Do Digital Startups Prepare for Technology Pivots? – An Initial Analysis of Job Adverts

Completed Research

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Abstract

Technology pivots help digital startups, which are operating in environments of great uncertainty, to make considerable adjustments to the technology underpinning their products. Technology pivots are resource intensive and risky endeavors, especially while growing into viable and sustainable businesses. For these reasons, a well composed team able to perform these pivots effectively is required. While existing research focuses on the identification of antecedents and consequences of technology pivots, we provide insights as to whether digital startups apply anticipatory mindsets throughout team composition, starting early with the formulation of job advertisements. We analyze the extent to which the antecedents of technology pivots form part of job advertisements published by digital startups. Performing a content analysis on 510 IT job advertisements we find very limited references to the (non-)technical antecedents of technology pivots. Our study provides the basis for research extending beyond the analysis of antecedences and consequences of technology pivots.

Keywords

Digital Startups, Lean Startup, Technology Pivots, Antecedents, Team Composition, Job Advertisements

Introduction

Pivoting in digital startups is said to be a "universal consequence of the conditions of extreme uncertainty" (Ries, 2017, p. 110) about the problem to be solved, the target customers, and the value proposition of their unique products and services. In this context of uncertainty (Packard et al., 2017), digital startups often have to perform structured technological course corrections – i.e. a technology pivot – to change their technology design and digital innovation (Bajwa et al. 2017; Klotins et al., 2018). Startup-related media has frequently suggested that dedicated digital startup teams should be set up to ensure the successful performance of technology pivots (TechCrunch, 2012; Forbes, 2015). This is especially important because "ideas change, products pivot, markets can take unexpected turns, but people are what hold everything together", for which reasons, "attract[ing] and retain[ing] the right people to build the technology" is essential (FastCompany, 2015). TechCrunch (2012) even highlights that pivoting is a function that should be afforded by everyone working in digital startups. The importance of composing appropriate digital startup teams able to successfully perform potential future technology pivots has been highlighted by CB Insights (2018) which, among the top 20 reasons for startup failure, cited (a) 'not the right team', (b) 'failure to pivot' a bad product, and (c) 'pivot gone bad' half way through the process. Recent contributions in academic literature have revealed that building entrepreneurial teams that have the "ability to evaluate and react to unforeseen events" and "thriv[e] under technological uncertainty" are a key challenge for digital startups (Giardino et al., 2015, p. 56). To manage these circumstances successfully, "a broad prior skill basis" is required, "including an ability to adjust to changes" quickly (Unterkalmsteiner et al., 2016, p. 102). For these reasons, human resource strategies in digital startups should complement technology choices and the prevailing uncertainties (Tambe and Ye, 2017). Yet, new ventures often use "muddle through" practices in composing teams, which can have "profound effects [...] on the firm's effectiveness and survival" (Cardon and Stevens, 2004, p. 297).

Academic literature concentrating on technology pivots has so far focused on identifying the antecedents and consequences of technology pivots (Terho et al., 2015; Bajwa et al., 2017; Bohn and Kundisch, 2018a, 2018b). From their findings we know about the existence of eight antecedent categories, consisting of technical (e.g. increasing system performance, increasing future viability, or increasing maintainability) and non-technical antecedents (e.g., seeking business opportunities, or compliance, or reducing business costs) that make the performance of technology pivots in digital startups necessary. It has also been found that the performance of technology pivots is a resource-intensive, risky endeavor and a reoccurring challenge for digital startups (Terho et al., 2015; Unterkalmsteiner et al., 2016). Yet, to the best of our knowledge, it is widely unknown whether and to what extent the antecedents of technology pivots are being considered during the composition of digital startup teams. This provides us with an interesting new avenue for research. Whilst existing literature on digital startups has highlighted the importance of context-specific and future-oriented startup teams, no attempt has been made so far to fill this gap (Unterkalmsteiner et al., 2016). The purpose of this study is to make a first step in this direction by exploring whether and to what extent digital startups explicitly refer to the antecedents of technology pivots in their job adverts for information technology (IT) positions. Our study aims to pave the way for more detailed research relating to pivoting and team composition in digital startups, starting as early as the formulation of job adverts (Cardon and Stevens, 2004). Hence, we pose the following research question:

To what extent do the antecedents of technology pivots form part of IT job advertisements published by digital startups?

