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A meta-analysis towards the effectiveness of startup accelerators

Nikolaus Seitz^{1,2} · Martina Buratti¹ · Erik E. Lehmann² · Julie Kurrle²

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Abstract

Accelerators have become crucial facilitators of entrepreneurial growth, yet empirical research on their effectiveness remains fragmented and inconclusive. To this extent, this paper conducts a comprehensive meta-analysis to synthesize quantitative findings and assess the impact of accelerator participation on new venture performance. By analyzing 21 primary studies and 68 effect sizes, the results reveal a statistically significant positive effect of accelerator participation. The study identifies key moderating factors, such as program duration, cohort size, sponsorship type, and regional context, which significantly influence venture outcomes. Additionally, the analysis highlights the presence selection biases within accelerator programs. This paper contributes to the theoretical understanding of accelerators by offering insights into their role in enhancing financial and operational dimensions of new venture performance. The findings provide valuable implications for both scholars and practitioners, laying the groundwork for future research on accelerator design and effectiveness.

Keywords Accelerator · New venture performance · Meta-Analysis · Entrepreneurship

✉ Nikolaus Seitz
nikolaus.seitz@uni-weimar.de

Martina Buratti
martina.buratti@uni-weimar.de

Erik E. Lehmann
erik.lehmann@wiwi.uni-augsburg.de

Julie Kurrle
julie.kurrle@ritterwald.com

¹ Bauhaus University, Weimar, Weimar, Germany

² University of Augsburg, Augsburg, Germany

1 Introduction

Accelerators are receiving increasing attention in entrepreneurship research because of their potential to enhance start-up performance by providing critical resources such as mentoring, funding, and networking opportunities (Cohen et al., 2019a, 2019b; Crişan et al., 2021). Accelerators are defined as “programs of limited duration [...] that help cohorts of start-ups with the new venture process” (Cohen, 2013, p. 19). These programs are structured, fixed-term initiatives designed to support early-stage ventures in rapidly scaling up and achieving key development goals (Hallen et al., 2020; Pauwels et al., 2016). Accelerators, along with incubators and science parks, are considered key intermediaries for the development of entrepreneurial activity within regional entrepreneurial ecosystems (Stam, 2015). However, unlike incubators, which provide long-term support with a broader focus, accelerators emphasize rapid growth through an intensive program that typically lasts three to six months (Hochberg, 2016). Accelerators aim to address critical challenges faced by nascent firms, including resource scarcity, limited access to investors and markets, and the need for strategic guidance in navigating early-stage business complexities (Roberts & Lall, 2019; Yu, 2020). Indeed, recently accelerators have become an integral part of the entrepreneurial ecosystem, supporting a wide range of industries and regions (Hallen et al., 2020). Their proliferation has been driven by the growing demand for structured entrepreneurial support, as well as by companies, investors, and policy makers recognizing their role in fostering innovation and economic growth (Pauwels et al., 2016).

However, existing literature presents a fragmented picture of the effectiveness of accelerator programs in enhancing start-ups performance (Hallen et al., 2020). Indeed, existing studies report mixed results regarding the effects of these accelerator programs, with some highlighting positive effects on fundraising success, market expansion, and firm survival (Crişan et al., 2021; Smith & Hannigan, 2015), while others suggesting that accelerators may not provide long-term benefits or could even lead to adverse effects such as premature scaling, equity dilution, and dependency on external support (Lukosiute et al., 2019; Roberts & Lall, 2019). Additionally, existing studies reveal considerable heterogeneity in accelerator design and operation, with variations in cohort size, program duration, funding models, and focus areas (Cohen et al., 2019a, 2019b). The divergence in existing findings is also evident by differences in research methodologies and contextual factors, making it difficult to draw generalized conclusions about the effectiveness of accelerators. Prior studies have largely relied on qualitative case studies or region-specific analyses, which limits their applicability across different regional entrepreneurial ecosystems (Crişan et al., 2021). Moreover, concerns regarding publication bias and data availability have led to calls for more comprehensive approaches to synthesizing existing evidence (Eisend & Tarrahi, 2014).

To this extent, this paper aims to address these research gaps by conducting a comprehensive meta-analysis to systematically evaluate the impact of accelerator participation on new venture performance. Specifically, we employ a random-effects model to estimate the aggregate effect size and investigate different moderating factors that may influence accelerator effectiveness. The moderators examined include program characteristics (e.g., duration, cohort size, and sponsorship models), start-up attributes (e.g., firm size, prior funding, and gender diversity), and contextual factors (e.g., geographic characteristics and cultural as well as institutional environment). Moreover, we give particular attention in assessing

the extent of publication bias and heterogeneity within the existing body of research on accelerator to ensure robust and unbiased conclusions.

The results of this paper reveal that accelerator participation has a statistically significant positive impact on venture performance, albeit with substantial heterogeneity across studies under analysis. Findings reveal the presence of publication bias, indicating that the existing literature may overrepresent studies with significant positive results while under-reporting studies with null or negative findings. This suggests a tendency within the field to publish studies that confirm accelerator effectiveness. Moreover, the findings suggest that accelerators are most effective when tailored to the specific needs of ventures and aligned with their strategic goals. Indeed, moderator analyses provide valuable insights into key factors influencing accelerator outcomes, such as the role of longer program durations in fostering sustained venture growth and the greater benefits observed in smaller start-ups with high growth potential. Also, the results reveal the presence of a selection bias, as many accelerator programs tend to favor start-ups that have already obtained some form of funding before entering the program. This raises concerns about the inclusivity of accelerators and their ability to support initiatives that do not have initial financial backing but may have significant potential. Furthermore, this paper identifies the influence of contextual factors, indicating that accelerators operating in emerging economies tend to have a greater impact than those in developed economies, filling institutional gaps and fostering regional entrepreneurial ecosystems.

The contributions of this paper are manifold. First, we consolidate fragmented empirical research by providing a comprehensive quantitative synthesis of accelerator effectiveness, offering a clearer understanding of their role in entrepreneurial success. Second, we identify key moderating factors that influence accelerator outcomes, such as program duration, cohort size, sponsorship models, and start-up characteristics, offering theoretical insights into the conditions under which acceleration is most beneficial. Third, our findings provide several implications for accelerator managers, policymakers, and investors, revealing successful characteristics of accelerator programs and strategic decision-making to better align accelerator resources with start-ups needs. Finally, we provide avenues for future research by encouraging further exploration into the long-term impact of accelerators and the role of program design variations across industries and regions, to ensure a more comprehensive understanding of accelerator effectiveness within different contexts and regional entrepreneurial ecosystems.

The paper is structured as follows: Chapter 2 describes the theoretical background, followed by Chapter 3, which outlines the data and methods. The results are presented in Chapter 4 and discussed in Chapter 5. Finally, Chapter 6 concludes with the contributions, limitations and a foundation of future research.

2 Theoretical background

2.1 Understanding the accelerator phenomenon

The importance of entrepreneurship has been recognized as a driver of economics and growth since Schumpeter and Swedberg (1934) identified innovation resulting from entrepreneurial activities as a critical factor for economic survival. Given its inherent features of

dynamism and disruptiveness, entrepreneurship is widely recognized as a vital mechanism for fostering innovation, addressing global challenges, and contributing to local and regional economic development (Audretsch & Keilbach, 2004; Barnes, 2016; Roberts & Lall, 2019). Entrepreneurs play a critical role in addressing today's challenges by introducing new industries and by promoting local development through job creation and the introduction of new products and services (Barnes, 2016; Davidson et al., 2021). Start-ups have thus become indispensable contributors to economic and social progress, with increasing global attention paid to their potential (GEM, 2022). Despite their potential, start-ups face significant challenges, indeed, according to the global start-up failure rate only 10% of start-ups survive, and among those, only a small fraction achieves substantial success (Startup Genome LLC, 2022). Key obstacles for new ventures include inadequate market understanding, resource shortages, and the "liability of newness" which hinders their ability to acquire resources and maintain operational stability (Stinchcombe, 1965; Chan et al., 2020). Moreover, also limited capacity, managerial inexperience, and insufficient exposure to markets further complicate the survival of start-ups (Chan et al., 2020; Stuart et al., 1999). Even those ventures that manage to survive often encounter difficulties transitioning through later stages of development, where new challenges emerge (Audretsch & Chowdhury, 2022). Additionally, the fear of failure experienced by founders can act as both a stimulus and an obstacle, influencing their ability to take risks and grow their businesses (GEM, 2022).

One promising response to help early-stage ventures are start-up intermediaries (Chan et al., 2020; Roberts & Lall, 2019). Among these intermediaries, accelerators address the challenges faced by start-ups through buffering and bridging mechanisms, providing critical resources like funding, mentorship, and office space while also fostering connections to essential networks of knowledge and support (Woolley & MacGregor, 2022). Indeed, by targeting key issues such as market entry and customer acquisition, accelerators help minimize uncertainties and enhance start-up success (Radojevich-Kelley & Hoffman, 2012; Yu, 2020).

Although accelerators have received limited attention in management, finance, and economics literature, their growing prominence in entrepreneurship research reflects their important role in new venture development and their economic impact (Yu, 2020). In particular, existing studies highlight that accelerators are fundamental components of innovation ecosystems, supporting start-ups in the development and implementation of new innovations (Audretsch & Keilbach, 2004; Drori & Wright, 2018).

While accelerators share some similarities with other types of intermediaries, particularly incubators, they have distinct characteristics in terms of structure, goals, and operational intensity. Incubators typically offer long-term support, including office space and mentoring, with a greater focus on creating a stable environment for startups to mature (Gately & Cunningham, 2014; Cohen, 2013). Accelerators, in contrast, are intensive, short-term programs often described as "boot camps" lasting three to six months and targeting ventures ready for rapid scaling (Dempwolf et al., 2014; Roberts & Lall, 2019). Another key distinction is their highly selective application process, which fosters a competitive environment and attracts high-potential ventures, unlike the noncompetitive admissions criteria often applied by incubators (Venâncio & Jorge, 2022; Woolley & MacGregor, 2022). Accelerators also differ in their use of cohort-based structures, also called "batches," which facilitate peer learning and the development of collaborative networks among participating startups (Cohen, 2013). Additionally, while incubators focus primarily on local ventures, accelera-

tors often operate on a regional or global scale, further extending their reach and impact (Dempwolf et al., 2014; Morris et al., 2009).

Accelerators offer intensive, structured support for early-stage ventures, addressing the specific needs of start-ups seeking rapid growth. Among their most distinctive features is the provision of personalized mentoring and networking opportunities. Participants benefit from frequent interactions with experienced advisors and industry experts, as well as successful alumni, who often serve as valuable resources and role models (Roberts & Lall, 2019; Yu, 2020). Additionally, entrepreneurs attend seminars and workshops, usually led by program directors or guest speakers, on topics critical to business success, such as fundraising, scaling strategies, and market entry (Cohen, 2013). Furthermore, most of the accelerator programs provide seed investments to participating start-ups, typically in exchange for equity, this allows entrepreneurs to focus on refining their business models and scaling their operations without the immediate burden of securing external capital (Wise & Valliere, 2014). The culmination of the program is often a demo day, where start-ups present their progress to investors and industry stakeholders, and also serves as a gateway to additional funding and partnership opportunities (Cohen & Hochberg, 2014).

Despite their many benefits, accelerators are also the costliest option for start-ups (Yu, 2020). Indeed, accelerators are predominantly for-profit organizations. They invest in start-ups in exchange for equity (Wise & Valliere, 2014). This model incentivizes accelerators to provide effective support measures, as their profitability depends on the success of their portfolio companies (Dempwolf et al., 2014). This also explains why many accelerators target specific industries, particularly technology-focused sectors, allowing to create homogeneous cohorts that benefit from shared industry insights (Chan et al., 2020).

In recent years, there has been a significant increase in research on accelerators, demonstrating the growing interest in their role as start-up intermediaries (Bańka et al., 2022; Crişan et al., 2021). However, the literature is still characterized by clear gaps and inconsistencies. Indeed, firstly, a large part of the existing studies focuses on corporate accelerators (García et al., 2019), secondly, most of the research remains qualitative or theoretical, with a lack of quantitative analyses addressing whether participation in accelerators fosters the success of new ventures (Crişan et al., 2021; Gonzalez-Uribe & Leatherbee, 2018).

