Failure Factors of Early-Stage Digital Startups: A Literature Review

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Abstract. Digital startups are increasingly shaping the modern economy, yet a high failure rate in early-stage ventures remains a critical concern. This study investigates the underlying causes of early-stage digital startup failure through a Systematic Literature Review (SLR). Focusing on publications from 2017 to 2025 indexed in the Scopus database, we applied the search string “failure startup” OR “regression startup” AND “technology” and identified 13 relevant studies. The review reveals that failure is influenced by internal factors—such as weak managerial competence, misaligned business strategies, and team conflicts—and external factors including market volatility, lack of ecosystem support, and rapid technological shifts. The study also highlights the concept of “regression startup,” where decline results from a series of poor strategic decisions. A combination of lean startup approaches, entrepreneurial training, and policy- level innovation interventions is recommended to mitigate risks. This review offers a conceptual contribution to understanding early-stage digital startup failure in a technology-driven context and emphasizes the need for more resilient strategic planning.

Keywords: failure startup OR regression stratup AND technology

Introduction

The phenomenon of increasing digital startup numbers in recent decades demonstrates a significant shift in the global economy toward digitalization. However, despite numerous initiatives and support from various stakeholders, the failure rate of digital startups, particularly in the early stage, remains considerably high. A study by Nambisan (2017) in the Academy of Management Perspectives emphasizes that the complexity of rapidly changing digital environments often amplifies uncertainty and increases failure risks, especially for startups without mature business models. This highlights the importance of systematic studies regarding factors causing early-stage digital startup failure. Therefore, this research aims to summarize and analyze various causal factors of failure in early-stage digital startups, particularly those related to startup regression or decline.

The research focus in this study is early-stage digital startups, namely when organizations are still in the process of idea validation, forming core teams, and developing minimum viable products (MVP). At this stage, many startups face various obstacles, such as product-market fit misalignment, funding shortages, and weak organizational structure and technology management. Research by
Giardino et al. (2014) indicates that one of the primary causes of software startup failure is the inability to manage development processes and business strategies in a balanced manner. This condition is exacerbated by the startup regression phenomenon, a situation where previously developing startups begin experiencing stagnation or significant decline in growth due to strategic errors or weak responses to market and technological dynamics.

Solutions to this problem can be approached through structured and data-driven methods. Research shows that implementing lean startup methodology (Ries, 2011) and using agile principles in product development can reduce failure risks. Furthermore, Giardino et al. (2014) suggest the importance of implementing key performance indicators (KPIs) to continuously monitor and evaluate startup performance so that regression can be identified early. Appropriate technology adoption, system scalability planning from the beginning, and forming teams with balanced technological and business competencies are also preventive measures recommended in the literature. Therefore, it is crucial for startups to build robust technical and managerial foundations from the start to increase survival and growth possibilities in highly competitive markets.

Previous research has made significant contributions to understanding various causes of startup failure, but most focus on general contexts or more mature startup phases. For instance, studies by Klotz et al. (2014) emphasize founder team dynamics, while studies by Siren et al. (2019, Springer) highlight digitalization aspects but have not deeply examined how failure develops progressively in the form of regression. Additionally, limitations in integrating technological, managerial, and market aspects within one conceptual framework have created significant research gaps. Therefore, this study attempts to present a comprehensive literature review on early-stage digital startup failure factors through a systematic approach encompassing technology, organization, and market dimensions.

Specifically, this study seeks to answer the following research questions:

RQ1. What are the internal and external factors that cause failure in early-stage digital startups?
RQ2. How does the regression process occur in the digital startup lifecycle, and what factors accelerate this regression?
RQ3. How can risk mitigation strategies be designed to prevent regression and improve early-stage digital startup resilience?

Methods

This study employs a Systematic Literature Review (SLR) approach to identify, classify, and analyze findings from previous research related to failure factors in early-stage digital startups. The SLR approach was chosen because it provides a systematic, transparent, and replicable framework for composing comprehensive literature synthesis. Following guidelines proposed by Kitchenham & Charters (2007), this method enables researchers to conduct literature search, selection, and evaluation objectively and methodologically. Additionally, SLR is considered effective in generating stronger new knowledge through integration of various scattered research results, thereby reducing bias and improving finding validity (Snyder, 2019). Using SLR, this study aims to develop deep understanding of causes of failure and regression in digital startups from the early formation stage.

