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What happens after market validation? Experimentation for scaling in technology-based startups

Silvia Sanasi [a,*], Antonio Ghezzi [b], Angelo Cavallo [b]

[a] Centre for Family Business Management, Faculty of Economics and Management, Free University of Bozen-Bolzano – Universitätsplatz 1, 39100, Bozen-Bolzano, Italy
[b] School of Management, Politecnico di Milano – Via Raffaele Lambruschini, 4/b, 20156 Milano, Italy

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A B S T R A C T

Scaling is one of the most critical phases in the lifecycle of technology-based startups: failure to scale often translates into failure to survive. Entrepreneurial experimentation has emerged as a method to reduce the likelihood of startup failure by anticipating market information. However, previous studies only described experimentation as the means to achieve market validation during the early stages of a startup's lifecycle. In our study, we have inductively investigated experimentation in technology-based startups after they had achieved market validation, conducting a comparative multiple-case study on four technology-based startups operating as digital platforms for financial and marketing services. Our findings conclude that technology-based startups continue to experiment extensively as they scale up. We present a process model of how experimentation for scaling focuses on probing for new customer segments, experimenting on customer relationships and channels, whilst carefully pacing and prioritizing experiments, and selecting the relevant growth metrics to monitor. Our study thus extends the current understanding of entrepreneurial experimentation beyond the accomplishment of market validation to the phase of scaling. This article also provides practical guidelines for technology entrepreneurs to direct their efforts towards experimentation during the challenging scaling phase.

1. Introduction

The first and foremost milestone in the lifecycle of all early-stage startups is product-market fit (Eisenmann et al., 2012). During the first stages of their existence, startups put most of their effort into ensuring that their value proposition is desirable for a target market, so as to achieve market validation (Andries et al., 2021; Ghezzi, 2019; Ghezzi and Cavallo, 2020). Once market validation is reached, startups must capitalize on their new-found status in order to scale up (Cavallo et al., 2019; Eisenmann et al., 2012; Eisenmann, 2014, 2021a; Picken, 2017). In the context of technology-based startups, scaling is referred to in previous studies as a startup's rapid growth (Gartner et al., 2022) whereby it increases its user base (Busch and Barkema, 2022; Huang et al., 2017) without increasing its commitments in resources and skills proportionally (Eisenmann and Wagonfeld, 2012; Huang et al., 2017; Nielsen and Lund, 2018; Varga et al., 2023).

In other words, scaling means expanding the startup's target audience ceteris paribus, while keeping its value creation infrastructure the same. This increase can be achieved through a variety of means, among which saturating the existing target market by tackling unserved customers, addressing new customer segments and communities, and enriching the startup's offering to widen its potential target market (Busch and Barkema, 2021, 2022; DeSantola and Gulati, 2017; Eisenmann, 2021a, 2021b; Eisenmann and Wagonfeld, 2012; Nielsen and Lund, 2018). Scaling is vital to the lifecycle of a technology-based startup (Picken, 2017; Cavallo et al., 2019), as it is the natural evolution of its transition towards a fully-rounded enterprise (Blank, 2013). Scaling startups are also significant at the policymaking level, and several studies indicate that high-growth firms have a substantial impact on a country's job creation capability (Henrekson and Johansson, 2010), owing to their innovation and R&D potential (Hölzl and Janger, 2013).

However, most technology-based startups fail at the point of scaling. A large-scale survey on 3200 startups showed that issues related to scaling are responsible for 74 % of their failures (Marmer et al., 2011). Similarly, a McKinsey & Company large-scale survey on 3000 technology-based startups (Kutcher et al., 2014) found that high rates of growth are a reliable predictor of long-term success. However, the survey also reported that a high growth rate can also be a cause of startup

* Corresponding author at: Centre for Family Business Management, Faculty of Economics and Management. Free University of Bozen-Bolzano – Universitätsplatz 1, 39100 Bozen-Bolzano, Italy

E-mail addresses: silvia.sanasi@unibz.it (S. Sanasi), antonio1.ghezzi@polimi.it (A. Ghezzi), angelo.cavallo@polimi.it (A. Cavallo).

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failure in itself.

For technology-based startups, failing to scale can often translate into downright failing to survive (DeSantola and Gulati, 2017). Scaling requires startups to make sure that their growing organizational and strategic complexity – such as keeping things in focus and managing an expanding market, while building their organizational structure (Blank, 2013; Eisenmann, 2014; Picken, 2017) – keeps up with their technology (Linton and Walsh, 2003), while coping with shortcomings in resources typical of entrepreneurial endeavours (Baker and Nelson, 2005; Katila and Shane, 2005). The overarching importance of high growth for technology firms is well recognized in the technology literature (e.g. Feeser and Willard, 1990). At the same time, the issue has mainly been investigated in practitioner-oriented studies (Eisenmann, 2014; Eisenmann, 2021a, 2021b) that put forward prescriptions, advising startups to find the *right* investors, only hire the *best* people, or refrain from scaling *too* rapidly. Even so, these prescriptions are often based on common sense and still lack sound empirical investigation and confirmation.

In previous literature, experimentation has been identified as a valid means to reduce failure in technology-based startups and find novel combinations of knowledge (Kang et al., 2019) by anticipating market information (Agrawal et al., 2021; McGrath, 1999). Despite the growing popularity of experimentation in both managerial (e.g. Blank, 2013; Lynn et al., 1996; Newbert et al., 2006; Ries, 2011) and scholarly studies (e.g. Agrawal et al., 2021; Ehrig and Schmidt, 2022; Gans et al., 2019; Pillai et al., 2020; Ghezzi and Cavallo, 2020), the vast majority of studies on experimentation in technology entrepreneurship only investigate experimentation used for market validation (e.g. Andries et al., 2021; Contigiani and Levinthal, 2019; Ghezzi, 2019). This approach only addresses the initial stages in the lifecycle of a technology-based startup and overlooks the challenging phase of scaling. The aim of our study is to bridge this gap in literature by describing the mechanisms that technology-based startups set in place to experiment for scaling.

In order to achieve the purpose of our study, we tackled this research objective through a comparative multiple-case study (Eisenhardt, 1989). We adopted an inductive viewpoint for our theory-building, drawing from primary and secondary data on four technology-based startups operating as digital platforms for financial and marketing services that proceeded to scale after market validation. We concentrated in particular on the mechanisms that technology-based startups put in place for experimenting during scaling. Based on these findings, we are proposing an original process model that describes experimentation for scaling in technology-based startups.

Our investigation makes two main contributions to the current body of literature. First, our findings disclose that technology-based startups which scaled successfully continued to experiment during the scaling process, although they adopt a special approach to experimentation. Experimentation for scaling entails probing for new customer segments, experimenting with new channels and customer relationships – hence focusing on the value delivery mechanisms in the startup's business model, rather than on those for creating value – pacing the experiments to obtain truthful results, and monitoring growth possibilities through carefully selected KPIs. We thereby extend the current scholarly understanding on experimentation beyond early-stage market validation (e.g. Andries et al., 2021; Ghezzi, 2019; McDonald and Eisenhardt, 2020), shedding light on the mechanisms of experimentation in the context of scaling in technology-based startups.

Furthermore, the startups in our sample all engaged in "growth hacking" (Bohnsack and Liesner, 2019; Troisi et al., 2020), a managerial approach to experimentation that has gained popularity in recent years among technology-based startups when they move from a "validated" business model to one that potentially enables them to grow at scale. We contribute to the existing literature in technology entrepreneurship and strategic management by drawing parallels between experimentation for scaling and the established literature on experimentation concerned with early-stage business model validation (Andries et al., 2021; Gans et al., 2019) by means of the lean startup method (Contigiani and Levinthal, 2019; Ghezzi, 2019; Shepherd and Gruber, 2020).

2. Theoretical background

2.1. Technology entrepreneurship and scaling in technology-based startups

The relationship between technology and company growth has traditionally caught the eye of both researchers and practitioners (Feeser and Willard, 1990). Technology is one of various firm-specific resources and skills that play a decisive role in a company's growth (Penrose, 1959; Kang et al., 2021; Lee, 2023). As a result, the link between strategy and technology, and relative fit and gaps, is pivotal to many firms, as technology should be managed strategically to enable potential growth (Walsh and Linton, 2011).

This is even more the case in technology entrepreneurship, by which we mean recognizing, creating and exploiting opportunities, and assembling resources around a technological solution (Spiegel and Marxt, 2011; Bailetti, 2012; Ratinho et al., 2015). Ever since Schumpeter's seminal works on the importance of entrepreneurship and innovation for economic development (Schumpeter, 1911, 1942), the notion of technology has been deeply enrooted in the entrepreneurship field (Walsh and Groen, 2013). Entrepreneurship research has gradually become decoupled from this strictly technological dimension and is now generally equated with the pursuit and exploitation of generic opportunities (Ratinho et al., 2015). Technology-based startups have often been associated with high growth rates, also spurred on by their ability to capture venture capital (VC) investments that produce growth (Bertoni et al., 2011) and also to reorganize their resources to cope with environmental uncertainty (Colombo et al., 2021).

The emerging field of digital entrepreneurship (e.g. Kraus et al., 2019; Nambisan, 2017) is re-establishing a clear connection between digital technologies as enablers of entrepreneurial endeavour and action, digital startups as the vehicles of such action, and high, unconstrained growth as one of the primary goals of digital startups. Scaling is a crucial step in a digital startup's lifecycle (Picken, 2017) and one of the greatest hurdles that must be overcome for it to be successful (Eisenmann, 2021a), as the affordances of digital technologies (Autio et al., 2018) and the resulting platform ecosystems enable high growth (Yanez et al., 2010) and rapid scaling (Huang et al., 2017; Varga et al., 2023).

