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What entrepreneurial decisions enable the breeding of digital platform unicorns?

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Abstract

Research Summary: Digital platforms have revolutionized business sectors; however, despite their significant success, platform unicorns remain rare. While extensive research exists on digital platform growth, it is uncertain what entrepreneurial decisions achieve unicorn status. We address the research question of what combination of complementary entrepreneurial decisions increases and decreases the likelihood of becoming a platform unicorn. The study examines 125 digital mental health platform ventures, including 12 unicorns, using the Dealroom database and decision tree methodology. We provide combinations of complementary decisions concerning fundraising timing, funding sources, digital technologies, and business model choices that affect a platform venture's probability of becoming a unicorn. The study offers decision profiles for navigating the uncertainties of the digital age. We discuss implications for strategic entrepreneurship and a judgment-based approach.

Managerial Summary: In the digital age, achieving unicorn status depends on the right combination of complementary decisions about fundraising timing, funding sources, digital

The authors are provided in alphabetical order to note equal contribution.

technology, and business model choices. Entrepreneurs dealing with uncertainty frequently rely on their intuition to make such decisions. Our research complements intuition with evidence that can now be obtained by deploying artificial intelligence tools like decision trees and highlights complementary decision profiles that have a higher likelihood of becoming unicorns, such as profiles with early-stage funding, no government funding, and deep tech serving the B2B market. Conversely, we identify combinations with less than 1% success rates, indicating failed judgments. Research insights can help entrepreneurs and investors make better-informed decisions to enhance mental health platform venture success and be aware of possible failure.

KEYWORDS
business model, deep tech, digital platform unicorns, entrepreneurial decision, funding, mental health

1 | INTRODUCTION

Entrepreneurs, investors, and policymakers acknowledge unicorns as influential role models of high-growth start-ups (Cristofaro et al., 2024; Giardino et al., 2023). Due to the highly regarded unicorn status, a nascent body of research has emerged to pinpoint the factors that increase the probability of ventures becoming unicorns (e.g., Bock & Hackober, 2020; Cusumano et al., 2023; Jinzhi & Carrick, 2019; Kotha et al., 2022).

Since the term was first empirically used by venture capitalist Aillen Lee, "unicorns" have been defined as "private firms that have market valuations of at least $1 billion" (Brown & Wiles, 2015, p. 34). Recently, new terms have emerged for ventures with different thresholds, such as decacorns (valued at $10 billion), minicorns (valued at $1 million), soonicorns (soon expected to reach $1 billion). Whatever the threshold, reference to "unicorn" implies a rarity of extreme success. In entrepreneurship, unicorns represent the "upper strata of ventures in terms of growth speed, resourcing, and exploiting opportunities" (Kotha et al., 2022, p. 461).

Digital platform[1] ventures,[2] due to their modular and scalable nature, have the potential to become unicorns and often achieve this faster than other ventures (Gawer, 2022; Kotha et al., 2022). According to Cusumano et al. (2023), private investors place a premium on digital platform ventures rather than non-platform ventures. However, reaching unicorn status is not guaranteed even for platforms; the entrepreneurial decisions of digital platform owners play a large role in it (Foss et al., 2019; Tekic et al., 2024). Although "opportunity" is often considered a fundamental unit of analysis in the entrepreneurship literature, Foss et al. (2019) propose that the essence of entrepreneurship is a decision to commit and control scarce and heterogeneous resources under uncertainty in the utilization of an entrepreneurial plan or project—in our case, the pursuit of unicorn status. Previous research on platform ventures has focused on unpacking platform competition, leadership, business models, ecosystems, and organizational forms (e.g., Cennamo & Santalo, 2013; Cusumano et al., 2019; Jacobides et al., 2024; Kretschmer et al., 2022; Meyer et al., 2024). However, still less is known about entrepreneurial decisions leading to platform unicorn status (Cusumano et al., 2023).

The judgment-based approach (JBA) asserts that entrepreneurial judgment under uncertainty is "residual, controlling decision-making about resources deployed to achieve some objectives; it manifests in the actions of individual entrepreneurs" (Foss & Klein, 2012, p. 78) and it is a core element and function of entrepreneurship (Foss & Klein, 2012; Klein, 2008; Klein & McCaffrey, 2022). This is particularly true for platform unicorns, which operate and compete under high uncertainty and risk, necessitating the effective deployment of scarce and heterogeneous resources (e.g., Cusumano et al., 2023). In essence, entrepreneurial judgment involves not only decision-making under uncertainty but also decisions about key resources that entrepreneurs need to acquire, combine, or commit to including funds, technological solutions, and business model constituents (e.g., Foss et al., 2019; Klein & McCaffrey, 2022).

Thus, our study draws from the JBA, which posits that venture profit/loss depends more on how the decision maker combines the scarce and heterogeneous resources they own and control rather than any metaphorical opportunity (e.g., Foss et al., 2019; Klein & McCaffrey, 2022). Our study on platform unicorns directly relates to the existing conversations among entrepreneurship scholars that "further opening the judgment black box is desirable" (Rapp & Olbrich, 2023, p. 194). The discussion is well grounded by Foss and Klein (2012), McCaffrey (2016), and Giménez Roche and Calcei (2021). So far, scholars have made significant attempts to "dimensionalize" entrepreneurial judgment (Foss & Klein, 2012; Rapp & Olbrich, 2023); however, *combinations of complementary entrepreneurial decisions (we use the entrepreneurial decision as a synonym for entrepreneurial judgment)* concerning fundraising timing, funding sources, digital technology, and business model constituents leading to unicorn status have yet to be explored (e.g., Packard et al., 2017).

We address this gap by exploring the research question of *what combination of complementary entrepreneurial decisions increases and decreases the likelihood of becoming a platform unicorn*. To answer this question, *we explore the distinct combinations of complementary decisions about fundraising timing, funding sources, digital technology, and business model constituents that increase and decrease the likelihood of becoming a platform unicorn*. We investigate 125 digital platform ventures, including 12 unicorns, through decision tree analysis (Breiman et al., 1984; Buntine, 1992). The results spotlight the so-far neglected discussion on entrepreneurial decision profiles and the hierarchy of fundraising timing, funding sources, digital technology, and business model constituents' choices that increase and decrease the likelihood of a platform becoming a unicorn. So far, entrepreneurial decisions have been studied as stand-alone acts of committing scarce and heterogeneous resources (Foss et al., 2019); however, in contrast, *we assume that achieving unicorn status is the result not of a single act but of a unique combination of complementary entrepreneurial decisions*.

The results of our study make a threefold contribution to strategic entrepreneurship and JBA knowledge. First, we have identified nine complementary entrepreneurial decision profiles that later in the discussion we have grouped into two categories: the first group includes profiles with a higher probability of becoming a mental health platform unicorn, while the second group consists of profiles with a lower probability of achieving this outcome. The profiles consist of hierarchically related complementary decisions where early-stage start-up funding has the highest significance, and the following variables, such as digital technology and the business model, have lower significance. Although entrepreneurship scholars have already analyzed stand-alone variables, to the best of our knowledge, this is the first attempt to study a combination of complementary entrepreneurial decisions concerning critical heterogeneous resources leading to platforms' unicorn status.

Second, we add to a better understanding of the role of digital technologies in achieving unicorn status. Deep-tech ventures are founded around scientific-technological discoveries, for example, artificial intelligence (AI), big data, robotics, and so on, and usually have a portfolio of intellectual property, such as patents. Our study shows that although deep tech has a higher probability of driving a venture to achieve unicorn status, it is not a "must-have." Shallow tech—relatively simple digital technologies, is more frequent among platform unicorns; however, when it is combined with the B2C market served and subscription income stream.

Third, we open a research stream on failed entrepreneurial judgments by identifying two key decisions that can impede platform ventures from achieving unicorn status, that is, a combination of entrepreneurial decisions to seek government funding and deep tech; and combining shallow tech and the B2B market served. The business model choices, contrary to some other scholars' notions, come into play after the entrepreneurial decisions on fundraising, source of funding, and technologies are taken. Usually, entrepreneurs have to rely on intuition or "gut instincts" to make such decisions under uncertainty (e.g., Foss et al., 2019; Packard et al., 2017); however, our study demonstrates that digital technology, such as AI tools (e.g., decision trees), can generate profiles of complementary entrepreneurial judgments with higher and lower probabilities of becoming unicorns and allow entrepreneurs to make better-informed decisions.

2 | THEORETICAL BACKGROUND

2.1 | Entrepreneurial JBA

To explicate entrepreneurial decisions leading to unicorn status, we refer to the JBA, that is, how economic resources are deployed in organizational, industry, and institutional contexts of high uncertainty (Foss & Klein, 2012, p. 38; Foss et al., 2019). Said differently, JBA involves decision-making concerning economic resource deployment when outcomes cannot be predicted according to known probabilities (Foss & Klein, 2012, p. 38). The JBA states that entrepreneurial judgment under uncertainty is a core element and a function of entrepreneurship (e.g., Foss & Klein, 2012; Klein, 2008). This is especially significant for unicorns, as they perform and compete under high heterogeneity, uncertainty, and risk and need to deploy scarce resources in an effective way (Cusumano et al., 2023).