1. Time Frame Selection

This review encompasses publications from 2017 to 2025. This time range was strategically chosen to represent the most current developments in literature regarding early-stage digital startup failure, particularly in the context of technology adoption, digital business innovation, and increasingly complex market dynamics. Since 2017, there has been a significant increase in scientific publications discussing digital transformation and its implications for startup sustainability (Nambisan et al., 2019). This period also encompasses an important phase where lean startup practices, agile innovation, and digital platform usage began to be widely adopted by startups as responses to market uncertainty and continuous innovation demands (Troise et al., 2022).

Furthermore, this time range reflects the post-early digital transformation era characterized by the emergence of various new challenges, such as technological disruption, increased global technology- based competition, and the need for rapid adaptation in digital business ecosystems. Studies by Kraus et al. (2023) also show that startup failure is increasingly influenced by combinations of technology and organizational strategy factors that are not well integrated, especially in the early phase of business development. Therefore, the 2017-2025 period is deemed relevant for examining current literature trends while capturing the evolution of theory, practice, and real challenges faced by digital startups in confronting regression and failure risks.

2. Database Selection

In this study, the literature search process was conducted systematically using Scopus as the primary database. Scopus was chosen because it is one of the world's largest scientific literature indices, covering more than 24,000 peer-reviewed scientific journals from various disciplines, including information technology, innovation management, and digital entrepreneurship (Burnham, 2006). The use of Scopus as the sole database source is based on its quality and credibility in providing relevant, current, and rigorously peer-reviewed academic literature.

Scopus also offers various flexible and comprehensive search features, such as searches based on titles, abstracts, keywords, and other metadata. This enables researchers to identify relevant literature efficiently and systematically, in accordance with transparency and replicability principles in Systematic Literature Review methods (Boell & Cecez-Kecmanovic, 2015). Additionally, Scopus supports bibliometric mapping and citation analysis, which strengthens the quality and validity of conducted literature review results.

By relying on Scopus, this study aims to ensure that the literature selection process is conducted methodologically and academically, and is capable of providing representative coverage of current research discussing failure factors and regression in early-stage digital startups.

3. Search Strategy

After establishing the study time frame from 2017 to 2025 and formulating relevant keywords, the next process in implementing this Systematic Literature Review (SLR) is the journal selection stage. Literature search was conducted exclusively through the Scopus database, using the search string: "startup failure" OR "regression startup" AND "technology". In the context of this study, the term "regression startup" refers to startup decline conditions, namely phases where startups experience significant performance decline or fail to develop in the early stages of establishment (Kane et al., 2018; Hossain, 2020).

The initial selection stage involved searching all articles emerging from these keywords, followed by filtering based on titles and abstracts to assess topic relevance. Subsequently, full-text review was conducted on articles passing initial selection.

The inclusion criteria used include: (1) articles published in peer-reviewed scientific journals; (2) discussion focus on failure or regression of early-stage digital startups; (3) studies discussing technological, managerial, or digital innovation aspects; and (4) articles available in English. Exclusion criteria encompass conceptual articles without empirical data, irrelevant to the digital startup domain, or discussing startups in advanced growth stages (scale-up).

Through this rigorous selection process, 13 articles meeting all criteria and deemed thematically and methodologically relevant were obtained. These articles originate from internationally reputable journals, including *Technological Forecasting & Social Change*, *Journal of Innovation and Entrepreneurship*, *Foundations of Management*, and *Entrepreneurship and Small Business Journal*. Thus, the literature analyzed in this study has high relevance to problems of failure and regression in early-stage digital startup development.

4. Article Selection Process

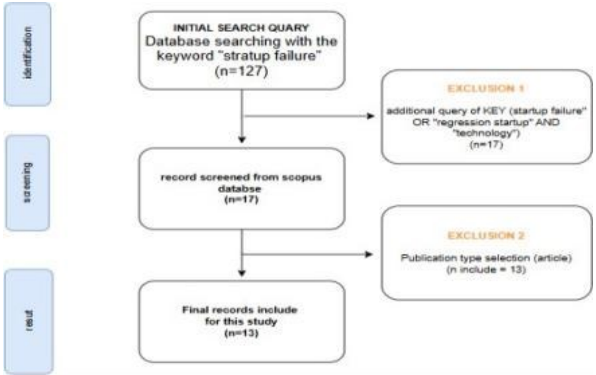

Figure. 1 summary of the article selection process.