Through an extensive content analysis of 510 IT job adverts published by 203 Berlin-based digital startups, we found that content relating to each of the technical antecedents can be found in fewer than half of the IT job adverts in our sample, while content relating to non-technical antecedents can rarely be found at all. We also present these differences during the maturation of digital startups. Our paper is structured as follows: In the background section we provide a description of the key concepts for our study and review the existing findings on technology pivots. In the methods section, we explain the approach we adopted for sampling job adverts and for content analysis. In the findings section, we explain our insights in detail with regards to both the technical and non-technical antecedents. Finally, we discuss our findings and present avenues for future research in a conclusion.

Background

Digital startups begin as immature and inexperienced organizations with little operating history and resources (Sutton, 2000). Following Steininger (2019, p. 19), digital startups provide “completely digitized products or services, digitally sold and delivered”. By utilizing digital innovations, digital startups realize offerings with a high market distinction, giving them a unique technological advantage. Yet, their limited resources also mean that they have to perform under intense time-pressure (Klotins et al., 2018). Initially, startups begin with an incomplete knowledge about the problem to be solved and the technologies required to fulfil customer needs, which may even change over time (Ries, 2011; Ojala, 2016). To technologically address these needs represents a considerable challenge (Giardino et al., 2015), including having to make crucial decisions about the design (i.e., architecture, components, interfaces, and their interrelations) in a context of high uncertainty, and comprising a selection of technologies and components that may eventually constitute the product (IEEE, 1990; von Briel et al., 2018). Simultaneously, digital startups are searching for a scalable and repeatable business model to suit their products and services (Ries, 2011). Considering the fast pace of today’s digital innovations, evolving market demands, and intense competition, being able to quickly change one’s own offerings to meet emerging developments and demands is therefore of crucial importance (Bianchi, Marzi and Guerini, 2018).

Technology Pivots as part of the Lean Startup Approach

Ries (2011) introduced the Lean Startup Approach (LSA) as a new process model for entrepreneurship, focussing on the uncertainties inherent in the creation of a new venture (Ojala, 2016; Packard et al., 2017). As mentioned previously, the problem to be solved is often poorly understood at the outset and the requirements for a solution are not yet known. The LSA proposes an iterative and hypothesis-driven approach for venture creation and product development to address these circumstances (Frederiksen and Brem, 2017). Digital startups have to decide regularly whether they are on the right track (in which case they ‘preserve’) or need to make adjustments to their strategy (‘pivot’). Pivots are “structured course corrections designed to test a new fundamental hypothesis about the product, business model, and engine of growth" (Ries, 2011, p. 178). Throughout conducting a pivot, the applied strategy is being changed while the vision is retained. It has been said that "by reducing the time between pivots, it is possible to increase the odds of success" (Bosch et al. 2013, p. 5) and, subsequently, to avoid startup failure. The importance of investigating pivots – and technology pivots in particular – in digital startups has been highlighted by different academics (Terho et al., 2015; Unterkalmsteiner et al., 2016). For example, it has been pointed out that digital startups "develop technology-intensive products" that "are more prone to the rapidly changing technology, causing pivots" (Unterkalmsteiner et al., 2016, p. 100). First exploratory studies on technology pivots (Terho et al., 2015; Bajwa et al., 2017, Bohn and Kundisch, 2018b) have focused almost exclusively on identifying individual antecedents and consequences. A quantitative study by Bohn and Kundisch (2018a) then combined and validated the findings made in extant literature about technology pivots. They created a preliminary theoretical model and described how technology pivots are performed in response to four technical (A1-A4) and four non-technical (A5-A8) antecedent categories (cf. Table 1). Each antecedent category consists of sub-categories and textual descriptions that elaborate on their meanings in more detail (Bohn and Kundisch, 2018a).