Some of the existing studies reveal the positive impact of accelerators but lack empirical evidence of the possible outcomes, such as higher funding or survival rates (Yu, 2020). For example, Regmi et al. (2015) report a 23% higher survival rate for accelerator graduates compared to non-accelerated ventures. Pioneering quantitative studies have recently emerged, but their results are mixed. Gonzalez-Uribe and Leatherbee (2018) explored the effects of the Chilean program “Start-Up Chile” showing that pairing basic services (e.g., workspace, funding) with entrepreneurial education improved startup performance. Similarly, Hallen et al. (2020) analyzed multiple U.S.-based accelerators, showing that most programs generated positive outcomes, such as increased funding and growth, but in a few cases, some programs failed to produce significant results. This variability reveals differences in treatment effects even among well-recognized accelerator programs. These findings call for an analysis of the effects across an even more diverse sample of accelerators, such as the ones from Davidson et al. (2021) or Roberts and Lall (2019), that by drawing on a worldwide sample of accelerators and early-stage businesses, they show that acceleration has a positive impact on participants across a multitude of countries and industries and that that by advancing various dimensions of financial and human resources, accelerators

are positively impacting the growth trajectories of young ventures. Other studies report neutral or negative effects. For instance, Bokhari et al. (2021) find that accelerated firms raised less cumulative funding and secured fewer deals compared to their non-accelerated counterparts. Smith (2019) observed that accelerated ventures experienced lower levels of long-term employment and venture capital funding, although they exited faster through acquisitions. Neville and Lucey (2022) further challenged the positive narrative, showing that high-tech SMEs outside accelerator programs were more likely to achieve profitability. Kotha, et al. (2022) find that while accelerators facilitate early funding opportunities, their impact on long-term scaling, such as achieving unicorn status, is negligible. These findings suggest that acceleration may have limited or short-term benefits and might not suit all ventures equally.

Moreover, several theoretical frameworks attempt to explain accelerators' impact. The resource-based view (RBT) posits that firm performance depends on access to valuable, rare, inimitable, and non-substitutable resources (Barney, 1991; Miles, 2012). Accelerators help ventures overcome resource constraints, providing financial, human, and social capital crucial for early-stage survival and growth (Miles, 2012; Woolley & MacGregor, 2022). However, Santamaria and Breschi (2021) note that the value of the resources provided to young entrepreneurs within an accelerator program critically depends on the prior resource configuration of the accelerated ventures. Furthermore, the effectiveness of provided resources depends on the venture's ability to utilize them, which may vary (Audretsch & Chowdhury, 2022). Also, the human capital theory (HCT) is widely applied to explain how accelerators influence start-up performance. According to HCT, human capital—defined as the skills, knowledge, and capabilities within a firm—is a critical resource that directly correlates with positive performance outcomes (Ployhart & Moliterno, 2011). This relationship is particularly pronounced in technology-driven ventures, a common focus of accelerators (Leitão et al., 2022). Factors such as education, experience, self-efficacy, and entrepreneurial skills, all tied to human capital, are significantly enhanced through accelerator participation (Dams et al., 2022). Accelerators play a pivotal role by offering mentorship, structured workshops, and experiential learning opportunities, enabling entrepreneurs to build these essential attributes (Leitão et al., 2022). Entrepreneurs with higher levels of human capital are better positioned to seize opportunities and effectively navigate the challenges of start-up growth (Honig & Davidsson, 2000). HCT aligns closely with organizational learning, which highlights the role of accelerators in accelerating experiential learning through peer interactions and mentorship (Hallen et al., 2020). Indeed, the learning process is task-specific and content-focused, supported by interactions with mentors, program directors, and cohort peers (Cohen & Bingham, 2013). Preconditions for effective learning, such as direct connections between participants and mentors and the venture's absorptive capacity, are typically fulfilled within accelerator programs (Cohen & Bingham, 2013). Lastly, signaling theory further highlights accelerators' role in reducing information asymmetries between start-ups and potential investors. Signals are observable markers that communicate a venture's quality and potential to external stakeholders (Spence, 1973). Accelerators provide these signals by endorsing start-ups through their rigorous selection processes and structured support programs (Venâncio & Jorge, 2022). By affiliating with reputable accelerators, start-ups gain legitimacy and attract fundings, as investors interpret this endorsement as a validation of the venture's growth prospects (Kotha, et al., 2022).

Despite the theoretical support for accelerators' value, the empirical evidence remains inconsistent. Studies reveal significant heterogeneity among programs, with differences in resources, services, and participant selection influencing outcomes (Chan et al., 2020). This variability suggests that accelerators are not a one-size-fits-all solution, and their effectiveness depends on program-specific and contextual factors (Woolley & MacGregor, 2022).

Accelerators differ in their selection criteria for ventures, particularly in terms of firm size, stage, and prior funding, all of which significantly impact program outcomes (Bokhari et al., 2021; Hallen et al., 2020). While most accelerators target early-stage businesses, definitions of "early-stage" vary, influencing the types of ventures admitted (Qian et al., 2018). Firm size, often measured by the number of employees, varies widely among accelerators, ranging from very small teams to firms with up to 250 employees (ANDE, 2022). Firms size may impact the ventures performance since smaller firms tend to grow faster post-acceleration, while larger ventures may benefit from established resources and networks (Storey, 1989).

2.2 Types and design of accelerators

2.2.1 Program structure and service offering

Research on accelerators often reveals divergent findings, which due to the structural differences and morphology among accelerator programs (Chan et al., 2020). While accelerators share core features such as mentorship, seed funding, and education, their design and service offerings vary significantly, influencing outcomes (Bańka et al., 2022; Cohen et al., 2019a, 2019b).

A defining characteristic of accelerators is their cohort-based structure, where groups of ventures progress through the program together rather than receiving individualized attention (Gonzalez-Uribe & Leatherbee, 2018), this helps peer learning and shared experiences, allowing entrepreneurs to benefit from the collective knowledge and insights of their counterparts (Hallen et al., 2020). The size of these cohorts varies widely, some accelerator programs accommodate eight to 15 start-ups at a time (Roberts & Lall, 2019), whereas others host batches of 100 or more ventures (Cohen et al., 2019a, 2019b; Gonzalez-Uribe & Leatherbee, 2018). The size of a cohort may influence resource allocation and program outcomes (Cohen et al., 2019a, 2019b). Larger cohorts may dilute individual attention and mentorship, potentially reducing the program's effectiveness due to resource constraints and increased competition among participants (Barnes, 2016). Empirical evidence supports this: studies have shown that larger cohort sizes negatively affect cumulative funding, access to external capital, and post-graduation valuations (Bokhari et al., 2021; Cohen et al., 2019a, 2019b). Similarly, in corporate accelerators, large batch sizes correlate with diminished program effectiveness (Seitz et al., 2019). However, larger cohorts also present potential advantages: they may enhance alumni networks, attract high-quality mentors and investors, and create stronger peer effects, improving decision-making and fostering collaboration (Barnes, 2016; Hochberg, 2016; Smith & Hannigan, 2015). Hallen et al. (2020) further highlight that larger cohorts provide more opportunities for ventures to form partnerships, a key driver of entrepreneurial growth.

In addition to cohort size, the composition of batches within accelerators can significantly influence participant outcomes. Historically, accelerators have operated as generalists,

welcoming start-ups from diverse industries, however, increasing economic diversification has heightened the demand for specialized knowledge, driving many accelerators to adopt industry-specific or target-group-focused models (Drori & Wright, 2018). Specialized cohorts offer the advantage of aligning participants with shared goals and similar support needs, which enhances network effects and facilitates knowledge exchange (Cohen et al., 2019a, 2019b; Drori & Wright, 2018; Seitz et al., 2019). Conversely, diverse cohorts foster inter-organizational learning and stimulate creativity by exposing start-ups to a variety of perspectives and experiences (Seitz et al., 2019).

Accelerators vary widely in program duration, with many adopting the 90-day model while others last as little as four weeks or extend over multiple years (Cohen, 2013; Roberts & Lall, 2019). Most accelerators, however, operate within a six-month timeframe, often considered optimal due to the ability to run multiple cohorts annually and attract committed mentors (Cohen, 2013). However, existing studies suggest that longer programs are linked to improved post-accelerator outcomes by providing long-lasting support that improves venture performance (Bokhari et al., 2021; Cohen et al., 2019a, 2019b). While these findings are primarily based on US accelerators, the benefits of extended support may be relevant in different contexts.

Accelerator programs may also vary based on the different services they provide. First, most accelerators operate with a for-profit orientation, offering varying investment models to participating start-ups (Cohen et al., 2019a, 2019b). Initial funding provided by accelerators varies widely across programs, with some accelerators focusing solely on non-financial support (Hochberg, 2016). Such financial resources are essential for early-stage ventures (Venâncio & Jorge, 2022). Indeed, even modest funding can provide significant support in a context of low technology costs (Hochberg, 2016). Second, accelerators may vary on the type of education and mentorship provided (Gonzalez-Uribe & Leatherbee, 2018). Accelerators usually combine formal education, such as workshops on marketing and legal issues, with hands-on entrepreneurial training to develop critical skills like pitching and leadership (Drori & Wright, 2018; Stayton & Mangematin, 2019). Mentoring can vary within accelerator programs, depending on different focuses such as different industries and markets, as well as connecting ventures with different experts, including business leaders, investors, and experienced entrepreneurs (Aljalalma & Slof, 2022; Cohen et al., 2019a, 2019b). Finally, Accelerator programs may differ in whether they provide office spaces, with the majority offering shared workspaces (Bokhari et al., 2021; Cohen et al., 2019a, 2019b). These spaces foster collaboration, facilitate resource access, and enhance mentoring opportunities (Yu, 2020). Existing studies suggest that providing office amenities has a statistically significant positive impact on start-up performance (Bokhari et al., 2021).

Accelerator programs differ significantly based on their sponsorship background, which influences their structure, objectives, and outcomes (Crişan et al., 2021; Woolley & MacGregor, 2022). Sponsorship can be categorized into public (e.g., government, universities, or NGOs) and private (e.g., corporates or investors) programs, with some accelerators combining both (Drori & Wright, 2018). Public sponsors, such as government-backed programs, often focus on fostering regional economic growth and entrepreneurship, targeting early-stage ventures regardless of their development stage (Cohen et al., 2019a, 2019b). These programs often struggle with long-term funding sustainability, as they typically rely on continuous public investment (Pauwels et al., 2016).

First, university accelerators aim to develop entrepreneurial talent within academic settings, providing services like mentoring and seed funding without equity demands (Dempwolf et al., 2014). They encourage moving innovative ideas from academia into the market and advancing students' entrepreneurial abilities (Cohen et al., 2019a, 2019b). Second, corporate accelerators, motivated by accessing innovative talent and technology, provide resources like market knowledge, strategic partnerships, and investments. These programs often specialize in building ecosystems around their corporate sponsors (Kohler, 2016; Pauwels et al., 2016). Social accelerators, in contrast, focus on ventures aiming for social or environmental impact, often supported by diverse funding models and targeting NGOs or hybrid businesses (Roberts & Lall, 2019). Third, for-profit accelerators, often sponsored by private investors or venture capital, focus on identifying high-growth ventures and earning returns on investment through equity stakes (Dempwolf et al., 2014). These corporate accelerators are the most common and specialize in supporting new ventures within specific industries to help them gain industry-specific expertise (Pauwels et al., 2016). Sponsorship type not only influences the resources available but also moderates the effectiveness of acceleration on venture outcomes, with government-sponsored programs often prioritizing broader economic goals over financial performance (Cohen et al., 2019a, 2019b).

Accelerators differ in their selection criteria for ventures, particularly in terms of firm size, stage, and prior funding, all of which significantly impact program outcomes (Bokhari et al., 2021; Hallen et al., 2020). While most accelerators target early-stage businesses, definitions of "early-stage" vary, influencing the types of ventures admitted (Qian et al., 2018). Firm size, often measured by the number of employees, varies widely among accelerators, ranging from very small teams to firms with up to 250 employees (ANDE, 2022). First, firm size may impact the ventures performance since smaller firms tend to grow faster post-acceleration, while larger ventures may benefit from established resources and networks (Storey, 1989). Second, firm age also plays a critical role, indeed, younger firms often experience greater growth and survival rates post-acceleration, while older ventures are perceived as more attractive to investors due to their track record and lower uncertainty (Qian et al., 2018; Stuart et al., 1999). However, older firms may face reduced agility and flexibility and lower growth rates during the program (Rawhouser et al., 2020). Third, prior funding status is another important factor, since ventures with prior funding may signal credibility and attract further investments, while those without prior financial support might demonstrate more substantial growth due to the program's direct impact (Bokhari et al., 2021; Roberts & Lall, 2019). However, research on the interaction between prior funding and accelerator outcomes remains limited. To conclude, gender dynamics in founding teams also influence acceleration outcomes, since female entrepreneurs face unique challenges, such as lower entrepreneurial self-efficacy and limited access to networks, leading to a gender funding gap (Brush et al., 2014). However, studies suggest that accelerators might have a more pronounced positive impact on women-led ventures, although findings on gender effects are mixed and require further investigation (Dams et al., 2022; Kher et al., 2022).