Entrepreneurial judgment is active, creating new opportunities, anticipating change, and exploiting it to yield profits. It relates to the theory of the firm in the way that entrepreneurial decisions acquire and combine assets and monitor how those assets are used (i.e., in line with the original decisions) as well as what judgmental power the entrepreneur delegates to subordinates (derived decisions) (Klein & McCaffrey, 2022). In other words, entrepreneurial judgment involves not only decision-making under heterogeneity and uncertainty but also decision-making about the resources the decision-maker owns and controls (Foss et al., 2019). The major resources that entrepreneurs need to acquire, combine, or commit are technology, funding, business models, and human resources (Klein & McCaffrey, 2022). *Concerning unicorns, often discussed factors are fundraising timing, funding source, technology type, and diverse business model constituents* (e.g., Bock & Hackober, 2020; Cusumano et al., 2023; Jinzhi & Carrick, 2019; Kotha et al., 2022; Piaskowska et al., 2021; Tekic et al., 2024; Venâncio et al., 2023) (also see Table A1).

Although the JBA has achieved some granularity over the past decade, little is still known about what, in real-world terms, entrepreneurial decisions and their hierarchical interdependence have led platform ventures to have a unicorn status; how decisions complement each other; and what decision combinations have the highest and lowest probability of transforming start-up to unicorn (e.g., Foss & Klein, 2012; Gerrard, 2024).

2.2 | Platform venture fundraising timing and funding source

For new ventures to become unicorns, they need scaling, which, in turn, depends (albeit not exclusively) on the accessibility and amount of funding (Kotha et al., 2022). Not all unicorns scale at the same pace (Kotha et al., 2022). Academic discourse suggests that innovative ventures, especially deep tech ventures, find it harder to secure financing; thus, obtaining funding is a pivotal challenge in the entrepreneurial journey (Lee & Kang, 2015).

In particular, deep tech ventures, known for developing radical technological innovations that arise from scientific advances that are unique, well protected, and often disrupt the market (Romme et al., 2023), take more risks in building their research-based technological innovations and fast-scaling strategies, including their business models. Higher risk is associated with longer deep-tech product or service development time and the need for vast research and commercialization resources that are crucial for developing new markets but hard to access (e.g., Mazzucato, 2013).

Concerning value creation, traditional businesses can rely heavily on physical assets such as machinery and inventory; in contrast, digital platforms derive their value largely from intangible assets such as software, algorithms, user data, and network effects (Bonina et al., 2021). Since intangible assets are context-specific and challenging to price, they are not easily used as security for loans (Mina et al., 2013).

Venture capital (VC) can be analyzed from different perspectives, depending on the venture's lifecycle, the VC type, fundraising timing, and funding source (Table A3). Unicorns are backed by VC and valued by these and other investors (Gornall & Strebulaev, 2020). Thus, venture capitalists are important not only for their investments but also for the way they perceive the potential of a start-up to become a unicorn. In other words, venture capitalists' expectations fuel the emergence of unicorns. Furthermore, if a venture has already received a VC investment in any stage of its start-up development, there is a higher probability that other venture capitalists will invest as well (Taraba et al., 2014).

2.2.1 | Early-stage start-up funding

Investors play a crucial role in the development of early-stage ventures, particularly in the seed and series A and B funding rounds. These investments provide the necessary financial resources for research and development, initial business planning, market expansion, and sales activities (Mocanu & Thiemann, 2023). Additionally, they convey the start-up's future potential value to the industry, which not only encourages subsequent funding rounds but also facilitates valuable collaborations (Agrawal et al., 2016). The valuation of early-stage VC-backed companies is essential for understanding the contractual terms crucial for both founders and investors (Gornall & Strebulaev, 2020). It guides decision-making and ensures the alignment of interests between parties.

Various types of investors participate in funding early-stage ventures, including business angels, crowdfunding platforms, incubators, accelerators, and sometimes CVC investors (Agrawal et al., 2016). Their support enhances the probability of a venture's success and its potential to become a unicorn—a start-up with a valuation exceeding $1 billion (Agrawal et al., 2016). However, VC firms typically avoid investing in deep-tech ventures during the early stages (Technology Readiness Levels[3] [TRLs] 2–7) because of high levels of technological, financial, and collaborative risk and uncertainty (Gerrard, 2024). They prefer to invest in ventures with a TRL of 8 or higher, where technologies are more mature and market needs are better understood (Romme et al., 2023).

While investors provide crucial support during critical early stages, their withdrawal can lead to significant challenges for start-ups (Cristofaro et al., 2024). Nonetheless, reliance on investors, especially private funding, is considered a crucial success factor by entrepreneurs (Taraba et al., 2014). Private funding offers flexibility and preserves entrepreneurial freedom, which might not be achievable with, for example, government investments (Taraba et al., 2014). Successful financing through crowdfunding is observed as relatively insignificant for investors, whereas the presence of active partners is considered more relevant for decision-making (Cristofaro et al., 2024). This underscores the importance of considering the dynamics associated with different types of investors and their impact on the success of early-stage ventures.

Finally, the connection between these investment characteristics and the scaling paths of platform unicorns is nuanced. While financial capital is undoubtedly critical, the strategic value brought by investors and supporters plays a vital role in navigating the complex ecosystem of digital platforms. Early-stage investments set the stage, but it is the continuous strategic alignment with investors and the leveraging of network effects that advance start-ups toward unicorn status.

2.2.2 | Government and nongovernment funding sources

Government support can act as a catalyst for the growth of start-ups, particularly in regions where the entrepreneurial ecosystem is still evolving. Initiatives such as grants, tax incentives, and participation in incubator or accelerator programs not only provide financial resources but also offer valuable knowledge and networks (Romme et al., 2023). This support is particularly advantageous for deep-tech platforms, given their longer and more capital-intensive development cycles.

Governmental venture capital (GVC) represents a form of public intervention aimed at addressing market failures associated with the undersupply of finance to early-stage high-tech or deep-tech firms (Minola et al., 2017; Minola & Giorgino, 2008). Many governments establish their own programs, often through independent government-sponsored VC investment funds, to achieve the benefits of VC financing. However, research suggests that firms backed by private VC funds tend to outperform those backed by GVC funds in terms of sales growth, headcount expansion, and initial public offering (IPO) performance (Cumming et al., 2023).

These differences in performance may stem from various factors, including the structure and operation of GVC schemes. These schemes can be categorized into guarantee systems, fund-of-funds systems, and direct investments in small and medium-sized enterprises (SMEs) by GVC investment funds (Alperovych et al., 2015).

Moreover, VC activity varies across different countries. In developed nations such as the United States and the United Kingdom, high-tech companies are predominant in the VC landscape. Conversely, VC companies in developing countries and emerging market economies often have lower technology content (Metrick & Yasuda, 2011). Government-funded programs, alongside VC companies, provide financial assistance to enterprises, offering loans, grants, tax incentives, and intellectual property protection (Zeng et al., 2023). This government support is crucial for businesses, particularly during challenging times, and plays a significant role in corporate financing. With government funding, there is a higher probability that other VCs will invest as well (Taraba et al., 2014).

2.3 | Deep tech versus shallow tech

Swati Chaturvedi, CEO of Propel(x), introduced the term “deep tech” in 2015, defining it as “companies founded on scientific discoveries or meaningful engineering innovations” (Chaturvedi, 2015, p. 1). These companies differ from digital-born unicorns in terms of their business model and competitive advantage. Digital-born unicorns typically rely on existing technologies to innovate their business models, whereas deep-tech companies create value through technological solutions to existing problems. *The business models of deep-tech companies are more difficult to replicate because of their foundation in scientific-technological discoveries* (Chaturvedi, 2015).

Deep-tech start-ups leverage deep technologies such as AI, big data, and robotics to gain a competitive edge (Dionisio et al., 2023). The “shallow tech” concept indicates that start-ups have no advanced digital technologies. Unlike digital start-ups, deep-tech ventures face challenges related to complex integration between software and hardware (Siegel & Krishnan, 2020). As a result, these start-ups offer unique and innovative solutions but struggle to find compatible existing technology architectures (Adner & Kapoor, 2010).

Deep tech-based start-ups must find early supporters to secure funding for their innovative projects, as deep tech can be difficult for many investors to understand (Vossen & Ihl, 2020). Historically, deep-tech companies have not received as much attention from funding organizations, venture capitalists, or policymakers compared to digital-enabled platform unicorns (Essen et al., 2023). However, recent research has highlighted the value of platforms in areas such as blockchain technologies, telemedicine, business intelligence, AI, and information systems (Essen et al., 2023).

Start-ups, especially technology start-ups, are crucial for building innovation ecosystems (Nambisan et al., 2018). They often aim to revolutionize their markets, which puts pressure on their development and business processes (Korper et al., 2020). However, technology-focused start-ups may struggle to maintain their development practices and can accumulate technical debt, limiting the scope for successful market implementation. Excessive focus on technology can also lead to less systematic and more ad hoc processes, contributing to failure, particularly in the early stages (Korper et al., 2020).

Technology start-ups have primarily been understood through engineering-related perspectives and challenges, yet start-ups mostly fail because of a lack of customers rather than a lack of technology (Giardino et al., 2014). Obtaining customer feedback is crucial for reducing perceived risk in software start-ups and validating functionality in real-world markets (Furr et al., 2012; Giardino et al., 2014).