Based on these findings, technology pivots have been described as "structured technological course corrections that allow the introduction of significant technical improvements for an existing offering as well as the introduction of IT-innovations to distinctly adapt and enhance the value created by products and services" (Bohn and Kundisch, 2018b, p. 13). Technology pivots commonly seek to address architecture redesigns, core-library switches or development framework changes (Bohn and Kundisch, 2018a). It was also found that technology pivots can occur multiple times across all life-cycle stages of digital startups from early *concept & development* to *growth*, and *stability* (Bohn and Kundisch, 2018a). Yet, these are risky endeavors for digital startups by consuming valuable time and other resources for their performance, as well as leading to internal conflicts and considerable overhead management, all of which can result in startup failure (Giardino et al., 2015; Bajwa et al., 2017; Bohn and Kundisch, 2018a).

	Antecedent Categories		Antecedent Sub-Categories
Technical	A1	Increasing System Performance	Increasing systems performance scalability; Increasing system stability; Reducing technological constraints; Resolving customer product feedback issues; Resolving bugs visible to the customers
	A2	Increasing Architectural Future Viability	Aiming for high internal software quality; Adapting to new technological standards; Avoiding technological obsolescence; Correcting insufficient initial technical validation; Replacing discontinued technology
	A3	Increasing System Maintainability	Reducing complexity of architectural design; Separating logical components into smaller services; Increasing team's understanding of system solution; Seeking to increase product functionality
	A4	Increasing Interface Components	Realising a shared boundary across which information can be exchanged (APIs)
Non-Technical	A5	Reducing Business Costs	Reducing costs through integration of third-party solutions; Reducing costs through internal improvements
	A6	Seeking Business Opportunities	Changing systems as prerequisite to implementing strategy changes; Pursuing market opportunities based on technological innovation; Targeting new customer segments
	A7	Seeking Compliance	Seeking regulatory compliance; Seeking compliance with IT standards
	A8	Previous Pivot	A technology pivot deemed desirable; A technology pivot deemed necessary

Table 1. Technology Pivot Antecedent (Sub-)Categories (Bohn and Kundisch, 2018a).

Technology Pivots and Job Advertisements

The circumstances in which digital startups operate differ considerably from those of established businesses, which means that digital startups need to compose context-specific and future-oriented teams (Kollmann et al., 2009) that are equipped to, among other tasks, manage great uncertainty (Packard et al., 2017) – including technology uncertainty (Giardino et al., 2015) – and perform technology pivots when required (Bajwa et al., 2017). Composing teams able to perform fast and flexible technological adjustments is essential as customers often steer requirements (Kollmann et al 2009) and developers must be ready to embrace change from day one. Yet, immature teams often do not sufficiently foresee these requirement changes and consequently do not envision technology that can equip the business for the future. This is all the more salient considering that digital startup teams need to counterbalance their lack of resources with smart technology decisions and design (Giardino et al., 2015). When technology pivots become necessary, feasibility needs to be satisfied, which in this context involves "the skill and knowledge-based ability to implement technological changes" required by a technology pivot (Bohn and Kundisch, 2018b, p. 8). If these are unavailable in-house, digital startups need to seek additional employees who have the required skill and knowledge-base. One common method for finding qualified applicants is through job adverts (Todd et al., 1995) which contain detailed descriptions of the position, related requirements, and responsibilities of the role. Job adverts need to be composed as accurately as possible in order to avoid missing promising applicants or encouraging potentially unqualified applicants to apply, thereby wasting limited organizational resources and delaying the performance of technology pivots (Todd et al., 1995). The formulation of qualified job adverts and subsequent composition of teams have therefore profound effects on digital startups (Baron, 2003). Given the importance of technology pivots and the challenge to get them to perform effectively, we believe digital startups should aim to prepare for them by composing teams that have the skill and knowledge-based ability to perform technology pivots motivated by different antecedents. Antecedents such as 'Increasing System Performance' require deep technical skills, commonly described as 'hard skills' in the context of job adverts. In order to understand whether and to what extent digital startups aim to compose teams that can perform technology pivots, we use job advertisements for IT positions published by digital startups as a proxy. If the content of adverts for IT positions relates to the antecedents of technology pivots, we would consider this to be an indication that they are preparing for (potentially) upcoming technology pivots. For this, a fundamental assumption in our study is that the content of job adverts published by digital startups is a valid representation of their current and future demands, particularly with regards to 'hard skills', as previous studies have assumed (Todd et al., 1995; Kennan et al., 2007; Harper, 2012).

