support function. This definition follows the logic of startup ecosystem assessments that distinguish technology-driven startups by age, independence, technology orientation and scalability, while adapting it to the Albanian registry and ecosystem context (Startup Genome, 2025).

The questionnaire was originally developed in English and translated into Albanian using a back-translation procedure. Two bilingual researchers independently translated and retranslated the instrument to ensure semantic equivalence. Minor discrepancies were resolved through discussion. A pilot test was conducted with ten ICT startup founders who were demographically similar to the final sample. The pilot resulted in minor wording and layout adjustments.

Data were collected online from March to May 2025. Invitation emails containing a survey link were sent directly to identified founders. Participation was voluntary and anonymous, and informed consent was obtained from all respondents. A total of 111 valid responses were retained for analysis. Because the sampling frame was compiled from overlapping

registry, ecosystem, and association sources, a precise, non-duplicated denominator could not be verified, and a formal response rate is therefore not reported. To assess potential non-response bias, early and late respondents were compared on key observable characteristics, including lifecycle stage, firm size and location. No substantively meaningful differences were observed.

The sample size is acceptable for an exploratory typology analysis with two clustering variables, where the solution is assessed through interpretability and stability checks rather than through population-level inference (Hair et al., 2019; Mooi & Sarstedt, 2014).

Sample characteristics

The sample reflects the characteristics of a young and knowledge-intensive startup population. Founders were relatively young, with the majority aged 25-44, and the gender distribution was balanced (55.9% male; 44.1% female).

In terms of firm development, startups were predominantly in early (58.6%) or growth (41.4%) stages. Market orientation was distributed across B2B, B2C and mixed strategies, while entrepreneurial activity was geographically concentrated in Tirana (61%), confirming its central role within the national ICT ecosystem. This geographic concentration is consistent with recent ecosystem assessments showing that Albanian startup activity remains strongly centered around Tirana and its surrounding support infrastructure.

Financing levels were generally modest, with most startups (80.2%) raising less than €50,000 and 19.8% securing larger investment rounds. Ownership structures were mainly sole proprietorships and limited liability companies, indicating relatively simple governance forms among ICT startups. These characteristics are consistent with an emerging startup ecosystem in which many ventures remain small, early-stage and dependent on founder resources, grants, informal finance, or limited external financing.

Conceptual and operational definitions of variables

The analysis focuses on four main constructs: perceived financial barriers (PFB), ecosystem support (ES), access to finance (AF) and startup performance (SP). All constructs were measured using multi-item Likert-type scales ranging from 1 (strongly disagree) to 5 (strongly agree) adapted from prior entrepreneurship and small business research.

Before calculating the composite scores, the items were screened for conceptual overlap with behavioral outcomes and financing-source measures. Items that captured behavior, funding outcomes or financing portfolio composition were excluded to avoid circularity between the clustering variables, comparison variables and financing-source outcomes.

Perceived Financial Barriers (PFB) were originally measured with eight items adapted from the entrepreneurial finance literature (Cowling & Sclip, 2023). The original item PFB2, "The requirements from financial institutions are not startup friendly," was excluded because it was conceptually broad and overlapped with general access-to-finance conditions rather than capturing a distinct perceived financial barrier. After this exclusion, the remaining seven items were renumbered sequentially as PFB1–PFB7 to avoid an item-numbering gap. Accordingly, the retained PFB2 in the final scale refers to the former PFB3 item, "Lack of collateral has prevented us from securing funding." The retained items capture founders' perceptions of difficulties in accessing external finance, collateral constraints, information asymmetry, application complexity, investor uncertainty, limited investor networks and perceived inaccessibility of external finance. Higher scores indicate stronger perceived financial barriers.

Ecosystem Support (ES) was measured with seven retained items adapted from entrepreneurial ecosystem research (Qian & Acs, 2023; Spigel & Harrison, 2018; Stam & van de Ven, 2021). The items assess perceived access to support programs, mentors, government initiatives, financial ecosystem actors, innovation culture, entrepreneurship events and university support. ES8 (participation in an incubator or accelerator) and ES9 (receipt of a public or donor grant) were excluded because they capture behavioral or funding outcomes rather than perceptions of ecosystem support. ES9 was also excluded because it overlaps with the financing-source indicator for grants or subsidies.

