HELP, I NEED SOMEBODY! BUSINESS AND TECHNOLOGY ADVICE IN EMERGING SCIENCE-BASED VENTURES

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ABSTRACT

Early-stage science-based ventures require a wide range of intellectual resources and practical know-how to successfully commercialize their technologies. Often entrepreneurs actively gain this knowledge through advisory relationships providing commercial and technical guidance. We explore the effects of those dual advice domains – business and technology – and their overlaps and complementarities with the knowledge bases of entrepreneurs. To directly capture early science-based venture progress, we introduce the concept of *application readiness* to represent a technology's evolution from scientific discovery to commercial solution. Using hand-collected longitudinal data from 112 emerging science-based ventures, we find that business advice has a positive impact on application readiness; counter-intuitively, technology advice does not confer the same benefit. Moreover, advice shows the strongest effects when its domain is complementary to the entrepreneur's experience. These insights help unpack the mechanisms through which advice – an often-used policy tool supporting entrepreneurship – is absorbed and implemented in emerging ventures.

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INTRODUCTION

Science-based ventures (SBVs) are created to commercially exploit scientific knowledge developed in universities and other private or public research organizations (Colombo et al., 2010). These entities play a crucial role in converting basic research into important outcomes, including innovations and economic value (Fini et al., 2019; George et al., 2016; Perkmann et al., 2021). However, turning science and early-stage technologies into successful market applications is challenging, as distinct knowledge domains – technology and market – need to be combined and multiple combinations are possible (Bruneel et al., 2020; Danneels, 2002; Gruber et al., 2008). Science-based venturing is further complicated by the increasingly complex ecosystem in which SBVs navigate; stakeholders may include universities, research parks, incubators, financiers, regulatory and funding agencies that SBVs engage with via joint ventures, strategic alliances, licensing agreements, or other research support (Clayton et al., 2018; Markman et al., 2008; Perkmann et al., 2013). These issues are exacerbated by the limitations of SBV founders, whose scientific knowledge typically exceeds their experience with venture launch (Murray, 2004). Supporting the process of converting technical insight into a commercial solution thus remains a fundamental question in scholarship regarding SBVs and technology entrepreneurship (Ambos and Birkinshaw, 2010; Shane, 2004).

In response to these challenges, SBV founders search for external information and knowledge (Clayton et al., 2018). One common source is advisors, with more than 80% of ventures engaging at least one (Robson and Bennett, 2000). Advice relationships enjoy popularity because they are easily created and typically consist of informal, *ad hoc* meetings. Unlike other relationships, advisors may start without financial obligations or commitments of equity stakes (Chrisman and McMullan, 2004; Cumming and Fischer, 2012). This fluidity may contribute to the relative paucity of scholarship on advisory relations in science commercialization, with academic focus directed instead to institutions such as technology transfer offices (Markman et al., 2008), universities (Fini et al., 2020; Hayter, 2016b) or intermediary organizations (Clayton et al., 2018). Therefore, whether and how advisors impact science commercialization in SBVs remains unclear.

Moreover, the expanding literature on knowledge intermediaries and external advisors has largely focused on the effectiveness of *general* business advice (Chatterji et al., 2019; Lyons and Zhang, 2018) while the role of externally sourced technological knowledge has attracted relatively scant attention. This focus contrasts sharply with the nature of science commercialization, which requires technology to be matched and adapted to reach a viable solution in the marketplace (Bruneel et al., 2020). While technology advisors may be trained scientists who offer guidance in their disciplines (Ding and Choi, 2011), less is known about their role in the SBV's larger business context. The growing prevalence of advisor relationships in public, private, and academic entrepreneurial settings (Belz et al., 2019; Huang-Saad et al., 2017; Leatherbee and Katila, 2020; Lyons and Zhang, 2018) calls for a more rigorous examination of the effects of different types of advice on SBV growth.

In this paper, we investigate the effectiveness of business and technology advice on an SBVs' *application readiness* (AR), defined as the SBV's progress in transforming its technological discovery into a commercial solution. The AR concept simultaneously captures technology and market feasibility, a linking process determining how a technology is connected to a market opportunity and customer segment (Gruber et al., 2008; Molner et al., 2019; Shane, 2000). As this linking process readies an SBV's technology for the market, application readiness can thus serve as an early-stage harbinger of SBV success.