An emerging scholarly debate is concerned with understanding what happens after startups achieve market validation and move on to scaling (Contigiani and Levinthal, 2019; DeSantola and Gulati, 2017; Shepherd and Patzelt, 2022; Snihur and Clarysse, 2022). At this stage, the freshly validated startups need to capitalize on the market's newly found awareness, and direct their efforts towards scaling (Eisenmann et al., 2012; Eisenmann, 2014, 2021a; Picken, 2017). Scaling in technology-based startups entails expanding the startup's user base without an equivalent increase in resource commitments (Eisenmann and Wagonfeld, 2012; Huang et al., 2017; Nielsen and Lund, 2018; Varga et al., 2023), and requires internal organizing to be synchronized with growth (DeSantola and Gulati, 2017). In other words, technology-based startup scaling means being able to achieve profitable growth by enlarging the startup's user base without increasing its operational capacity proportionately (Huang et al., 2017; Eisenmann, 2014). Startups must instead be able to reassemble and build on key resources and skills that support profitable growth (Eisenmann and Wagonfeld, 2012; Nielsen and Lund, 2018). Scaling in technology-based startups is no longer connected to traditional measures of growth, such as profitability, sales and market share, but at its core is the potential reach of a given company – i.e. the growth of its customer base (Eisenmann and Wagonfeld, 2012; Huang et al., 2017). This idea of scaling has also been referred to as "breadth" scaling in the literature on social entrepreneurship, reconducting scaling to meaning a broadening of the venture's target audience (Busch and Barkema, 2022). Breadth scaling has been made possible by today's digital affordances, which leverage on digital infrastructures to enable unprecedented possibilities for value creation and appropriation without committing resources on an equivalent level (Autio et al., 2018).

Although scaling plays an essential part in a startup's lifecycle (Picken, 2017), being the natural evolution towards a fully-rounded enterprise (Blank, 2013), previous works have reported that scaling is one of the riskiest steps in a technology-based startup's lifecycle (Kutcher et al., 2014; Marmer et al., 2011), because scaling issues often lead to the venture's outright failure (Eisenmann, 2021a, 2021b). In previous studies, it has been claimed that the most serious challenge faced by startups when scaling is when they transition from a validated business model to a model suitable for scaling (Picken, 2017). As stated in previous literature, startups should not attempt to scale until the target market has validated their customer value proposition (Eisenmann, 2014; Nielsen and Lund, 2018).

Startups use different means and channels when they embark on scaling. Among the possibilities are saturating the existing target market by attacking the vast majority of potential customers, working on new customer segments, opening new distribution channels to reach a wider audience, and enriching the startup's offering to broaden its potential target market (Eisenmann and Wagonfeld, 2012; Eisenmann, 2021a, 2021b; Nielsen and Lund, 2018). Choosing which segments to pursue first can mark the success (or failure) of the scaling process (Teece, 2018), and potentially of the entire startup, as failure to scale is often translated into failure to survive (DeSantola and Gulati, 2017; Eisenmann and Wagonfeld, 2012; Eisenmann, 2021b; Nielsen and Lund, 2018).

As scaling is one of the most threatening and decisive moments in a startup's lifecycle (Eisenmann, 2021a; Picken, 2017), it should be given much care and attention. Technology-based startups face several issues related to scaling. They must keep their focus, position their offering in their expanded market, build a proper management system and develop the processes and infrastructures they need to run and scale the business. They must also build a sustainable source of revenue, develop a culture that reflects the company's strategy, and manage the vulnerabilities and risks that could be amplified when scaling (Picken, 2017). The current scholarly understanding of scaling is, however, limited and to date there is no theory encompassing all the possible methods employed by startups to undertake this difficult stage. To investigate this area, we built on Contigiani and Levinthal (2019) argument that "While the literature on lean startups maintains that learning is important throughout all phases of a startup's development, the emphasis on self-conscious, dedicated effort on experimentation is specific to the first phase" (p. 554). We thus argue that scholarly investigation should put more effort into theorizing how experimentation can be extended to the problematic phase of startup scaling.

2.2. Experimentation for scaling

Experimentation is rooted in technology entrepreneurship research and entrepreneurship education (Harms, 2015; Ratinho et al., 2015). Building on previous technology management research and approaches such as the "probe and learn process" (Lynn et al., 1996), "disciplined entrepreneurship" (Sull, 2004), and even "muddling through" (Newbert et al., 2006), the startup narrative over the past two decades has pointed out clearly that constant experimentation is vital to startups' survival and success (e.g. Camuffo et al., 2020; Ehrig and Schmidt, 2022; Gans et al., 2019; Pillai et al., 2020). Experimentation in entrepreneurship, as inherited from the historical formulation of the scientific method (e.g. Popper, 1959), encompasses the early feedback collected from the market, assembled into falsifiable hypotheses about the startup's business model (Blank, 2013; Ghezzi, 2019, 2020), all in aid of market validation. To add a level of complexity, market validation is not a clear-cut outcome, it is rather an awareness that the startups' value proposition matches the needs of the market they are targeting (Andries et al., 2021; Eisenmann and Wagonfeld, 2012; Ghezzi, 2019; Ghezzi and Cavallo, 2020; McDonald and Eisenhardt, 2020).

Furthermore, experimentation in entrepreneurship entails applying a "scientific" approach to entrepreneurial choice (Agrawal et al., 2021; Camuffo et al., 2020; Ehrig and Schmidt, 2022; Gans et al., 2019; Murray and Tripsas, 2004; Zellweger and Zenger, 2022). Such experiments are useful when market information about the success (or failure) of a given entrepreneurial endeavour cannot be anticipated through simple reasoning (Pillai et al., 2020). In their experimentation, entrepreneurs act as scientists who formulate a theory about their vision of the world (Alvarez and Barney, 2010; Dimov, 2021; Ehrig and Schmidt, 2022) and seek validation (or falsification) of its underlying assumptions (Agrawal et al., 2021; Zellweger and Zenger, 2022) to reduce the inherent uncertainty in their entrepreneurial action (McMullen and Shepherd, 2006). Entrepreneurial experimentation consists in developing falsifiable business hypotheses, designing and running experiments to test these hypotheses, and analysing their results (Murray and Tripsas, 2004).

In previous studies, experimentation has been shown to be a valid means for innovative and nascent ventures to learn about the environment they operate in (Andries et al., 2021) and make more appropriate decisions in highly uncertain contexts (Agrawal et al., 2021; Murray and Tripsas, 2004; Pillai et al., 2020). Studies have shown that the scientific approach applied to entrepreneurial decision-making produces better results than heuristics (Camuffo et al., 2020), in that it enables startups to learn from experiments about the viability of their strategy (Agrawal et al., 2021; Gans et al., 2019) and continuously revise it (Ott and Eisenhardt, 2020; Rindova and Kotha, 2001) by "pivoting" away from unsuccessful strategic choices (Berends et al., 2021; Pillai et al., 2020; Sanasi and Ghezzi, 2022). Additionally, several recent studies point to how experience and experimentation could function as knowledge accumulation strategies to cultivate a company's growth (Kang et al., 2019). Here, however, experimentation is equated with the notion of novel ways of combining knowledge, as opposed to "repetitive learning" (i.e. adhering to existing learning strategies), while the actual experimentation process and methods are not covered in this study.

Therefore, startups "muddle along" with the scant information available (Baum and Bird, 2010) and mitigate the possibility of their endeavour's failure by testing the underlying assumptions of their strategies, thus anticipating market information (e.g. Contigiani and Levinthal, 2019; Ghezzi and Cavallo, 2020; McDonald and Eisenhardt, 2020). In previous studies on experimentation in entrepreneurship (Kerr et al., 2014; Contigiani and Levinthal, 2019; Ghezzi and Cavallo, 2020; McDonald and Eisenhardt, 2020), experimentation was found to be a valid means to help startups make do with the limited resources at their disposal (Baker and Nelson, 2005; Katila and Shane, 2005). They leverage on communities of interest – such as users or customers – to carry out inexpensive tests and learn about a prospective market interest (Bremner and Eisenhardt, 2021; Garud and Karunakaran, 2018). Others have argued that you need resources to experiment and test a given strategy, but the very fact of committing resources means that the experiment is not really an experiment. (Gans et al., 2019; Pillai et al., 2020). This paradox can only be solved by compromising on the accepted level of noise in the experiment's results (Agrawal et al., 2021) and knowing how to draw valid conjectures from the results of less costly experiments (Ehrig and Schmidt, 2022).

Startups that adopt a scientific approach use experimentation to validate the assumptions underlying their value proposition and surrounding activity system in their target market (Ghezzi and Cavallo, 2020; McDonald and Eisenhardt, 2020). Experimentation informs startups about whether their value proposition can fulfil unserved needs in their targeted market (Eisenmann, 2014; Zuzul and Tripsas, 2020). As far as it goes, entrepreneurial experimentation serves the purpose of achieving market validation (Andries et al., 2021; Contigiani and Levinthal, 2019; Stevenson et al., 2022). Market validation implies reaching an ideal fit between the startup's value proposition and the target market identified (Eisenmann et al., 2012). Only when a startup has achieved market validation, is it ready to move on to scaling (Contigiani and Levinthal, 2019; DeSantola and Gulati, 2017; Eisenmann, 2014; Eisenmann and Wagonfeld, 2012; Picken, 2017).