Access to Finance (AF) was measured with five retained items reflecting perceived ease of obtaining financing and satisfaction with financing conditions (M. Berger & Hottenrott, 2021; Block et al., 2018). AF6 was removed from the AF scale because it measures the use of multiple financing sources and therefore overlaps with financing diversification and portfolio composition.

Startup Performance (SP) was measured with nine self-reported items assessing revenue growth, customer expansion, team expansion, financial improvement and competitive progress over the previous twelve months (Chandler & Hanks, 1993; Dess & Robinson, 1984).

All constructs were operationalized as mean composite scores calculated from the retained items. The final measurement model contains 28 retained items: AF1-AF5, PFB1-PFB7, ES1-ES7 and SP1-SP9. Respondents also reported their use of specific financing sources through binary indicators, including personal savings, friends and family, retained earnings, bootstrapping, angel investors, venture capital, private equity, bank loans, trade credit, grants and crowdfunding. Financing diversification was calculated as the count of distinct sources used. Lifecycle stage was coded as a binary variable distinguishing early stage from growth stage firms.

Data analysis

The analysis proceeded in five stages. First, descriptive statistics were computed for the principal constructs, and the internal structure of the multi-item measures was assessed using principal component analysis (PCA) with varimax rotation, along with reliability analyses. The PCA was conducted on the 28 retained items. The Kaiser–Meyer–Olkin statistic, Bartlett's test of sphericity and Cronbach's alpha coefficients were used to examine measurement adequacy and internal consistency. These diagnostics are interpreted as evidence of internal consistency and an expected exploratory component structure, not as confirmatory validation.

Second, a K-means cluster analysis was conducted using standardized scores of perceived financial barriers and ecosystem support to identify internally coherent startup typologies. Standardization ensured equal weighting of the two clustering dimensions. Access to finance, startup performance, financing sources, financing diversification, lifecycle stage and other firm characteristics were not included in the clustering procedure. To select the retained cluster solution, the k = 2, k = 3, and k = 4 solutions were compared using silhouette coefficients, cluster-size balance, interpretability, and stability diagnostics. The K-means algorithm was run with 100 random initializations and a convergence tolerance of 0.000001 to reduce sensitivity to starting values. Outliers were assessed using the standardized PFB and ES scores before clustering. Cluster stability was further examined using bootstrap resampling and split-half validation, with the adjusted Rand index (ARI) used to assess the consistency of cluster assignments across repeated solutions.

Third, differences across the identified typologies were examined using variables that were not included in the clustering procedure. One-way analysis of variance (ANOVA), followed by Tukey post-hoc tests where appropriate, was used to assess differences in access to finance and startup performance. Differences in PFB and ES are not treated as independent evidence of cluster validity, as these variables define the clusters. Differences in specific financing sources were examined using contingency-table procedures. Because several financing-source categories contained small or zero cells, Monte Carlo p-values were calculated and Cramer's V was reported as an effect-size measure.

Fourth, financing diversification was examined separately using the count of distinct financing sources and tested using both ANOVA and the non-parametric Kruskal–Wallis test. This separate test is necessary because differences in financing-source composition do not automatically imply broader financing diversification.

Fifth, a multinomial logistic regression model was estimated to profile typology membership. The financially constrained typology served as the reference category. To avoid circularity, the clustering variables were excluded from the regression model. Access to finance, prior startup experience, firm size measured as the natural logarithm of employees and lifecycle stage were included as predictors. The model does not aim to estimate causal effects, but to identify how observable characteristics are associated with the likelihood of belonging to different startup typologies.

The probability of startup *i* belonging to typology *k* is specified as follows:

$$P(Y_i = k) = \frac{\exp(\beta_{0k} + X_i'\beta_k)}{\sum_{j=1}^{K} \exp(\beta_{0j} + X_i'\beta_j)}$$

Using typology 1 (financially constrained startups) as the reference category, the model is estimated as:

$$\log\left(\frac{P(Y_i=k)}{P(Y_i=1)}\right) = \beta_{0k} + \beta_{1k}AF_i + \beta_{2k}EXP_i + \beta_{3k}SIZE_i + \beta_{4k}STAGE_i, \quad k=2,3$$

where Y_i denotes typology membership, AF_i is access to finance, EXP_i is prior startup experience, $SIZE_i$ is the natural logarithm of employees, $STAGE_i$ is lifecycle stage. Estimated coefficients indicate associations with the relative odds of membership in each typology compared with the financially constrained reference group.