To investigate the effect of business and technology advice on SBV application readiness, we build on existing research positing that an entrepreneur's learning capacity matters for advice absorption (Cumming and Fischer, 2012; Zahra et al., 2019). In particular, we examine the effects of overlaps versus complementarities between the proffered advice (i.e., business or technology) and the entrepreneur's associated expertise (i.e., entrepreneurial or technical experience). Our study addresses the following two research questions: *(1) What is the impact of business and technology advice on an SBV's application readiness?* and, *(2) How do knowledge overlaps and complementarities between entrepreneur and advisor moderate this relationship?* We use a novel longitudinal data set consisting of survey data from 112 lead founders of emerging SBVs participating in a training program for new technology entrepreneurs. Therefore, this sample represents a set of ventures engaged in the earliest stages of the commercialization process.

Our analysis shows that application readiness is accelerated by business advice, in contrast to technical advice. We also demonstrate that advice is most helpful when it complements, rather than overlaps with, the entrepreneur's pre-existing knowledge base. This work contributes to and synthesizes learnings in many fields. First, we report on how two distinct knowledge domains match an SBV-founder's experience, thereby showing key combinatorial conditions in entrepreneur-advisor relationships. We also extend ongoing debates on excessive knowledge overlaps during business venturing by showing that connecting technology experience and technology advice does not advance application readiness. In addition, by conceptualizing and measuring application readiness, we emphasize technology-market linking in SBVs and provide a new instrument for assessing early-stage venture progress. Finally, we offer insights for management of technology commercialization programs in the public and private spheres.

BACKGROUND AND HYPOTHESES

Technology commercialization and application readiness

A science-based venture typically starts with a novel technological idea that – if commercialized successfully – has the potential for considerable impact on society (Ambos and Birkinshaw, 2010; Rotolo et al., 2015). The worlds of academic and public policy alike have turned their attention to SBVs for their potential to source radically novel technologies that can enable fast growth (Rotolo et al., 2015). Founding and growing SBVs is subject to significant market risks and uncertainty (Belz and Giga, 2018; Cohen et al., 2013; Gu, 2005) and the process – typically involving multiple constituents, such as individual entrepreneurs, teams, industry partners, venture capitalists, and universities – can take years (Fini et al., 2019).

Early-stage commercial potential of SBVs is often evaluated with indicators such as product status and maturity, with investors weighing technology maturity indicators in their investment decisions (Baum and Silverman, 2004; Conti et al., 2013; Maxwell et al., 2011). In the public arena, similar considerations manifest in the widespread use of technology readiness schemes to qualify SBVs for funding. This practice is common in large technology-rich agencies, such as the United States Department of Defense and the National Aeronautics and Space Administration (NASA) (Dubos and Saleh, 2011; Government Accountability Office, 2017; Magnaye et al., 2010; Terrile and Jackson, 2013; Ward et al., 2012). Retiring technical risk is thus an important indicator of early-stage SBV progress.

The fungibility of technologies and the diverse possibilities for applications (Shane, 2000) can make the commercialization pathway less straightforward, even for SBVs with a high technology maturity. The challenges of identifying a market space for a new technology has been expressed as follows: "the identification of market spaces (i.e., technology-to market linkages that present new product development opportunities) for early-stage technologies is perhaps the most fundamental yet most elusive marketing competence for managers and firms in technology industries" (Molner et al., 2019: p.1). Therefore, tracking SBV's commercialization progress should include making advancements in identifying market spaces, especially in light of recent academic emphasis on and adoption of discovery-based and lean startup approaches focusing on identifying and learning from customers (Blank, 2013; Camuffo et al., 2020; McGrath and MacMillan, 2009; Ries, 2011).

Overall, scholarship thus highlights two critical insights: that technical risk – often measured by technology readiness schemes – must be addressed to achieve other milestones, such as fundraising; and that successful commercialization relies on identifying viable market spaces for the SBV's technology. We synthesize these insights into a new concept that we label *application readiness* (AR), defined as the venture's progress in transforming its technological discovery into a commercial solution, thereby capturing its readiness for a market application. We conceptualize AR as consisting of six steps that broadly map onto well-established science-based venture stages: technology discovery (AR=1, "effect demonstrated in laboratory"), technology development (AR=2, "application identified" and AR=3, "technology and application validated in laboratory environments"), market identification (AR=4, "technology and application validated in relevant environments" and AR=5, "prototype ready"), and market application (the most advanced stage of AR: AR=6, "product fully realized"). Figure 1 indicates how an SBV explores potential markets and business models in the market identification phase and implements the discovered solutions in the market application phase. Altogether, the level of analysis is the technology, such that the endpoint of the application readiness scale represents a technology ready for commercialization to be managed by SBV-founders. Application readiness resonates with the Technology Readiness Level (TRL) scale used widely in the aerospace industry (Mankins, 1995), but it is broader in that it represents both technological *and* commercial potential during early-stage science-based venturing.