However, the existing understanding of entrepreneurial experimentation stops at market validation. We therefore build on Contigiani and Levinthal (2019) to claim that, although experimentation is gaining in popularity as a valid means to counter startup failure by anticipating market information (Agrawal et al., 2021; McGrath, 1999), in the vast majority of studies on this topic, experimentation is only seen as a method to ensure success in the initial phases of a startup's lifecycle (e.g. De Cock et al., 2020; McDonald and Eisenhardt, 2020), in its quest for market validation (Agrawal et al., 2021; Ghezzi and Cavallo, 2020). Conversely, these existing studies overlook the fact that experimentation could translate into scaling (Contigiani and Levinthal, 2019). Although scaling is such a critical and fundamental step in a startup's lifecycle (Picken, 2017), the current literature on scaling is still unclear about how experimentation can address the specific purpose of scaling in technology-based startups (Harms, 2015) as adeptly as it served market validation. Moreover, the role played by differing types of technology in experimentation should not be downplayed (Linton and Walsh, 2003). There are as many paths from science to product as there are from selling locally made products to offering a high-growth product on a global market. As a result, the experimentation process and method are likely to vary as the technology being experimented upon changes, and this should be taken into account in technology and digital entrepreneurship research.

3. Method

Our study is set up as a multiple-case study (Eisenhardt, 1989, 1991; Eisenhardt and Graebner, 2007; Yin, 2014) to address our research objective with the aim of generating novel theory by analysing data inductively (Eisenhardt, 1989; Glaser and Strauss, 1967; Strauss and Corbin, 1990). The case study approach was deemed the most appropriate given the exploratory nature of this study (Goffin et al., 2019) and the scarcity of research on scaling technology-based startups and, consequently, the need for theory building (Eisenhardt and Graebner, 2007). Case studies also give researchers the opportunity to delve deeply into each case, and collect additional data whenever needed (Eisenhardt, 1989). We selected the multiple-case study approach to address the limitations of single-case studies, thereby increasing the generalisability of our results and comparability of our findings (Eisenhardt, 1989, 1991; Yin, 2014). We decided to look at only a small number of cases, as this meant we could retain the depth of interaction with focal companies that is a key element in single-case studies (Eisenhardt, 1989, 1991).

This study is concerned with examining scaling in technology-based startups from a process perspective. To achieve this purpose, we selected four startups that operate digital platforms for financial and marketing services which were all busy scaling up. We have labelled them *Start-A*, *Start-B*, *Start-C* and *Start-D* to maintain confidentiality. We selected the four startups because they had achieved market validation and had begun the process of scaling at the time of our investigation. The four startups were founded between 2014 and 2017, all are privately owned and funded by external investors (see Table 1 for a summary).

Building on previous studies (e.g. Cavallo et al., 2019; Ghezzi, 2019), our empirical setting consists of startups that leverage on digital technologies as a core element in their strategy. Digital technologies are the combination of the technologies that come into play in information, computing (hardware and software), communication and connectivity (protocols such as internet and mobile web). These technologies are fundamentally reshaping traditional business strategy in that they are modular, distributed, cross functional and global business processes that enable work to be carried out across boundaries of time, distance and function (Bharadwaj et al., 2013). Against this backdrop, digital startups are the embodiment of technology-based entrepreneurship with a focus on high growth (Yanez et al., 2010). Scaling is currently largely recognized as the discriminating factor between a successful digital startup and an unsuccessful one. Digital entrepreneurial ecosystems present important affordances in terms of resources and infrastructure (Autio et al., 2018; Nambisan et al., 2019), owing to digital technologies that are particularly effective at spurring scaling (Huang et al., 2017; Gartner et al., 2022). Based on these considerations, our decision to set our investigation in the landscape of digital startups was driven by our intention to put the spotlight on scaling for the purposes of our inquiry. Our unit of analysis is represented by the mechanisms employed in each of the startups during the scaling process to increase their customer base and scale.

Table 1
Case description.

Case	Year of foundation	Core value proposition	Target customer	Equity funding stage at the beginning of the scaling process
Start-A	2015	Digital platform for corporate expenses	B2B	Series B (approx. 11mn $)
Start-B	2016	Digital wallet for personal finance management	B2C	Series B (approx. 12mn $)
Start-C	2014	Digital platform for sharing expenses	B2B & B2C	Series B (approx. 8mn $)
Start-D	2017	Digital SEO tool powered by AI	B2B	Series B (approx. 9mn $)

3.1. Case selection

Informed by previous studies, we purposely selected startups that had sought and received venture capital funding, which is a proxy for market validation and a milestone for venture quality (Cavallo et al., 2019; De Cock et al., 2020; Eisenmann, 2021b), signalling that these startups had taken the decision to try and scale. In particular, given the purpose of our research in the field of scaling, we selected startups that had received Series B financing of comparable entity, taking a hint from the venture capital world, which considers Series B rounds of funding as the threshold that marks the beginning of the scaling process (Eisenmann, 2021b).

We deliberately selected startups that said they had experimented during the scaling process to get a better view of their underlying mechanisms. Our sample consists of "polar types" (Eisenhardt and Graebner, 2007), meaning that we were able to observe contrasting patterns in our data (De Massis and Kotlar, 2014). Two of the startups did not in fact reach their expected scaling objectives, which eventually led to both startups slowing down their growth to prevent bankruptcy. One of the unsuccessful startups – *Start-C* – managed to continue operating at a low volume of business, whereas the other – *Start-D* – was eventually acquired by a distressed fund. The other two startups instead turned out to be very successful, with *Start-A* collecting more than $ 200 million in Series C funding, and *Start-B* agreeing a multi-million trade sale exit. Table 1 gives an overview on the four startups and their characteristics.

3.2. Data collection

This study draws on a rich and extensive dataset collected by the authors over two years, 2019 to 2021. We collected data from multiple sources of information, including two rounds of semi-structured interviews with selected informants, and other primary sources of information such as informal conversations. The first round of semi-structured interviews held between March and October 2019 told us about the decisions made by each startup to scale and the methods they used in the scaling process. The second round of interviews, from March to September 2020, was meant to follow up and monitor the results of the startup's scaling process. In parallel, we collected large volumes of information from secondary sources, both in the public domain and from documents provided by the informants themselves (e.g. public interviews and presentations given by the informants, internal presentations, news articles and financial statements) to triangulate the data and monitor published results on the four startup's scaling exercise, as well as to mitigate observer and recollection biases (Eisenhardt, 1989; Gioia et al., 2013; Goffin et al., 2019; Yin, 2014). Table 2 lists our data sources.

Table 2
Sources of evidence in the data collection process.

Data type	Quantity	Original data source
Semi-structured interviews	3 pilot interviews	1 CEO of startup not in the sample 2 External consultants with scaling expertise, unconnected to startups in the sample
	31 in-depth interviews	Informants
	Start-A (8 interviews)	CEO and co-founder (1 interview) COO (2 interviews) CMO (2 interviews) Marketing Manager (2 interviews) Marketing Specialist (1 interview)
	Start-B (8 interviews)	CEO and co-founder (1 interview) COO and co-founder (3 interviews) Product Manager (2 interviews) Marketing Specialist (2 interviews)
	Start-C (8 interviews)	CEO and founder (3 interviews) CMO (3 interviews) Marketing Specialist (2 interviews)
	Start-D (7 interviews)	CEO and co-founder (3 interviews) COO and co-founder (2 interviews) CRO (1 interview) Marketing Specialist (1 interview)
Asynchronous communication	71 informal emails	Informants
Observations	9 presentations (private lectures, public presentations, networking events, incubators, and accelerator pitches)	Informants and other startup employees
External documents and sources	37 web pages 43 news articles 9 online videos 3 podcast episodes	Company websites Informants News outlets Online content platforms Public databases
Unstructured interviews	21 informal conversations	Informants
Funding and financial information	Funding information 12 financial statements	Proprietary database containing information on 1187 equity-funded Italian hi-tech startups, their funding rounds and the sums they received at each round, from 2012 to 2021 Public databases (e.g. Crunchbase, Pitchbook, Dealroom, Chamber of Commerce database) News outlets

In the primary process to gather data from the semi-structured interviews, we held planned interviews with key informants involved in the scaling process (Aguinis and Solarino, 2019; Gioia et al., 2013), i.e. startup founders, C-level managers and key employees. We prepared for the first round of semi-structured interviews by gathering information about the startups from secondary sources, so to reduce any risk of being swayed by the informants' personal opinions. We therefore conducted three pilot interviews, the first with the Chief Executive Officer at a digital startup not in the sample, to check that our interview protocol could meet the objectives of our study. The other two pilot interviews were held with consultants specializing in startup scaling to ensure that our questions were well-suited to the circumstances and objectives of our study. We consequently narrowed down the perspective of our interview protocol to ask specifically about the methods employed, including questions such as: "How did you make decisions about the scaling proceedings?", "How did you identify your scaling objectives?", "How did you assess the viability of your actions while scaling?", "How did you monitor results?" and "What steps did you take to analyse the most promising direction to scale?". Following completion of the protocol, we held thirty-one in-depth semi-structured interviews with the startups' managers and employees who were involved in the scaling process. When planning the interviews, we aimed for theoretical saturation, and stopped gathering data when we were no longer adding even marginally to our pool of information (Strauss and Corbin, 1990). We did not ask the informants explicitly about whether they also experimented during scaling to avoid influencing their responses. The outcome of the interview process was to create a coding tree for each startup being analysed.

3.3. Data analysis

Each of the interviews was recorded and fully transcribed, as were the secondary sources where it was possible (e.g. public presentations, online videos, podcast episodes). Whenever we felt that data were missing or incomplete, we asked the informants for further details.