In sum, technology pivots are frequently being performed in digital startups based on changing requirements and evolving digital innovations (Bajwa et al. 2017; Klotins et al., 2018). They constitute a considerably risky endeavor. To enable their performance, a well composed team should satisfy the feasibility prerequisite. Yet, whether and to what extent digital startups prepare for the performance of technology pivots by aiming to assemble teams that can handle technology pivots effectively is widely unknown. Our approach draws on studies (Todd et al., 1995; Harper, 2012; Tumbas et al., 2018) that have similarly analyzed job adverts to derive insightful findings on a particular subject by looking for references to the subject in question – in our case, antecedents of technology pivots in IT job adverts. By combining extant literature on technology pivots (focused on antecedent and consequence identification) with a new data set (job adverts) we provide an important first step for further research in this direction.

Method

Based on the fundamental assumption that the content of job adverts is a valid representation of current and future demands (Todd et al., 1995; Harper, 2012; Tumbas et al., 2018), we use content analysis (Krippendorff, 2013) to derive insights on whether and to what extent IT job adverts published by digital startups refer to the antecedents of technology pivots. For this, we consider the suggestions for rigor proposed by Harper (2012). We also analyse our data for differences between digital startups at different stages of maturation. Content analysis of job adverts is a commonly used technique for two reasons. First, published adverts include explicitly formulated descriptions of the positions to be filled and the qualifications required to meet the needs of the business. These descriptions are likely to reflect the position and ideal candidate well (Todd et al., 1995; Harper, 2012). Second, analyzing secondary data allows to include a considerable sample size in a study (Harper, 2012).

Data Collection

Our study is based on data obtained from a platform that advertises job opportunities exclusively for startups based in Berlin, i.e., BerlinStartupJobs.com (BSJ). The vast majority of the job adverts on BSJ are published in English. The platform has gained considerable popularity among startups in Berlin for its specific focus and moderate prices. BSJ categorizes each job advertisement into one of ten sections (e.g., "IT/software", "operations & support", "marketing", and "sales") (BerlinStartupJobs, 2018). We identified the "IT/software" section as the most relevant for the purpose of our study as it contains IT and software engineering-specific positions (e.g., frontend and backend engineering positions). On discovering that the "operations & support" section advertises relevant positions such as "technical client support" and "IT system administrator" we decided to include it in our study. In our first step of data collection, we crawled all job adverts from the "IT/software" and "operations & support" sections published between 1 April 2018 and 31 October 2018 to achieve a suitably large sample. Second, after the crawl was completed, we filtered out those job adverts not published by *digital startups*, i.e. those that do not provide "fully digitized products or services, digitally sold and delivered" (Steininger, 2019, p. 19). Furthermore, we filtered out adverts from the "operations & support" section that were not relevant for the purpose of our study such as "executive assistants", "HR managers" or "office managers". Finally, we removed a small fraction (<2%) of job adverts that were published in German.

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Job Ads.	1 (1)	*17 (3)*	*14 (3)*	*7 (4)*	*22 (5)*	*31 (4)*	*20 (7)*	*20 (10)*	*51 (18)*	*56 (26)*	*73 (28)*	*70 (32)*	*68 (28)*	*28 (18)*	*32 (16)*	510 (203)

Table 2. Job Adverts in Final Sample Ordered by Digital Startup Founding Year (Number of Digital Startups Publishing the Job Adverts in Brackets).

This left us with a final sample of 510 IT job adverts published by 203 digital startups (e.g., Babbel, Remerge, and Wooga) over a period of seven months (cf. Table 2). The sample contains on average 2.5 adverts per digital startup (std. dev. = 2.6), each publishing between a minimum of 1 and a maximum of 25 adverts. Each job advert contains 468 words on average (std. dev. = 130). In a third step, we enriched each advert with additional meta information about the founding year of the publishing digital startup. These steps provided us with the following information for each job advertisement included in our final sample (cf. Table 3): (1) startup data, (2) position data and (3) job advertisement content.

Information	Sample Content	
Startup	Name	Data Artisans
	Year Established	2014
Position	Title	Senior Distributed Systems Engineer
Ad Content	Publishing Date	23 May 2018
	Word Count	415
	Main Text	Data Artisans is building the next-generation platform for programming data-intensive applications. We are tackling some of the biggest technical challenges [...].

Table 3. Sample Job Advertisement Information Used in Study.