Location and the institutional context play a crucial role in shaping the effectiveness of accelerators and the outcomes they achieve for participating ventures. Scholars emphasize that the environment in which accelerators operate directly influences entrepreneurial ecosystems, determining how accelerators function and the value they provide to start-ups (Bustamante et al., 2021). National and regional factors, including cultural values and institutional frameworks, shape the conditions for venture development, in these perspective

accelerators reciprocally impact their environments by fostering entrepreneurship, strengthening local ecosystems, and influencing broader economic dynamics (Fehder & Hochberg, 2014). Emerging economies often present unique challenges and opportunities for accelerators. In regions with weak institutional frameworks, accelerators fill gaps in infrastructure and reduce information asymmetries, providing stability and support to nascent ventures (Kher et al., 2022; Rawhouser et al., 2020). In contrast, in developed economies, accelerators may encounter diminishing returns, as existing institutions already provide extensive resources and networks (Roberts & Lall, 2019). However, research on accelerators remains heavily concentrated in developed economies, particularly the USA and Europe. Nearly 90% of studies published before 2015 focused on these regions, reflecting the historical concentration of accelerators in these areas and a potential publication bias favoring significant results from US-based programs (Crişan et al., 2021; Wise & Valliere, 2014). US accelerators often exhibit advantages, such as larger investments, larger cohort sizes, and a supportive cultural and institutional context, which partially explains their prevalence in the literature (Cánovas-Saiz et al., 2020). Yet, as accelerators expand into emerging markets, their role in addressing institutional voids and driving entrepreneurship in challenging contexts is increasingly recognized (Roberts & Lall, 2019).

Moreover, cultural values are particularly significant in understanding the interplay between accelerators and their environments. Hofstede's (2001) cultural dimensions provide a framework for exploring these influences. For instance, countries with high power distance (PDI), where power is unequally distributed, often restrict entrepreneurial opportunities to a select elite, limiting accelerators' ability to democratize venture creation (Mitchell et al., 2000). Conversely, low uncertainty avoidance (UAI) cultures encourage risk-taking and innovation, creating favorable conditions for start-ups to thrive, while high UAI cultures may exhibit hesitancy in venture financing and innovation due to risk aversion (Dubina & Ramos, 2013; Oo et al., 2018). Similarly, individualistic cultures, which prioritize personal achievement and self-reliance, align well with entrepreneurial mindsets, fostering greater initiative and proactive venture creation (Oo et al., 2018). Masculinity (MAS), another cultural dimension, reflects a society's emphasis on competitiveness and achievement, traits that are closely tied to entrepreneurial success (Dubina & Ramos, 2013). Overall, these cultural contextual factors are important since they may affect both accelerator programs as well as ventures performance.

In addition to culture, different economic and institutional factors may shape the effectiveness of accelerator programs. The Global Entrepreneurship Monitor (GEM) evaluates the effectiveness of different entrepreneurial ecosystems by analyzing framework conditions and measuring "total early-stage entrepreneurial activity" at country level (GEM, 2022). These indicators offer policymakers and practitioners valuable insights into the factors that enable or hinder entrepreneurial success. Similarly, also the "Index of Economic Freedom" highlights the impact of government spending on entrepreneurial environments. While public expenditures can foster growth by supporting accelerators and start-ups, excessive spending can lead to inefficiencies and long-term economic constraints (Kim, 2023).

As highlighted above, the state of research on accelerators is highly fragmented, with limited consensus on their effects on new ventures' performance. This calls for a deeper understanding of how acceleration programs impact start-ups while accounting for the diversity of program designs and contextual factors that differentiate accelerators. Additionally, existing methods for assessing and measuring accelerator performance are var-

ied, complicating comparisons across studies and limiting the ability to derive consistent conclusions. Indeed, existing studies broadly evaluate accelerators on three levels: their impact on participating ventures, their performance as organizations, and their influence on the broader entrepreneurial ecosystem (Crişan et al., 2021). Most research focuses on the venture level, analyzing whether acceleration provides value to start-ups (Hochberg, 2016). Commonly used performance measures include financial outcomes, operational performance, and strategic advancements, with financial metrics being the most prevalent due to their quantifiable nature and alignment with accelerator objectives (Cohen, 2013). However, the reliance on short-term data limits insights into long-term impacts, particularly for operational and strategic measures (Davidson et al., 2021).

To address these challenges, we apply a meta-analytic approach to evaluate the effect of accelerator participation on start-up performance. This method synthesizes existing quantitative research to provide a robust estimate of the relationship between acceleration and venture outcomes. By incorporating a moderator analysis, we also aim to identify the implications of program variations and contextual differences. With our findings we aim to contribute to both theory and practice by offering a comprehensive understanding of the effectiveness of accelerator programs on new ventures performance.

3 Data and method

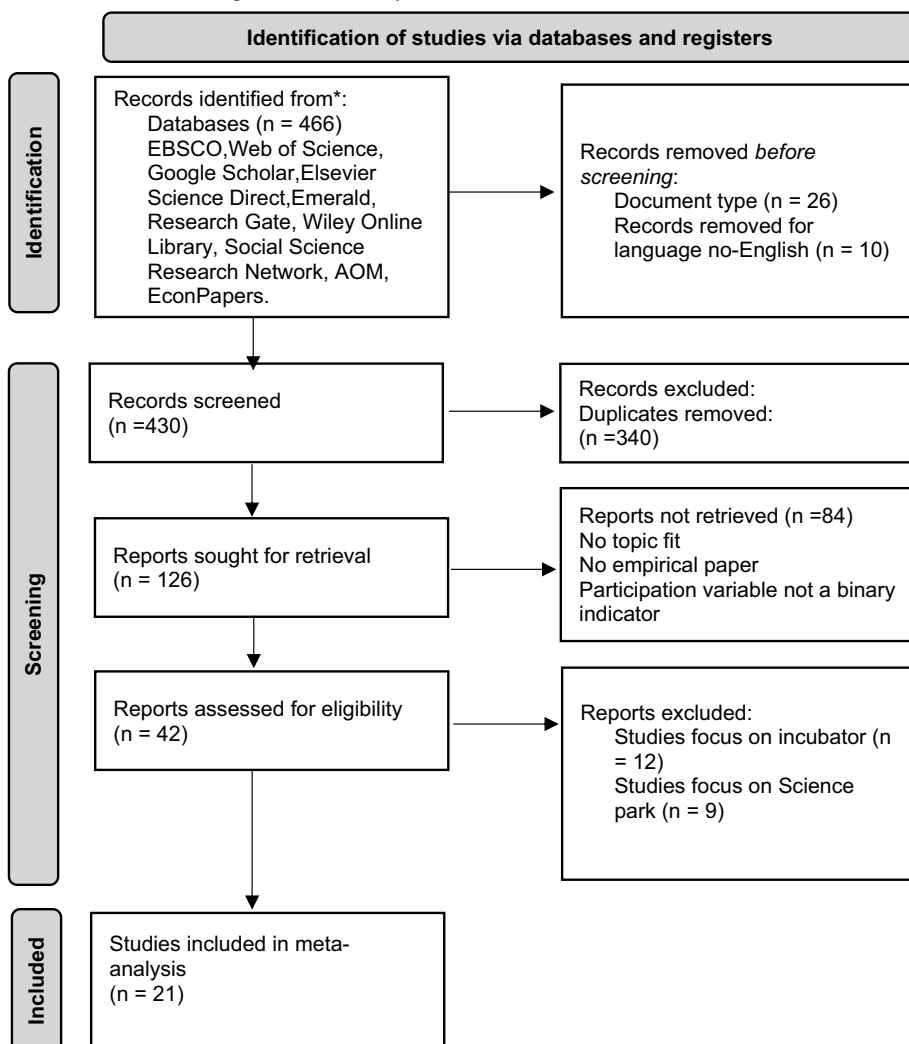
3.1 Selection criteria

In this paper we conduct a meta-analysis to investigate the impact of start-up accelerators on venture performance. To ensure completeness of the final sample of studies, different search strategies were applied to find appropriate empirical work. We rely on a robust and representative dataset constructed following existing studies (Bramer et al., 2017) and by prioritizing studies that empirically analyzed the relationship between accelerator participation and new venture performance. Therefore, we rely on a list of databases including EBSCOhost, Elsevier Science Direct, Emerald, WoS, Research Gate and the Wiley Online Library. Moreover, we include databases listing unpublished works within Social Science Research Network, Academy of Management, and EconPapers, to reduce potential publication bias. Also, we control for potentially overlooked studies in formal databases, using Google Scholar. First, we collected existing papers focusing on both incubators and accelerators, recognizing that both are commonly considered intermediaries supporting entrepreneurial ventures. Indeed, this approach reflects the growing body of literature that highlights the distinctions between these two types of programs (e.g., Hausberg & Korreck, 2021). Moreover, we use backward searching to consider relevant cited papers (Card, 2012). We identify 466 studies related to the topic of accelerators and incubators. In particular, 126 studies were identified to analyze the impact of these intermediaries on the performance new ventures. Furthermore, we included different criteria of selection of papers. First, we selected studies relative to a period of time from 2000 up to 2022. Second, we rely on published as well as unpublished quantitative studies and only in English language. Furthermore, books and book chapters were excluded. Topic characteristics were defined to filter for papers that fit the research question in terms of measured constructs. Hence, studies that investigated intermediaries in terms of accelerator, incubator or science park were included. Moreover, we control for

statistical characteristics refer to data collection, processing, and representation of the different studies to understand if studies investigate the impact of intermediaries on new venture performance. After applying these inclusion criteria, the final dataset was reduced to 21 primary studies including three that analyzed both accelerator and incubator programs. The data collection with the exclusion criteria was conducted following the PRISMA statement approach (Page et al., 2021). Table 1 shows our PRISMA flow diagram.

In total, the number of new ventures participating in accelerator programs accounts for 32,000. And in studies that analyzed both accelerator and incubator programs have a joint sample of 1,100 start-ups.

Table 1 PRISMA flow diagram for meta-analysis



3.2 Variables for the meta-analysis

The independent variable in this analysis is accelerator participation, identified through specific selection criteria. These criteria are essential for meta-analysis, as different terms and operationalizations may refer to the same constructs (Card, 2012). In particular, we rely on existing studies that refer to startup accelerators as business accelerators, entrepreneurship accelerators, innovation accelerators, or simply startup accelerators. Furthermore, accelerators are categorized by their organizational type, including corporate accelerators, university accelerators, and ecosystem accelerators. These distinctions allow us to capture the programs diversity of accelerators and assess their impact on venture performance. To this extent, accelerator participation is a binary variable with a value of 1 if a venture has participated in one of the accelerator programs and 0 otherwise.

We use as dependent variable “new venture performance”, this variable includes different outcome measures related to asses the performance of new firms participating in accelerator programs. Indeed, according to Hallen et al. (2016), it is common practice to triangulate the influence of accelerators by relying on various performance variables. Nevertheless, we selected performance measures only in studies that used quantitative assessment methods. Consequently, we consider measures relative to the development of seed-stage ventures and that can be assessed on a quantitative scale (Roberts & Lall, 2019). Moreover, we clustered the different performance measures, extracted from the existing studies under analysis, into financial, operational and strategic performance (Akcomak, 2009; Phan et al., 2005; Vij & Bedi, 2016), as illustrated in Fig. 1.