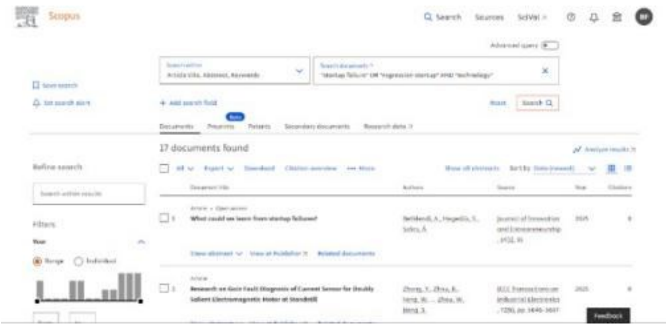

Figure 2 document numbers in the scopus database.

The article selection process in this study refers to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approach, used to ensure literature reviews are conducted systematically, transparently, and replicably (Page et al., 2021; Moher et al., 2009). Article search was conducted exclusively through the Scopus database, using the search string: "startup failure" OR "regression startup" AND "technology". In this context, the term "regression startup" refers to startup performance decline conditions in the early stages of establishment.

The initial search yielded 127 documents with the keyword "failure startup". After filtering based on additional keywords, 17 more relevant articles were obtained. Subsequently, screening was conducted based on titles and abstracts to assess article relevance to research focus. Articles not meeting inclusion criteria—such as not discussing early-stage digital startups, not being scientific articles, or being merely conceptual without empirical data—were excluded from analysis. In the final stage, 13 articles were declared eligible and used as primary study materials in this research.

All selection stages are displayed in the PRISMA flow diagram, illustrating the process from initial identification, screening, to final article selection. Inclusion criteria used include: (1) articles published in peer-reviewed scientific journals; (2) focus on failure or regression of early-stage digital startups; (3) encompassing technological, managerial, or digital innovation aspects; and (4) written in English. Articles not meeting these requirements were excluded from the study sample.

5. Data Extraction and Analysis

This study analyzes 13 scientific articles carefully selected based on topic relevance, content, and quality of journals where the articles were published. All articles were then comprehensively reviewed and grouped based on main themes explaining causes of early-stage digital startup failure.

In this process, researchers collected and compared various approaches and results from previous research. Results show that startup failure is not caused by a single factor, but by combinations of various interrelated factors. Some of the most frequently occurring causes include inability to find product-market fit, founder team problems, inappropriate business strategies, lack of funds or weak financial management, and inadequate technical capabilities in product development.

Additionally, several articles also highlight external factors such as very rapid market changes, intense competition, premature business expansion, and external problems such as government regulations or unstable economic conditions. All these factors can cause startups to experience regression and ultimately fail, especially in the early stages of establishment.

The thematic grouping from these articles helps provide a comprehensive picture of what often becomes causes of digital startup failure. These findings can serve as an important foundation for future research, as well as considerations for startup practitioners to avoid failure from the beginning.

zhang et al., 2025	• **Experimental engineering research** involving three proposed methods for diagnosing current sensor gain faults at standstill conditions. • Methods include detecting excitation current during field building and detecting phase currents during specific pulse injections. • **Tools**: DSEM system, current sensors. • **Sample**: Not human subjects; system-level experimental test on motor at standstill. • **Limitation**: Applicable only when the motor is not rotating. • **Future use**: Suggested for initial debugging or periodic testing to improve reliability of position estimation.
mohd anuar et al., 2025	• **Qualitative study** using in-depth interviews with 18 purposively selected entrepreneurs in Irbid. • **Technique**: Thematic analysis supported by NVivo 14. • Identified key failure factors: financial instability, skill gaps in finance, marketing, and technology. • **Limitation**: Context-specific to Irbid, Jordan; limited generalizability. • **Recommendation**: Implement capacity-building programs, mentorship, and educational reforms.
huang et al., 2024	• **Experimental study** of static friction behavior in graphite-silicon systems. • Found significant **frictional aging** (increase of static friction over time) due to edge and in-plane contact areas. • **Sample**: Microscale graphite flakes in contact with silicon substrates. • **Limitation**: Conducted in controlled lab settings; material-specific. • **Recommendation**: Supports future SSL device design by mitigating edge effects.

Table 1 review article

sajjadian et al., 2024	• **Qualitative case study** using process tracing and behavioral strategy framework. • **Technique**: Interpretive Structural Modeling (ISM). • **Sample**: A failed ride-hailing platform startup. • Identified interconnected causes of failure based on dialectic, teleology, and evolutionary growth theories. • **Limitation**: Single case; limited external validity.