---Insert Figure 1 about here ---

Advice in emerging science-based ventures: business and technology advice

An advisor's role is defined by several characteristics, starting with loose ties to the venture. Meetings are generally informal and held at a frequency depending on the entrepreneur's needs (Ramsden and Bennett, 2005). In that sense, the advisor relationship differs from that with an investor, as the latter is formally defined by financial interest and accountability. Advisors often support specific firm functions, such as reviewing operations and capital budgets, developing long-term strategic plans for growth, ensuring the proper use of assets, or developing a technology roadmap (Hisrich et al., 2016). Furthermore, advisors offer access to knowledge and resources not readily available and may serve as signals to other resource providers. Their expertise and reputation can compensate for the common liabilities of newness (Rotger et al., 2012), and they may improve the entrepreneur's management skills (Chatterji et al., 2019) or ability to overcome typical setbacks (Patzelt and Shepherd, 2011).

Advisors are popular, with over 80 percent of entrepreneurs reporting the use of at least one (Robson and Bennett, 2000). Private, government, and academic organizations increasingly encourage or even formally require the use of advisors in programs to help scientist-entrepreneurs commercialize their technologies (Belz and Zapatero, 2019; Huang-Saad et al., 2017; Leatherbee and Katila, 2020; Lyons and Zhang, 2018). Despite their popularity and the common assumption that advice benefits young (science-based) ventures, academic support for this is scarce. Some studies find a positive impact (Chrisman and McMullan, 2004; Cumming and Fischer, 2012; Rotger et al., 2012), whereas others report no link (Westhead and Birley, 1995) or even negative effects (Chrisman et al., 2005). The relevant literature is fragmented and indicates that advice effectiveness is linked to many factors, such as the number of advisors, the type of advice, and the specific outcome in question.

Just as studies predict that exposure to diverse sources of information provides the "requisite variety" of ideas and knowledge needed to create innovations (Dahlander et al., 2016), the advice literature typically presumes that the aggregate value and accuracy increases with the number of advisors to reduce the random error of individual recommendations by enabling triangulation between the opinions of multiple, uncorrelated suggestions (Bonaccio and Dalal, 2006). In the context of science-based venturing, knowledge variety at the levels of the technology and the market can be paramount for advancing toward a specific application (Molner et al., 2019; Sullivan and Marvel, 2011). Despite the importance of having domain knowledge in both technology *and* markets for SBVs, most studies on advice have focused only on *business* advice as that advice domain focuses on the identification of target markets and the development of a business model. In this study, we add to the discussion on business advice with an explicit investigation of the impact of *technology* advice.

Business advice

Business advisors provide knowledge of customer problems and markets, as well as information regarding supplier relationships, sales techniques, or capital equipment requirements (Shane, 2000; Urban and Von Hippel, 1988). They take a holistic perspective and can manage complexity, with some possessing the ability to integrate across seemingly contradictory tensions (Smith et al., 2010). This generalist approach can be critical to managing technology commercialization processes comprising numerous constituents and multiple potential market spaces (Fini et al., 2019; Molner et al., 2019). A business mindset that appreciates iterative business model exploration (McGrath, 2010; Teece, 2010) may be instrumental in preparing an emerging SBV for the market (Molner et al., 2019).

Business advisors also bring important network benefits to an SBV. While SBVs typically have strong links to scientific communities, this may not be true for their commercial equivalents (Wright et al., 2007). In those instances, business advisors may compensate by providing access to a network and endowing the entrepreneur with trust and credibility (Hayter, 2016a), by facilitating subsequent resource acquisition from network participants like investors (Zhang et al., 2010), or by giving access to other entrepreneurs' critical technological, market and financial knowledge (McGrath et al., 2003; Shane and Cable, 2002). Often, these support mechanisms help SBVs develop their first distribution and sales channels or even land a first customer. In sum, business advice may help an SBV identify a commercial purpose for its technology and point to the associated resources, contributing positively to the SBV's application readiness. Therefore, we hypothesize:

Hypothesis 1a (H1a): Business advice will contribute positively to emerging SBV application readiness.