It is important to note that most of the selected studies on intermediaries relied in particular on financial performance measures, that include fundraising, revenue, profit, value, and expenditures. First, fundraising was measured in primary studies using variables such as subsequent funding, equity financing, and VC funding (Bokhari et al., 2021; Canfield & Anzola, 2018; Carbó-Valverde et al., 2022; Chen, 2009; Dams et al., 2022; Gonzalez-Uribe & Leatherbee, 2018; Hallen et al., 2020; Qian et al., 2018; Rothaermel & Thursby, 2005; Santamaria & Breschi, 2021; Smith, 2019; Wallenius, 2018; Woolley & MacGregor, 2022), as well as, with smaller attention, the venture’s ability to raise debt (Roberts et al., 2017; Venâncio & Jorge, 2022). Some scholars took an even closer look and analyzed the capital structure of accelerated ventures in detail (Venâncio & Jorge, 2022). Second, several studies measured venture performance in terms of growth in sales and revenue (Diez-Vial & Fernández-Olmos, 2017; Ferguson & Olofsson, 2004; Lindelöf & Löfsten, 2004; Löfsten & Lindelöf, 2001; Rothaermel & Thursby, 2005; Styve & Stubberud, 2018). Both sales and revenues were also deemed appropriate proxies for the survival of a start-up (Amezcu, et al., 2013; Lasrado et al., 2016). Third, existing studies consider profit as a suitable perfor-

Cluster 1	Financial	Operational	Strategic
	- Fundraising - Revenue	- Human resources - Assets	- Digital - R&D
Cluster 2	- Profit - Value - Expenditures		

Fig. 1 Clustering of performance measures

mance measurement for start-ups (Honig & Davidsson, 2000; Kotha et al., 2022; Löfsten & Lindelöf, 2001; Neville & Lucey, 2022; Styve & Stubberud, 2018). Fourth, acquisition has been considered a proxy for the value of a venture (Smith, 2019). Fifth, studies measuring value added or evaluations of firms were included (Dvouletý et al., 2018; Gilles et al., 2021; Styve & Stubberud, 2018). Finally, also expenditures as well as R&D expenditures were adopted to measure new venture investments and innovation performance (Sedita et al., 2019; van Rijnsoever et al., 2017).

Furthermore, relative to operational performance measures, existing studies focus on human resources as well as firm assets. First, Human capital measures are indeed considered important proxy indicator for venture growth (Lasrado et al., 2016; Piezunka & Dahlander, 2015). In particular, within the human resource dimension the variables used by existing studies included employment growth (Diez-Vial & Fernández-Olmos, 2017; Ferguson & Brannick, 2012; Gonzalez-Uribe & Leatherbee, 2018; Löfsten & Lindelöf, 2001; Log & Parsatemijani, 2019), personnel expenses (Styve & Stubberud, 2018), the number of employees (Canfield & Anzola, 2018; Chen, 2009; Colombo & Delmastro, 2002; Gonzalez-Uribe & Leatherbee, 2018; Hallen et al., 2020; Kher et al., 2022; Lukeš et al., 2019; Roberts & Lall, 2019; Roberts et al., 2017; Rothaermel & Thursby, 2005; Smith, 2019; Yang et al., 2009). Second, balance sheet, turnover of assets and size of total assets were included in our selected studies as outcome measures of new ventures (Almeida et al., 2021; Dvouletý et al., 2018).

Finally, we identify within strategic performance cluster, digital or R&D measures. Indeed, the effects of adopting digital technologies or enabling digitalization is considered in the studies of Carbó-Valverde et al. (2022) and Kotha et al. (2022) as a proxy of firm's ability to attract potential attention from customers and investors. Also, existing studies, identify R&D efforts, measured in terms of number of patents, copyrights, or trademarks, as a good proxy for new ventures performance in terms of innovation outcomes (Audretsch & Chowdhury, 2022; Diez-Vial & Fernández-Olmos, 2017; Rothaermel & Thursby, 2005; Sedita et al., 2019; Siegel et al., 2003; Yang et al., 2009).

Moreover, to account for heterogeneity across the studies included in the analysis, we selected additional variables that capture the variability associated with different methodological approaches, accelerator program characteristics, start-up attributes, and locations. This approach is important for conducting a moderator analysis, as it helps identify factors that may influence the observed differences in outcomes, thereby enhancing the overall understanding of the impact of accelerator programs. The selected variables and their operationalization are listed in Table 2.

First, we use information relative to study characteristics including author, title, year, journal, and type of work. Here, we also differentiate between published and unpublished studies to control for possible publication bias. Additionally, we identify if papers under analysis use longitudinal data, or cross-sectional data as well as if they rely on secondary data or self-reported through a survey. Second, we take into account the different characteristics of the specific programs to differentiate the intermediaries in their types, focus, sponsorship backgrounds, and design features. The differentiation of types was relevant for selecting only papers with accelerator programs. Also, we distinguish between public and private accelerator programs in terms of social/governmental accelerators and investor-led accelerators. Furthermore, programs varied in their design features concerning cohort size, specialization, duration, service offer, and experience. In terms of sponsorship background,

Table 2 Variables for moderator analysis

Variable	Description
<i>Study characteristics</i>	
ID	Filled with “Author, Year, (a/b/c), pm*, iv*” serves as identifier for the paper included in the analysis; pm* identifies studies of which more than one effect was extracted, iv* identifies studies of which more than one independent variable was extracted
Author	Authors’ last names and initials
Year	Year in which the work was published (or last revised)
Title	Title and subtitle of work
Journal	Name of the journal in which the work was published (or left blank)
Type of work	Type of work differentiated across paper, working paper, report, dissertation, thesis
Published	Dummy-variable coded 1 (published) or 0 (unpublished)
Longitudinal	Dummy-variable coded 1 (longitudinal) or 0 (cross-sectional)
Source	Dummy-variable coded 1 (secondary data) or 0 (survey)
<i>Intermediary characteristics</i>	
Type	Type of start-up intermediary differentiating between accelerator or incubator (or both)
Focus	Accelerator type differentiated (social/governmental or investor-led)
Cohort size	Dummy variable coded 1 if more than 50 ventures were recruited into one cohort, 0 if the cohort was smaller than 50
Specialization	Dummy variable coded 1 for specialized and 0 for generic programs
Duration	Dummy variable coded 1 for programs that lasted up to 6 months, 0 for longer programs
Provides network	Dummy variable coded 1, if the intermediary provides networking opportunities to new ventures, 0 otherwise
Provides financing	Dummy variable coded 1, if the intermediary provides seed funding, 0 otherwise
Provides office space	Dummy variable coded 1, if the intermediary provides free office space, 0 otherwise
Provides mentoring	Dummy variable coded 1, if the intermediary provides mentoring, 0 otherwise
Age	Dummy variable coded 1, if years of experience since founding (calculated at the end of 2022) was greater than five, 0 for younger programs
Sponsorship	Dummy variable coded 1 if intermediary receives sponsorship or 0 if it is exclusively investor-led
Sponsor	Type of sponsor differentiated as public or private
<i>Venture characteristics</i>	
Average # of employees	Average number of people employed by the venture at time of acceleration/incubation
Average age	Average age of ventures at time of acceleration/ incubation
Prior funding	Dummy-variable coded 1 if ventures received funding prior to entering the intermediary, 0 otherwise
Gender	Dummy variable coded 1 if more than 50% of the sample were female-led ventures, 0 otherwise
<i>Location characteristics</i>	
Continent	Continent on which the sample of intermediaries is located
Country	Country in which the sample of intermediaries is located
USA	Dummy-variable coded 1 if sample of intermediaries is exclusively from the USA, 0 otherwise
PDI	Dummy variable coded 1 if the power distance index of country is considered low and 0 if it is considered high
UAI	Dummy variable coded 1 if the uncertainty avoidance index of country is considered low and 0 if it is considered high

Table 2 (continued)

Variable	Description
IDV	Dummy variable coded 1 if country is characterized by individualism and 0 if it is characterized by collectivism
MAS	Dummy variable coded if country is characterized by masculinity and 0 if it is characterized by femininity
EFC > 6	Dummy variable coded 1 if the number of EFCs scored as sufficient exceeds 6 out of 13
TEA > 10	Dummy variable coded 1 if country has a total early-stage entrepreneurial activity rate greater than 10%, 0 otherwise
Government Spending	Dummy variable coded 1 if the government spending score is larger than 50 and 0 if it is smaller than 50

we assess whether accelerator programs were based exclusively on a revenue-generating business model or received additional funds from public or private sponsors.

Third, we consider the characteristics of the accelerated new ventures by including information about firms' number of employees and age of the ventures. Also, we rely on a dummy-variable "prior funding" for new ventures that had received funding from other sources prior to entering the accelerator program, to control for potential bias of their financial performance in the selection process. Furthermore, we use a dummy-variable "gender" to assess whether the impact of accelerators differs for female-led ventures.

To conclude, we control for location characteristics, to understand the effects of cultural, entrepreneurship, and government conditions in the respective countries of the accelerator programs (Dubina & Ramos, 2013; Shetty et al., 2020). Most of the studies under analysis refer to accelerator programs within USA, to this extent we include a dummy variable to differentiate between samples from the USA and elsewhere to control for potential bias. Moreover, to assess the impact of culture on the effectiveness of accelerator programs we control four of Hofstede's cultural dimensions relative to power distance, uncertainty avoidance, individualism, and masculinity, since these conducive culture characteristics are considered drivers of entrepreneurial mindsets and activities (Dubina & Ramos, 2013). Furthermore, to better assess the entrepreneurial conditions, we control for the "EFC" index that refer to enhancing or impeding new venture foundation in each country using data from GEM (2022). Additionally, we include also the "TEA" index which measures the percentage of adults committed to starting a new business or already running it without having yet paid wages (GEM, 2022). Finally, we control for the index of economic freedom (Kim, 2023), to better assess the government spending for each country.

3.3 Meta-analytical approach

We select the Pearson product-moment correlation coefficient as the effect size metric for our meta-analysis, since effectively captures the relationship between a dichotomous independent variable (accelerator participation) and a continuous dependent variable (venture performance) (Card, 2012). Furthermore, this correlation coefficient has a standardized nature that allows us to account for differences in the original scales of the included metrics (Borenstein et al., 2009).

To ensure consistency across studies, we extract correlation coefficients directly when reported. When these were not available, we apply established formulas for converting

alternative data into the correlation metric, following Borenstein et al. (2009). Indeed, in cases where only p -values were reported, we consequently include an effect size based on lower-bound threshold values (Card, 2012). By adopting an effect-based approach, we incorporate studies under analysis multiple times if they reported different relevant outcome variables assessing the effectiveness of accelerators. This approach allowed us to capture the heterogeneous dimensions of accelerators programs and new venture performance. Consequently, the total sample size included 68 individual effect sizes. Key characteristics of the selected papers, such as publication year, geographic focus, sample size, and performance measures, are detailed in Appendix A.

After we apply a Fisher's (Z) transformation of the correlation coefficients (r) following Card (2012). Consequently, we convert Pearson correlation coefficients from each study as follow:

$$Z_r : Z_r = \frac{1}{2} \ln \left(\frac{1+r}{1-r} \right)$$

The Fisher Z_r transformation produces a symmetric distribution, making it more suitable for comparison and combination of effect sizes (Card, 2012).

Moreover, following Hunter and Schmidt (2006) the single effect sizes were weighted by each study's sample size, more precisely its standard error $\hat{\sigma}$, to ensure correction for sampling error. This approach adjusts for sample size in the studies under analysis, giving greater weight to studies with larger samples in determining the overall mean effect size compared to those with smaller sample sizes. Additionally, we consider 95% confidence intervals around the mean for evaluating the significance of effect sizes.

Finally, we employ a random-effects model to generalize and analyze the effects of accelerator participation on new venture performance (Card, 2012). As at least some level of generalization is desired for this analysis' results on intermediary effects, a random-effects model was used. In particular, we rely on a random-effects model due to the heterogeneity of studies included in the analysis which hindered the assumption that effect sizes across all studies are identical (Borenstein et al., 2009). Consequently, random-effects models conceptualize a distribution of effect sizes for the population, while fixed-effects models assume a single population effect size (Card, 2012). In general, this distribution is modeled as normally distributed (Borenstein et al., 2009).

4 Results

4.1 The overall mean effect

Table 3 presents the results of our meta-analysis using random-effects model and summarizing 68 effect sizes investigating the impact of accelerator participation on new venture performance. Findings indicate that participation in an accelerator program has a statistically significant and positive impact on new venture performance, providing robust evidence for the effectiveness of accelerators ($r=0.102$; $p=0.00$).

To gain an overview of the primary studies' contribution to this effect, a forest plot was generated and included in Appendix B.