RESULTS AND DISCUSSION

Descriptive analysis and measurement quality

We first assessed the measurement structure and reliability of the multi-item constructs. The data showed satisfactory sampling adequacy, with a Kaiser–Meyer–Olkin value of 0.795, and Bartlett's test of sphericity was statistically significant ($\chi^2 = 3375.199$, df = 378, $p < 0.001$), supporting the factorability of the data. Principal component analysis (PCA) with varimax rotation and Kaiser normalization was conducted on the 28 retained items. Four components were extracted, corresponding to startup performance (SP), ecosystem support (ES), perceived financial barriers (PFB), and access to finance (AF). The four-component solution explained 73.566% of the total variance. The initial eigenvalues were 11.316, 4.615, 2.938, and 1.729. After rotation, the variance was redistributed across the four components, with rotated sums of squared loadings of 7.227, 5.133, 5.015 and 3.223, respectively. The rotated component loadings are presented in Table 1.

All scales showed strong internal consistency (Cronbach's α: PFB = 0.915; ES = 0.918; AF = 0.862; SP = 0.957). The rotated component pattern supports measurement adequacy and item-level construct distinctiveness. Given the exploratory and PCA-based nature of the assessment, however, these results are not interpreted as confirmatory evidence of discriminant validity. The reliability and component results therefore support the use of construct scores in the subsequent analyses.

Table 1. Rotated component matrix

	Component			
	SP	ES	PFB	AF
AF1. Our startup has been able to obtain the external financing it needs to grow				0.610
AF2. We have successfully accessed at least one form of external capital (loan or equity) in the last 12 months				0.722
AF3. It has been relatively easy to secure external financing from banks or investors				0.769
AF4. We did not face major delays in receiving the financing we applied for.				0.763
AF5. The terms (cost, interest rates, equity requirements) of financing were acceptable				0.623
PFB1. Accessing external financing has been a major challenge for our startup			0.803	
PFB2. Lack of collateral has prevented us from securing funding			0.721	
PFB3. The information asymmetry between our firm and financiers has been a barrier			0.774	
PFB4. Bureaucracy and application complexity have discouraged us from applying.			0.861	
PFB5. Investors perceive our revenue/growth as too uncertain			0.832	
PFB6. Insufficient networks with investors have negatively impacted my access to external funding			0.841	
PFB7. I perceive external financing sources (e.g., banks) as inaccessible for startups in my industry			0.773	
ES1. In our country, there are sufficient incubators, accelerators, or support programs for startups		0.822		
ES2. We have easy access to mentors, advisors, or experienced entrepreneurs who can support our startup		0.870		
ES3. Government programs (e.g., grants, incentives) effectively support startups like ours		0.618		
ES4. The local financial ecosystem (investors, venture capitalists, angel networks) is accessible to startups		0.820		
ES5. The regional entrepreneurial environment encourages innovation, collaboration, and new business creation		0.809		
ES6. There are frequent events (meetups, hackathons, competitions) promoting startups.		0.767		
ES7. Universities actively promote entrepreneurship		0.632		
SP1. Our startup has experienced positive revenue growth over the past 12 months.	0.793			
SP2. We have successfully achieved key product development or market milestones during the past year.	0.770			
SP3. Our team has expanded to support business growth and operations.	0.793			
SP4. Our customer base has grown steadily over the past 12 months.	0.845			
SP5. Our startup's financial performance has improved compared to the previous year.	0.883			
SP6. Our startup has made significant progress toward financial sustainability.	0.769			
SP7. Our competitive position in the market has improved relative to key competitors.	0.763			
SP8. We have successfully introduced new or improved products or services during the past year.	0.845			
SP9. Overall, our startup's performance has improved significantly over the past 12 months.	0.877			

Note: Extraction method: Principal component analysis. Rotation method: Varimax with Kaiser normalization. Loadings below 0.30 are suppressed. SP = startup performance; ES = ecosystem support; PFB = perceived financial barriers; AF = access to finance.