Technology advice

Technology advisors offer insights in the newest technical recipes, research and development paths, subsystem or system architecture, or user requirements. Their advice builds on a scientific paradigm with best practices and problem-solving heuristics (Dosi and Nelson, 2010). Many technology advisors are scientists in advanced career stages who can connect the firm with their academic networks or talent (Ding and Choi, 2011). Furthermore, technology advisors may inform the team's scientific strategy and experimental design (Murray and Graham, 2007).

On the other hand, technology experts may persist in scientific habits inspired by steady and solid academic cycles (Furr, 2019), prioritizing norms like invention quality (Ding and Choi, 2011; Owen-Smith and Powell, 2004). Past operating experiences and innovation success may also make them prone to "functional fixedness", or the penchant to use a previously successful problem-solving method, even when it is inappropriate or suboptimal for a new problem (Bilalić et al., 2008; Dane, 2010). Moreover, driven by the hope that good products will eventually sell themselves, technology advisors may undervalue early-stage market-oriented activities, such as rapid prototyping and market testing (Dougherty, 1992; Gruber et al., 2012), focusing instead on lengthy scientific search processes and costly research experiments that potentially limit fast market entrance, hinder pivots, and ultimately application readiness. Although acquiring knowledge from technology advisors' networks may lead to beneficial outcomes, such as higher product innovativeness (Sullivan and Marvel, 2011), this desire may come at the cost of exploring potential market applications and subsequently delay application readiness rather than advance it[1]. We hypothesize:

Hypothesis 1b (H1b): Technology advice will contribute negatively to emerging SBV application readiness.

Advice absorption: the moderating role of the entrepreneur's experience

Scholars have noted that the integration of external information into an organization depends on a venture's ability to translate and internalize it (Dahlander et al., 2016; Tortoriello et al., 2015), as well as on its ability to synthesize new with existing knowledge (Autio et al., 2008; Cohen and Levinthal, 1990; Kogut and Zander, 1992). In line with these scholarly insights and because the

[1] To be clear, we do not expect that technology advice will necessarily have a negative impact on application readiness in the sense that it will lead to a reduction in application readiness (e.g., going from AR = 2 to AR = 1) but rather, we expect that technology advice will not advance AR and may even (temporarily) delay it.

founder-scientist has a central decision-making role (De Jong et al., 2013; Gurdon and Samsom, 2010; Stuart and Ding, 2006), we theorize that external advice absorption rests on a founder's advice-taking capacity (Cumming and Fischer, 2012; Zahra et al., 2019), which we view largely determined by the founder's prior experience (Corbett, 2005).

The relevant founder experience in the SBV context can be deconstructed into entrepreneurial and technology experience (Hsu, 2008). *Entrepreneurial experience* refers to a broad background in starting and managing ventures. It is a more general type of business experience, and can provide the entrepreneur with valuable lessons in sequencing activities and developing approaches to attracting customers, suppliers, and other stakeholders (Dimov, 2010). Entrepreneurial experience is positively associated with successfully founding a business (Rotefoss and Kolvereid, 2005) and initial venture progress (Samuelsson and Davidsson, 2009). On the other hand, *technology experience* describes expertise in research and development, often stemming from an advanced degree (PhD) in a specific scientific, technological, or engineering laboratory (Murray, 2004). Acquiring technology knowledge has been linked to creating breakthrough innovations, new business development project success, and creating economic and cost-related advantages (Sullivan and Marvel, 2011).

We suggest that the effect of advice on SBV application readiness will depend on the specific knowledge combinations of external advice and founder experience. The types of advice (business and technology) and experience (entrepreneurial and technology) form a 2x2 matrix with four possible advice-experience combinations. Two combinations constitute *overlapping* knowledge domains (business advice-entrepreneurial experience and technology advice-technology experience) and two form *complementary* ones (business advice-technology experience and technology advice-entrepreneurial experience). We argue that this latter combination will be most beneficial for SBV application readiness. Figure 2 summarizes our advice-experience framework and associated hypotheses.