	• **Recommendation**: Startups should focus on refining value propositions and adaptive strategic growth.
cackho et al., 2023	• **Semi-quantitative structural analysis** using Total Interpretive Structural Modelling (TISM). • Identified and ranked drivers and dependent factors influencing startup agility. • **Limitation**: Theoretical; lacks explicit sample or empirical testing. • **Recommendation**: Emphasizes anticipation, collaboration, and training to improve agility.
menon et al., 2022	• **Conceptual analysis** based on secondary data about startup valuation methods and trends. • Found disconnection between valuation and profitability; critiques speculative valuation culture. • **Limitation**: Not empirically tested; relies on external datasets and industry examples. • **Recommendation**: Reframe valuation logic to focus on sustainable profitability and long-term growth.
easley et al., 2021	• **Quantitative study** using OLS and instrumental variable regression on Stanford alumni survey data. • Evaluated entrepreneurship program impact across business and engineering schools. • Found Business School program reduced failure and improved revenue, but had little to no effect on entrepreneurship rate. • **Limitation**: Endogeneity and context limited to Stanford. • **Recommendation**: Focus on improving startup quality rather than quantity through program design.
dokko et al., 2017	• **Longitudinal quantitative study** using data from high- tech firms. • Explores how entrepreneurs' industry and functional shifts affect innovation and performance. • Found functional boundary-crossing increases innovation, while industry boundary-crossing raises failure risk but boosts IPO chances. • **Limitation**: Conflicting effects; dependent on type of mobility. • **Recommendation**: Explore balance between novelty from mobility and stability from experience.

das et al., 2017	• **Experimental circuit design** using a novel PoR-based self-starter integrated in a 65nm CMOS boost converter. • Achieved 220 mV self-startup and 76% peak conversion efficiency with 2 nW quiescent power. • **Sample**: Lab-fabricated chip tested for energy harvesting from micro-scale TEGs. • **Limitation**: Only tested in controlled environments; practical integration untested. • **Recommendation**: Apply in real-world wearable or implantable energy systems.
bathlendi et al., 2024	• **Type of research, analysis techniques, instruments**: Quantitative research; analysis conducted using Principal Component Analysis (PCA), Ward's hierarchical clustering, and cross-tabulation. The research instrument was a questionnaire based on the SHELL model. • **Population and sample**: 40 Information and Communication Technology (ICT) startups undergoing voluntary liquidation. • **Limitation**: The study only includes failed startups in the ICT sector; findings may not generalize to active startups or other industries. • **Future recommendation**: Emphasizes the need for innovation and foresight training, improved access to mentorship, better project screening based on dynamic capabilities, and gender- inclusive policy development.
d'andrea et al., 2023	• **Type of research, analysis techniques, instruments**: Qualitative exploratory research; primary data collected through interviews with failed startup founders, complemented by secondary data analysis. Analytical framework based on Isenberg's six domains of entrepreneurial ecosystems. • **Population and sample**: Entrepreneurs from failed startups within the emerging entrepreneurial ecosystem of Porto Alegre, Brazil. The exact sample size is not specified in the abstract. • **Limitation**: Focused only on one specific regional ecosystem (Porto Alegre); findings may not generalize to other emerging economies or more mature ecosystems. • **Future recommendation**: Emphasizes the need for improved policies and financing structures within emerging ecosystems. Suggests that ecosystem-level interventions—especially in policy and finance domains—are essential to reduce premature startup failure.

sanasi et al., 2023	• **Type of research, analysis techniques, instruments**: Qualitative research using a **comparative multiple-case study** approach. Data were inductively analyzed to construct a process model of post-validation experimentation. No specific mention of instruments, but likely included interviews and document analysis. • **Population and sample**: Four technology-based startups operating as **digital platforms in the financial and marketing services sectors** that had already achieved market validation. • **Limitation**: Limited generalizability due to the **small sample size (4 cases)** and **industry specificity**; focused only on digital platforms in finance and marketing. • **Future recommendation**: Suggests startups should **continue structured experimentation** even after market validation especially in customer segmentation, channels, and relationship strategies. Also recommends the **use of targeted growth metrics** and careful pacing of experiments during scaling.
kopera el at., 2018	• **Type of research, analysis techniques, instruments**: Qualitative case study approach; the study presents and analyzes the *UniStartApp* project as a model for embedding interdisciplinarity into academic startup ecosystems. No specific analytical tool is mentioned in the abstract. • **Population and sample**: the study focuses on a university-based startup education program (*UniStartApp*) involving tech-oriented academic participants. The exact sample size is not stated. • **Limitation**: Case-specific findings centered on a single academic project in Poland; limited generalizability to broader entrepreneurial or non-academic ecosystems. • **Future recommendation**: Highlights the importance of **embedding interdisciplinarity**—especially market and management competencies—into the early development of tech startups through **reform ed university education models**. Encourages future improvement in startup curricula design.