Regarding the growth of technology start-ups, having the ability to identify technology with both technological and market potential can act as a catalyst for growth (Jinzhi & Carrick, 2019). Some unicorns, however, such as Airbnb, achieved their status without having a high-tech business model, indicating that a research-intensive approach may not be the sole path to success (Bock & Hackober, 2020).

In conclusion, deep-tech companies use technologies based on scientific discoveries or meaningful engineering innovations to gain a competitive advantage. This "deep tech" is the promise of distinct and innovative value propositions for a platform venture. However, when a platform venture relies on deep tech, it faces unique challenges in integrating software and hardware and finding a business model. Since finding a business model is challenging but critical, understanding the interplay between technology and market potential becomes essential for a deep-tech platform's start-up success.

2.4 | Platform venture business model

One of the definitions of the business model refers to the value architecture of a firm (Teece, 2010). The business model defines how the firm delivers value to customers, entices customers to pay for value, and converts those payments to profit. This is the process of value creation, delivery, and capture (Teece, 2010, p. 172). Furthermore, the scientific literature argues that no single entrepreneurship or strategic management theory can fully explain the value creation potential of e-business (Amit & Zott, 2001). Thus, the research stream of business models draws from a combination of various theories, including entrepreneurship theory, transaction cost economics, resource-based views of a firm, and strategic network theory (Demil et al., 2015; Ghezzi & Cavallo, 2020).

Täuscher and Laudien (2018) proposed a digital platform business model definition that aims to facilitate a systematic and traceable understanding of Teece's (2010) original business model concept. They argue that the dimension of value creation refers to the architecture and the mechanisms it employs to develop the value proposition, and it is composed of the platform type (e.g., mobile app or web-based platform), key activity (e.g., community building, matching, allowing transactions), price discovery (e.g., fixed price, dynamic pricing), and review system (e.g., allowing, not allowing reviews). Next, value delivery, which refers to business model components generating value directed for a specific group of target customers, encompasses key value proposition, transaction content (e.g., cost efficiency, providing emotional or social value), transaction type (e.g., product platform, service platform), industry scope (e.g., vertically or horizontally aligned), market served (e.g., business to customer (B2C), business to business (B2B), customer to customer (C2C) and other), and geographic scope (e.g., local, international). Crafting these elements can steer digital platforms toward varied trajectories. For instance, Tekic et al. (2024) argue that platforms balancing equally core technology and market capabilities experience faster growth than those that primarily concentrate on either technology or market development alone. In addition, platforms serving the B2B market and demonstrating a balanced orientation exhibit faster growth rates than their B2C counterparts with the same balanced orientation (Tekic et al., 2024).

Finally, the business model's value capture dimension explicates the mechanisms through which the firm transforms the value provided to customers into tangible sources of revenue and profits and is composed of the key revenue stream (e.g., commissions, subscriptions, advertising, sales), pricing mechanism (e.g., fixed pricing, dynamic, etc.), price discrimination (quantity or timing-based), and revenue source (e.g., seller, buyer, other platform parties) (e.g., Jia et al., 2023). In platform business models, just as in any other form of business, deciding on key revenue streams such as commissions or subscriptions is crucial. Furthermore, to establish a competitive advantage, these businesses need to ensure that all elements of the business model are co-specialized and function effectively as a cohesive system (Teece, 2010).

Innovators run the risk of not being able to deliver or realize the value of their innovations without a strong business model. Establishing the right business model for a platform venture is a multisided challenge due to the complexity of the entrepreneurial decisions (e.g., value creation mechanisms, activities, market served, income streams, and others) to be made (Täuscher & Laudien, 2018). Furthermore, the business model is not a one-time decision; it dynamically changes depending on fundraising timing (early vs. late stage), funding source (government vs. private), and technology (deep-tech vs. shallow tech) (e.g., Chaturvedi, 2015; Cusumano et al., 2023; Tekic et al., 2024). However, the specific interdependences and the sequence of these factors leading to unicorn status have yet to be revealed.

3 | METHODOLOGY

3.1 | Decision tree analysis

Our paper aims to disentangle which combinations of complementary entrepreneurial decisions increase and decrease the probability of a mental health platform becoming a unicorn. To meet the aim of the paper, we use a decision tree approach (Quinlan, 1986), also known as a classification tree, when the target variable is categorical (Breiman et al., 1984; Buntine, 1992). This nonparametric method is particularly useful when seeking to identify the most relevant variables in the classification or prediction-of-outcomes process, such as the one we address in this paper in relation to achieving unicorn status. Indeed, decision (classification) trees have gained popularity across various research fields that involve complex scenarios where decisions need to be made, including business, finance, and economics (Yeo & Grant, 2018).

This statistical method is a machine learning technique that facilitates classification and decision-making under uncertainty. It involves the construction of a hierarchical tree structure where each node represents a feature- or attribute-based decision, and each leaf node represents a class or category. The tree is built recursively by selecting the best logical split at each node that permits accurate prediction and classification of cases, resulting in different profiles. Thus, the process identifies the most significant factors of success for the outcome variable based on the responses of the cases grouped in each node. For our context, the method allows us to identify different entrepreneurial decision profiles (combinations) that have a higher or lower probability of achieving unicorn status and, in turn, which variables are more determinant in leading to unicorn status.

Decision trees[4] present several advantages, such as ease of use, straightforward visualization of results, and interpretability. Additionally, they can handle mixed data types (both numerical and categorical) variables and are robust against outliers. In addition to these advantages, we chose this method to analyze our data for several reasons. First, decision trees efficiently use automated algorithms that can handle medium-to-large datasets with multiple variables (such as the one we address in this paper), making them optimal for complex data. Second, unlike conventional predictive analysis, decision trees are nonparametric, meaning that they do not require strict assumptions about the data and its distribution. Third, when using qualitative variables, the method allows the introduction of numerous categories without the need for data calibration or variable restructuring, which is often necessary for other common methods applied to qualitative data, such as qualitative comparative analysis (QCA). Fourth, decision trees are effective in identifying complex interactions between variables, with the nodes reflecting the influence of multiple factors and allowing for different relationships between variables in different parts of the measurement space. This makes interpretation more straightforward and reliable than the causal interactions derived from QCA configurations. Finally, decision trees have strong predictive and classification power, enabling the prediction of future outcomes and the identification of both success and failure factors.

3.2 | Industry selection

Mental health is broadly defined by the World Health Organization (WHO) as "a state of mental well-being that enables people to cope with the stresses of life, to realize their potential, to learn and work well, and to contribute to their communities. Mental health is an integral part of health and well-being and is more than the absence of mental disorders" (WHO, 2022, p. 8). According to a WHO report, mental disorders are common and affect one in eight people worldwide—not only adults but also adolescents and children (WHO, 2022). In 2020, a systematic review of cost-of-illness studies from around the world revealed that "the average annual societal cost of mental health conditions, adjusted for purchasing power parity to US price levels, ranges from US$ 1180 to US$ 18313 per person treated, depending on the condition" (WHO, 2022, p. 51).

The mental health industry is relevant to answering our research question for several reasons. First, mental health, as stated above, significantly affects societal well-being, and platform unicorns are recognized as a pertinent solution in this context. Adults and children with mental illness do not receive adequate treatment because of barriers, which include stigma, high costs or insufficient funding, a lack of providers or a lack of knowledge of where to find them, and long wait times (Moroz et al., 2020). Digital mental health platform unicorns can overcome or reduce transactional costs (Iorfino et al., 2019). The platform unicorns' promise of better, faster, and less costly care can help restructure entire industries and create business model innovations (Pundziene et al., 2022).

Second, by focusing on mental health platforms, we answer Tekic et al.'s (2024) call to explore a mixed sample of unicorns and non-unicorns to be able to compare them. In the Dealroom dataset, unicorns in the health industry, including all sub-industries such as medical devices, health platforms, biotechnology, and pharmaceuticals, have a low representation at 1.59%. When we narrow it down to health platforms, the representation increases to 2.40%. Focusing further on mental health platforms, the representation increases to 6.61%. With our sample of 125 platform ventures and 12 platform unicorns, the representativity is 9.6%. Therefore, by focusing on the mental health sector, we increase the representativity of unicorns for our sample and thus the validity and reliability of our results. While we recognize the strengths of an industry-specific approach, we also acknowledge that focusing solely on the mental health industry may be a limitation, as discussed in more detail in the Limitation section.

Third, our choice of the specific sector was motivated by several calls for more attention to the role of the industry context in entrepreneurship research (von Briel et al., 2018; Zahra et al., 2014) and platform research (Cennamo & Santalo, 2013; Teece et al., 2022). As argued by von Briel et al. (2018), focusing on a sector should provide insights that are more valid for that sector and similar industries than insights that come from an attempt at "contextless" theorization. Choosing the mental health sector allowed us to control for differences that may arise from sector-specific factors.

3.3 | Data and variables

To collect our data, we used a Dealroom database that provides a global and relatively complete dataset on technological start-ups and firms. In contrast to other databases such as Pitchbook or Crunchbase, Dealroom has several advantages: (1) extensive coverage of platform ventures, including unicorns by industry; and (2) relatively rich selection of venture characteristics, including industry and technology tags found in company profiles. Indeed, the use of this database has recently garnered increased attention in academic research (van Meeteren et al., 2022; Weik et al., 2024).