--Insert Figure 2 about here--

Overlapping advice. Excessive knowledge focus can cause firms to overexploit existing knowledge and engage in undue search depth (Katila and Ahuja, 2002). While large overlaps in knowledge and experiences support rich intra-domain flows and focus, they limit variation in perspectives (Caner et al., 2017). Such domain focus inhibits the balance of novel and common domain knowledge needed for advancing complex discoveries (Garud et al., 2011). In addition, high overlaps in the entrepreneur's and advisor's knowledge domains can signal affirmative information to the founder, making him/her confident in one particular solution at the expense of better alternatives or more open-ended problem solving. *In extremis,* overlapping advice will only confirm what is already known to the entrepreneur. Overlapping advice-experience combinations may thus stagnate or delay an SBV's application readiness. Consistent with recent evidence that entrepreneurs knowledgeable in the advice domain benefit less from it (Chatterji et al., 2019; Cumming and Fischer, 2012), we formulate the following hypothesis:

Hypothesis 2 (H2). Prior founder experience in the same knowledge domain as the offered advice (i.e., entrepreneurial experience-business advice, or technology experience-technology advice combinations) will negatively moderate the effect of advice on application readiness.

Complementary advice. In contrast, exposure to novel perspectives and unfamiliar knowledge can "shake up" established ideas (Zhou and Li, 2012). For instance, in innovation contests, individuals technically or socially distant from the focal problem were more likely to solve intractable scientific challenges precisely because they brought a novel perspective (Jeppesen and Lakhani, 2010). This is aligned with prior observations of problem solvers arriving at better solutions by making "long jumps" and by exploring solutions based on different hypotheses and functionalities (Levinthal, 1997). In the entrepreneurial context, diversity or unique knowledge contributions can lead to positive startup outcomes (Fern et al., 2012; Furr et al., 2012). Advisors can likewise introduce complementary knowledge challenging the founder's long-standing assumptions derived from earlier encounters with particular venture problems. Moreover, when founders internalize and absorb complementary advice, a novel or a wider knowledge base can be triggered, helping the founder navigate the complex technology commercialization process better. We therefore expect that complementary advice will help advance the SBV's application readiness. Our final hypothesis states:

Hypothesis 3 (H3): Prior founder experience in a knowledge domain complementary to that offered by the advisor (i.e. entrepreneurial experience-technology advice, or technology experience-business advice combinations) will positively moderate the effect of advice on application readiness.

METHODS AND DATA

Sample and data collection

Our sample is drawn from new technology entrepreneurs who elected to participate in training provided by Innovation Node – Los Angeles (IN-LA). These free two-week training sessions on identifying marketplace needs through customer discovery were advertised through university channels, particularly in schools of engineering, life sciences, and natural sciences. Other than a university affiliation requirement, there were no conditions to enter the program. The target audience consisted primarily of doctoral students, post-doctoral fellows, and faculty members. Therefore, our sample does not represent typical student entrepreneurs but rather a population of scientists and engineers with various levels of training, who primarily seek ways to commercialize their basic research. The training program neither required nor assigned advisors. Still, nearly 87% of the firms reported engaging at least one advisor, consistent with previous studies (e.g. Robson and Bennett (2000) record an engagement rate of 84%).

During the training session, we created an opportunity for all participants to respond to our Accelerating Commercialization of Collegiate Engineering and Science (ACCESS) study. We administered a first survey (t=1) to all program participants from December 2014 through November 2017 and allocated time for the survey during the program, leading to an initial response rate close to 100% (307 complete surveys). In our study, we focus on responses from lead founders since they actively build the team, make final decisions, and have the greatest impact on the venture (De Jong et al., 2013). About one year after the initial survey, we distributed a subsequent survey (t=2) measuring our study's dependent variable, application readiness, and obtained a response rate of 36.5% (112 lead founders for 112 nascent ventures), in agreement with that of other studies (Rutherford et al., 2017).

We ran t-tests on all our variables to compare respondents who completed only the first round survey with those respondents completing both rounds. We only found minor significant differences (p<0.05) between the two groups in that those who only completed the first survey round were on average slightly less educated, had fewer founding team members and had raised more external resources. Overall, as none of our core variables (experience, advisors, and application readiness) were affected, attrition bias is unlikely to affect our analysis.