Descriptive statistics reported in Table 2 show variation across all four construct scores, with responses covering the full scale range from 1 to 5. Perceived financial barriers have the highest mean score, while ecosystem support and access to finance have lower mean scores. This indicates that respondents generally report stronger financial barriers than ecosystem support or financial access. The pattern is consistent with research on emerging-economy startup contexts, where finance-related constraints and uneven support structures often coexist (Cao & Shi, 2021; Samara & Terzian, 2021). The observed variation supports the use of a typology-oriented analysis, as startups differ meaningfully in their reported levels of financial barriers, ecosystem support, access to finance and performance.

Table 2. Descriptive statistics of construct scores

Construct	Mean	SD	Min	Max
Perceived Financial Barriers (PFB)	3.179	0.939	1.0	5.0
Ecosystem Support (ES)	2.759	0.909	1.0	5.0
Access to Finance (AF)	2.497	0.993	1.0	5.0
Startup Performance (SP)	3.078	0.970	1.0	5.0

Note: Values are construct means.

Correlations among the main constructs

Table 3 reports Pearson correlations among AF, PFB, ES, and SP. The coefficients follow the expected theoretical pattern: access to finance is positively associated with ecosystem support and startup performance, and negatively associated with perceived financial barriers. Perceived financial barriers show weaker negative associations with ecosystem support and performance. The matrix indicates theoretically meaningful associations without suggesting excessive overlap among the constructs. The association between ecosystem support and access to finance is therefore interpreted as expected construct convergence rather than as independent external validation of the ecosystem-enabled typology.

Table 3. Correlation matrix among the main constructs

Construct	AF	PFB	ES	SP
AF	1			
PFB	−0.343**	1		
ES	0.617**	−0.185	1	
SP	0.662**	−0.167	0.501**	1

Note: Pearson correlations are reported. **$p < 0.01$, two-tailed.

Cluster analysis: Identification of startup typologies

To examine whether startups form distinct profiles, K-means clustering was applied using standardized scores of perceived financial barriers and ecosystem support. Only these two variables were used in the clustering procedure. Access to finance, startup performance, financing sources, financing diversification and firm characteristics were reserved for external profiling and comparison. Alternative cluster solutions were compared before selecting the final model. As shown in Table 4, the two-cluster solution produced relatively broad groups and did not distinguish startups with low ecosystem support from those with high financial barriers. The four-cluster solution produced a marginally higher silhouette coefficient, but included a very small cluster, limiting its interpretability. The three-cluster solution provided the clearest balance between statistical adequacy, interpretability and usable group sizes.

Table 4. Alternative cluster solutions

Solution	Cluster sizes	Silhouette	Inertia
k = 2	64 / 47	0.341	139.962
k = 3	60 / 22 / 29	0.409	86.849
k = 4	45 / 39 / 21 / 6	0.410	64.443

The K-means algorithm was run with 100 random initializations and a convergence tolerance of 0.000001 to reduce sensitivity to starting values. Before clustering, standardized PFB and ES scores were screened to identify unusual values and possible data-entry errors. No cases were excluded, as the observed variation reflected meaningful differences in founders' perceptions. Stability checks further supported the retained three-cluster solution. Across 200 bootstrap resamples, the mean adjusted Rand index (ARI) was 0.704, while across 200 split-half samples, the mean ARI was 0.662. These values indicate moderate stability for an exploratory typology analysis and support the use of the three-cluster solution for descriptive profiling rather than causal inference.

Table 5. Final Cluster Centers

Cluster	n	PFB	PFB SD	ES	ES SD	Startup typology
Cluster 1	60	3.86	0.530	2.76	0.581	Financially constrained
Cluster 2	22	2.20	0.655	3.94	0.559	Ecosystem-enabled
Cluster 3	29	2.53	0.607	1.87	0.627	Ecosystem-disconnected

Note: PFB and ES are unstandardized cluster means. Clusters were estimated using standardized scores.

The three-cluster solution identifies three interpretable startup typologies. Cluster 1 (n = 60) combines high perceived financial barriers (PFB = 3.86) with moderate ecosystem support (ES = 2.76) and is labeled ‚financially constrained'. Cluster 2 (n = 22) combines low financial barriers (PFB = 2.20) with strong ecosystem support (ES = 3.94) and is labeled Ecosystem-enabled. Cluster 3 (n = 29) shows moderate financial barriers (PFB = 2.53) but weak ecosystem support (ES = 1.87) and is labeled Ecosystem-disconnected.