Dealroom enables us to access categorized and precise information specifically tailored to health platform ventures. It classifies companies in different industries and subindustries, which allows us to identify a tight group of unicorn companies classified as (1) companies, (2) health industry, (3) health platforms, and (4) mental health. The database also specializes in detecting and categorizing comprehensive and detailed information about ventures and provides data about business characteristics, funding sources, and technologies used.

Our initial sample comprised 289 ventures, but after we discarded all those with incomplete data, our final sample consisted of 125 mental health platforms, of which 12 were unicorns. All of them were launched after 2010. We deliberately added the filter of 12 years because 2010 was the launch year of the first mental health platform unicorn, Ginger (description provided in Table A2). We note that while the selected sample may appear small at first glance, this is not the case. Unlike other studies with larger sample sizes (Table A1), our research is specifically tailored to a particular industry, offering nuanced insights that may be overlooked in larger, more generalized samples. Indeed, this industry-specific approach allows for better control over variations between companies and enriches the depth of our findings, facilitating the identification of key characteristics distinguishing companies that achieve unicorn status.

With respect to the selection of variables to be included in the analysis, we obtained information on both the quantitative and qualitative characteristics of the mental health platforms (Table 1). Table 2 presents the descriptive statistics of the quantitative variables as well as the proportion of companies that belong to each group of categorical variables.

The summary descriptive statistics for the quantitative variables (i.e., valuation, funding, employees, and funding rounds) show higher values for unicorn companies than for non-unicorn companies, confirming that unicorn

TABLE 1 Variables and definitions used in the analysis (based on Dealroom source).

Variables	Definitions	Value(s)
Total funding (Y1)	The total amount of money obtained by the company across all funding rounds.	In millions of US dollars ($).
Employees (Y2)	The company's workforce size through the last number of employees available.	Number of employees.
Valuation (Y3)	The estimated economic value.	In millions of US dollars ($).
Funding rounds (Y4)	The total number of funding rounds received.	In the number of funding rounds.
Market served (Y5)	The type of customer segment a company targets, categorized as B2B (Business-to-Business), B2C (Business-to-Consumer).	Categorical variable: 1 = B2B models; 2 = B2C models; 3 = mix of B2B and B2C.
Income streams (Y6)	The main income stream of the company, said differently the main way a company generates revenue from its operations, categorized as commission or subscription.	Categorical variable: 1 = commission; 2 = subscription; 3 = otherwise (other income streams from those included in groups 1 and 2).
Technologies (Y7)	A company's implementation of at least one of the following deep technologies: AI, natural language processing, machine learning, and big data.	Categorical variable: 1 = implemented at least one of the following deep technologies: AI, natural language possessing, machine learning, big data; 0 = otherwise.
Early-stage start-up funding (Y8)	A company's acquisition of funding during its early stages. This includes capital obtained from sources such as crowdfunding, incubators, or business angels.	Categorical variable: 1 = received money from crowdfunding, business angels, or incubators; 0 = otherwise.
Late-stage start-up funding (Y9)	A company's acquisition of funding during its development stages. This includes capital obtained from sources such as venture capital firms, corporates, or accelerators.	Categorical variable: 1 = received money from a venture capitalist, corporates, or accelerators; 0 = otherwise.
Government/ nonprofit (Y10)	A company's acquisition of public funding coming from government agencies or nonprofit organizations	Categorical variable: 1 = received public funding; 0 = otherwise.

TABLE 2 Summary of the descriptive statistics.

Unicorn companies in the sample	12	9.60%			
Descriptive statistics of key variables	**Mean**	**Q1**	**Median**	**Q3**	**s.d.**
Funding (Y1)*	67.97	1.77	8.50	53.63	159.13
Unicorns	442.88	203.75	406.77	579.10	298.08
Non-unicorns	28.16	1.52	6.20	24.50	51.49
Employees (Y2)	196.82	16.00	62.00	192.00	337.84
Unicorns	883.00	656.25	807.00	1005.50	447.24
Non-unicorns	123.95	14.00	50.00	120.00	225.65
Valuation (Y3)*	387.99	7.50	27.50	100.00	1146.05
Unicorns	3251.05	1792.50	2985.00	5025.00	2160.83
Non-unicorns	83.94	6.00	22.00	80.00	155.06
Funding rounds (Y4)	4.28	2.00	4.00	6.00	2.82
Unicorns	8.17	6.75	8.00	10.00	2.66
Non-unicorns	3.87	2.00	3.00	5.00	2.51
	B2B		**B2C**		
Market served (Y5)	23	18.40%	63	50.40%	
Unicorns	1	8.33%	8	66.67%	
Non-unicorns	22	19.47%	50	44.25%	
	Commission		**Subscription**		
Income streams (Y6)	53	42.40%	66	52.80%	
Unicorns	3	25.00%	9	75.00%	
Non-unicorns	50	44.25%	57	50.44%	
	Yes				
Technologies (Y7)	29	23.20%			
Unicorns	10	83.33%			
Non-unicorns	27	23.89%			
Early-stage start-up funding (Y8)	55	44.00%			
Unicorns	11	91.67%			
Non-unicorns	44	38.94%			
Late-stage start-up funding (Y9)	120	96.00%			
Unicorns	12	100.00%			
Non-unicorns	108	95.58%			
Government/nonprofit (Y10)	26	20.80%			
Unicorns	2	16.67%			
Non-unicorns	24	21.24%			

*In millions of US dollars ($)

companies are the largest and most successful companies in our sample. Indeed, one of the main characteristics of a unicorn company is reaching a valuation of at least $1 billion. Thus, by default, they typically receive substantial funding and have high valuations. However, we included these variables since their examination still provides crucial information on the organizational, industry, and institutional context for understanding unicorn status.

Otherwise, when we look at the qualitative variables (i.e., market served, income streams, technologies, and those referring to investor type), the difference in the distributions is not so obvious and justifies a more rigorous analysis to understand the main characteristics that increase the probability of being a unicorn company.

Therefore, given the considerations mentioned in the previous paragraph, before implementing the decision tree analysis, we first analyze the relationship between the unicorn companies and the quantitative and qualitative variables. To do this for the quantitative variables, we run one-way analyses of variance (ANOVA) to determine whether there are statistically significant differences between the groups of unicorn and non-unicorn companies. The results are shown in Table 3.

From the ANOVA results in Table 3, it is possible to reject the null hypotheses, establishing that the average values for the quantitative variables in both groups are equal. There are significant differences. Furthermore, as we previously observed in Table 2, the average values for unicorns are always the highest. Therefore, if we include these variables in our decision tree, they will be the main characteristics that define unicorn companies.

We also analyzed the relationship between the unicorn firms and the qualitative variables by using a chi-squared statistic test. The results are provided in Table 4. Table 4 shows that, based on the *p*-value of the chi-squared test, for most of the variables, we do not reject the null hypothesis of no relationship between the categorical variables; that is, they are independent of being or not being unicorns. We find the exception to be the early-stage start-up funding variable (Y8), which has a *p*-value lower than .05; as a consequence, there is a statistically significant relationship. This result shows that investors' involvement in early-stage start-ups is a key characteristic of current digital platform unicorns in mental health.

After this preliminary analysis, in which we examined the relationships between the quantitative/qualitative variables and the groups of unicorn/non-unicorn companies, we obtained clear differences for the quantitative variables (e.g., investment size, revenues, and number of employees). In contrast, the differences are not as obvious for the qualitative variables (e.g., fundraising timing, funding source, and technology). Thus, we analyze different entrepreneurial decision profiles that increase the probability of being a mental health platform unicorn while considering only the qualitative variables.

TABLE 3 Unicorn versus quantitative variables (ANOVA).

Quantitative variables	*F*	Prob > *F*
Funding (Y1)	180.09	<0.00
Employees (Y2)	97.28	<0.00
Valuation (Y3)	247.60	<0.00
Funding rounds (Y4)	31.51	<0.00

TABLE 4 Relation of unicorn to qualitative variables (contingency tables and chi-squared test).

Qualitative variables	Chi-squared test	Prob > χ^2
Market served (Y5)	1.59	0.45
Income streams (Y6)	2.82	0.24
Technologies (Y7)	0.32	0.57
Early-stage start-up funding (Y8)	12.24	0.00
Late-stage start-up funding (Y9)	0.55	0.46
Government/nonprofit (Y10)	0.14	0.71

4 | FINDINGS

4.1 | Digital platform unicorns' entrepreneurial decision profiles

In this section, we present the results from the classification tree, where the variables of interest are being or not being a mental health platform unicorn venture, as well as the categorical entrepreneurial decisions related to fundraising time and funding source, the technologies utilized, and the business model constituents (market served and income streams). Before presenting our results, we note two important considerations. First, given that in our context, the response variable is categorical, our model fits the probabilities estimated for the response levels, minimizing the residual log-likelihood chi-square, which is proportional to twice the entropy. Second, considering the particularities of our data, the idea of becoming a unicorn is not a priori the most likely situation in our industry. Therefore, for validation purposes, we run a contingency table that modifies the original cut-off point of the confusion matrix to classify an observation as unicorn or non-unicorn. In doing so, we consider a 9.60% cut-off point, which corresponds to the percentage of unicorns in our sample (12 out of 125). Our results show that we would correctly classify all unicorns (12/12) and classify 65.48% of the non-unicorns as non-unicorns (74/113), but we would make a mistake in classifying 34.51% as unicorns. The global accuracy percentage is 68.80% ((74 + 12)/125).