Table 3 Meta-analysis summary using random-effects model

Venture performance	
Accelerator participation	0.102*** (0.0231)
Observations	68
Chi ²	<0.05
Homogeneity Q	732.31
Heterogeneity: Tau ²	0.0124
I ²	93.89

This table reports the results of random-effects meta-analysis summary considering the weighted effect sizes of the studies under analysis. The dependent variable is venture performance. The independent is accelerator participation. Robust standard errors are in brackets

The positive result of the overall correlation confirms the theoretical arguments in favor of accelerators' positive impact on nascent ventures. Nonetheless, the small size of the effect indicates that accelerator participation is not a guarantee for new venture success. While a positive correlation gives credit to the main body of empirical research touting and proving positive effects of accelerators, it downplays the significantly negative findings from other studies. To further explore why effects diverged substantially in different papers, but still yielded a positive overall effect, heterogeneity tests and subgroup analysis are necessary.

4.2 Assessing heterogeneity and publication bias

4.2.1 Heterogeneity

The resulting effect sizes differ between studies as Appendix B reveals, due to variations that arise from heterogeneity (Deeks et al., 2022), or random error (Borenstein et al., 2009). To assess this issue, we investigate the heterogeneity of the studies analyzed. First, as reported in Table 2 as well as Appendix B, with the Q-statistic, the null hypothesis of homogeneity was tested, with $Q = 732.31$ with a p -value of 0.00, indicating significant heterogeneity across studies (West et al., 2010). The between-study variance (τ^2) was estimated at 0.0124, though this value is difficult to interpret conclusively (Borenstein et al., 2009). Furthermore, the I^2 statistic revealed that 93.89% of variability is attributable to high heterogeneity among the studies under analysis rather than sampling error. All these three indicators lead to the same conclusion that there is high heterogeneity arising from differences in effect sizes of our studies.

To further analyze heterogeneity, we use a Galbraith plot, which offers a visual representation of variation and helps in detecting potential outliers. In Fig. 2, the horizontal axis represents the precision of the studies (inverse of standard error), while the vertical axis shows the standardized effect sizes (θ) divided by their standard errors (se). Each circle in the scatterplot corresponds to an individual study, plotting its precision against its effect size. The plot includes a horizontal reference line at $y=0$, indicating no effect across all levels of precision. Most studies are positioned above this line, reflecting positive effect sizes, while a smaller number of studies with negative effects are situated below the line. The red regression line ($r=0.102$) represents the overall positive effect size estimate across

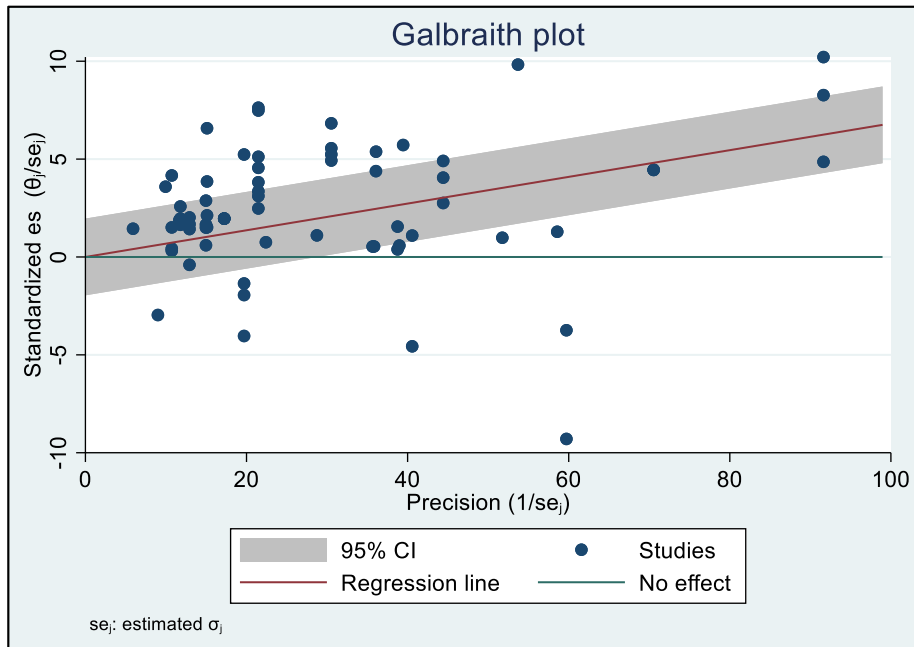


Fig. 2 Galbraith plot

the analyzed studies. To evaluate heterogeneity, the distribution of the data points relative to the shaded region (95% confidence interval around the regression line) is examined. In this case, a significant portion of the data points lies outside the shaded region, suggesting substantial heterogeneity among the studies. This observation aligns with the results from Table 2, further indicating that differences between studies extend beyond random sampling error.

Moreover, we control for the presence of possible outliers since some studies are located rather far from the mean effect line. Hence, we perform a leave-one-out analysis, by conducting several meta-analyses and stepwise excluding each individual study under analysis. However, the analysis did not show any outliers.

Moreover, we assess the presence of publication bias in our studies under analysis. Publication bias occurs when the studies included in a meta-analysis may not be representative, due to the preference towards statistically significant findings in published research, and null or non-significant results may remain unpublished (Eisend & Tarrahi, 2014). First, to address publication bias we perform a basic funnel plot (Fig. 3) in order to assess the relationship between study-specific effect sizes and their standard errors (Light & Pillemer, 1986). The majority of studies are concentrated near the top of the funnel with smaller standard errors, indicating larger sample sizes. These studies cluster closely around the estimated overall effect size (red vertical line), reflecting consistency in the findings. However, slight asymmetry in the lower portion of the plot and a few outliers falling outside the pseudo 95% confidence interval suggest the potential presence of small-study effects. These smaller studies, characterized by larger standard errors, tend to report more variable and occasionally exaggerated effect sizes, consistent with prior literature on publication bias

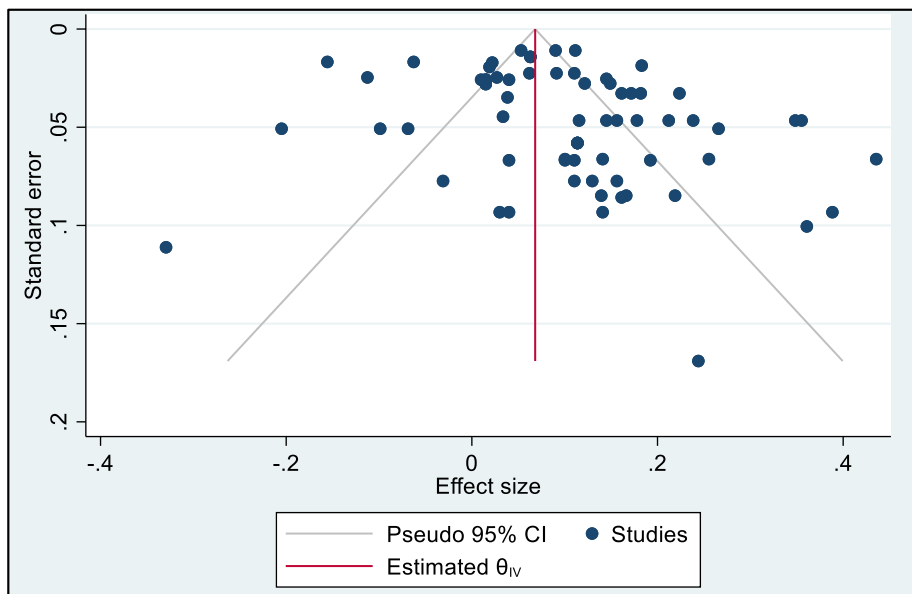


Fig. 3 Funnel plot after exclusion of outliers

(Sterne et al., 2006). Despite these minor indications, the overall symmetry of the plot supports the robustness of the meta-analytic findings.

Second, to investigate potential publication bias, a contour-enhanced funnel plot was created, introducing statistical significance thresholds ($p < 0.01$, $p < 0.05$, $p < 0.10$) as contour lines (Peters et al., 2008). This approach helps discern whether asymmetry in the plot arises from publication bias or other underlying factors. The resulting plot reveals a right-skewed distribution, with the majority of studies concentrated on the right side in statistically significant regions, while fewer are located in nonsignificant areas on the left. Such a pattern suggests the potential presence of publication bias, as smaller studies with larger effect sizes are overrepresented, whereas smaller studies with small or nonsignificant findings appear underrepresented. This distribution may indicate that studies with nonsignificant results are less likely to be published or included in the analysis, a common characteristic of publication bias (Card, 2012).

We also used Egger's test to examine the presence of small-study effects, where smaller studies with nonsignificant results are less likely to be published, leading to an overrepresentation of studies with significant results (Sterne et al., 2006). Results in Table 4, reveal a beta coefficient of $\beta = 1.18$ ($p = 0.032$) positive and significant, rejecting the null hypothesis and revealing the existence of small-study effects in our meta-analysis.

4.3 Moderator analysis

4.3.1 Methodological differences

We perform a moderator analysis to examine the methodological differences among the different studies under analysis. To clarify how methodological choices may influence research

Table 4 Egger test for small-study effects

Regression-based Egger test for small-study effects	
Random-effects model	
Method: REML	
H0: $\beta_1 = 0$; no small-study effects	
$\beta_1 =$	1.18
SE of $\beta_1 =$	0.550
$z =$	2.15
Prob > $ z =$	0.0320

findings, we perform a subgroup analysis of three different methodological factors relative to publication status, research design and data sources of the studies. We group different studies based on the different methods applied and we measure the mean effect size for each subgroup, in order to control for heterogeneity and assess the impact of the groups on the overall effect sizes.

First, we measure the effect sizes of published and unpublished (working papers, dissertations/ theses, or reports) papers under analysis, since differences in effect sizes allowed to examine the presence of potential publication bias. The results of this subgroup analysis are presented in Table 9. The effect size for published studies was slightly larger than the overall effect size and significant ($r=0.123$, $p=0.00$), while the estimated effect size for unpublished studies was lower than the overall effect size and significant ($r=0.057$; $p=0.043$). These results suggest that research on accelerators is affected by publication bias. Furthermore, the test of group differences is statistically significant ($Q_b=4.11$, $p=0.043$), revealing that the effect sizes of the two groups are different enough to draw relevant conclusions. We can confirm our previous findings (Fig. 4 and Table 3), indeed, the presence of publication bias suggests that the published accelerator literature may not fully represent the complete body of studies conducted on this topic (Card, 2012).

Second, we create a binary variable to differentiate between studies that used longitudinal data and those that drew on cross-sectional research designs. Results show that, while longitudinal studies prevailed in the sample ($k=45$), cross-sectional studies seem to be more adequate for capturing the positive effect ($r=0.117$; $p=0.00$). A possible implication of the rather low mean effect size measured for longitudinal studies ($r=0.095$; $p=0.00$) could be associated with the fact that accelerators yield only a temporary advantage for start-ups (Stam et al., 2014), which would explain lower effect sizes of primary studies measuring the acceleration effect at several points in time. However, the difference between the two groups is not statistically significant.

Third, we analyze the effects of different data sources a moderator for the strength of the accelerated ventures' performance. Our studies under analysis rely on data drawing either on existing databases or on survey data. Results in Table 5 reveal that both types of data collection seem to be equally appropriate in accelerator research as they produced similar and significant effect sizes ($r=0.104$; $p=0.00$ and $r=0.102$; $p=0.00$). However, also in this case, the difference between the two groups is not statistically significant.

Overall, the different methodological variables have low power to explain possible existing heterogeneity, given that, apart from the subgroup of cross-sectional studies ($I^2=80.11\%$), all groups are characterized by very high levels of heterogeneity ($I^2>90\%$).

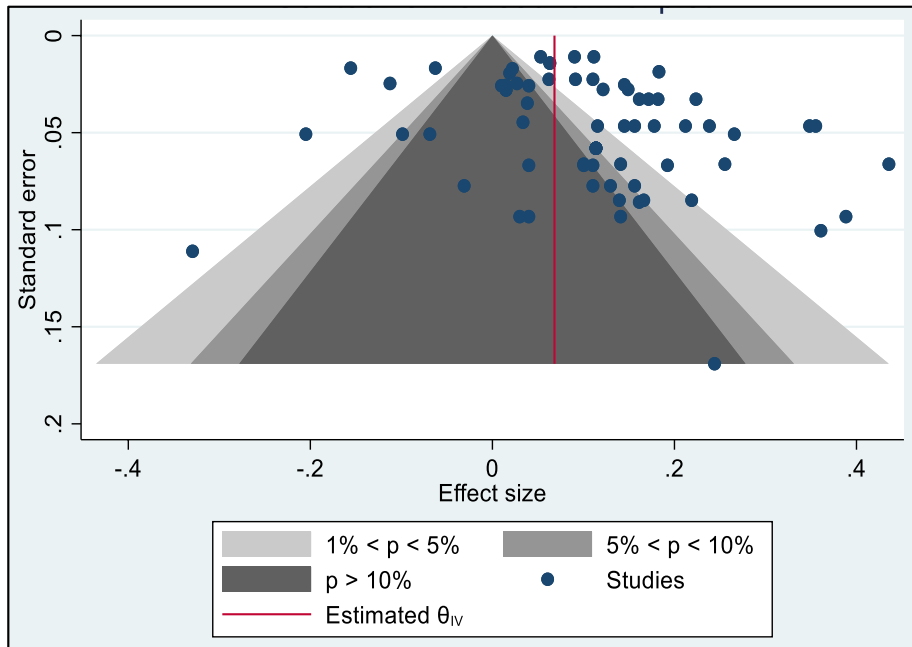


Fig. 4 Contour-enhanced funnel plot

These findings indicate that other factors moderating the relationship under study might exist, which calls for an in-depth analysis of the contextual dimensions of variability.