These findings provide partial support for H1 as an exploratory classification. ICT startups operating within the same ecosystem can be grouped into interpretable profiles defined by different combinations of barriers and support. The results should not be read as evidence of naturally occurring population types. They identify analytically useful patterns consistent with configurational approaches in entrepreneurship research, in which firm-level differences emerge from combinations of conditions rather than isolated factors (Fiss, 2011; Misangyi et al., 2017). The findings also support the view that ecosystem resources are not evenly available across ventures but are accessed and mobilized differently depending on firms' positions within the same environment (Wurth et al., 2023).

Because PFB and ES were used to form the clusters, differences on these dimensions are interpreted descriptively rather than as independent evidence of cluster validity. The retained solution is therefore assessed by comparing it with alternative k solutions, cluster sizes, interpretability, and stability checks. The label Ecosystem-disconnected should be understood specifically as weak connection to formal ecosystem support structures, not as a lack of all informal networks.

Differences in financing behavior and financing portfolio composition

Differences across typologies were examined using variables not included in the clustering procedure. Table 6 reports differences in access to finance and startup performance. The results show significant differences across typologies for both access to finance, $F(2,108) = 18.004$, $p < 0.001$, $\eta^2 = 0.250$, and startup performance, $F(2,108) = 10.127$, $p < .001$, $\eta^2 = 0.158$. Tukey post hoc tests indicate that ecosystem-enabled startups report significantly greater access to finance than both financially constrained and ecosystem-disconnected startups. A similar pattern is observed for startup performance, where the ecosystem-enabled group reports higher scores than the other two groups.

Table 6. External comparison of startup typologies

Variable	Cluster 1 Mean	Cluster 2 Mean	Cluster 3 Mean	F	p	η^2	Main post-hoc differences
Access to Finance	2.243	3.491	2.269	18.004	< 0.001	0.250	C2 > C1; C2 > C3
Startup Performance	2.994	3.808	2.697	10.127	< 0.001	0.158	C2 > C1; C2 > C3

Note: One-way ANOVA with Tukey post-hoc tests. AF and SP were not used in the clustering procedure.

These findings indicate that the typologies are associated with meaningful differences beyond the clustering variables. In particular, the ecosystem-enabled group reports stronger access to finance and higher performance. However, the AF difference is interpreted as expected construct convergence rather than as strong independent external validation, because access to finance is conceptually related to ecosystem support through signaling, brokerage, legitimacy transfer

and reduced information opacity (Dourado Freire et al., 2023; Ngoasong, 2018). The results should not be interpreted causally. The cross-sectional design shows an association between typology membership, reported AF, and reported SP, not whether ecosystem support produces better financing outcomes or performance.

Financing-source use was then examined using Monte Carlo p-values because several categories contained small or zero cell counts. Cramer's V is reported as an effect-size measure.

Table 7. Financing-source use by startup typology

Financing source	Cluster 1 n = 60	Cluster 2 n = 22	Cluster 3 n = 29	Monte Carlo p	Cramer's V
Personal savings	53 (88.3%)	16 (72.7%)	27 (93.1%)	0.088	0.208
Friends and family	26 (43.3%)	6 (27.3%)	11 (37.9%)	0.414	0.126
Retained earnings	13 (21.7%)	4 (18.2%)	9 (31.0%)	0.525	0.111
Bootstrapping	4 (6.7%)	8 (36.4%)	4 (13.8%)	0.004	0.322
Bank loans	9 (15.0%)	2 (9.1%)	0 (0.0%)	0.099	0.211
Investor equity	6 (10.0%)	6 (27.3%)	2 (6.9%)	0.059	0.223
Trade credit	0 (0.0%)	0 (0.0%)	3 (10.3%)	0.026	0.280
Public or donor grants	21 (35.0%)	10 (45.5%)	8 (27.6%)	0.441	0.126
Crowdfunding	0 (0.0%)	6 (27.3%)	0 (0.0%)	< 0.001	0.481

Note: Values are n (%). Monte Carlo p-values are reported because of sparse cells. Investor equity combines angel investors, venture capital, and private equity. Bank loans combine short- and long-term bank loans.