Figure 1 shows the results for the classification tree, which uses a minimum size of five observations as a splitting criterion. Each node shows the total number of cases (Counts) within each group (i.e., unicorns and non-unicorns) and the predicted probability of becoming a unicorn (Prob). At the leaf nodes (the endpoints of the tree), you see the final profiles summarizing the results of the entire decision path. Moreover, for each node, there is a G^2 (likelihood ratio chi-square), that is, a fit statistic used for categorical responses (lower values indicate a better fit).

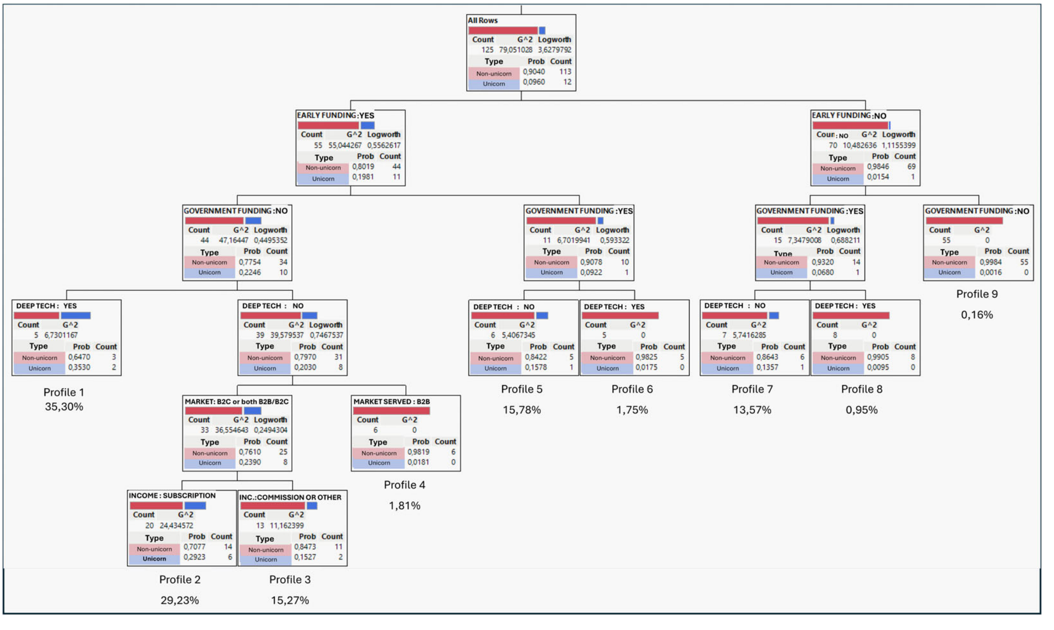

FIGURE 1 Classification tree results. G^2: It is a fit statistic used for categorical responses. Lower values indicate a better fit, being values equal to zero an indication of a "pure" node leaf; Log: Logworth statistic is the log transformation of the p-value used in the node splitting criteria, which indicates how well a variable divides the data into each class. The optimal split is the one that maximizes the logworth. Prob: It is the predicted probability for that node of the tree.

The results in Figure 1 show that the main qualitative characteristic that increases the probability of becoming a mental health platform unicorn is receiving funding at early stages from at least one of the following investors: crowdfunds, angels, and incubators. These results confirm the results obtained in the preliminary analysis, in which this variable was significant. Moreover, if a mental health platform receives early-stage start-up funding, the probability of becoming a unicorn is particularly high if it does not receive government funding and possesses deep tech related to AI, natural language processing, machine learning, and/or big data (Profile 1, probability 35.30%, $G^2 = 6.73$). In the case of not possessing one of the deep techs, ventures also increase their probabilities when they generate their revenue through subscriptions and serve the B2C market (Profile 2, probability 29.23%, $G^2 = 24.43$).

Moreover, suppose that a venture obtains early and government funding but does not possess deep tech (Profile 5, probability 15.78%, $G^2 = 5.41$); its probability of becoming a unicorn is similar to those mental health platforms that have early funding, do not obtain government funding, do not possess deep tech, generate revenue through income streams other than subscriptions, and serve the B2C market (Profile 3, probability 15.27%, $G^2 = 11.16$).

Furthermore, these last profiles present increases in the probability of 2.21% (for profile 5) and 1.70% (for Profile 3) compared with those mental health platforms that do not obtain early funding but do obtain government funding and do not possess deep tech (Profile 7, probability 13.57%, $G^2 = 5.74$).

Finally, the group of companies that have a lower probability of becoming mental health platform unicorns are characterized by (1) no early-stage funding and no government funding (Profile 9, probability 0.16%, $G^2 = 0.00$), (2) no early-stage funding but government funding and deep tech (Profile 8, probability 0.95%, $G^2 = 0.00$), (3) early-stage funding, government funding, and deep tech (Profile 6, probability 1.75%, $G^2 = 0.00$), and (4) early-stage funding but no government funding, no deep tech, and B2B (Profile 4, probability 1.81%, $G^2 = 0.00$).

Table 5 summarizes the nine profiles leading to successfully becoming a mental health platform unicorn or failing. We also provide each profile with real mental health platform unicorns that meet the criteria for each combination of entrepreneurial decisions. In the following subsections, we further explain the combinations of entrepreneurial decisions that lead to a higher or lower probability of achieving mental health platform unicorn status.

Next, to streamline the analysis, we aggregate the nine entrepreneurial decision profiles into two groups. The first group consists of entrepreneurial decision profiles with a higher probability of becoming platform unicorns (Profiles 1, 2, 3, 5, and 7), while the second group includes profiles with a lower probability of achieving this outcome (Profiles 4, 6, 8, and 9). Both groups are discussed in detail below.

4.2 | Combinations of complementary entrepreneurial decisions with a higher probability of becoming a platform unicorn

Our findings offer five entrepreneurial decision profiles (Profiles 1, 2, 3, 5, and 7) that have a relatively high probability of reaching unicorn status. Profile 7, with a 13.57% probability of becoming a platform unicorn, has no early-stage funding; however, it has received government funding but has no deep tech. Decision tree analysis shows (Figure 1 and Table 5) that adding early-stage start-up funding to Profile 7's combination of complementary entrepreneurial decisions increases the probability of becoming a platform unicorn by 2% (see Profiles 5 with 15.78%). Furthermore, if we eliminate government funding from Profile 5 and add a B2C or mixed market served and commission or mixed-income stream (see Profile 3 with 15.27%), the probability of becoming a platform unicorn decreases by 0.51%. However, if the entrepreneur under Profile 3 chooses a subscription income stream, the probability of becoming a platform unicorn increases by 13.96% (see Profile 2 with 29.23%). Thus, in this case of a mental health platform, a *subscription income stream is a differentiating factor* for a higher probability of the entrepreneurial decision combination leading to platform unicorn status. Finally, the probability of becoming a mental health platform unicorn can still be increased by combining early-stage start-up funding, no government funding, *and deep tech*. Thus, choosing deep

TABLE 5 The nine entrepreneurial decision profiles with high and low probabilities of becoming platform unicorns are supported by platform unicorn examples.

		Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Profile 6	Profile 7	Profile 8	Profile 9
Probability of being a unicorn		35.30%	29.23%	15.27%	1.81%	15.78%	1.75%	13.57%	0.95%	0.16%
# of unicorns		2	6	2	0	1	0	1	0	0
# of nonunicorns		3	14	11	6	5	5	6	8	55
Funding decision	Early funding	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
	Govt. funding	No	No	No	No	Yes	Yes	Yes	Yes	No
Technology	Deep tech	Yes	No	No	No	No	Yes	No	Yes	
Business model	Market served		B2C or mix	B2C or mix	With B2B					
	Income stream		Subscription	Commission or mix						
Real cases of mental health platform unicorns		Spring Health Ginger	Calm Health Ro Health Cityblock Health Cerebral Lyra Health Headspace	Modern health Alan		Talk Space		Omada Health		

tech can increase the probability of becoming a platform unicorn to 35.30% (see Profile 1) with the right combination of funding choices.

Thus, the two leading combinations of complementary entrepreneurial decisions with a higher likelihood of becoming a mental health platform unicorn are (1) the platform venture has early-stage start-up funding, no government funding, and deep tech (see Profile 1); (2) the platform venture has early-stage start-up funding, no government funding, no deep tech, serves a B2C or mixed market, and has a subscription income stream (see Profile 2). Combining a no-deep-tech with relevant business model constituents such as B2C or mixed market served and the subscription income stream significantly increases the likelihood of the venture becoming a mental health platform unicorn. Furthermore, non-deep-tech platform unicorns are more frequent than deep-tech platform unicorns, although they have a higher probability of becoming such (also see Table 5).

4.3 | Combinations of complementary entrepreneurial decisions with a lower probability to become a platform unicorn

When comparing Profiles 1 and 2 (Figure 1 and Table 5), the probability of becoming a mental health platform unicorn decreases by 6.07% when the mental health platform has no deep tech. Both profiles have early start-up funding and no government funding; they differ only in their possession of deep tech. Furthermore, when comparing Profile 4 with Profiles 2 and 3, we can see that the choice of the market served further decreases the probability of becoming a unicorn to 1.81%. It appears that serving a B2B market in combination with no deep tech radically decreases the probability of becoming a mental health platform unicorn.