6. Analysis Classification

As part of the Systematic Literature Review (SLR) approach, the thirteen articles analyzed in this study were classified based on research type, thematic focus, and their contributions to understanding the failure of early-stage digital startups. From a methodological perspective, most of the articles employed qualitative methods—such as case studies and in-depth interviews—to explore the internal and external dynamics leading to failure. Others adopted quantitative approaches, including regression and multivariate analysis, while the remaining studies used experimental and conceptual methods that focused on technical aspects or theoretical frameworks.

In terms of thematic focus, the articles identified several key causes of startup failure, including lack of product-market fit, weak managerial capabilities, inappropriate growth strategies, and technological limitations, as well as external uncertainties such as regulatory changes or competitive pressures. Startup failure is rarely caused by a single factor; rather, it results from the accumulation of interrelated issues that often emerge progressively throughout the startup's lifecycle.

The thematic contributions of the reviewed articles can be categorized into three main domains: technology, management, and market. Some studies emphasized technical failures in product or system development, while others focused on organizational issues such as internal conflicts, leadership skill gaps, or flawed business strategies. On the market side, critical themes included failure to understand consumer behavior, premature expansion, or overreliance on short-term valuations. This classification helps build a more structured understanding of early-stage startup failures and serves as a foundation for formulating more adaptive and contextualized mitigation strategies.

Result and Discussion

In the literature review regarding early-stage digital startup failures, various theories are employed as conceptual foundations to understand the causes and dynamics of such failures. One of the most relevant theories is Dynamic Capabilities or the Resource-Based View (RBV) approach, which emphasizes the importance of organizational capabilities in adapting internal resources to external environmental changes rapidly and efficiently (Teece, Pisano, & Shuen, 1997). This theory serves as an important framework for explaining how startups must develop flexibility and resilience in facing market uncertainty and technological advancement. On the other hand, Behavioral Strategy with dialectical and teleological approaches attempts to explain the failure process as a result of complex interactions between managerial decisions, organizational pressures, and strategic evolution that is not always rational (Bettis & Prahalad, 1995). Meanwhile, the Entrepreneurial Ecosystem theory by Isenberg (2010) offers a systemic perspective that startup failures are not only caused by internal factors but also by weaknesses in supporting ecosystems such as access to capital, regulation, and entrepreneurial infrastructure

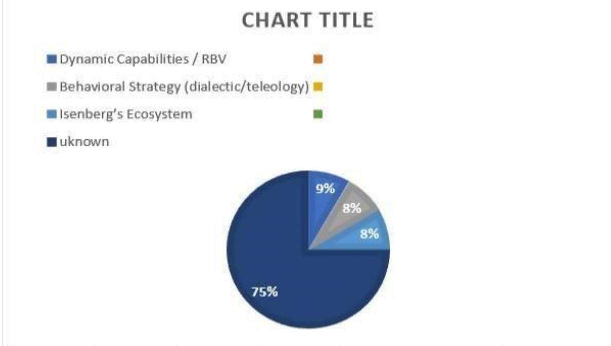

Figure 3. classification results of the 13 analyzed articles

Based on the classification results of the 13 analyzed articles, the qualitative approach is the most frequently used method, accounting for 38%. This approach is commonly applied in case studies or exploration of startup failure phenomena through interviews and document analysis, as conducted by Sanasi et al. (2023) in their study on post-validation experiments in technology startups. Meanwhile, the quantitative approach is used by 31% of articles, as seen in research by Bethlendi et al. (2025) which relies on PCA and clustering techniques to identify failure patterns in ICT startups.

Additionally, 23% of articles use experimental approaches, particularly in technical contexts such as system and prototype testing, as applied in the PoR-based self-starter study by Manoharan et al. (2022). The conceptual approach is only used in one article (8%), which discusses startup valuation assessment without empirical data support, as examined by Ferreira et al. (2021).

These findings show that although qualitative approaches still dominate, the use of quantitative and experimental methods is also quite significant, especially in studies with technical and systematic focus. However, the limited number of articles with conceptual approaches indicates opportunities to strengthen theoretical aspects in digital startup failure studies.