Table 7 shows that the typologies differ mainly in the composition of financing sources. Bootstrapping and crowdfunding are more common among ecosystem-enabled startups, suggesting that these firms are better positioned to use financing channels linked to visibility, networks and non-bank intermediation. By contrast, the trade-credit result should be interpreted cautiously because it is based on sparse cells and a small number of observations. Its presence among ecosystem-disconnected firms may indicate reliance on transactional relationships where formal ecosystem support is weaker.

Several non-significant and borderline findings are also informative. Personal savings are common across all groups, which is expected in an early-stage ecosystem where founder finance remains central. Public or donor grants do not differ significantly across typologies, indicating that grant use alone does not distinguish ecosystem position. Investor equity is more common among ecosystem-enabled startups, but the association is only borderline ($p = 0.059$). This is consistent with the limited depth of angel and venture-capital markets in this context. Bank loans also show only a weak association ($p = 0.099$), suggesting that conventional debt finance is not the primary basis for differences among these startup typologies. Financing diversification was tested separately from financing-source composition. As shown in Table 8, ecosystem-enabled startups report a somewhat higher mean number of financing sources, but the difference is not statistically significant using either ANOVA, $F(2,108) = 2.739$, $p = 0.069$, $\eta^2 = 0.048$, or the Kruskal–Wallis test, $H = 3.992$, $p = 0.136$. These findings provide partial support for H2: the typologies differ in financing-source composition, but not in overall financing diversification.

Table 8. Financing diversification by startup typology

Cluster	Mean	SD	Median	Min	Max
Cluster 1: Financially constrained	2.23	0.95	2	1	5
Cluster 2: Ecosystem-enabled	2.82	1.37	3	1	5
Cluster 3: Ecosystem-disconnected	2.21	1.05	2	1	4

Note: Financing diversification is the count of distinct financing sources used. ANOVA: $F = 2.739$, $p = 0.069$, $\eta^2 = 0.048$. Kruskal–Wallis: $H = 3.992$, $p = 0.136$.

These results clarify the interpretation of financing behavior. The typologies differ more clearly in the types of financing sources used than in the number of sources. Therefore, the findings should be described as differences in financing-source composition rather than as evidence that one typology has a significantly broader or more diversified financing portfolio.

Profiling typology membership

A multinomial logistic regression model was estimated to profile typology membership, using the financially constrained group as the reference category. Perceived financial barriers and ecosystem support were excluded from the model because they were used to form the clusters. Founder age and education were also excluded because sparse categories produced unstable estimates. The model is therefore parsimonious and is interpreted as a profiling model rather than a causal model. It is statistically significant, LR χ^2 (8) = 46.481, $p < 0.001$, with McFadden $R^2 = 0.209$. Results are reported in Table 9.

Table 9. Multinomial logistic regression

Predictor	C2 vs C1 OR	95% CI	p	C3 vs C1 OR	95% CI	p
Access to Finance	4.923	[2.180–11.114]	< 0.001	0.970	[0.509–1.841]	0.926
Previous startup experience	1.364	[0.304–6.114]	0.686	3.998	[1.199–13.329]	0.024
Firm size (log employees)	0.849	[0.363–1.984]	0.707	0.220	[0.079–0.611]	0.004
Early stage (vs. growth)	1.263	[0.258–6.188]	0.773	0.205	[0.061–0.687]	0.010

Note: C1 = financially constrained; C2 = ecosystem-enabled; C3 = ecosystem-disconnected. OR = exp(B). Reference category: C1. Model fit: LR χ^2 (8) = 46.481, $p < 0.001$; McFadden $R^2 = 0.209$; N = 111.

The regression results provide partial support for H3. Access to finance is positively associated with membership in the ecosystem-enabled group relative to the financially constrained group. Because access to finance was not used to form the clusters, this result is treated as an adjusted profiling association and as expected construct convergence, not as evidence of a causal effect. This pattern is consistent with ecosystem research showing that support structures may improve startups' visibility, legitimacy and access to resource channels, particularly through networks and intermediary organizations (Spigel & Harrison, 2018; Wurth et al., 2023). Prior startup experience is associated with higher odds of membership in the ecosystem-disconnected group, suggesting that experienced founders may be better able to continue operating even when formal ecosystem support is weaker. This interpretation is consistent with research showing that founder experience and learning shape how young ventures mobilize resources and navigate financing constraints under uncertainty (Cassar, 2014; Ngoasong, 2018). Firm size is negatively associated with membership in the ecosystem-disconnected group, suggesting that smaller firms are more likely to exhibit this profile. Early-stage status is also negatively associated with membership in the ecosystem-disconnected group, relative to growth-stage status, after controlling for the other predictors. This lifecycle result is interpreted cautiously. It suggests that lifecycle stage helps profile membership rather than serving as a standalone explanation of the typologies.