Our next step was to analyse our data meticulously, re-reading our transcripts to start forming connections between concepts, and also selecting representative quotes (Strauss and Corbin, 1990). While collecting and organizing the data, we aggregated them into case descriptions, to give structure to the large volume of data collected (Eisenhardt, 1989).

We analysed our data through an interpretive approach, employing tables and charts, following Gioia et al. (2013) guidelines for analysing qualitative data, to condense the body of data and structure our interpretive scheme (Cloutier and Ravasi, 2021; Strauss and Corbin, 1990). Following Gioia et al., 2013, Gioia et al., 2022), we considered the informants as "knowledgeable agents", and started by interpreting their words and voices, grouping similar concepts around first-order categories. We then proceeded to aggregate the first-order categories into second-order themes grouped by homogeneous properties and dimensions (Strauss and Corbin, 1990) and proceeded iteratively to compare our coding and analysis, progressively fine tuning our interpretation (Glaser and Strauss, 1967). Although this task should start with a clean slate, it is virtually impossible to interpret results with no preconception whatsoever of what the applicable theories could be (Eisenhardt, 1989). The second-order themes were then further aggregated into overarching dimensions, with the aim of contributing to theory building (Glaser and Strauss, 1967; Strauss and Corbin, 1990). As a result, we structured our data around two overarching dimensions, identifying categories and themes related to (i) the identification of a scaling opportunity and (ii) the use of experimentation to support the scaling efforts. Fig. 1 illustrates our data structure.

The results from each of the cases were first analysed individually, and then compared to one another to bring up common patterns and idiosyncrasies, and so fully exploit the benefits of our multiple and comparative case study design (Eisenhardt, 1989, 1991; Eisenhardt and

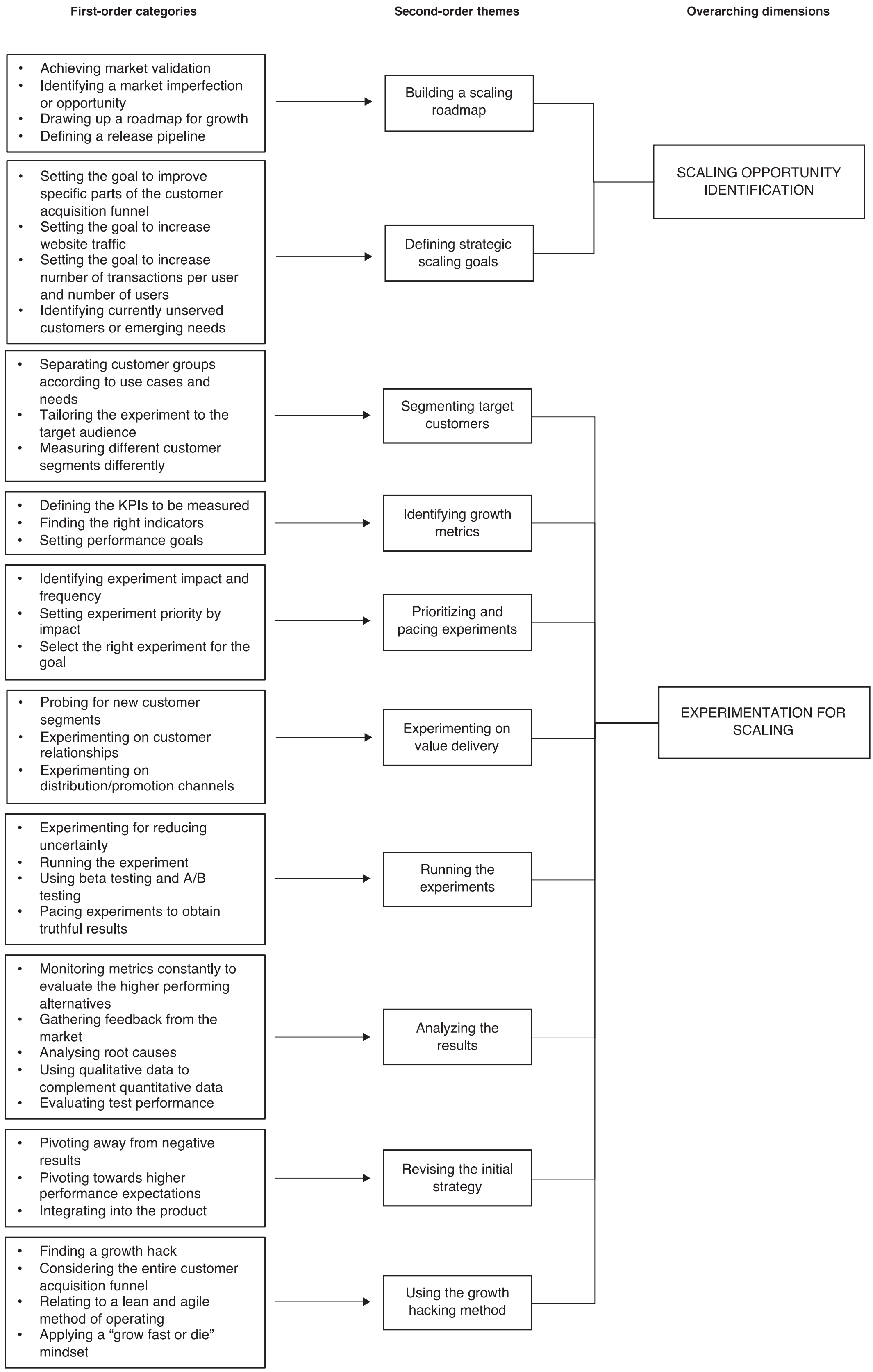

Fig. 1. Data structure.

Graebner, 2007). In the following sections, we describe how we leveraged on these comparisons, presenting a cross-case analysis which builds on our second dimension, that of applying experimentation in scaling. The empirical data supporting our cross-case analysis is set out in Table 3.

4. Findings

Our investigation sheds light on the mechanisms underlying experimentation for scaling in technology-based startups. We observed our four startups throughout their scaling process and, building on the insights we gleaned from comparing them, we identified the mechanisms used in each startup to experiment while they scaled and the specificities of experimenting when scaling. Elaborating on these findings, we have summarized the concepts in an original process model, proposed here, that describes how technology-based startups experiment during scaling (Fig. 2).

The following cross-case analysis is organized into two main sections, each built around the dimensions of our data structure to guide the reader through our inductive reasoning (Berends and Deken, 2021). In the first section, we describe the moment when the startups identified an opportunity to scale, which is the step before they start experimenting for scaling. Next, we present our findings on the mechanisms underlying experimentation for scaling in technology-based startups, elaborating on the particular aspects of experimentation in this context. Complementing these sections, Table 3 gives a selection of supporting evidence for each second-order theme and Fig. 2 presents a visual summary of our findings.

4.1. Scaling opportunity identification

All the startups in our study reportedly decided to embark on scaling after achieving market validation. As the Chief Operations Officer (COO) and co-founder of *Start-B* stated: "*The validation of our business model marked a sort of watershed for the company. As soon as we had it validated, things changed*". Similarly, *Start-D*'s CEO and co-founder reported that, as soon as their core value proposition was validated on the market, they had to ensure their business model's sustainability and, for that to happen: "*We soon realized we needed more users*".

All four startups defined a roadmap to keep a close eye on their progress in attaining the results they needed to grow to scale. Each startup set out a scaling roadmap, as it helped them define their growth target and split it into smaller, more manageable milestones. As *Start-A's* Marketing Manager said: "*As a scaling startup, we have a product roadmap […] We have our growth objectives, and we try to keep to a growth-oriented approach based on impact on these objectives*". The objectives are generally set by management, which then ask their team to segment organizational objectives into smaller targets which can be achieved by each team independently. In the words of *Start-B*'s Product Manager: "*Each team has its own goals*" and again "*We have a general roadmap drawn up by our founders, and it states that we need to release our new banking product by September and reach a certain number of users also by September. We then split these big goals into smaller ones, and we tackle them in sprints one by one. Every small goal achieved should help us reach our big final goal*".

Based on their roadmaps, the startups' various teams set themselves measurable goals, each being a step towards achieving the growth targets set out by management. These targets include, for example, expanding their user base or increasing traffic to their website. As stated by *Start-B*'s Product Manager: "*Our main goal is always, of course, to get more users. What we must do is make our product better so people use it. Everything we try should work*".

As scaling in technology-based startups entails more active users, identifying new potential target users is one area requiring some effort. Startups detect new users by looking for currently unserved customers or emerging needs, which in turn could pave the way to additional target customers and previously untapped segments. All four startups reported

Table 3
Representative supporting data for second-order themes and first-order categories in digital financial and marketing services.