Next, when comparing Profiles 6 and 8, we can observe that, regardless of whether the mental health platform has early start-up funding, the choice to receive government funding when the mental health platform has deep tech decreases the likelihood of becoming a unicorn to less than 2% (1.75% for profile 6 and 0.95% for profile 8).

And, of course, without any funding (Profile 9), no unicorn can be born (0.16%). Thus, the two failure combinations of complementary entrepreneurial decisions with a lower likelihood of becoming a mental health platform unicorn are (1) the mental health platform venture has early-stage start-up funding, no government funding, and no deep tech and serves the B2B market (see Profile 4); (2) the mental health platform venture has governmental funding and deep tech (see Profiles 6 and 8) (also see Figure 2).

5 | DISCUSSION AND CONTRIBUTION

We aimed to answer the question of what combination of complementary entrepreneurial decisions increases and decreases the likelihood of becoming a platform unicorn. Our study used retrospective descriptive data from the Dealroom database and the decision tree methodology to identify different profiles of complementary entrepreneurial decisions to assess the likelihood of becoming a mental health unicorn. This is a unique attempt to investigate the interdependencies and sequence of entrepreneurial decisions in which diverse combinations have different probabilities of achieving platform unicorn status. Our study aggregates *two groups of entrepreneurial decision profiles*. The first group (Profiles 1, 2, 3, 5, and 7) has a higher probability, and the second group (Profiles 4, 6, 8, and 9) has a lower probability of becoming a mental health platform unicorn. These two groups allowed us to define mental health platform ventures' successful and failure choices concerning fundraising time and funding sources, technology, and business model constituents leading to unicorn status compared to non-unicorn ventures.

To succeed or mitigate failure, platform unicorns require resources dynamically tailored to organizational, industry, and institutional contexts, making the right combination of entrepreneurial judgments critical to their survival. While the start-up literature on early success provides valuable insights, it does not fully address the unique challenges and strategies specific to unicorns (Cristofaro et al., 2024, p. 2). By analyzing successful and failure

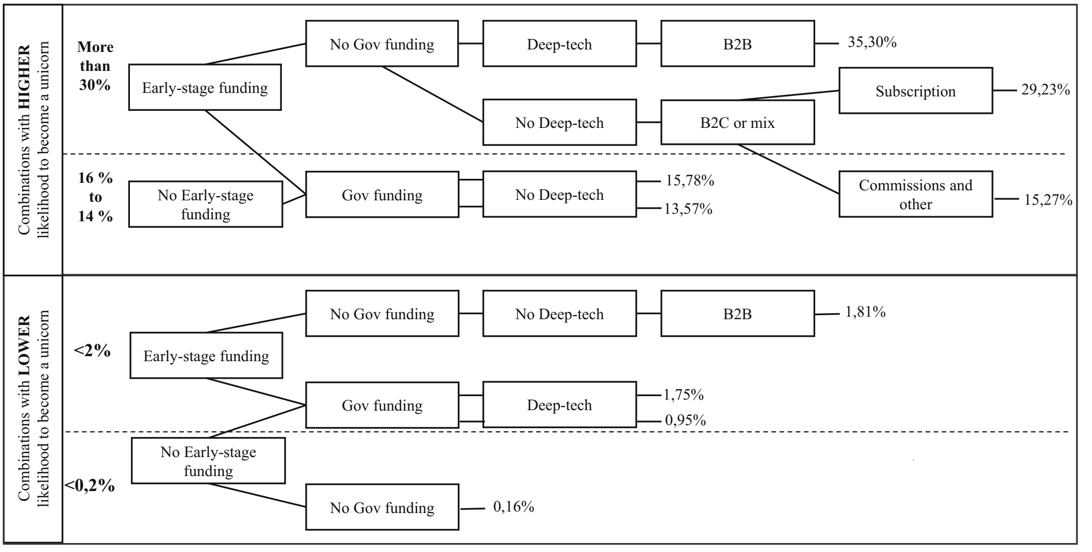

FIGURE 2 Complementary entrepreneurial decision profiles with a higher and lower likelihood of reaching mental health platform unicorn status.

combinations of entrepreneurial judgments, our study provides more granularity into the former discussion on the unique challenges of mental health platform unicorns and how to address them. For example, early-stage funding and no governmental funding are significant decisions in becoming mental health platform unicorns because (1) early-stage funding is needed to accelerate growth and market penetration, increase investors' confidence and higher valuation, and access strategic guidance and networks (Böttcher et al., 2021); (2) private venture capital (VC) better addresses mental health venture needs because, in addition to financial support, they have mental health industry-specific connections and active monitoring in contrast to government venture capital (GVC) backed ventures. The GVC can lack a deeper level of industry expertise and incentives to engage with portfolio companies (Croce et al., 2018). Furthermore, VCs often have stringent selection processes, targeting firms with high growth potential and scalable business models. GVCs, however, might invest based on policy objectives, such as regional development or job creation, which may not always align with high-growth ventures (Breschi et al., 2021).

Entrepreneurial judgments are also affected by the choice of the types of technology (e.g., deep tech or no deep tech), the market served, and the business model. Deep tech better fits the B2B market because it engages with large organizations, such as hospitals, insurance companies, and corporate employers, allowing them to secure substantial contracts and recurring revenue streams. This business model facilitates rapid scaling and significant sales growth. On the other hand, no deep tech ventures have the potential to reach a vast number of individual consumers, enabling rapid user acquisition and revenue scaling. This extensive individual customer base can lead to accelerated sales growth compared with B2B firms, which typically have a narrower network; however, B2B firms are able to invest in innovations for a longer period of time needed to develop deep tech, the audience of business clients (Zare & Persaud, 2024). Digital B2C firms can leverage technology to scale operations efficiently, reaching a global audience without a proportional increase in operational costs. This scalability supports both sales growth and headcount expansion as the company grows (Moro-Visconti, 2022).

Based on the results of our study, we offer three theoretical contributions to strategic entrepreneurship literature and the JBA. First, *we propose that entrepreneurial decisions are not made as stand-alone choices; instead, their success depends on the combination of complementary entrepreneurial judgments*. The results of the study propose success and failure combinations when seeking mental health unicorn status. Second, the findings highlight the *significant role of deep tech when individuals are seeking a unicorn status*. Although deep-tech mental health platforms with early-stage venture funding have the highest probability of becoming platform unicorns, they are *not compatible with government funding*. Furthermore, non-deep tech mental health ventures have a similar probability and more frequently become unicorns only when utilizing a particular combination of complementary entrepreneurial judgments. Third, funding timing and source are critical entrepreneurial decisions; for example, failure *to establish early-stage platform funding significantly decreases the likelihood of achieving unicorn status*.

5.1 | The combination of complementary entrepreneurial decisions matters, not a stand-alone judgment

The quality of entrepreneurial judgment—acquisition, combination, reconfiguration, and being responsible for productive resources—under high uncertainty determines the success or failure of the business (e.g., Foss et al., 2019; Rapp & Olbrich, 2023). Thus, entrepreneurs are responsible for combining heterogeneous resources but also, as our study shows, *for the continuous, sequential, and hierarchical combination of judgments that increase the probability of success in the long run*. An entrepreneurial manager who dynamically makes resource recombination decisions was depicted by Teece (2007) when he discussed micro-foundations of dynamic capabilities. However, the dynamic capabilities framework does not cover combinations of judgments leading to a specific purpose. To fill this void, our study reveals successful and failure *combinations of complementary entrepreneurial decisions* that lead or impede platform ventures to reach unicorn status. For instance, although deep tech significantly increases the probability of becoming a platform unicorn, ventures without deep tech become platform unicorns by relying on B2C or mixed markets and subscription income streams.

Our results extend the JBA by providing combinations of complementary entrepreneurial decisions leading to platform unicorn status. Although JBA scholars have significantly denationalized the "black box" of entrepreneurial judgments (e.g., Foss et al., 2019; Klein & McCaffrey, 2022), our study, by focusing on one specific industry, is one of the first attempts to highlight the hierarchical interdependencies between the entrepreneurial decisions leading to unicorn status. The findings enable informed choices among diverse entrepreneurial decision profiles while individuals are seeking unicorn status.

5.2 | Deep tech is a differentiating factor in becoming a platform unicorn

In response to Nambisan's (2017) call for a digital technology perspective on entrepreneurship, we provide empirical evidence on the role of digital technology in combination with complementary entrepreneurial decisions. Although deep tech ventures often have radical value propositions based on scientific discoveries and, thus, are difficult to imitate, they also face business pressures to attract early-stage investors due to high uncertainty, risk, and often long, deep development cycles (Chaturvedi, 2015; Cusumano et al., 2023; Taraba et al., 2014). Our study suggests that, in mental health, if a deep-tech platform venture succeeds in acquiring early-stage start-up funding, it has the highest probability of becoming a unicorn.