CONCLUSION

This study examined whether ICT startups in Albania form distinct typologies based on founders' perceptions of financial barriers and ecosystem support, and whether these typologies differ in financing behavior and firm characteristics. Using survey data from 111 startups, the analysis identified three exploratory typological profiles: financially constrained, ecosystem-enabled and ecosystem-disconnected startups.

The findings provide partial support for H1. Startups operating within the same ecosystem do not report the same combination of perceived financial barriers and ecosystem support. The financially constrained typology combines high perceived financial barriers with moderate ecosystem support. The ecosystem-enabled typology is characterized by stronger support and lower barriers, whereas the ecosystem-disconnected typology is weakly connected to formal ecosystem-support structures. These results suggest that entrepreneurial ecosystems should not be examined only at the aggregate level, but also through the uneven ways in which startups perceive, access and use support conditions.

H2 is partially supported. The typologies differ in financing-source composition, especially bootstrapping and crowdfunding. The trade-credit finding should be interpreted cautiously because it is based on sparse cells and a small number of observations. Ecosystem-enabled startups appear better placed to use sources linked to visibility, networks and non-bank intermediation. Ecosystem-disconnected startups show weaker engagement with formal support channels and some reliance on more transactional financing arrangements. However, the number of financing sources used does not differ significantly across typologies. The findings therefore indicate differences in financing-source composition, but not in overall financing diversification.

H3 is also partially supported. Access to finance, prior startup experience, firm size and lifecycle stage help profile typology membership. Given the exploratory and cross-sectional design, these findings should be interpreted as adjusted associations rather than causal effects.

The study contributes to entrepreneurial ecosystem research by showing that support structures are not experienced evenly by startups operating in the same setting. It also contributes to entrepreneurial finance research by distinguishing financing-source composition from financing diversification. Startups may differ in the kinds of funding sources they use even when they do not differ in the number of sources used. This distinction helps explain financing behavior as part of a startup's position within ecosystem and financial channels, rather than only as an isolated firm-level funding decision.

The findings also point to differentiated support needs. Financially constrained startups may benefit from assistance with funding readiness, investor communication and navigation of available instruments. Ecosystem-enabled startups may need follow-on finance, investor-readiness support and stronger links to regional or international funding networks. Ecosystem-disconnected startups require more active outreach, mentoring and brokerage to connect them with formal support structures. A uniform support model is therefore unlikely to address the needs of all startup profiles.

The findings should be interpreted within the Albanian context and should not be assumed to generalize directly to larger or more mature startup ecosystems. The three profiles identified here may not appear in the same form in other countries. Nevertheless, similar internal differentiation may also exist in other small or institutionally developing startup ecosystems.

The study has several limitations. It uses self-reported, cross-sectional data, which limits causal inference and may not fully capture objective financing conditions. The sample is limited to ICT startups in Albania, and the modest sample size requires caution when interpreting regression results and less frequently used financing sources. The cluster solution should be treated as exploratory, typology-oriented and context-sensitive, although its interpretability and stability checks support its use for descriptive profiling.

Future research could examine whether startups move between typologies over time and how such transitions relate to financing trajectories, growth and survival. Comparative studies across emerging economies would help assess whether similar patterns appear in other small ecosystems. Combining survey data with objective financing records and qualitative interviews with founders, investors and ecosystem intermediaries would also help explain how signaling, brokerage, legitimacy transfer and information opacity shape financing behavior.

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Author contribution statement

Iris Kruja: Conceptualization, Methodology, Data Curation, Formal Analysis, Investigation, Visualization, Writing – Original Draft Preparation, Writing – Review & Editing. **Ana I. Irimia-Diéguez**: Conceptualization, Methodology, Supervision, Writing – Review & Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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