Second-order themes	*Selected evidence on second-order themes and first-order categories*
Overarching dimension: SCALING OPPORTUNITY IDENTIFICATION	
Building a scaling roadmap	Achieving market validation "*The validation of our business model marked a sort of watershed for the company. As soon as we had it validated, things changed*". – COO and co-founder, *Start-B* "*It was really a make-or-break moment for the company. It's the time when you really find out if what you're doing makes sense. It's the market deciding and, let me tell you, it was a serious moment for us*". – COO and co-founder, *Start-D* Drawing up a roadmap for growth "*As a scaling startup, we have a product roadmap […] We have our growth objectives, and we try to keep to a growth-oriented approach based on impact on these objectives*". – Marketing Manager, *Start-A* "*We have a general roadmap drawn up by our founders and it states that we need to release our new banking product by September and reach a certain number of users also by September. We then split these big goals into smaller ones, that we tackle them in sprints one by one. Every small goal achieved should help us reach our big final goal*". – Product Manager, *Start-B* Defining a release pipeline "*We have a release train, so every three weeks we know we can issue a new release of our app to the store*". – COO and co-founder, *Start-B*
Defining strategic scaling goals	Setting the goal to improve specific parts of the customer acquisition funnel "*We started to acquire a great number of customers, but soon realized that if we didn't activate them, our efforts were useless. We now focus primarily on user activation, because that's really what our objective should be*". – CMO, *Start-A* "*Retention is really important to us. We want users to understand they can use our product for different purposes*". – CEO and co-founder, *Start-B* Setting the goal to increase website traffic "*Our main metric is awareness, so just visits to our webpage. This metric was set to drive a lot of traffic to our blog*". – Marketing Specialist, *Start-C* Setting the goal to increase the number of transactions per user and number of users "*Our main goal is always, of course, to get more users. What we must do is make our product better so people use it. Everything we try should work*".– Product Manager, *Start-B* "*We soon realized we needed more users*". – CEO and co-founder, *Start-D* Identify currently unserved customer segments or emerging needs "*We already had the product in place; it was simply a matter of tweaking it to cater to this fresh demand*". – CMO, *Start-A*
Overarching dimension: EXPERIMENTATION FOR SCALING	
Segmenting target customers	Separating customer groups based on use cases and needs "*We look for clusters of users with given features, extract them from our database and send them a cluster-specific message. We then sit back and wait for their reaction, and measure it*". – COO and co-founder, *Start-B* "*We sought new use cases to address, and we tailored new services to them*". – CMO, *Start-D* Measuring differently with different customer segments differently "*It depends also on whether the company is a small business or a big enterprise. Because, in a small business, you need fewer cards, while in a big enterprise you need plenty, so it requires more time. So you have to measure things differently*". – Marketing Manager, *Start-A* Tailoring the experiment to the target audience "*Our pricing was aggressive as it was meant to target both*

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Table 3 (*continued*)

Second-order themes	*Selected evidence on second-order themes and first-order categories*
	freelancers and companies". – Marketing Manager, *Start-A*
Identifying growth metrics	Finding the right indicators "*We want to increase growth in terms of accounts and revenue, we take a percentage of a transaction. So every time someone uses our card, we get the transaction fee. The fee is very low, like 1 or 2 %, so we need to get customers to use their card more and we also need to increase the number of users*". – CMO, *Start-A* Defining KPIs to measure *"We have to work out the proper metrics to measure whether we are doing things right or not. My team, for example, looks after our the existing product, and we try to get people to use the app more. I then send these metrics on to the marketing team*". – Product Manager, *Start-B* *"Our last experiment was based on average ticket"*. – CRO, *Start-C* Setting performance goals "*We started with a scenario, where we had to achieve a certain goal and that goal was easy to achieve because of our previous agreements. However, this scenario withered over time, and we had to invest in a new strategy, – the school sector – which is very complex landscape and has little low appeal*". – CMO, *Start-C*
Prioritizing and pacing experiments	Identifying experiment impact and frequency *"The frequency with which we measure the impact of our tests is proportional to the amount and type of data that we identified to establish whether the test is successful or not"*. – Marketing Specialist, *Start-A* "*We perform lots of tests, but not simultaneously, instead rather as joint experiments. We launch tests that matter for each vertical, depending on what's needed for that vertical, but we cannot run, say, 50 experiments in parallel. We may be able to run, say, 2 or 3 tests. You have to be sure that what you do brings growth. You cannot run tests that give you a 0.1 % growth, it wouldn't make sense*". – Marketing Specialist, *Start-C* Selecting the right experiment for the goal "*When I propose a new feature I need for customer acquisition, and explain what KPI I'm going to tweak and have an idea of the measure of the impact, I stand a better chance to jump over some other priority that instead is not particularly well-defined. Then, after some time, we measure the results and decide whether it's worth doing or not*". – CMO, *Start-A* "*We prioritize experiments based on our own polar star. You have to have one. If, sometimes in the year, our polar star is not directing us towards increasing our profits but our user base, then, in that period, we can concentrate on the part of the funnel or process concerned with user acquisition and referral. If you don't care about monetization, you can prioritize tests by usability and retention. It depends on the reality of things, there is no standard model*". – CMO, *Start-C*"
Experimenting on value delivery	Probing for new customer segments *"We had to check who could be interested in our service, and we had to set up a growth strategy on LinkedIn to measure it"*. – CMO, *Start-C* "*We start off with micro-tests to see, for example, if and how a certain target responds to our offering, and then we start targeting them"*. – CEO and founder, *Start-C* Experimenting on channels/customer relationships *"Say we want to check whether the Register 'call to action' works or not. The click through rate is a good proxy to see the effect of this test. It can be a test that lasts for days, it's the kind of test you check within a week, if not sooner"*. – Marketing Manager, *Start-A* "*We carried out several tests to see whether a message or a video popping up at the critical point in the subscription process helped prevent users from getting stuck when they had to key in their IBAN"*. – Product Manager, *Start-B*
Conducting the experiments	Experimenting for reducing uncertainty *"We always experiment before deploying a new feature or service. Everything passes through market feedback and acceptance"*. – CEO and co-founder, *Start-A* *"Before launching a product, it would have been impossible to know what the market feedback would be, and we had to be able to estimate it somehow"*. – CMO, *Start-A* Running the experiment *"When we decide what we want to test, it's just a matter of launching it and seeing what kind of reaction it triggers in our customers"*. – CEO and founder, *Start-C* "*We decide what feature our users may expect and then we launch a product. Most of our analysis comes after the launch, we have volumes of data that allow us to tweak things afterwards*". – COO and co-founder, *Start-D* Using beta testing and A/B testing "*Every change to our website, every new feature, is always run through an A/B test. Basically, we split visitors into two sets and show them two different versions of the website to each. Sometimes we may just change the colour of a button, sometimes they may go through an entirely different experience*". – Marketing Manager, *Start-A* "*We first run the experiment by a selected group of customers we know we can trust"*. – Marketing Specialist, *Start-D* Pacing experiments to obtain truthful results "*If we launched a test like this today, we wouldn't get the answers we want on revenue un under a month. This is because only a part of our newly acquired customers use the product the first month so we can't see the full results*". – Marketing Manager, *Start-A* *"The smaller tests, like revising how we write the copy of an email, take three days, while if we notice that we are missing bits of the app that could bring value, we need three or four sprints, as we have to design and then implement it"*. – Product Manager, *Start-B*
Analysing the results	Evaluating test performance "*The difficult thing is weighing up the feedback. You get lots of anecdotes, and can come up with a theory if you merge all this qualitative stuff with quantitative data you can understand"*. – Marketing Manager, *Start-A* "*Results are meaningless for us before we actually learn what their implications are for our growth*". – CEO and founder, *Start-D* Gathering feedback from the market *"We gather feedback nonstop. Every interaction between users and the product gives us feedback. We learn from everything they do"*. – CEO and co-founder, *Start-A* Analysing root causes *"When you don't understand the reason, at least you want to understand how to give users what they want. For example, some of our customers went to our competitors even though it meant paying much more. We surveyed our clients and realized that they sometimes use our competitors' products because they have a flat rate. We carried out a test on pricing and we tripled our volumes. You have to get to the bottom of it"*. – CEO, *Start-C* *"We make educated guesses about what went wrong, and we fix it"*. – Marketing Specialist, *Start-D* Use qualitative data to complement quantitative results "*To us, qualitative analysis is also very important, so we have a UX research team on it*". – COO, *Start-A*
Revising the initial strategy	Pivoting away from negative results *"Surprisingly, we realized users can be sceptical about products that are free. We decided to drop that strategy and go for something they have to pay for, even if it's just a little. Not all markets work the same …"*. – Marketing Manager, *Start-A* Pivoting towards higher performance expectations *"We have always started with simple products and simple functions, and then we improve them over time taking up the suggestions and requests from our users"*. – CMO, *Start-C* Integrating into the product *"The most difficult part is getting the product team on board. But if tests show that a new feature works and we can reach a wider number of customers, then there is not much to argue about"*. – Marketing Manager, *Start-A*

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Table 3 (*continued*)

Second-order themes	*Selected evidence on second-order themes and first-order categories*
Using the growth hacking method	Finding a growth hack "*We seek that one feature, that killer application that can really give us access to the audience we need. Marketing people may call it a 'growth hack'*". – CEO and co-founder, *Start-A* *"Everything we look for is what will help us … 'boom'!"* – Product Manager, *Start-B* Considering the entire customer acquisition funnel "*When you want to test a new feature, you have to consider the entire AARRR [Acquisition, Activation, Retention, Referral, Revenue] funnel. We may acquire new customers, but what really matters to us is activation and retention*". – Marketing Manager, *Start-A* "Most *experiments go into customer activation, retention and reactivation"*. – COO and co-founder, *Start-B* "*Our main idea for growth is to focus primarily on referral*". – CEO and co-founder, *Start-D* Relating to a lean and agile method of operating *"Growth hacking for us is the natural evolution of the lean startup method, but used for customer acquisition, activation and retention"*. – Marketing Manager*, Start-A* *"We are a very lean organization, everything is organized around the customer acquisition funnel"*. – COO and co-founder, *Start-B* *"We do something similar to agile, a sort of micro-testing"*. – CEO and founder, *Start-C* Developing a"growth fast or die" mindset "*We launch new products because we see opportunities in the market to capture a wider audience. If it doesn't happen, there's no reason to stick with them. Our philosophy is growth and we seek it by all means*". – CEO and co-founder, *Start-A* *"We try to maintain a growth-oriented approach which is based impact on our objectives"*. – Marketing Manager, *Start-A* "*If a feature performs below our KPIs, it's soon out of the window*". – COO and co-founder, *Start-B*

that they were working towards converting, in mass, acquired users into active users, or, by leveraging on their existing skills and technological infrastructures, had developed additional offerings that could widen their audience.