In contrast to prevailing expectations that unicorns are bred on deep tech (which is partially true) (Cusumano et al., 2023; Gawer, 2022; Kotha et al., 2022), our mental health platform unicorns' study results indicate that only two platform unicorns reported deep tech as the technology they utilize (Spring Health and Ginger); 10 unicorns out of 12 had no deep tech in their complementary decision combinations yet succeeded in becoming unicorns by relying on a particular business model (B2C or mixed and subscription income stream) and mainly on early-stage venture funding. This can be explained on the one hand by the pressure from VCs to scale quickly (while deep tech takes time to develop), and on the other hand, the B2C business model with basic platform technology allows efficient scaling and reaching a global audience without a proportional increase in operational costs (Croce et al., 2018, 2019; Moro-Visconti, 2022).

To date, JBA scholars have not differentiated between deep tech and shallow tech when discussing the acquisition and management of complementary resources to ensure the superior performance of the platform venture. Thus, we extend the JBA by, on the one hand, acknowledging the value of deep tech (Jinzhi & Carrick, 2019) and, on the other hand, providing combinations of complementary entrepreneurial decisions that lead to platform unicorn status without deep tech.

5.3 | Entrepreneurial judgment concerning funding timing and source

When mental health platform ventures are seeking unicorn status, early-stage start-up funding is crucial in increasing the probability of becoming a platform unicorn. Thus, when early-stage funding is not acquired during the first stage of the venture lifecycle, it decreases the likelihood of becoming a mental health platform unicorn (see Profiles 8 and 9). While this result confirms previous research arguing that early-stage funding is significant (Tekic et al., 2024), our Profile 8 nuances it. Indeed, a platform entrepreneur can become a unicorn without early funding if they seek government funding and have not invested in deep tech.

Furthermore, entrepreneurs scaling mental health platforms should be careful in receiving government funding when developing deep tech (see Profiles 6 and 8). This can be because of not only the bureaucratic nature of government funding (e.g., Piaskowska et al., 2021) but also the intellectual property (IP) management between public and private entities (Breschi et al., 2021). Traditionally, government funding has been viewed as an external form of public intervention aimed at addressing market failures related to the undersupply of finance to early-stage deep tech firms (Minola et al., 2017; Minola & Giorgino, 2008). However, our results suggest that entrepreneurs with deep tech should avoid seeking government funding. This finding indicates that government funding is a double-edged sword. While obtaining government funding depends on external actors, the decision to seek it should be considered a judgment call made by entrepreneurs. Nonetheless, these results may be context-specific, as government funding is more valued in planned economies, such as China (Jinzhi & Carrick, 2019).

We extend strategic entrepreneurship and JBA knowledge by identifying the significance of early-stage platform venture entrepreneurial decisions related to fundraising time and funding sources. Furthermore, we posit that even if early-stage funding is addressed, it should be combined with the right decisions concerning technology type and business model constituents to reach unicorn status.

5.4 | Managerial implications

Our study provides some actionable strategies for business leaders, supported by examples of selected mental health platform unicorns. Although it comes as no surprise that funding is one of the key factors for venture success, entrepreneurs need to be careful when choosing the source and timing of funding. Our results (Figure 1, Tables 5, and A2) show that platform ventures are more likely to become unicorns if they prioritize early-stage start-up funding from non-governmental sources. The data indicate that early-stage private funding—such as business angels, crowdfunding, or incubators—significantly increases the probability of reaching unicorn status. If the platform venture secures early-stage funding, deploying deep tech can be beneficial. Furthermore, companies utilizing deep tech in the early stages have a higher probability of becoming mental health platform unicorns. Look at Ginger and Spring Health as examples. Ginger pioneered a digital and on-demand mental health service using unlicensed therapists called "coaches" and deep tech, such as natural language processing, to monitor member chats. Spring Health provides comprehensive, personalized mental health solutions to employers and health plans, using precision mental healthcare to navigate over 200 diagnoses and care options, similar to Google algorithms. Both ventures had early-stage start-up funding, no government funding, a B2B market, and, respectively, subscription and commission income streams.

However, platforms should avoid deep tech if they plan to seek government funding. Government funding, especially in deep tech (e.g., AI, natural language processing, machine learning, and big data), tends to decrease the likelihood of becoming a unicorn. The bureaucratic burden and slow adaptability associated with government funding could hinder rapid innovation and scaling. Although rare, some companies, such as Omada Health and TalkSpace, have achieved unicorn status with government funding. Omada Health, a virtual care provider founded in 2011, helps patients manage chronic conditions with support between clinical visits and receives $195,660 from the Small Business Innovation Research (SBIR) fund. Omada Health had no early-stage start-up funding. TalkSpace, an online counseling service, was awarded over $6.95 million in grants by the National Institutes of Health for exploring the efficacy of teletherapy and, in addition, received early-stage funding. Both of the start-ups became unicorns without cultivating deep tech, deploying a B2C business market and subscription income model.

Even without deep tech, early-stage start-up funding combined with the right business model (B2C or mixed market and a subscription or commission-based income stream) can still lead to unicorn success. Companies such as Cerebral, Calm Health, Alan, and Ro Health, which provide affordable mental health care, illustrate this approach well. Cerebral's services offer efficient access to treatment for anxiety and depression, generating revenue through monthly user subscriptions. Modern Health offers an inclusive mental health solution that drives outcomes, is cost-effective, and is most engaging.

In summary, real-world examples of mental health unicorns show that several combinations of entrepreneurial decisions lead to unicorn status. However, entrepreneurs need to find the best configuration between fundraising timing, funding source, technology type, and business model (Figure 2) and be aware that some combinations might reduce their chance of becoming a unicorn and be considered "failed judgment" to unicorn status (Figure 2).

6 | LIMITATIONS AND FUTURE RESEARCH

Our study provides insights into the combinations of complementary entrepreneurial decisions that lead to mental health platform unicorn status, but it also has some limitations that suggest future research topics. First, to avoid industry variation, we focused on one industry—health care, particularly mental health. The healthcare sector has shown exponential growth worldwide for unicorns. Thus, this sector choice allowed the emergence of significant profiles that a broader sample might not have had. However, it limits the generalization of the results to other industries, especially beyond the healthcare sector, particularly those with different entrepreneurial dynamics or significantly lower unicorn representation. For future research, it would be interesting to examine whether other industries with varying levels of unicorn representation and entrepreneurial dynamics yield comparable results when combining entrepreneurial decisions on fundraising timing, funding sources, the technology utilized, and business model constituents' choices. Expanding the analysis to include ventures from diverse sectors could enhance the robustness and generalizability of the findings, although this would require addressing potential challenges in data consistency and comparability across industries.

Second, we relied on the Dealroom database and its data classification methodology, as Dealroom provides reliable and comprehensive secondary data. We assumed that when AI, deep tech, natural language, machine learning, and big data were not mentioned, the platform venture was based on shallow tech. Given that entrepreneurial decisions can evolve through time (Demil & Lecocq, 2010), it is possible that some of the platforms labeled by Dealroom were not deep tech from the start or became so after the Dealroom labeling process. This opens a longitudinal research opportunity, especially an opportunity to explore whether there are specific entrepreneurial decision profiles that firms tend to choose over time. As suggested by Piaskowska et al. (2021), one way to investigate this empirically would be to use transition probability matrices to examine the likelihood of a platform unicorn remaining in its profile through time. Moreover, while using only Dealroom as a data source, we limit the resolution of certain nuances in the findings. While a larger sample would be desirable to enhance the robustness of the analysis, expanding the sample makes it challenging as additional data sources often vary in accuracy, consistency, completeness, and timeliness.

Furthermore, based on the results, we have identified some promising future research directions. First, qualitative approaches such as case studies are encouraged to understand in depth why government funding is not compatible with deep tech and why shallow tech is not compatible with serving a B2B market, including the benefits of subscription versus commission income streams. Furthermore, the case studies could add new complementary entrepreneurial decisions to the already defined combinations and could further increase the likelihood of the venture becoming a platform unicorn beyond 30%. Second, more in-depth studies on the organizational, industry, and institutional context and their impact on the dynamics of combinations of complementary entrepreneurial judgments can lead to interesting discoveries. Finally, we have demonstrated the value of AI-driven tools such as decision trees to support entrepreneurs' and investors' intuition to make the successful and failed combination of decisions. Thus, further research can bring insights into the effectiveness of diverse AI-driven tools and their added value under different contexts.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] Digital platform is defined as a shared, common set of services and architecture that serves to host complementary offerings, including digital artifacts (Nambisan, 2017, p. 1031).

[2] Digital platform venture is a firm, the platform owner, which establishes the modular platform and orchestrates both value creation and value appropriation (e.g., Gawer & Cusumano, 2014).

[3] Technology readiness level (TRL) https://esto.nasa.gov/trl/.

[4] See Loh (2011) for a comprehensive introduction to decision trees.

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APPENDIX A

TABLE A1 Data-informed research on factors increasing the probability of becoming a unicorn.