4.3.2 Program variation

To further explore heterogeneity beyond methodological characteristics, we conduct a moderator analysis of subgroups relative to accelerator program characteristics. In particular, we assess moderators based on four dimensions of program variation: program structure and service offer, sponsorship, batch selection criteria, and location and institutional context. Results are reported in Tables 6 and 7.

First, in terms of program structure, the moderator analysis revealed effects that diverge from findings of prior studies and provided evidence for the arguments raised in favor of large batches. Surprisingly, the mean effect for studies that analyzed cohorts with more than 50 participants is larger than the overall effect ($r=0.187$; $p=0.00$). Unfortunately, no statistically significant effect was found for batches smaller than 50 participants. The test of group differences revealed that the mean effect sizes from the two subgroups were statistically significant ($Q_b=19.93$; $p=0.000$). These findings suggest that the advantages of large cohorts potentially outweigh their limitations. Referring to the contradicting arguments of existing studies like Smith and Hannigan (2015), peer effects seem to play an important role in large cohorts allowing for mutually beneficial exchanges, while increased competition for follow-on funding might have a positive impact on ventures' ambition and performance. To avoid the concern of anonymization raised by Barnes (2016), accelerators recruiting larger batches must adapt their processes and offers accordingly, so that ventures profit indi-

Table 5 Subgroup analysis on methodological factors

	k	n	r	95%	CI	w (%)	z	Prob $\geq$ z	sig	Q/Qb	Prob $\geq$ Q	I ² (%)	τ^2
Overall	68	87,106	0.102	0.073	0.131	100.00	6.84	0.000	***	732.31	0.000	93.89	0.0124
Methodological factors													
Publication bias													
Published	46	63,291	0.123	0.091	0.154	68.18	7.62	0.000	***	4.11	0.043	92.54	0.0095
Unpublished	22	23,815	0.057	0.002	0.112	31.87	2.03	0.043	*	294.99	0.000	93.66	0.0146
Research design													
Longitudinal	45	72,138	0.095	0.058	0.133	68.64	4.96	0.000	***	0.58	0.446	95.70	0.0145
Cross-sectional	23	14,968	0.117	0.076	0.157	31.41	5.61	0.000	***	102.25	0.000	80.11	0.0066
Data source													
Self-reported	21	50,949	0.104	0.063	0.145	33.48	4.92	0.000	***	0.01	0.936	94.80	0.0081
Archival	47	36,157	0.102	0.064	0.140	66.57	5.25	0.000	***	535.88	0.000	91.49	0.0145

vidually but also collectively. Observing heterogeneity statistics, cohort size clearly had an impact on the meta-analysis results, as variation in the statistically significant subgroup was reduced to 67% ($\tau^2=0.0073 < 0.0124$). We can conclude that cohort size was one of many moderators of the relationship between accelerator participation and venture outcomes.

Second, we control for the effect of the different level of specialization (relative to industry similarities) of the batches of firms within the different accelerator programs. The moderator analysis revealed small but statistically significant effect differences for specific ($r=0.079$; $p=0.00$) and generic ($r=0.111$; $p=0.00$) programs respectively, with slightly larger effects for generic programs compared to the overall effect. Hence, new ventures in the sample seem to have benefitted slightly more from the positive implications of greater batch diversity in terms of industry than from being grouped together with entrepreneurs of the same industry background. This finding contradicts existing empirical evidence found in the context of corporate accelerators (Seitz et al., 2019). However, the test of group differences was not statistically significant.

Third, the analysis of program duration revealed that both short and long programs can be beneficial for start-ups, as the mean effect sizes for both groups were larger than the overall effect and statistically significant ($r=0.116$, $p=0.00$; $r=0.170$, $p=0.00$). Unfortunately, the effect for durations longer than six months was based on a comparatively small sample of 565 start-ups ($k=4$), which complicates generalization and sends misleading signals in terms of heterogeneity reduction ($Q=0.47$, $I^2=0.000$). Moreover, the test of group differences was not statistically significant.

Fourth, observing the services offered by accelerator programs in our sample, the majority provided financing ($k=53$), networking ($k=40$), and mentoring ($k=55$) to their participants, while office space ($k=19$) was not commonly included. Interestingly, while all services seem to help start-ups, office space seems to be an important factor for the effectiveness of the accelerator as it increased the effect size to $r=0.145$ ($p=0.00$). However, despite the statistical significance of each effect, the service offer does not appear to effectively explain between-study heterogeneity as the test statistics reported very high heterogeneity within each subgroup.

Lastly, we analyze the age of the accelerator as a subgroup to identify the impact of experience of certain programs on the outcomes of their ventures. This factor has not been explored in previous literature, but the observed mean effect followed a logical inference, that more experienced programs might provide greater benefits to their participants ($r=0.137$, $p=0.00$). However, the test of group differences was not statistically significant.

Moreover, we investigate also the different type of sponsorship of accelerators. First, the subgroup analysis aimed at spotting differences between accelerators exclusively following the seed accelerator approach and those that receive additional sponsoring. Results reveal that the mean effect of additional sponsoring was significantly larger than the overall effect ($r=0.205$, $p=0.00$). The positive implications for additional sponsorship were supported further by the significance of group differences ($Q_b=4.45$, $p=0.035$). Second, we investigate if the accelerator programs received funds mainly from public institutions or by private investors. Results reveal additional sponsoring of mainly public institutions yielded a positive effect suggests that theoretical arguments regarding public sponsors as well as prior evidence should be questioned. Accelerators with public sponsors were expected to yield lower effects, as they often focus on wider economic development goals and direct their attention

Table 6 Subgroup analysis on program structure & service offer, sponsorship, batch selection criteria

	k	n	r	95%	CI	w (%)	z	Prob $\geq$ z	sig	Q/Qb	Prob $\geq$ Q	I ² (%)	τ^2
Overall	68	87,106	0.102	0.073	0.131	100.00	6.84	0.000	***	732.31	0.000	93.89	0.0124
Program structure & service offer													
Cohort size													
<50	8	12,000	-0.053	-0.148	0.044	12.88	-1.07	0.285	ns	19.93	0.000		
$\geq$ 50	23	6,442	0.187	0.144	0.229	30.5	8.42	0.000	***	94.69	0.000	96.02	0.0180
Specialization													
Specific	15	23,828	0.079	0.052	0.106	22.93	5.65	0.000	***	65.43	0.000	66.78	0.0073
Generic	52	63,278	0.111	0.075	0.147	77.12	5.97	0.000	***	2.11	0.146		
Duration													
$\leq$ 6 months	32	24,272	0.116	0.058	0.172	44.98	3.95	0.000	***	47.35	0.000	71.53	0.0017
>6 months	4	565	0.170	0.088	0.250	4.55	4.03	0.000	***	640.11	0.000	94.26	0.0150
Services										1.15	0.283		
Financing	53	77,526	0.107	0.073	0.141	79.59	6.12	0.000	***	484.11	0.000	94.44	0.0239
Network	40	59,646	0.112	0.076	0.148	60.56	6.8	0.000	***	0.47	0.925	0.00	0.0000
Mentoring	55	70,953	0.119	0.088	0.150	80.64	7.48	0.000	***				
Office space	19	18,167	0.145	0.078	0.210	28.42	4.21	0.000	***	676.13	0.000	95.13	0.0139
Age of accelerator													
<5	6	3,863	0.081	-0.027	0.188	7.97	1.47	0.142	ns	319.18	0.000	94.10	0.0114
$\geq$ 5	12	5,276	0.137	0.038	0.233	18.2%	2.71	0.007	**	422.41	0.000	93.28	0.0113
Sponsorship										450.21	0.000	94.73	0.0201
Sponsoring										0.56	0.455		
Yes	12	4,277	0.205	0.157	0.252	16.79	8.24	0.000	***	38.23	0.000	87.14	0.0140
No	20	7,306	0.109	0.032	0.185	25.75	2.78	0.006	**	140.44	0.000	92.56	0.0285
Accelerator Type										4.45	0.035		
Social/Governmental	24	49,973	0.121	0.087	0.155	38.08	6.95	0.000	***	28.07	0.003	60.32	0.0044
Investor-led	20	7,306	0.109	0.032	0.185	25.75	2.78	0.006	**	176.68	0.000	89.62	0.0258
Batch Selection Criteria										0.08	0.771		
Age of venture										129.00	0.000	91.88	0.0059
										176.68	0.000	89.62	0.0258
										0.91	0.339		

Table 6 (continued)

	k	n	r	95%	CI	w (%)	z	Prob $\geq$ z	sig	Q/Qb	Prob $\geq$ Q	I ² (%)	τ^2
<2	11	36.175	0.012	-0.059	0.083	18.21	0.33	0.085	ns	150.19	0.000	97.53	0.0133
≥ 2	15	26.167	0.097	0.056	0.138	24.03	4.64	0.000	***	889.93	0.000	99.60	0.0054
Number of employees													
<10	16	20.420	0.160	0.113	0.207	25.78	6.55	0.000	***	9.43	0.002		
≥ 10	16	36.824	0.030	-0.039	0.098	23.66	0.85	0.397	ns	137.09	0.000	90.65	0.0083
Prior funding													
Yes	18	37.592	0.103	0.073	0.131	27.02	5.47	0.000	***	0.00	0.982		
No	50	49.514	0.103	0.066	0.140	73.03	5.44	0.000	***	99.59	0.000	89.00	0.0044
Gender													
<50% Females	28	54.331	0.101	0.060	0.142	45.06	4.77	0.000	***	615.47	0.000	93.55	0.0151
$\geq 50\%$ Females	7	10.560	0.141	0.079	0.202	11.78	4.41	0.000	***	1.09	0.296		
										245.71	0.000	95.34	0.0113
										36.01	0.000	90.50	0.0065

Table 7 Subgroup analysis on location & institutional context and performance measures

	k	n	r	95% CI	w (%)	z	Prob $\geq$ z	sig	Q/Qb	Prob $\geq$ Q	I ² (%)	τ^2
Overall	68	87,106	0.102	0.073	0.131	100.00	6.84	***	732.31	0.000	93.89	0.0124
Location & institutional context												
Continents									15.88	0.001		
North America	29	25,377	0.079	0.023	0.135	41.16	2.78	**	367.70	0.000	94.36	0.0201
Latin America	9	1,190	0.211	0.155	0.267	13.37	7.17	***	26.96	0.001	69.98	0.0055
Europe	8	3,851	0.079	-0.027	0.184	9.16	1.46	ns	21.22	0.004	70.73	0.0167
USA-Bias									3.71	0.054		
USA	29	25,377	0.079	0.023	0.135	41.16	2.78	**	367.70	0.000	94.36	0.0201
Non USA	17	8,475	0.149	0.090	0.207	24.28	4.90	***	117.70	0.000	83.52	0.0127
Hofstede dimensions												
Low PDI & UAI	27	24,595	0.095	0.040	0.149	38.18	3.38	***	347.12	0.000	93.89	0.0178
High PDI & UAI	19	5,041	0.122	0.049	0.193	25.51	3.28	***	136.26	0.000	86.82	0.0220
Individualism	35	25,785	0.091	0.043	0.139	47.34	3.72	***	375.71	0.000	92.21	0.0170
Collectivism	11	3,851	0.148	0.052	0.242	16.35	3.00	**	111.12	0.000	91.13	0.0247
Masculinity	28	24,679	0.085	0.027	0.142	39.08	2.88	**	356.45	0.000	94.50	0.0206
Femininity	18	4,957	0.141	0.075	0.205	24.61	4.21	***	117.86	0.000	83.66	0.0164
EEs framework conditions									2.57	0.109		
≤ 6 scored sufficient	10	3,935	0.172	0.078	0.263	49.42	3.55	***	50.61	0.000	88.81	0.0206
> 6 scored sufficient	36	26,483	0.086	0.039	0.133	14.27	3.57	***	387.61	0.000	92.28	0.0171
Total early-stage entrepreneurial activity score									0.40	0.525		
> 10	38	29,173	0.103	0.051	0.153	54.3	3.92	***	549.56	0.000	94.38	0.0228
≤ 10	8	1,245	0.127	0.071	0.182	8.26	4.07	***	5.93	0.548	0.00	0.0000
Government Spending									2.57	0.109		
low expenditures	10	3,935	0.172	0.078	0.263	49.42	3.55	***	50.61	0.000	88.81	0.0206
high expenditures	36	26,483	0.086	0.039	0.133	14.27	3.57	***	387.61	0.000	92.28	0.0171
Measuring effectiveness												
Performance measure									3.73	0.155		
Financial	49	70,674	0.112	0.076	0.148	73.05	6.05	***	636.69	0.000	95.22	0.0145

Table 7 (continued)

	k	n	r	95%	CI	w (%)	z	Prob $\geq$ z	sig	Q/Qb	Prob $\geq$ Q	I ² (%)	τ^2
Operational	10	9,046	0.092	0.033	0.151	13.69	3.05	0.002	**	25.30	0.003	78.55	0.0057
Strategic	9	7,386	0.044	-0.015	0.103	13.31	1.47	0.142	ns	40.60	0.000	81.25	0.0058

towards these more than towards their own economic goals (Cohen et al., 2019). However, the test of group differences is not statistically significant.