4.2. Experimentation for scaling in technology-based startups

All four startups in our sample had reportedly engaged in extensive experimentation to increase their customer base and give themselves a chance to scale. In the same way as they had meticulously tested their assumptions when striving for market validation, the startups designed ad-hoc experiments when pursuing their scaling goals. As stated by *Start-A*'s CEO and co-founder: *"We always experiment before deploying a new feature or service. Everything passes through market feedback and acceptance"*. Through their experimentation, startups build up their knowledge about their market, thereby reducing uncertainty when making decisions about whether to opt for one product or another in order to grow their user base.

Building on their insights into emerging needs and unserved segments, startups carry out experiments on target segment of users, as described by *Start-B*'s COO and co-founder: *"We look for clusters of users with given features, extract them from our database and send them a cluster-specific message. We then sit back and wait for their reaction, and measure it"*. Working along these lines, the startups can fine-tune their product in order to target each segment.

By segmenting users before experimenting on them, technology-based startups move on from simply determining interest in their value proposition, which was the objective when seeking market validation, to accurately detecting which product features and characteristics appeal most to a given user target. As a Marketing Specialist at *Start-D* noted: *"We first run the experiment by a selected group of customers we know we can trust"*. In this way, the startup runs experiments on a niche group of users who will not get upset if things do not go as planned, and are also able to control which users are involved in the test and their demographics.

The startups made it clear that, throughout their experiments, they spent a considerable amount of time and effort on coming up with the most appropriate metrics that drive growth. This meant that they could include a large number of metrics, such as conversion rate and website impressions, that have a significant direct impact on the goals for user base growth set out when they designed their scaling roadmap. Startups thus develop accurate KPIs to measure the impact of their experiments on growth, and these become their growth metrics. As stated by *Start-B*'s Product Manager: *"We have to work out the proper metrics to measure whether we are doing things right or not. My team, for example, looks after our existing product, and we try and get people to use the app more"*. On a similar note, *Start-C*'s Chief Revenue Officer (CRO) noted: *"Our last experiment was based on average ticket"*. Growth metrics become particularly important during the scaling phase, and are pivotal in driving growth and, potentially, success. As noted by *Start-A*'s Chief Marketing Officer (CMO),: "*We started to acquire a great many customers, but soon realized that if we didn't activate them, our efforts were useless. We now focus primarily on user activation, because that's really what our objective should be*".

As shown by our findings, the key growth metrics targeted in each experiment can vary but they are all carefully selected so that we never lose sight of our ultimate goal – i.e. increase our user base. Technology-based startups also prioritize between experiments to make sure the most promising get the lion's share of their limited supply of resources and effort. As suggested by *Start-C*'s CMO, the goal works almost like a

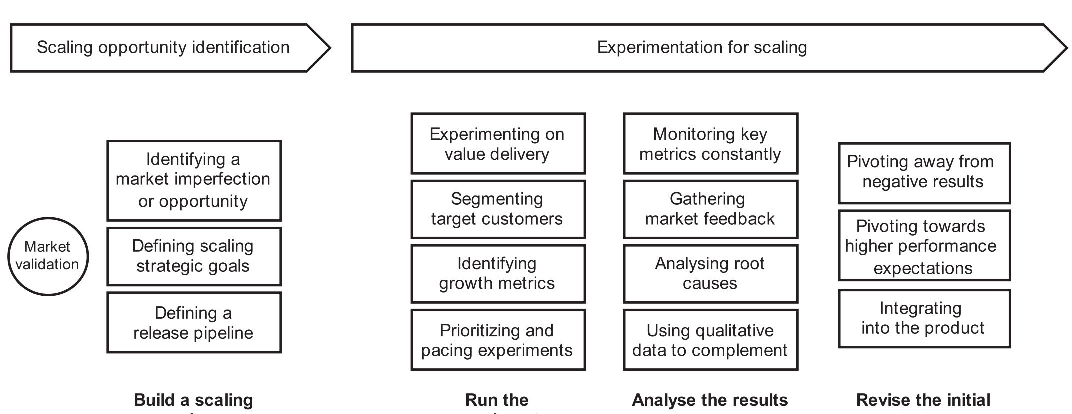

Fig. 2. A process model of experimentation for scaling in technology-based startups.

polar star: *"We prioritize experiments based on our own polar star. […] If, sometimes in the year, our polar star is not directing us towards increasing our profits but our user base, then, in that period, we can concentrate on the part of the funnel or process concerned with user acquisition and referral"*. The priorities are mostly led by the impact, and thus the urgency, of its experiments on the startup's final goal. As reported by the CMO at *Start-A:* "*When I propose a new feature I need for customer acquisition, and explain what KPI I'm going to tweak and have an idea of the measure of the impact, I stand a better chance to jump over some other priority that instead is not particularly well-defined. Then, after some time, we measure the results and decide whether it's worth doing or not"*.

As described by our informants, another important aspect of experimentation for scaling in technology-based startups is to pace experiments very carefully. Instead of the fast and inexpensive tests they use for market validation, in scaling, technology-based startups seem to spend more time on carefully selecting the right experiments, and observing the results. *Start-B*, for example, reported that it runs experiments much less frequently than before its market validation. Its teams, however, organize their work into two-week sprints, so as to set up experiments and gather feedback on a periodical basis. By prioritizing experiments, startups consider both the impact of each experiment on their final goal and the pacing of the different experiments before placing them in the pipeline of experiments to be conducted. As stated by *Start-A*'s Marketing Manager: "*If we launched a test like this today, we wouldn't get the answers we want on revenue in under a month. This is because only some of our newly acquired customers use the product the first month so we can't see the full results"*.

When experimenting for scaling, technology-based startups develop a sort of experiment portfolio, where they can test different aspects of their product/s and business model, targeting very different features and thus promising significantly different impacts on their business. In *Start-A*, for example, *"We use tests in a different order and frequency"* (Marketing Manager, *Start-A*). In this way, startups can deploy experiments at different points in time, or in a different order, to observe how the results obtained with the same experiment differ and what effect different pacing has.

In all four startups, the experiments revolved around specific features that are responsible for reaching and appealing to given user segments and can maximize the metrics acting as proxies for user base growth. When scaling, technology-based startups also direct their efforts towards elements in their business model that are most likely to drive user base growth, such as customer relationships, promotion and distribution channels. In the words of *Start-A*'s Marketing Manager: *"Every change to our website, every new feature, is always run through an A/B test. Basically, we split visitors into two sets and show them two different versions of the website. Sometimes we may just change the colour of a button, sometimes they may go through an entirely different experience"*. Startups can use ad-hoc experiments, such as A/B testing on landing pages or direct messages to the users, which may target customer growth more effectively. As *Start-B*'s COO and co-founder stated: *"Most experiments go into customer activation, retention and reactivation"*.

Startup teams in all four cases carefully monitor the customer acquisition funnel and the performance of their products with new target segments. Startups constantly verify the results of their tests and keep track of the lower performing areas, enabling them to carry out root-cause analyses and conceivably design a solution to any potential problem. For example, *Start-B* realized that most users floundered at a particular point in the subscription process – i.e. when they had to key in their International Bank Account Number (IBAN). Therefore, the team designed experiments to assess how to get users over that obstacle and ease the customer acquisition process. In the words of *Start-B's* Product Manager: "*We carried out several tests to see whether a message or a video popping up at the critical point in the subscription process helped prevent users from getting stuck when they had to key in their IBAN"*.

For technology-based startups, it is not always easy to understand the root causes of lower performing experiments or features. All four startups underlined that, to get the most from their analyses, they supplement the metrics they monitor with significant amounts of qualitative data. For example, *Start-A*'s COO stated: *"Qualitative analysis is also very important for us, so we have a UX [User Experience] research team on it"*. Qualitative data can sometimes turn the negative results of a test into a new customer relationship mechanism that can be tested later. As explained by *Start-C*'s CEO and founder, collecting qualitative data from users gives them a clearer picture of why a given feature fails: *"When you don't understand the reason, at least you want to understand how to give users what they want. For example, some of our customers went to our competitors even though it meant paying much more. We surveyed our clients and realized that they sometimes use our competitors' products because they have a flat rate. We carried out a test on pricing and we tripled our volumes*".

4.2.1. *Experimentation using the growth hacking method*

The informants often referred to a popular management method when reporting on their approach to experimentation for scaling, i.e. growth hacking (Ellis and Brown, 2017). *Start-A* and *Start-B*'s informants mentioned growth hacking repeatedly. In *Start-A*, growth hacking is considered a central method and key to the success of experimentation for scaling in technology-based startups. As reported by the CEO and co-founder, "*We seek that one feature, that killer application that can really give us access to the audience we need. Marketing people may call it a 'growth hack'*". In *Start-B,* several informants also noted that the organization was designed around the different phases of the customer acquisition funnel to facilitate experimenting. *Start-B's* COO and co-founder stated: "*We are a very lean organization, everything is arranged around the customer acquisition funnel*". Interestingly, at *Start-C*, only the CEO and founder referred directly to growth hacking, describing it as follows: *"We do something similar to agile, a sort of micro-testing"*. The other informants involved in scaling and experimentation at *Start-C* did not explicitly seem to be familiar with this approach. Lastly, nobody in *Start-D* mentioned growth hacking at all. Their CEO and co-founder reported that: "*Our main idea for growth is to focus primarily on referrals*". Although a referral programme could be the result of applying growth hacking, the informants did not expressly mention it as their experimentation method.