Data Analysis

The main text of each job advert is typically divided into four parts. The first part describes the employer and the nature of the business. The second part typically discusses the tasks and responsibilities associated with the position. The third part explains the required skills, prior experience and characteristics of the ideal candidate. The final part presents a call to action. The second and third part of each job advert contain the information most relevant to our study. To extract the desired information and not be overwhelmed by information outside the scope of this study, a semi-automatic coding approach was used, based on a progressively composed dictionary (Todd et al., 1995; Krippendorff, 2013). The dictionary supported the identification and classification of content referring to one of the eight antecedent categories.

In a first step, we sourced a dictionary of terms with relevant words for each of the eight antecedent categories deductively based on the textual descriptions, including those for its sub-categories (cf. Table 1), by Bohn and Kundisch (2018a, 2018b). One author and two IS scholars independently derived words from these descriptions, relevant for identifying content referring to each antecedent category. These words were then compared, discussed and agreed upon. For example, for "increasing systems performance scalability (A1)", including its sub-categories, the following set of words were derived: "performance", "scalability", "stability", "constraint", "resolve", "customer", "feedback" and "bug", which were then stemmed and combined as a regular expression, i.e., [perform*|scal*|stabil*|constrain*|resolv*|customer*|feedba*|bug*]. Applying this approach to all antecedent categories, we obtained a set of eight deductively derived regular expressions (cf. Table 4). Second, in order to not only rely on deductively derived terms, one author and one research assistant inductively derived terms relevant to identifying each of the eight antecedent categories. Specifically, they classified each phrase from a pilot sample of 75 job adverts into one of the eight antecedent categories if they were used to semantically express the same meaning as described by Bohn and Kundisch (2018a, 2018b). Based on this inductive classification, the most relevant terms were independently extracted and then discussed and agreed upon jointly (Todd et al., 1995). For example, for A1, we inductively identified the following terms, "reliable", "experience", "debug" and "bottleneck" which were stemmed and combined in the following regular expression [reliab*|exper*|debug*|bottleneck*] (cf. Table 4). This step resulted in an additional set of inductively derived words per antecedent category. Third, we then merged the deductively and inductively derived regular expressions and applied the merged regular expressions one by one to the full text of all 510 job adverts of our final sample. For this analysis step, we used the semi-automatic coding function in Atlas.ti 8 which allows to search for phrases matching regular expressions. It was performed by one author and one research assistant independently. For each of the search results found for the regular expressions, we analyzed them for a semantic overlap with the respective antecedent category, which included reading the sentences before and after the search result, and then coded them if semantic overlap was identified. The initial inter-coder reliability, based on Krippendorff's (2013) alpha was at 0.84. Conflicting codings were discussed and resolved. A total of 1.715 phrases were coded in this way.

	Antecedent Category	Regular Expression	Terms
Technical	A1: Increasing System Performance	Deductive	[perform*|scala*|stabil*|constrain*|resolv*|scale*|customer*|feedba*|bug*]
		Inductive	[reliab*|exper*|debug*|bottleneck*]
	A2: Increasing Architectural Future Viability	Deductive	[quality*|adapt*|standard*|obsolen*|correct*|replac*|discont*|future*|archit*|insuffic*|valid*]
		Inductive	[vision*|anticipat*|stack*|code*|reus*|paradig*| pract*|pattern*|princip*|infrastr*|exten*]
	A3: Increasing System Maintainability	Deductive	[maintain*|complex*|architect*|logic*|component*|service*|understand*|function*| efficienc*|control*]
		Inductive	[implement*|reduc*|feature*|implement*|mainten*|improv*]
	A4: Increasing Interface Components	Deductive	[interface*|integrat*|extern*|boundar*|component*|exchang*]
		Inductive	[third*|3rd*|interconnect*|import*|export*|API*]
Non-Technical	A5: Reducing Business Costs	Deductive	[reduc*|cost*|third*|part*]
		Inductive	[budget*|efficien*|automat*]
	A6: Seeking Business Opportunities	Deductive	[strateg*|opport*|innovat*|business*|possib*|grow*|target*|custom*|segment*]
		Inductive	[adapt*]
	A7: Seeking Compliance	Deductive	[regula*|compli*|standard*]
		Inductive	[assuranc*|protect*|legal*|polic*]
	A8: Previous Pivot	Deductive	[pivot*|chang*|course*|correct*]
		Inductive	[rebuil*|migr*]

Table 4. Derived Regular Expressions Used for Analysis of our Sample.