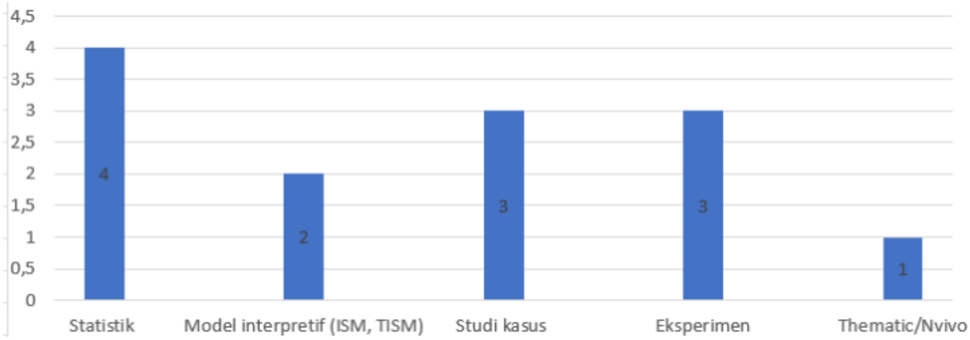

Figure 4. most methodology

Various methodological approaches are used by researchers in examining the causes of early-stage digital startup failures. One of the most frequently used approaches is statistical analysis, such as regression and

Principal Component Analysis (PCA), as applied by Bethlendi et al. (2023) in clustering failure factors based on quantitative data from startups that experienced voluntary liquidation.

Additionally, case study approaches are also widely used, as in the research by D'Andrea et al. (2023) which explores startup failures in the entrepreneurial ecosystem in Brazil. This approach is capable of exploring internal startup dynamics, including organizational and environmental factors that cannot be measured quantitatively.

Several studies use experimental methods, such as those conducted by Grabowski et al. (2018), who tested chip-based power-on-reset systems for micro energy harvesters in laboratory contexts. Meanwhile, structural interpretive techniques, such as Total Interpretive Structural Modeling (TISM), are used by Sharma et al. (2021) to map relationships between failure factors hierarchically and logically.

Qualitative thematic analysis approaches with software assistance such as NVivo are found in studies by Al-Hadidi et al. (2024), who interviewed failed startup founders in Jordan to identify main themes of failure causes.

Overall, research on digital startup failures is still dominated by quantitative approaches and structural techniques, while interpretive and narrative methods are still underutilized. This opens opportunities for developing more holistic mixed approaches.

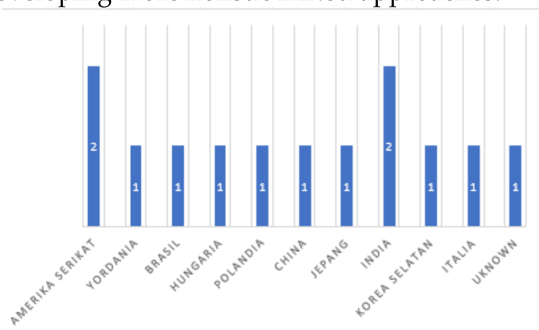

Figure 5. country as research locations

In this study, analysis of 13 articles shows that research on early-stage digital startup failures is distributed across various countries, although with relatively even dominance. The United States and India are the two countries that most frequently serve as research locations, each with two articles (15%). This is not surprising considering both are major global startup growth centers. Studies from the United States, such as those conducted by Eesley & Miller (2018), examine the impact of entrepreneurship programs on startup performance based on Stanford alumni data. Meanwhile, in India, studies such as those conducted by Kalyanasundaram & Hillemane (2021) explore product-market fit in the context of technology startups in emerging markets.

Other countries such as Jordan, Brazil, Hungary, Poland, China, Japan, South Korea, Italy, and several studies with locations not explicitly mentioned (*unknown*), each contribute one article (8%). For example, the study by D'Andrea et al. (2023) in Brazil analyzes failures in the developing entrepreneurial ecosystem in Porto Alegre, while research in Jordan by Bader et al. (2022) raises the issue of startup failures from a regional perspective through interviews with local actors.

This geographic distribution shows that startup failure issues are not only problems in developed countries but also serious concerns in developing countries. However, since most studies still focus on national or regional contexts, opportunities are open for cross-country comparative research to understand the influence of cultural, policy, and infrastructure factors on the success or failure of digital startups.