Furthermore, we analyze the effects of the dimension of batch selection criteria, that refers to the group of ventures that is most suited to be accelerated and points out how some of their characteristics moderate the relation between accelerator participation and performance outcomes. First results according to the age of ventures did not provide clear guidance, as the subgroups did not differ significantly from each other ($Q_b=0.91$; $p=0.339$). The effect for ventures older than two years ($r=0.097$, $p=0.00$) was statistically significant but did not differ greatly from the overall effect. Second, concerning the optimal size of ventures, the results reveal that the effect for firms with less than ten employees was larger than the overall effect ($r=0.160$, $p=0.00$) and statistically significant, while for the group of firms with more than ten employees the effect was not significant. Smaller ventures in the sample profit more from acceleration than larger ones. This is in line with the argumentation that smaller firms have greater potential to grow and are less limited in their agility to implement new processes (Rawhouser et al., 2020; Storey, 1989). These results are supported further by the significance of group differences ($Q_b=9.43$, $p=0.002$). Third, the results regarding batches, whether they had received prior funding or not, are statistically significant and showed the same effect for both groups ($r=0.103$, $p=0.00$). However, the test of group differences was not statistically significant. Consequently, a historical fundraising differential does appear to neither impact the true overall performance of accelerated ventures, nor bias financial performance measures. This finding is in line with research findings from Davidson et al. (2021) whose data indicated that during acceleration, ventures attracted equal levels of follow-on investments independent of the level of funds before entering the program. Finally, we control for the impact of gender on the accelerator-venture-relationship. Test statistics revealed that the group of studies that investigated a sample of which more than 50% of the ventures were female-led, yielded a statistically significant effect of $r=0.141$ ($p=0.00$), which was larger than the overall effect. This indicates that women might profit more from acceleration programs than men. However, the effect sizes of both groups did not differ significantly from each other, and heterogeneity indicators were still high, which leads to the conclusion that gender does not seem to be a strong moderator for the analyzed studies.

We assess the moderating effects of location and institutional context along a range of different variables in Table 6. Initially, we investigate variation across different continents of the accelerator programs: North America, Latin America and Europe. Moreover, since many of the studies under analysis have accelerator programs located in USA, we control for potential bias relative to accelerator programs in USA. The specific effects for each group are significantly different ($Q_b=15.88$, $p=0.001$) with a large effect for Latin America ($r=0.211$, $p=0.00$). While the effect reported for Europe is not statistically significant, the effect for the USA ($r=0.079$; $p=0.005$) is lower than the overall effect and different from the collective of studies that originated outside the USA ($Q_b=3.71$, $p=0.054$). This suggests that our sample is not biased towards the studies focus on USA accelerators.

Moreover, we control for the cultural perspective with the Hofstede dimensions (Hofstede, 2001). Results reveal that the greatest performance outcomes were achieved for firms located in countries characterized by high PDI and UAI ($r=0.122$, $p=0.001$), by collectivism ($r=0.148$, $p=0.003$) rather than individualism ($r=0.091$, $p=0.00$) and by femininity

($r=0.141$, $p=0.00$) rather than masculinity ($r=0.085$, $p=0.00$). While all individual effects were statistically significant, the differences within each cultural dimension were not.

In addition to Hofstede's cultural dimensions, three different variables were included to proxy the entrepreneurial ecosystem framework conditions (EEFC) in which start-ups are founded, accelerated, and operated, associated with the government expenditures. Countries that are characterized by low government expenditures also score low on EEFC in general. However, accelerators in countries that meet few of the relevant EEFC and that have low government expenditures have a larger impact on venture outcomes ($r=0.172$, $p=0.00$) than the overall effect, while the opposite is true for countries with higher expenditures and better EEFC ($r=0.086$, $p=0.00$). However, the test of group differences is not significant ($Q_b = 2.57$, $p=0.109$). These findings are complemented by the effect differences regarding the total TEA (Total early-stage entrepreneurial activity score). The effect of accelerators on venture outcomes is stronger than the overall effect for countries with lower scores ($r=0.127$, $p=0.00$). However, no statistically significant difference between the subgroups was found and extremely low levels of heterogeneity were probably caused by a small number of effects ($k=8$). Consequently, conclusions on the institutional context need to be derived carefully. A possible explanation for these existing results can be relative to the fact that a proper endowment with institutional conditions supporting entrepreneurship and the economy make the intervention of accelerators redundant. At the same time, the lack of institutional support structures can be compensated by the interference of accelerators helping ventures to overcome hurdles arising from geographical context. Overall, the country analysis points in the direction that accelerator programs more effectively contribute to venture outcomes when they are operating in regions characterized by a poor institutional context, low entrepreneurial activity, and a lack of conducive cultural factors. The results further suggest that accelerators might be less needed in industrialized countries with a strong entrepreneurial culture and support system like USA.

Lastly, the moderating effect of different performance measures adopted in existing studies under analysis was considered. Results reveal that the greatest relation between accelerator participation and venture performance is found using financial measures ($r=0.112$, $p=0.00$). Operational measures yield a slightly smaller impact than the overall effect ($r=0.092$; $p=0.002$) but reduce heterogeneity in this group to $I^2=78.55\%$. The effect for strategic measures is not statistically significant. Furthermore, the test of group differences is not statistically significant. Keeping in mind that no absolute statements can be made, it appears that financial measures might be most appropriate to measure the impact of accelerators. Moreover, we can also conclude that an accelerator's contribution is tied to the financial aspects of performance in line with their provision of seed investments, while it appears that further components of their support offer do not boost a venture's strategic performance. Nevertheless, the results might be biased by the prevalence of financial outcomes ($k=49$) in the sample and by the fact that the analysis included mainly business accelerators. As different types of accelerators draw on different start-up metrics to quantify performance and private programs heavily rely on financial measures (Ursache, 2020), diverging results might be found for university-led, government-led, or corporate accelerators.

5 Discussion

The fragmented existing literature on accelerators calls for a comprehensive understanding of their impact on start-up performance. While previous studies have provided valuable insights, their findings often diverge due to differences in methodological approaches, contextual factors, and program characteristics (Crişan et al., 2021; Gonzalez-Uribe & Leatherbee, 2018; Roberts & Lall, 2019). The findings of the meta-analysis in this paper address these inconsistencies by synthesizing quantitative evidence on accelerator effectiveness, offering valuable insights into their impact on start-up performance. The analysis confirms that accelerator participation is generally associated with positive outcomes, yet the degree of impact varies depending on several contextual and program-specific factors. Indeed, the results confirm that accelerator programs, on average, have a positive and statistically significant effect on new venture performance. However, the modest effect size suggests that the benefits of acceleration are depending on different factors such as program design, sponsorship structure, and geographical context. Indeed, the high level of heterogeneity observed across studies indicates substantial variability in outcomes. This further suggests that accelerator effectiveness is influenced by multiple contextual and program specific factors, such as differences in cohort size, program duration, and sponsorship structure (Borenstein et al., 2009; Cohen et al., 2019a, 2019b). Our robustness tests indeed confirm the presence of significant variance, suggesting that while accelerators generally provide value, their impact is not uniform across new ventures. Moreover, the heterogeneity analyses revealed evidence of publication bias. This suggests a tendency in the literature to favor studies reporting significant positive effects, potentially underrepresenting non-significant or negative findings (Sterne et al., 2006). As a result, the existing body of research on accelerators may overstate the benefits of accelerator programs, highlighting the need for greater transparency and inclusion in future studies.

To this extent, in this study we also contribute to the literature by providing empirical evidence, through moderator analyses, that accelerator programs are not a one-size-fits-all solution, and their effectiveness depends on the strategic alignment between program offerings and the specific needs of start-ups. In particular, in this paper we broadened our understanding that accelerators play a significant role in promoting start-up growth, particularly by improving access to financial and non-financial resources. The positive correlation identified between accelerator participation and start-up performance highlights their function as facilitators of venture growth, providing and supporting start-ups with diverse resources such as mentorship, networking opportunities, and early-stage funding. These findings are consistent with previous research suggesting that accelerators help mitigate resource constraints faced by nascent firms, thereby increasing their chances of survival and success (Gonzalez-Uribe & Leatherbee, 2018; Roberts & Lall, 2019). However, the analysis also reveals that accelerators primarily drive financial outcomes, while their impact on strategic and operational performance measures remains less pronounced. This suggests that the value proposition of accelerators may be more aligned with short-term financial growth rather than long-term strategic growth.

A significant finding revealed by our moderator analysis is the influence of program duration on start-up outcomes. Findings suggest that longer accelerator programs tend to yield better performance results compared to shorter, more intensive programs. This observation aligns with prior literature indicating that extended support allows entrepreneurs to

fully capitalize on the resources provided, refine their business models, and establish stronger networks (Cohen et al., 2019a, 2019b). On the other hand, shorter programs, while beneficial for rapid learning and networking, may not provide sufficient time for ventures to implement strategic changes effectively (Rawhouser et al., 2020). These insights offer valuable implications for accelerator managers seeking to optimize program structures by balancing the trade-off between program duration and venture capacity to absorb and act on the knowledge and resources provided.

Similarly, this paper sheds light on the impact of cohort size, revealing that larger cohorts tend to yield better performance outcomes than smaller ones. Our findings indicate that, contrary to previous concerns regarding resource dilution and increased competition within larger groups (Smith & Hannigan, 2015), larger cohorts provide enhanced peer-learning opportunities and foster a more dynamic environment that promotes venture development. The significant positive effect observed in large cohorts suggests that the benefits of knowledge exchange and collaboration may outweigh potential drawbacks such as reduced individualized support (Cohen et al., 2019a, 2019b). However, to mitigate the risk of resource dilution, accelerator managers should carefully design their mentorship and resource allocation strategies.

Another important finding concerns the role of accelerator sponsorship, which significantly moderates the acceleration effect. Start-ups that receive additional sponsorship—whether from public or private sources—tend to experience enhanced program effectiveness, as the additional funding allows access to a broader range of resources, that can be particularly beneficial in addressing long-term challenges faced by ventures, such as scaling operations and accessing critical industry networks (Cohen et al., 2019a, 2019b; Pauwels et al., 2016). However, our findings also reveal a potential selection bias favoring start-ups that have already demonstrated success in securing funding prior to acceleration. This bias raises concerns that accelerators may primarily attract ventures with a proven track record, thereby limiting opportunities for those seeking their first round of financing. Consequently, this practice may hinder the potential of truly early-stage ventures that require initial funding and strategic guidance to unlock their growth potential (Davidson et al., 2021).