Findings

First, we present general findings with regards to technical and non-technical antecedents. Second, we describe our findings with regards to the maturity of digital startups.

Technical Antecedents

We found that the technical antecedents (A1-A4) that frequently lead up to technology pivots in digital startups are not reflected in the majority of the IT job adverts in our sample (cf. Table 5). On average 0.64 (std. dev. = 0.99) technical antecedents were found per job advert.

	A1: Increasing System Performance	A2: Increasing Architectural Future Viability	A3: Increasing System Maintainability	A4: Increasing Interface Components
Job ads containing content referring to antecedent (abs. number)	45% (236)	32% (164)	47% (243)	33% (169)
Average number of references to antecedent per job ad (std. dev)	2.11 (1.95)	1.86 (1.21)	1.90 (1.69)	1.67 (1.14)
Startups with at least one job ad referring to antecedent (abs. number)	55% (112)	43% (88)	63% (128)	50% (101)

Table 5. Occurrence of Content Referring to the Technical Antecedents in our Sample.

While 81% consist of at least one reference to any of the technical antecedents, for a considerable number (21%) we did not find any references to any of the technical antecedents (examples provided as an online resource: www.tinyurl.com/yahd88nc). However, especially conceptual knowledge such as being able to build high-performance solutions that are easy to maintain and adapt as well as being future-proof is crucial for digital startups, as indicated in previous research (Kollmann et al., 2009). It is also argued that increasing system performance is among the most frequent reasons for digital startups performing technology pivots (Bohn and Kundisch, 2018a) and that poor maintainability can lead to considerable development delays and customer unhappiness (Klotins et al., 2018). In the following, we present our findings for each technical antecedent. All citations from job adverts indicate the startup's founding year.

Increasing System Performance (A1): We found that 45% of the job adverts in our sample had content referring to increasing system performance. Among all digital startups, 55% refer to increasing their systems' performance within at least one of their published job adverts. Statements include, for example, "to improve our product's stability and performance" (est. 2016) and "to help us to scale [...] through the innovative use of technology" (est. 2018). The remaining 55% of the job adverts did not have any content related to building products or services with high-performance, or even to increasing current performance.

Increasing Architectural Future Viability (A2): In our sample, 32% of the job adverts published by 43% of digital startups refer to the development of new and viable IT-architectures for the future, or to an increase in the viability of existing IT-architectures. Statements include, e.g., "to drive our architecture forward" (est. 2015) and "to build modern architectures for mission-critical applications" (est. 2013). Although an important antecedent of technology pivots (Bohn and Kundisch, 2018b), building future-proof IT-architectures is the least often referred to antecedent in our sample.

Increasing System Maintainability (A3): Being able to create products and services that are easily maintainable is referred to in 47% of the job adverts by 63% of the digital startups in our sample. It is the most frequently referred to antecedent in our sample. Statements include e.g., "previous experience building maintainable and scalable systems based on reliable and fault-tolerant services" (est. 2016) or "strong interest in maintainability and clean code" (est. 2006).

Increasing Interface Components (A4): Being able to design and create interfaces for external applications is referred to in 33% of the job adverts by 50% of the digital startups of our sample. Relevant statements include e.g., "to maintain and develop our customer-facing and internal APIs and integrate third-party data sources" (est. 2013) and "be responsible for [...] third-party API integrations" (est. 2012).

Non-Technical Antecedents

In our sample, the non-technical antecedents of technology pivots are rarely referred to in IT job adverts (cf. Table 6). Only between 3 to 13% of the job adverts, and 6 and 14% of digital startups have referred to either one of the four antecedents (A5-A8). Across our sample, on average 0.15 (std. dev. = 0.54) non-technical antecedents were found mentioned per job advertisement. We did not identify a single job advert in our sample which refers to all four non-technical antecedents, while 82% of the job adverts do not refer to any.