Authors	Research question	Factors explored	Venture funding	Digital technology (e.g., deep tech)	Platform business model
Tekic et al., 2024	Do unicorns predominantly emerge from a focus on developing novel technologies or on understanding market needs, or from a balanced integration of both? How do these three strategic orientations correlate with unicorns' growth rates?	Factors explored: • timing of their first patent and trademark filings • initial institutional funding • B2B vs. B2C • stand-alone product vs. digital platform • product-oriented vs. service-oriented.	Unicorns receiving seed funding before filing their first patents or trademarks tend to exhibit significantly higher median growth rates compared to those filing for intellectual property rights (IPR) before securing seed funding.	Developing both: core tech and market capabilities grow faster than those that primarily focus on technology or market. The majority of those who become unicorns do not rely on IPR to signal their growth potential and above-average returns to venture capitalists.	A balanced orientation is beneficial for both B2B and B2C unicorns, but B2B start-ups may derive greater growth benefits from focusing on market and technology at the same time.
Venâncio et al., 2023	How do digital entrepreneurial ecosystems contribute to how fast a start-up becomes a unicorn (time-to-unicorn)?	Factors explored: • supply and demand conditions • innovation and change, institutional environment • digital trust • device and Broadband uptake.	Not explored.	The combination of conditions increased the average national speed of a start-up becoming a unicorn. Resources and infrastructure were key elements of the process's success.	Not explored.
Cusumano et al., 2023	Do private investors place a premium on pre-public companies with platform business models compared to non-platforms? Do investors offer a premium for different types of platforms or subtypes?	Factors explored: • platformness (platform business model or not) • type of platform business (innovation, transaction, or hybrid and subtypes) • product or service orientation	Not directly explored.	Not explored.	A 25% premium for B2B in Europe suggests that B2B companies are considered more valuable than B2C companies.

TABLE A1 (Continued)

Authors	Research question	Factors explored	Venture funding	Digital technology (e.g., deep tech)	Platform business model
		• B2B or B2C orientation • Industry and firm age			
Kotha et al., 2022	What are the attributes of ventures that reach a billion-dollar valuation, and what factors are associated with the speed at which they attain unicorn status?	Factors explored: • founder/CEO characteristics • venture characteristics (location, age, profitability, IP, accelerators, business model) • industry effects and investment characteristics (equity, deal size, and media coverage).	Significant: • deal size • percentage of VC equity ownership. Not significant: • VC centrality • seed funding • accelerator affiliation.	Not significant having IP.	B2B and B2C are used for descriptive statistics only to account for different industries in the dataset.
Piaskowska et al., 2021	Are there any distinct scale-up modes that firms choose when scaling, and, if so, what are they?	Factors explored: • business model (platform vs. pipeline, digital vs. physical) • financing (capital raised and investors) • innovation (patent) • digitization (web-based relationship building, human-capital intensity) • acquisitive activities • board and SMT composition • geographic zone.	Finance might constrain the scaling mode (if there are different financing choices across the scale-up modes).	One scale-up mode called "focused scalers" prioritizes the exploitation of high-quality technology.	Business model (platform vs. pipeline, digital vs. physical) used to describe four different scale-up modes.

(Continues)

TABLE A1 (Continued)

Authors	Research question	Factors explored	Venture funding	Digital technology (e.g., deep tech)	Platform business model
Bock & Hackober, 2020	Which factors lead to crossing the $1 billion valuation threshold? Which growth strategy do investors favor for unicorns?	Factors explored: • geography inter-country level • CVC investors' reputation • aggressive add-on acquisition • post-money valuation.	Ventures benefit primarily from CVC support before they become high-valued unicorns.	Not explored.	Not explored.
Jinzhi & Carrick, 2019	What paths, positions, and processes are important to developing Chinese unicorns?	Factors explored: • pursuit of technology development • strategic alliances with industry and government partners • public support or funding from federal, provincial, or local governments • founders' previous alliance and previous relationship • organizational learning process • rounds of funding • process of dealing with investors.	Government influences are important to early growth; founders need to be able to establish strong relations with the government.	A unique technology influenced the direction of the firm.	Not explored.

TABLE A2 Description of the mental health platform unicorns.

Name	Short description (from Dealroom and unicorn website)	Launch year	Year become a unicorn	Valuation (USD, Mln)	Employees	Total funding (USD, thousands)	Nb. funding rounds	Funding origin	Technology	Market served	Income stream	Profile #
Spring Health	Spring Health provides a comprehensive and effective solution for employers to provide their employees with mental well-being. Spring Health drives precision in mental health. It connects the employees of its customers to a proven, personalized solution	2016	2021	2500	1277	365	6	Early/Late	Machine learning; deep tech; artificial intelligence	B2B	com.	1
Ginger	A digital mental health program for people with depression and anxiety. Acquired by Headspace in 2021.	2010	2021	3000	216	213	9	Early/Late	Big data; deep tech; recognition technology	B2B and mix	sub.	1
Ro Health	A direct-to-consumer telehealth company that handles everything from diagnosis to convenient delivery of medication. Ro is for adults who are experiencing health issues or want to improve or support their health and prefer to do so from the comfort of their homes. For mental health, it *matching service connecting* users with therapists, a personalized prescription, and a free delivery at home of the drug.	2017	2020	7000	790	1026	7	Early/Late	No deep tech	B2C	sub.	2

(Continues)

TABLE A2 (Continued)

Name	Short description (from Dealroom and unicorn website)	Launch year	Year become a unicorn	Valuation (USD, Mln)	Employees	Total funding (USD, thousands)	Nb. funding rounds	Funding origin	Technology	Market served	Income stream	Profile #
Lyra Health	Lyra Health Lyra is a digital health startup providing evidence-based *mental health care services* combined with a concierge member experience for every employee of its clients' companies.	2015	2020	5850	1841	690	8	Early/ Late	No deep tech	B2C and mix	sub.	2
Cityblock Health	City Block is a technology-driven provider for communities with complex needs. Cityblock provides access to medical, mental, and social care—whenever and wherever.	2017	2020	5700	915	891	8	Early/ Late	No deep tech	B2C	sub.	2
Cerebral	Cerebral is a mission-driven telemedicine company that provides affordable, efficient access to treatment for anxiety and depression mainly (but also bipolar, chronic, schizophrenia to broader mental health)—all from the convenience and privacy of the home.	2020	2021	4800	1421	462	3	Early/ Late	No deep tech	B2C	sub.	2
Headspace Health	Headspace is a mobile app providing every person access to lifelong mental health support. Through evidence-based meditation and mindfulness tools, mental health coaching, therapy, and	2010	2021	3000	388	175	11	Early/ Late	No deep tech	B2C	sub.	2

TABLE A2 (Continued)

Name	Short description (from Dealroom and unicorn website)	Launch year	Year become a unicorn	Valuation (USD, Mln)	Employees	Total funding (USD, thousands)	Nb. funding rounds	Funding origin	Technology	Market served	Income stream	Profile #
	psychiatry, Headspace helps create life-changing habits to support its users' mental health and find themselves healthier and happier.											
Calm Health	An app for sleep, meditation, and relaxation. Calm Health offers evidence-based mental health programs and tools focused on anxiety and depression that are designed to support payers, plan sponsors, and providers.	2012	2019	2000	594	218	10	Early/Late	No deep tech	B2C	sub.	2
Alan	A digital health insurance. It focuses on user experience with excellent price-quality ratio health plans. Alan takes care of the physical and mental well-being daily.	2016	2021	2970	863	542	7	Early/Late	No deep tech	B2C and mix	com.	3
Modern Health	Modern health is a global platform built on evidence-based principles with therapists, coaches, and digital content accessible all in one app. It offers an inclusive mental health solution that drives outcomes, is cost-effective, and is most engaging.	2017	2021	1170	795	167	6	Early/Late	No deep tech	B2C	com.	3

(Continues)

TABLE A2 (Continued)

Name	Short description (from Dealroom and unicorn website)	Launch year	Year become a unicorn	Valuation (USD, Mln)	Employees	Total funding (USD, thousands)	Nb. funding rounds	Funding origin	Technology	Market served	Income stream	Profile #
TalkSpace	Online Therapy, marriage counseling. Talkspace is therapy for all. Online counseling lets you connect with a licensed therapist from the privacy of your device—at a significantly lower cost than traditional, in-person counseling.	2011	2021	22,56	819	114	13	Early/Late/Gov	No deep tech	B2C	sub.	5
Omada Health	Online programs combine world-class science, technology, and design to inspire and enable people everywhere to live free of chronic disease. A virtual-first, integrated solution to care, Omada helps members	2011	2022	1000	677	448	10	Late/Gov	No deep tech	B2C	sub.	7

Note: Data are extracted from the Dealroom and platform unicorn web pages in Spring 2023.

TABLE A3 Summary of the venture funding features in line with its lifecycle stages.

	Venture lifecycle			
Funding features	**Seed**	**Start-up development (series A and B)**	**Start-up growth (series C and later)**	**Exit**
Purpose of the funding	Research and development (TRL 6–8), initial business plan	Establish market and sales activities (TRL 9), growth	Scaling—exponential market growth, internationalization	Initial Public Offering (IPO), acquisition, trade sale, liquidation
Source of funding	Private (from individuals), sometimes government and corporate	Financial institutions, government, corporations, and sometimes private	Financial institutions, government, corporate	Financial institutions, government, in case of IPO, public
Early-stage start-ups' investors	Business angel (BA), crowdfunds, incubators and sometimes corporate venture capital (CVC)	VC, CVC, government venture capital (GVC), and sometimes BA, crowdfund, and accelerators		
Late-stage start-ups', *platform unicorns'* investors			VC, CVC, GVC	VC

Note: Table produced by the authors based on Alperovych et al. (2015), Cavallo et al. (2019), de Clercq et al. (2006), and Mocanu and Thiemann (2023).