Furthermore, we explored the selection criteria employed by accelerator programs regarding the composition of their batches. Our results indicate that firm size is a critical determinant of accelerator outcomes. Specifically, smaller ventures with fewer than ten employees tend to have greater benefits from accelerator participation compared to larger firms. This finding supports the argument that early-stage start-ups, due to their lean structures and adaptability, are more responsive to the intensive mentorship, networking, and resource provision that accelerators offer (Rawhouser et al., 2020). Larger firms, on the other hand, may face challenges in fully leveraging accelerator resources, as their organizational complexity and established processes may limit their capacity for rapid change and experimentation. These insights emphasize the need for accelerators to carefully consider firm size when designing their programs to ensure that their services align with the specific needs of participating ventures.

Moreover, our results highlight the critical role of geographic and institutional context in shaping accelerator effectiveness. The analysis reveals that accelerators operating in less developed ecosystems tend to provide greater value in terms of bridging institutional voids and compensating for a lack of formal support structures (Kher et al., 2022). In countries characterized by weak institutional frameworks and limited access to entrepreneur-

ial resources, accelerators act as fundamental enablers of entrepreneurial activity, offering access to funding, mentorship, and market linkages that might otherwise be unavailable. This is particularly evident in Latin America, where the effect size of acceleration programs was found to be significantly higher than in other regions. Conversely, in developed economies such as the USA, where entrepreneurial ecosystems are already well-established, accelerators appear to have a comparatively smaller impact. These findings align with prior research suggesting that the presence of strong institutional support may reduce the incremental value that accelerators can provide (Roberts & Lall, 2019).

6 Conclusion

This study overall provides a comprehensive synthesis of the fragmented literature on accelerators by conducting a meta-analysis to assess their impact on new venture performance. The findings contribute to both theory and practice, offering empirical insights into the overall effectiveness of accelerators.

From a theoretical perspective, the study advances the understanding of accelerators by synthesizing empirical evidence across various contexts and highlighting key moderating factors that influence their effectiveness. This meta-analysis validates that accelerator programs provide significant value to start-ups, primarily by offering access to resources such as mentorship, networking opportunities, and funding (Cohen et al., 2019a, 2019b). However, the findings suggest that accelerator participation is not a one-size-fits-all solution, as program success is relative to different factors such as program design, sponsorship models, and regional economic conditions. These insights extend prior research by demonstrating the variability in accelerator effectiveness and the importance of aligning program characteristics with the needs of participating ventures.

This paper also offers several implications for practitioners, including accelerator managers, policymakers, investors, and entrepreneurs. Indeed, the findings suggest that accelerator programs aiming to enhance start-up performance should consider optimizing program duration, cohort composition, and service offerings to maximize their impact. Moreover, policymakers, particularly in emerging economies, can take advantage of these findings to design accelerator initiatives considering the specific challenges faced by local entrepreneurs, such as limited access to capital and underdeveloped entrepreneurial ecosystems (Roberts & Lall, 2019). Moreover, this study provides valuable insights for entrepreneurs by helping them make informed decisions about accelerator participation. Entrepreneurs should carefully assess program fit, considering their own business needs and potential. For investors, the results reinforce the value of accelerator programs as a mechanism to mitigate uncertainty around the quality of early-stage ventures. The accelerator process provides a rigorous selection and evaluation process, helping investors identify promising start-ups with validated business models and growth potential (Colombo et al., 2023; Yu, 2020). Additionally, the findings suggest that investors should pay particular attention to ventures graduating from experienced accelerator programs, as these programs tend to yield higher returns.

Despite the significant contributions of this study, several limitations must be acknowledged. First, the heterogeneity of the studies analyzed reveal a challenge, as accelerators vary widely in their design, target industries, and regional focus. The high heterogeneity

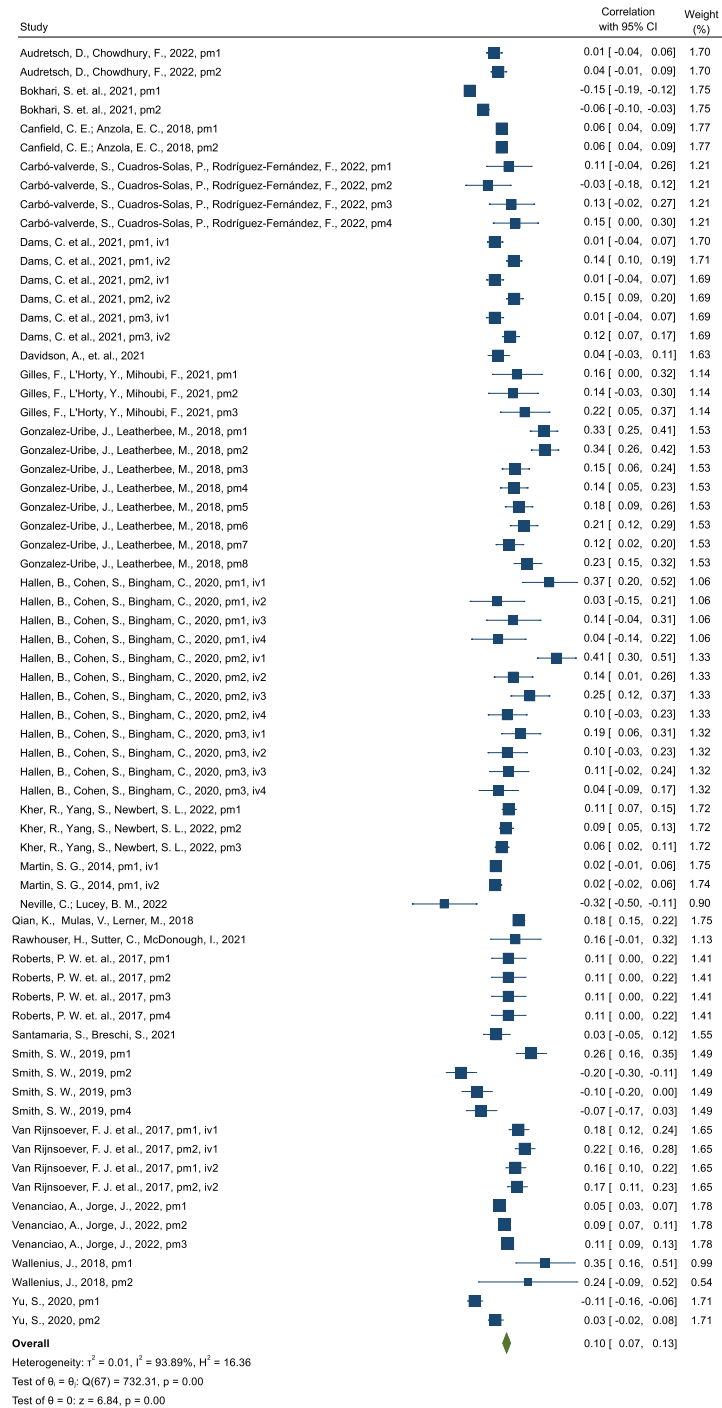
identified through statistical tests suggests that caution should be exercised when generalizing the results across different contexts. While the meta-analysis accounted for moderator variables, unexplored factors may still influence the observed effects. Second, publication bias remains a concern, as studies with significant positive results are more likely to be published than those reporting null or negative findings (Eisend & Tarrahi, 2014). The funnel plot and statistical tests suggest the presence of bias, indicating that the overall effect might be somewhat overestimated. Future research should aim to include unpublished studies to provide a more balanced perspective. Third, the quality and design of the studies under analysis reveal further limitations. Differences in data collection methods, control group selection, and outcome measures create inconsistencies in the results. Some studies rely on self-reported survey data, which may introduce biases related to subjective assessments of performance (Venâncio & Jorge, 2022). Additionally, the focus of many primary studies on financial outcomes overlooks other critical aspects of start-up success, such as long-term sustainability and strategic growth. Fourth, the geographical focus of the included studies presents a bias towards developed economies, particularly North America and Europe. While these regions host a significant number of accelerators, emerging markets remain underrepresented, limiting the generalizability of findings to less mature entrepreneurial ecosystems. Given the unique challenges faced by start-ups in developing countries, further research is needed to understand how accelerators operate in different economic and cultural contexts (Shetty et al., 2020). Lastly, our analyses are constrained by the availability of data. Certain program features, such as the role of mentorship intensity and industry specialization, were not consistently reported across studies, limiting the depth of analysis. Moreover, the meta-analysis was unable to capture the dynamic nature of acceleration, as most studies focused on short-term outcomes without considering long-term trajectories of accelerated ventures.

Building on these findings, we identify several directions for future research. First, further longitudinal studies are needed to assess the sustained impact of accelerator programs beyond the immediate post-acceleration phase. Indeed, investigating how start-ups evolve in the years following graduation would provide deeper insights into the long-term value created by accelerators (Hallen et al., 2020). Second, future research should explore alternative performance measures, such as innovation outcomes, customer acquisition, and market expansion. Broadening the scope of evaluation beyond financial metrics would allow for a more comprehensive understanding of accelerator impact. Third, more comparative studies across different accelerator types, including corporate, university, and social accelerators, that are needed to identify best practices tailored to specific target groups. Understanding how different models operate and what types of ventures they best support would provide clearer guidance for stakeholders and policymakers (Seitz et al., 2019). Fourth, future studies should focus on underrepresented regions, particularly in emerging economies, to capture the unique challenges and opportunities accelerators face in these environments. This would contribute to the development of context-specific acceleration strategies. Finally, there is a need for policy-oriented research to examine the interplay between accelerators and broader entrepreneurial policies. Investigating how government interventions complement accelerator initiatives and how public–private partnerships can help to maximize the impact of these programs and would be valuable for fostering effective entrepreneurial ecosystems (Wurth et al., 2023).

Table 8 List of primary studies included in the meta-analysis

	Author(s)	Year	Country	Measure	Sample	Effect size	Comment
1	Andretsch, D. B., Chowdhury, F.*	2022	Multiple	Strategic	1505	+ 0.03	Social focus
2	Bokhari, S., et. al.*	2021	USA	Financial	3569 from 56 programs	- 0.11	
3	Canfield, C. E., Anzola, E. C.	2018	Multiple	Financial Operational	4979	+ 0.06	
4	Carbó-Valverde, S., Cuadros-Solas, P. J., Rodríguez-Fernández, F.	2022	Spain	Financial Strategic	170	+ 0.09	Joint effect for incubator & accelerator participation
5	Dams, C., et al.	2021	USA	Financial	1375	+ 0.08	Gender investigation
6	Davidson, A., et. al.**	2021	Multiple	Financial	829 from 212 programs	+ 0.04	
7	Gilles, F., L'Horty, Y., Mihoubi, F.*	2021	France	Financial	142 from 1 program	+ 0.17	Non-financial accelerator, government sponsor
8	Gonzalez-Urbe, J., Leatherbee, M.	2018	Chile	Financial Operational	464 from 1 program	+ 0.21	Ecosystem focus, government sponsor
9	Hallen, B., Cohen, S., Bingham, C.	2020	USA	Financial Operational	192 from 3 programs	+ 0.16	
10	Kher, R., Yang, S., Newbert, S. L.	2022	Multiple	Financial Operational	1976 from 383 programs	+ 0.09	Social focus, gender investigation
11	Martin, S. G.*	2014	Multiple	Financial	3058 from 63 programs	+ 0.02	
12	Neville, C., Lucey, B. M.	2022	Ireland	Financial	84	- 0.32	Joint effect for incubator & accelerator participation
13	Qian, K., Mulas, V., Lerner, M.**	2018	Multiple	Financial	2887 From 68 programs	+ 0.18	
14	Rawhouser, H., Sutter, C., McDonough, I.	2021	Central America	Financial	139 from 1 program	+ 0.16	Ecosystem focus, corporate sponsor
15	Roberts, P. W., et. al.**	2017	Multiple	Financial Operational	300 from 43 programs	+ 0.11	
16	Santamaria, S., Breschi, S.*	2021	Multiple	Financial	505	+ 0.03	
17	Smith, S. W.**	2018	USA	Financial Operational	391 from 2 programs	- 0.03	
18	Van Rijnsoever, F. J., et al.	2017	Multiple	Financial	935	+ 0.18	Joint effect for incubator & accelerator participation
19	Venancio, A., Jorge, J.	2022	Multiple	Financial	8399	+ 0.08	
20	Wallenius, J.*	2018	USA	Financial Strategic	70 from 19 programs	+ 0.29	
21	Yu, S.	2020	USA	Strategic	1649 from 13 programs	- 0.04	

Source: own representation (*unpublished, **report)

Table 9 Forest plot based on effects

Appendix A

See Table 8.

Appendix B

See Table 9.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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