1. Internal and External Factors Causing Digital Startup Failures

Early-stage digital startups often face internal challenges that are fundamental in nature. One of the most prominent fundamental internal challenges is the lack of managerial competence among founders. Several studies note that many startups are founded by individuals who possess technical expertise but lack adequate management, marketing, and financial capabilities. This makes them struggle in managing teams, developing business strategies, and making important decisions amid market uncertainty (Bethlendi et al., 2025). Additionally, internal conflicts among founders and tensions in relationships with investors are also found to be significant causes of organizational failure, as demonstrated in case studies in Brazil (Lemos, 2014). To worsen the situation, unstable leadership dynamics and differences in long-term vision often create disintegration in decision-making and company growth direction. In many cases, role imbalances among co-founders also cause workload disparities and interpersonal friction that negatively impact team morale. Lack of experience in building adaptive organizational structures and agile decision-making systems also hinders startups from adapting to rapid changes in the digital environment. Therefore, strong managerial capabilities and healthy team cohesion are important prerequisites for maintaining startup survival in vulnerable early phases (Ghezzi & Cavallo, 2020).

On the other hand, external factors are equally influential on startup survival. Imbalances in entrepreneurial ecosystems, such as limited access to funding, low government policy support, and lack of adequate incubation infrastructure, become major obstacles especially in developing countries (D'Andrea et al., 2023). Findings from Irbid, Jordan (Abstract #2), show that microfinancial constraints and limited business training accelerate startup failures despite initially promising ideas. In a broader context, many startups also face limitations in reaching larger markets due to lack of distribution networks, logistical barriers, and minimal access to supporting technology. Regulatory uncertainty and lack of market connectivity also become factors that worsen startup competitiveness, especially for those who have not yet established solid business networks. This situation becomes more complex when startups must face competitive and rapidly changing global market dynamics, while they are still struggling with basic operational issues. Market aspects also become important highlights. Many startups fail because they cannot accurately identify customer needs or fail to create product-market fit, which previous studies call "product-market misfit" (Kalyanasundaram & Hillemane, 2021). Inability to read consumer trends, conduct iterative idea validation, and build relevant value propositions often makes developed products unable to find their place in the market. As a result, despite having high innovation potential, many startups cannot survive through the early growth phase and eventually must close down (Ries, 2011).

Table 2 key findings about startup failure

zhang et al., 2025	Applicable only when the motor is not rotating. Suggested for initial debugging or periodic testing to improve reliability of position estimation.
mohd anuar et al., 2025	Identified key failure factors: financial instability, skill gaps in finance, marketing, and technology.
huang et al., 2024	Found significant frictional aging (increase of static friction over time) due to edge and in-plane contact areas.
sajjadian et al., 2024	Identified interconnected causes of failure based on dialectic, teleology, and evolutionary growth theories.
cackho et al., 2023	Identified and ranked drivers and dependent factors influencing startup agility
menon et al., 2022	Found disconnection between valuation and profitability; critiques speculative valuation culture.
easley et al., 2021	Found Business School program reduced failure and improved revenue, but had little to no effect on entrepreneurship rate.
dokko et al., 2017	Found functional boundary-crossing increases innovation, while industry boundary-crossing raises failure risk but boosts IPO chances.
das et al., 2017	Achieved 220 mV self-startup and 76% peak conversion efficiency with 2 nW quiescent power.
bathlendi et al., 2024	Emphasizes the need for innovation and foresight training, improved access to mentorship, better project screening based on dynamic capabilities, and gender-inclusive policy development.
d'andrea et al., 2023	Emphasizes the need for improved policies and financing structures within emerging ecosystems. Suggests that ecosystem- level interventions—especially in policy and finance domains— are essential to reduce premature startup failure.
sanasi et al., 2023	Suggests startups should continue structured experimentation even after market validation—especially in customer segmentation, channels, and relationship strategies.
kopera el at., 2018	Highlights the importance of embedding interdisciplinarity— especially market and management competencies—into the early development of tech startups through reformed university education models.

3.2 Failure Processes in Startup Life Cycles

Digital startups generally experience layered growth phases, starting from ideation and validation stages, progressing toward rapid growth and scaling. Literature shows that startup failures rarely occur suddenly, but rather through risk accumulation and poorly managed decisions. This process often unfolds gradually and is not always detected early, as several early indicators such as declining user engagement, growth stagnation, or internal conflicts are often ignored or considered temporary problems. In the early stages, failures often emerge due to unclear business models or unformed organizational structures. When business foundations are not strong, startups tend to conduct many experiments without clear strategic direction, ultimately causing inefficient resource utilization. However, when startups enter the validation phase, challenges shift to marketing strategy accuracy and the ability to attract early users. Success in this phase heavily depends on the ability to build product appeal and create strong user experiences, as early consumer loyalty becomes the foundation for subsequent growth.