In general, we observed that the explicit and deliberate growth mindset strongly advocated in the growth hacking method was present in the successful startups, *Start-A* and *Start-B*. As noted by *Start-A*'s CEO and co-founder, "*We launch new products because we see opportunities in the market to capture a wider audience. If it doesn't happen, there's no reason to stick with them. Our philosophy is to grow and we seek it by all means*". On the contrary, *Start-B* also described a culture of "fast failure" and learning from mistakes, which is typical of growth hacking. As noted by the COO and co-founder, "*If a feature performs below our KPIs, it's soon out of the window*".

As the Marketing Manager of *Start-A* observed, their use of growth hacking as a method for experimentation for scaling in technology-based startups is similar to using the lean startup method to experiment during early-stage market validation, "*Growth hacking for us is the natural evolution of the lean startup method, but used for customer acquisition, activation and retention*".

In conclusion, our findings show that, even when the startups in our sample had achieved market validation, they still continued to experiment when they moved on to scaling. All four continued to probe for new customer segments, experimented on channels and customer relationships and carefully prioritized and paced their experiments, always meticulously selecting which metrics to monitor. The two startups that were successful in scaling seemed deliberately intent on following growth hacking guidelines, and saw it as an extension of lean startup to the scaling phase in a startup's lifecycle. Fig. 2 shows the main takeaways of our cross-case findings.

5. Discussion

Our investigation sheds light on the mechanisms underlying experimentation for scaling in technology-based startups. While the emphasis in the existing literature is on how technology-based startups engage extensively in experimentation in their attempt to attain market validation, our evidence suggests that the startups continued to experiment throughout their scaling process. In other words, our investigation found that the startups experimented on the aspects of their business model that would serve their growing user base – i.e. distribution and promotion channels, customer relationships – as well as seeking out new segments to target, carefully pacing and prioritizing their experiments and defining the most important metrics for growth.

Building on these findings, our study makes two contributions to the literature, and these are elaborated further in the following sections. First, we extend the current scholarly understanding on experimentation beyond early-stage market validation (e.g. Andries et al., 2021; Contigiani and Levinthal, 2019; Ghezzi, 2019; McDonald and Eisenhardt, 2020), casting light on how experimentation takes place in the context of scaling in technology-based startups.

All four startups employed an approach to experimentation for scaling that has gained popularity in recent years among practitioners of technology-based startups, known as growth hacking (Bohnsack and Liesner, 2019; Ellis and Brown, 2017; Troisi et al., 2020), when transiting from a "validated" business model to a model that would enable them to scale. We thus contribute to the existing literature in technology entrepreneurship and strategic management by drawing parallels with the established lean startup approach and experimentation for early-stage market validation in technology-based startups (Contigiani and Levinthal, 2019; Ghezzi, 2019; Ghezzi and Cavallo, 2020; Shepherd and Gruber, 2020).

5.1. Scaling in technology-based startups through entrepreneurial experimentation

Our study contributes to the ongoing debate on entrepreneurial experimentation and applying a scientific approach to entrepreneurial decision-making (e.g. Agrawal et al., 2021; Camuffo et al., 2020; Ehrig and Schmidt, 2022; Ott and Eisenhardt, 2020; Zellweger and Zenger, 2022). It also responds to the recent calls raised in previous studies (Contigiani and Levinthal, 2019) for further insights into scaling experimentation, in that it extends the current scholarly understanding of entrepreneurial experimentation, typically associated with a startup attaining market validation in its early stages of development (e.g. Andries et al., 2021; Ghezzi and Cavallo, 2020; McDonald and Eisenhardt, 2020), to the domain of startup scaling.

In particular, our results revealed that technology-based startups continue to experiment as they scale, although they test other aspects of their business model than when experimenting to achieve market validation (e.g. Ghezzi and Cavallo, 2020; McDonald and Eisenhardt, 2020). This finding is in line with previous works that investigated how approaches that encompass heuristics, such as entrepreneurial bricolage (Baker and Nelson, 2005; Ghezzi, 2019), may not be limited only to temporary circumstances of constraints in resources, but can be extended to opening new distribution channels in order to scale up (Busch and Barkema, 2021). Technology-based startups engaged in scaling reportedly experiment on the mechanisms in their business model to deliver value: they test new customer relationships and new promotion and distribution channels, and probe for new potential target segments. This finding contradicts what is known today about experimentation for market validation purposes, which centres on the core elements of a startup's business model, its value proposition (Camuffo et al., 2020).

In addition, when experimenting for scaling, technology-based startups prioritize experiments that may serve the purpose of increasing their user base and, thus, may promote growth. Technology-based startups also pay careful attention to the pacing, as well as the prioritization of their experiments. Differently from the "early and rapid" experimentation of the early startup stages (Ghezzi and Cavallo, 2020; Bianchi et al., 2020), experimentation for scaling requires a careful evaluation of experiment frequency and duration. This is in line with recent studies (e.g. Berends et al., 2021; Wood et al., 2021), that call for more careful consideration of temporal commitments relating to entrepreneurial action.

Lastly, our results document the way technology-based startups deploy experimentation for the purposes of scaling. The startups put most of their effort into identifying the best options to increase their user base by altering aspects of their business model (promotional channels and customer relationships) that enable them to reach a wider audience. This finding is consistent with the idea of scaling in previous literature on technology-based startups (Huang et al., 2017; Varga et al., 2023), with emphasis on the affordances that digital technologies entail (Autio et al., 2018; Nambisan et al., 2019). Digital platforms make it easier for startups to set up their experiments because (i) they operate through a website, which can easily be modified to cater for the tests, and (ii) they submit their tests to users digitally, and thus within easy reach.

This finding is not only consistent with previous literature on how digital technologies are key to scaling in the digital era (Gartner et al., 2022), but also complement previous literature on experimentation in early-stage technology-based startups for market validation (Ghezzi, 2019) and how technology can support product experimentation (Magistretti et al., 2020).

5.2. Experimentation for scaling in technology-based startups: Moving beyond experimentation for market validation

Our findings also contribute to extending the current understanding of experimentation beyond market validation. With our study, we contribute towards highlighting the idiosyncrasies that are a feature of experimentation for scaling in technology-based startups. Prior studies spent considerable attention on looking at how startups make use of experimentation to achieve market validation, investigating it in a wide variety of contexts, including nascent markets (McDonald and Eisenhardt, 2020), digital startups (Ghezzi, 2019, 2020; Ghezzi and Cavallo, 2020), growth-oriented ventures (De Cock et al., 2020), business model innovation in established firms (Hampel et al., 2020a; Sanasi et al., 2022), and specific circumstances where market validation must be reappraised – e.g. crises (Sanasi and Ghezzi, 2022) and industry discontinuities (Pillai et al., 2020). These studies still disregard the way experimentation is conducted when technology-based startups are engaged in scaling, or rather, once startups achieve market validation and they need to switch to growing their customer base. Our findings extend the existing understanding on experimentation as a means to achieve market validation to the domain of scaling in technology-based startups. Table 4 gives a comparison between the two approaches.

As mentioned, the traditional perspective on experimentation covers the early stages of a startup's development (De Cock et al., 2020; McDonald and Eisenhardt, 2020), when its business viability is assessed and validated (Blank, 2013; Bocken and Snihur, 2020; Eisenmann et al., 2012; Ries, 2011). Our study instead responds to recent calls about extending these considerations to the domain of startup scaling (Contigiani and Levinthal, 2019; DeSantola and Gulati, 2017; Picken, 2017), with specific focus on technologybased startups. Market-validated startups check out whether there are any opportunities to scale as the consequence of, for example, an emerging market imperfection or an opening to a previously unserved customer segment.

In previous literature on experimentation for market validation, it has been claimed that experimentation in the early stages of a startup's lifecycle concentrates strongly on validating the startup's business model's core elements, such as its value proposition and primary target segments (Camuffo et al., 2020; Ghezzi, 2019). Our findings instead show that experimentation when technology-based startups are scaling

Table 4
Experimentation for scaling in technology-based startups compared to experimentation for market validation.

Dimension of comparison	Experimentation for market validation (elaborated from existing literature)	Experimentation for scaling (authors' original elaboration)
Audience	Early-stage startups looking for a viable business model (Andries et al., 2021; Gans et al., 2019; De Cock et al., 2020; Ghezzi, 2020; McDonald and Eisenhardt, 2020)	Startups, having attained market validation, are looking for a scalable business model
Starting point	Assess business viability of an entrepreneurial vision (Blank, 2013; Bocken and Snihur, 2020; Eisenmann et al., 2012; Ries, 2011)	Evaluate a scaling opportunity (e.g. market imperfection, opportunity to address new market segment)
Object of experimentation	Fundamental elements of the business model (Blank, 2013; Camuffo et al., 2020), such as the value proposition	Value delivery mechanisms of the business model, e.g. probing for new customers, experimenting on channels and customer relationships
Frequency	Occasional, until market validation or when promoted by external stakeholders (Camuffo et al., 2020; Cavallo et al., 2019)	Structural, inherent to the organizational structure of the startup to enable continuous experimentation
Data collection method	Running ad-hoc experiments with a minimum viable product to gather market feedback (Bocken and Snihur, 2020; Eisenmann et al., 2012; Ries, 2011; Shepherd and Gruber, 2020)	Continuous monitoring of user behaviour + running ad-hoc experiments on the product to gather user feedback
Experiment prioritization	Prioritize experiments based on the riskiest assumptions (Contigiani and Levinthal, 2019; Eisenmann et al., 2012; Ries, 2011)	Prioritize experiments based on growth opportunities, and pace the order and frequency of experiments to compare results at different points in time
KPIs	Relevant metrics of customer/user interest as a proxy of value (Ries, 2011)	Relevant growth metrics + qualitative data for result interpretation
Outcome	Market validation + reduced uncertainty (Bocken and Snihur, 2020; Ghezzi and Cavallo, 2020; Shepherd and Gruber, 2020)	Customer base increase + reduced uncertainty
Decision-making	Pivot, persevere or perish (Berends et al., 2021; Contigiani and Levinthal, 2019; Eisenmann et al., 2012; Ries, 2011; Sanasi and Ghezzi, 2022)	Pivot away when results are negative, pivot because of unmet expectations, or to integrate features into the product
Management methods	Lean startup method (Ries, 2011; Contigiani and Levinthal, 2019; Eisenmann et al., 2012; Shepherd and Gruber, 2020)	Growth hacking method (Bohnsack and Liesner, 2019; Ellis and Brown, 2017; Troisi et al., 2020)