	A5: Reducing Business Costs	A6: Seeking Business Opport.	A7: Seeking Compliance	A8: Previous Pivot
Job ads containing content referring to antecedent (abs. number)	5% (25)	13% (66)	3% (17)	3% (17)
Average number of references to antecedent per job ad (std. dev)	1.32 (0.57)	2.36 (2.40)	1.31 (0.46)	1.21 (0.56)
Startups with at least one job ad referring to antecedent (abs. number)	9% (19)	14% (28)	6% (13)	7% (14)

Table 6. Occurrence of Content Referring to the Non-Technical Antecedents in our Sample.

Extant literature has emphasized the increasing importance of business skills relative to technical skills for IT positions in new ventures (Kollmann et al., 2009; Tambe and Ye, 2017). The literature further suggests that recognizing and envisioning new business opportunities is an important entrepreneurial competence (Kollmann et al., 2009) which should not only be held by the founding team. In the following we present our findings for each technical antecedent.

Reducing Business Costs (A5): Content referring to reducing business costs was found in 5% of the job adverts in our sample, published by 9% of the digital startups. Relevant statements include e.g., "understanding how to balance simplicity with maintainability, quality, and cost" (est. 2012) and "maintaining our infrastructure and optimizing costs" (est. 2015). Cost-efficient development of products and services seems to be rarely stipulated as essential. Yet, startups are organizations with limited resources and need to be careful in how they use them, in order to extend their runway (Unterkalmsteiner et al., 2016).

Seeking Business Opportunities (A6): In our sample, 13% of the job adverts, published by 14% of digital startups, refer to such knowledge or experience. Relevant statements include, e.g., "help nurture and sustain new business opportunities" (est. 2014) and "boost performance and address business opportunities" (est. 2012). As shown in prior research (Bohn and Kundisch, 2018b), startups perform technology pivots to repeatedly seek and exploit new business opportunities.

Seeking Compliance (A7): Software development compliance with data protection or financial regulation is referred to in 3% of the job adverts by 6% of the digital startups. The associated statements include, e.g., "keeping a close eye on compliance and the safety of our organization" (est. 2007) and "to ensure compliance with legal/regulatory requirements" (est. 2014). This antecedent is highly depended on the industry that a digital startup operates in, as well as the product it provides.

Previous Pivot (A8): Managing the consequences of previous pivots is only mentioned in 3% of job adverts and by 7% of the digital startups. Together with A7, A8 is the least often referred to non-technical antecedent in our sample. Statements identified include, e.g., "we are completely rebuilding our proven core product from scratch with React, Redux & GraphQL" (est. 2012), as a consequence of another pivot to the digital startup. Yet, prior research has shown that dependencies between pivots exist, and that so-called domino-pivots can occur (Terho et al., 2015). These dependencies with different consequences and effects then need to be managed effectively (Bohn and Kundisch, 2018a).

(Non-)Technical Antecedents and Digital Startup Maturity

Considering the maturity of digital startups while analyzing the occurrence of content relating to the technical antecedents of technology pivots, we found first indications that antecedents A1-A3 (respectively, increasing system performance, architectural viability, and system viability) were the least often referred to by young startups (0-2 years), compared to medium aged (3-5 years) and mature digital startups (6+ years) (cf. Table 7). These findings suggest either a lack of awareness among young digital startups about potential technological complications related to performance, maintainability and future viability (which could require them to perform technology pivots) or a dedicated decision against the inclusion of these aspects. By contrast, A4, increasing interface components, is the most referred to by young startups (0-2 years), perhaps to ensure easy integration with their new solutions by clients and the external services they aim to use. With regards to the maturity of digital startups and the occurrence of content relating to the non-technical antecedents, no pattern was observable in our sample. Extant literature suggests that recruitment in digital startups should be in sync with the degree of uncertainty they face and related complications (Tambe and Ye, 2017). We thus find it worthwhile to further investigate whether and why young startups seem to integrate less content relating to the technical antecedents A1-A3.

	Technical Antecedents				Non-Technical Antecedents			
	A1	A2	A3	A4	A5	A6	A7	A8
0-2 Years	38% (13)	24% (8)	53% (18)	56% (19)	6% (2)	18% (6)	6% (2)	0% (0)
3-5 Years	57% (85)	45% (40)	65% (57)	53% (47)	10% (9)	11% (10)	9% (8)	7% (6)
6+ Years	60% (49)	49% (40)	65% (53)	43% (35)	10% (8)	15% (12)	4% (3)	10% (8)

Table 7. Percentage of Digital Startups Referring to the Antecedents of Technology Pivots in at least one Job Advert by Maturity (Absolute Number of Digital Startups in Brackets).