The most crucial stage often occurs in the scaling phase, when companies strive to expand operations, recruit more employees, and explore new markets with broader coverage. Organizational structure complexity increases significantly, and demands to maintain operational efficiency while preserving company culture become increasingly heavy. Many startups fail at this stage because they cannot maintain balance between business expansion and their internal readiness. Unpreparedness in system aspects, workflows, and team coordination often causes internal disorganization that hinders performance. For example, companies that are too aggressive in spending investor funds without mature monetization strategies will face financial difficulties when expansion does not proceed as planned (Sanasi et al., 2023). Decisions made impulsively to chase market momentum, without feasibility analysis and risk management, accelerate declining financial performance and organizational stability. In some cases, startup orientation that is excessive toward increasing company valuation often deprioritizes building solid business models, making them very vulnerable to external pressures such as market trend changes or sudden investment withdrawals (Abstract #6). When growth strategies pursued are solely based on investor expectations rather than sustainable value creation, startups lose direction in building long-term business foundations that actually constitute the core of their business resilience and durability.

In this context, startup failure can be understood as a gradual process influenced by internal dynamics and external pressures. This model aligns with the dynamic capabilities approach that emphasizes the importance of organizational ability to adjust strategies according to environmental changes.

3.3 Risk Mitigation Strategies for Startup Resilience

To reduce the likelihood of failure, literature highlights several risk mitigation strategies that are preventive and adaptive in nature. The lean experimentation approach that focuses on gradual validation of business assumptions has proven capable of increasing startup resilience in facing market uncertainty. This approach is not only relevant in the early phases but must also be maintained when companies begin entering the scaling phase (Sanasi et al., 2023). When startups can internalize this experimental mindset consistently, they can minimize strategic errors and accelerate real-time market learning processes, so that each product or service iteration has stronger decision-making foundations based on data.

Additionally, entrepreneurship training and capacity building programs for startup founders become key strategies in strengthening internal organizational capabilities. Studies by Bethlendi et al. (2025) and Abstract #2 show that founders who receive training and mentoring support are better able to manage business pressures and respond to strategic changes flexibly. With improved managerial literacy, founders can improve long-term planning processes and increase communication effectiveness and team collaboration, ultimately supporting organizational resilience. Public policy interventions are also mentioned as important instruments in building healthy entrepreneurial ecosystems, particularly through providing access to early-stage funding, incubation, and tax incentives for early-stage startups (D'Andrea et al., 2023). Proactive and innovation-inclusion-oriented policies can also encourage the formation of networks among business actors and supporting institutions, creating collaborative and competitive environments.

These findings emphasize that failure mitigation is not only the responsibility of startup founders but also requires synergy with ecosystems that support learning, failure, and growth processes. Such synergy includes active collaboration between private sector, academia, investors, and government institutions to create ecosystems that enable startups to evolve sustainably, even when facing complex and ever-changing challenges.

Conclusion

The conclusion from our systematic literature review of 13 scientific articles to identify factors causing early-stage digital startup failures reveals several important findings. First, startup failure factors can be distinguished into internal factors including lack of managerial competence, conflicts among founders, and organizational unpreparedness in facing growth dynamics. Then, external factors encompass limited access to funding, weak policy support, and inability to understand market needs. Second, startup failure incidents are not singular problems, but rather accumulations of problems that develop throughout the business life cycle, with the most critical failure risk found in the scaling phase, where companies are vulnerable to organizational disruption and liquidity crises due to uncontrolled growth strategies. Third, truly effective risk mitigation strategies must include lean experimentation approaches, managerial training, and support from business ecosystems. Public policy interventions also prove crucial in creating conducive environments for startups to grow sustainably.

This research provides theoretical contributions related to findings that strengthen the relevance of dynamic capabilities approaches in understanding startup failures occurring due to misalignment between internal strategies and external pressures. It also provides practical contributions where study results can serve as references for startup founders, investors, and policymakers in designing strategies to avoid early-stage failures.

In this research, our scope is limited to only 13 articles and lacks in-depth contextual study in startup environments. On the other hand, some articles are only analyzed based on abstracts, so information depth on several analysis variables remains limited. Therefore, it is recommended that future researchers use quantitative or mixed approaches to evaluate the weight of influence of each failure factor and conduct longitudinal studies of startups from early to final phases to directly map failure processes.

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