is more concerned with identifying potential new target segments, new customer relationships and new channels for the startup's business model, i.e. its value delivery mechanisms, while leveraging the startups' existing skills and technological infrastructure. There have also been criticisms in past literature, with experimentation for market validation being perceived as a one-off theoretical exercise (Camuffo et al., 2020; Felin et al., 2020), often promoted by external stakeholders in the form of venture capital investors, incubators and mentorship programmes (De Cock et al., 2020; Cavallo et al., 2019). On this point, our findings indicate otherwise, revealing that experimentation in startup scaling can be an ongoing approach to look for new customer segments, new channels and new customer relationship mechanisms. We also found that, alongside setting up ad-hoc experiments to test new features, scaling startups also monitor their users continuously. This means that experimentation becomes more central to the organization, shaping the decision-making processes within the startup. The role of experimentation as a decision-making tool throughout the startup scaling process gives it a new type of importance. Experimentation thus is no longer simply the means to attain market validation (Contigiani and Levinthal, 2019; Ghezzi and Cavallo, 2020; McDonald and Eisenhardt, 2020) and build legitimacy in the eyes of external stakeholders (McDonald and Gao, 2019; Hampel et al., 2020b), but is rather a continuous mindset embedded in the organizational tissue. This finding is consistent with recent studies that underline the need to account for the organizational complexity involved in scaling (DeSantola and Gulati, 2017; Shepherd and Patzelt, 2022), as well as to align employee expectations with the outcomes of experimentation as the organization grows (Snihur and Clarysse, 2022).

Our findings also go beyond the idea of setting up occasional experiments that are sequenced according to the risk given to each business model assumption tested (Blank, 2013; Eisenmann et al., 2012; Ries, 2011). We promote the idea of pacing experiments in terms of their sequencing and frequency in order to gather more detailed and informative results. This approach is in line with previous research that highlighted the importance of continuous entrepreneurial "intelligence", even as the startups are scaling (Baum and Bird, 2010).

In experimentation for scaling in technology-based startups, the KPIs used in scaling to determine the success of an experiment are also different from those used in market validation. Our results show that these KPIs shift from being metrics to assess the target customers' interest in the startup's value proposition (Ries, 2011), to become more complex metrics that can reveal patterns of growth and which, when coupled with qualitative data, can point startups towards actions that maximize their capability to target a wider audience. The actions taken as a result of the experiments are consistent with those reported in previous literature on experimentation for market validation, i.e. "pivot, persevere or perish" (e.g. Berends et al., 2021; Sanasi and Ghezzi, 2022). The reasons behind pivoting in startup scaling may not be limited to falsifying business model assumptions (Bocken and Snihur, 2020; Gambardella and McGahan, 2010), but may instead stem from missing KPI targets that would have maximized customer base growth. On the contrary, positive results in an experiment can lead to a feature becoming integrated within an existing product, made especially easy by to the affordances provided by digital technologies.

Lastly, most previous studies on experimentation have found that the lean startup method is the most common approach used in entrepreneurial experimentation to achieve market validation (Bocken and Snihur, 2020; Contigiani and Levinthal, 2019; Ghezzi, 2019; Ghezzi and Cavallo, 2020; Shepherd and Gruber, 2020). In our study, we equate growth hacking (Bohnsack and Liesner, 2019; Ellis and Brown, 2017; Troisi et al., 2020) with the lean startup method for experimenting when technology-based startups are engaged in scaling.

5.3. Implications for practice

The implications of our findings can also inform the world of practice. Our study may provide practical guidelines for technology entrepreneurs on how to direct their experimentation efforts during the challenging scaling phase. As reported in several managerial studies (e.g. Blank, 2013; Eisenmann, 2021a, 2021b; Eisenmann and Wagonfeld, 2012; Kutcher et al., 2014; Marmer et al., 2011), entrepreneurs find the process of moving from a startup to a fully functioning organization at scale is one of the greatest challenges that startups, and particularly technology-based startups, encounter in their lifecycle. With our study, we provide practitioners with an actionable process model for technology-based startup engaged in scaling. Furthermore, our findings suggest that successful technology-based startups employ growth hacking (Ellis and Brown, 2017) as the equivalent of the popular lean startup method (Blank, 2013; Ries, 2011) in the scaling phase. Our study can support technology managers and entrepreneurs who need to transition from the initial stages of an entrepreneurial endeavour to the phase of scaling, providing them with insights into how to experiment for scaling.

5.4. Limitations and future research directions

Our study also contains a number of limitations. First, we purposedly decided to focus on scaling in technology-based startups that were operating in the context of digital platforms for financial and marketing services. Therefore, as the products were very similar, it was easier to isolate the dynamics in play linked to the products' features and properties and prevent them from contaminating our considerations on the actual experimentation process and structure deployed in each startup. Although the selected startups have very different value propositions and target significantly diverse markets, our choice of only selecting digital startups operating in financial and marketing services could impact on the generalizability of our results. We thereby invite academics to address the matter of experimentation in scaling through wider samples, possibly targeting other industry environments, ones that have not been impacted by digital technologies and where the scaling experimentation effect may be different. Second, our study only looks at startups. However, scaling also troubles well-established corporations in their entrepreneurial endeavours, such as launching new business models or even restructuring themselves organizationally. As mentioned by some of our informants at *Start-B*, companies may feel the need to experiment on their internal organizational structure, to assess how to accommodate new solutions and the learning generated through experimentation. Although this issue goes beyond the scope of our research, this promising gap could be addressed in future studies. Lastly, although our comparative multiple-case study design gave us the means to compare two cases of successful scaling against two with negative results, our study cannot extend to the performance implications of the process and structural choices made by our four startups. This is another area that could also be covered in future studies, looking at how different ways of how a business organises itself in view of experimentation can affect the success of the scaling effort in question.

6. Conclusions

Our study explores how technology-based startups employ experimentation after they have attained market validation. We present a process model of experimentation for scaling in technology-based startups that highlights the mechanisms and peculiarities of experimenting during the scaling process. Our findings reveal that experimentation for scaling centres on the value delivery mechanisms of the startup's business model, i.e. probing for new customers, experimenting on channels and customer relationships, all the time carefully evaluating the priority and pace of the experiments, and the most relevant metrics to monitor. Our informants also reported that they leverage on the growth hacking method to conduct experiments within their technology-based startups, complementing the popular lean startup method and extending its core principles to testing in the scaling phase.

Building on these findings, our study contributes to both theory and practice in scaling in technology-based startups, extending the current understanding of experimentation beyond market validation to support the difficult phase of scaling in a startup's lifecycle. Lastly, we have drawn up some practical guidelines for technology entrepreneurs who intend to experiment during their scaling in order to direct their work and help them set up an adequate experimentation programme during the challenging stage of scaling.

CRediT authorship contribution statement

Silvia Sanasi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Visualization, Writing - original draft, Writing - review & editing. **Antonio Ghezzi:** Conceptualization, Methodology, Supervision, Validation, Writing - review & editing. **Angelo Cavallo:** Conceptualization, Data curation, Methodology, Writing - original draft.

Data availability

The data that has been used is confidential.

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Silvia Sanasi, Ph.D. is a Postdoctoral researcher in Entrepreneurship, Innovation and Management at the Free University of Bozen-Bolzano's Faculty of Economics and Management – Centre for Family Business Management. She received her Ph.D. from Politecnico di Milano's School of Management, where she is part of the extended faculty. Her

primary research interests encompass how organizations–both new and established–innovate and experiment in idiosyncratic contexts (e.g., during crises, under reputational threats, looking at distant futures), using inductive methods such as grounded theory and computer-aided methods.

Antonio Ghezzi, Ph.D. is Associate Professor of Strategic Management and Entrepreneurship, and Head of the "Hi-tech Startups" and "Space Economy" applied research centers at the Department of Management, Economics and Industrial Engineering – Politecnico di Milano. His main research fields are Strategy and Digital Entrepreneurship, with a focus on incumbents' and startups' business model design, innovation and validation, and the role of Lean Startup Approaches for experimentation. He is author of more than one hundred scientific journal articles (appearing in outlets such as *International Journal of Management Reviews*, *Journal of Business Research*, *Technological Forecasting and Social Change*, *International Journal of Production Economics*, *R&D Management* and *Research-Technology Management*), books, book chapters and conference proceedings.

Angelo Cavallo, Ph.D. is Assistant Professor at Politecnico di Milano, Italy. His main research areas include Strategic Management and Entrepreneurship. He has been mainly involved in analyzing business models of digital startups and modeling dynamic and complex systems such as the Entrepreneurial Ecosystem. He is author of journal articles (appearing in outlets such as *Journal of Business Research*, the *International Entrepreneurship and Management Journal* and *Business Process Management Journal*), book chapters and conference proceedings.