Conclusion

Technology pivots allow digital startups to perform structured technological course corrections to introduce significant technical improvements as well as distinctly adapt and enhance products and services on their way to growing into a viable and sustainable business (Unterkalmsteiner et al., 2016; Bohn and Kundisch, 2018a). It has been found that they represent a risky endeavor, which can lead to the failure of either the pivots or even the startup as a whole (Giardino et al., 2015; CB Insights, 2018). Subsequently, prior to their performance, it is essential to set up teams that are able to make fast and flexible technological adjustments.

We aim to contribute insights on the preparation for technology pivots with regards to team composition in digital startups, derived from a content analysis of IT job adverts. We investigate whether and to what extent 510 job adverts for IT positions published by 203 digital startups relate to the antecedents of technology pivots. Our study identifies that each of the technical antecedents are referred to in fewer than half of the job adverts in our sample, and each of the non-technical antecedents by fewer than a fifth. We were unable to identify any content relating to technical antecedents in 21% of the adverts, and to non-technical antecedents in 82%. We were surprised to find that a considerable number of IT job adverts only partly refer to technical antecedents, if at all. Yet, we did find indications for an increase in content relating to technical antecedents with startup maturation. Further, it seems crucial to us to better understand why non-technical antecedents hardly ever feature in IT job adverts in digital startups when they so heavily rely on technology as a value-creating and business-enabling resource (Ojala, 2016). As described above, technology pivots require well composed teams for their performance (Unterkalmsteiner et al., 2016). The overall low occurrence of content relating to the antecedents of technology pivots in job adverts makes us wonder whether digital startups sufficiently consider the high level of (technical) uncertainty they are facing on their way to growing into a viable business (Ojala, 2016) while composing teams able to deal with them. From our point of view, this provides a good starting point for more detailed research on the subject of digital startups, team composition, and how to prepare for effective technology pivot performance.

Our study contributes to research on the LSA (Frederiksen and Brem, 2017) and pivoting in digital startups (Unterkalmsteiner et al., 2016; Bajwa et al., 2017) by providing insights which go beyond the discovery of the antecedents and consequences of individual types of pivot – the dominant theme in prior research. Our findings provide first insights useful to future research on preparation activities for the performance of technology pivots. Our findings also carry important implications for practice. While knowing that 'not the right team', 'failure to pivot' and 'pivot gone bad' are among the top reasons for the failure of digital startups (CB Insights, 2018), it seems reasonable for startups to carefully consider whether the low level of content referring to both the technical and non-technical antecedents of technology pivots in IT job adverts is indicative for the challenges lying ahead. Given the flexibility required to tackle technology pivots, it seems to make all the more sense to aim to compose context-specific and future-oriented teams able to tackle these challenges.

Our research has certain limitations. First we assume that job adverts are a good mirror for a startup's awareness about its current and future reality and challenges. Since the formulation of inaccurate position descriptions would lead to wasting resources or hiring the wrong employees, we have no reason to believe that they would not be accurate, as other studies similarly did before us (Todd et al., 1995; Tumbas et al., 2018). Second, some positions might not be advertised, which means that there is some data which may be unavailable for our study (Harper, 2012). Yet, even with parts missing, publicly published positions should still reflect the extent to which digital startups actively consider the antecedents of technology pivots. Third, our analysis relies on a semi-automatic coding approach based on a progressively composed dictionary. Although thoroughly composed inductively and deductively, there remains the possibility that relevant search terms were not identified. Future research can extend our findings in at least two promising directions. First, it could integrate prior entrepreneurial experiences by the founders of digital startups and their effect on the occurrence of content referring to the antecedents of technology pivots in IT job advertisements. Second, future research could investigate via case studies of digital startups, which other efforts digital startups perform to compose teams capable of performing technology pivots as part of their hiring processes beyond what we have identified in job adverts. Furthermore, via case studies, the reasons for the differences in occurrence between technical and non-technical antecedents could be analysed.

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