The study design allowed for measuring the independent variables in the initial survey (t=1) and the dependent variable, application readiness, in the subsequent survey (t=2). Common method variance, often of concern in cross-sectional single-respondent studies (Phillips, 1981), is largely alleviated in our study by the one-year time period between both surveys. Nonetheless, using Harman's one-factor test for all study variables (Podsakoff and Organ, 1986), we verified that common method variance was not an issue.

Variables

Dependent variable: Application readiness (t=2).

Our dependent variable is application readiness (AR), which captures a venture's progress in converting a technological discovery into a market application. We measured it using a six-item ordinal ranking based on the widely used nine-level Technology Readiness Level scale of the aerospace and defense industry (Mankins, 1995, 2009). A technology readiness scheme indicates the maturity level as it progresses through research, development and deployment phases. It is frequently used to manage industrial innovation (Magnaye et al., 2010; Ward et al., 2012), and can influence startup investment (Brush et al., 2012). As the original scale was designed for corporate or publicly funded resource-intensive R&D settings and corporate production environments, we adapted it by consolidating the most advanced stages (i.e., migration from prototype to implementation in a production environment) to better measure early progress toward a market application. Furthermore, this consolidation reflects the view that few young science-based ventures and projects operate at the highest levels of technology readiness (De Silva et al., 2018). Our AR scale items then are: 1=*"*effect demonstrated in laboratory*"*, 2=*"*application identified*"*, 3=*"*technology and application validated in laboratory environments*"*, 4=*"*technology and application validated in relevant environments*"*, 5=*"*prototype ready", and 6="product fully realized". Higher values indicate more mature technologies and represent more advanced ventures in terms of product fit in the market. Our data corroborates this: the lowest levels (AR=1 and AR=2) correlate negatively with having identified potential customers or having researched their willingness to pay ($p<0.10$). Conversely, the highest level (AR=6) correlates positively with having identified customers and understanding their willingness to pay, and more importantly, with having generated actual revenues from selling the venture's goods or services ($p<0.05$). Overall, these significant correlations with related measurements provide support for the AR's construct validity.

Independent variables.

We asked respondents to report the total number of advisors of the firm. For their five most important advisors, they provided more detailed information regarding the subject matter (business, technology, both or neither), as well as how well they knew these advisors. Examining only the top five advisors is appropriate because it does not require respondents to recall details about too many individuals (Cowan, 2001), and the maximum number of five falls in the range of 1-10 used previously (Bonaccio and Dalal, 2006). Based on the top five advisors, two independent variables were derived from this data, each having a range of 0-5:

Business advice. This variable measures the number of advisors who provided business advice, according to respondents.

Technology advice. This measure refers to the number of advisors who provided technology advice, according to respondents.

Moderator variables.

Entrepreneurial experience. This measure indicates the number of years the founder had worked in startups prior to the SBV under consideration. This variable is highly correlated with the number of startups the respondents (co-)founded in the past ($p<0.0001$). In our sample, about 37% of respondents indicated having (co-)founded a venture in the past.

Technology experience. This variable measures the number of years the founder had conducted research in a field related to the venture's technology. This variable is an appropriate measure of the founder’s technical experience and was previously shown to contribute to the growth of new technology-based firms (Colombo and Grilli, 2005).

Control variables.

Gender. This dummy variable indicates whether the entrepreneur is male (0) or female (1).

Education. This variable measures respondents’ highest level of education as an ordinal variable with ten categories ranging from 1="up to eighth grade" to 10="Law, MD, PhD and EdD degrees", based on the Panel Study of Entrepreneurial Dynamics (PSED, 2011).

Industry experience. This variable measures the number of years the founder had worked in the new venture's sector (e.g., Dimov, 2010). Such experience can aid growth and survival (Brüderl et al., 1992; Cooper et al., 1994).

Number of founders. We control for the number of founders (including the respondent) because larger teams may have more knowledge and experience and are more likely to reach critical entrepreneurial milestones (Beckman et al., 2007) and survive longer (Geroski et al., 2010).

Business model development. We control for the extent to which the firm’s business model had been developed, since this can be related to the firm’s application readiness. The survey showed respondents a set of 16 items capturing the business model, based on the categorization scheme by Andries et al. (2013), and asked them whether their venture had already made a choice for each business model item. The variable is calculated as the reverse-coded count of the number of business model items for which firms had not yet made a choice. Higher values indicate more developed business models.

Initial application readiness. As technological path-dependencies determine later evolution (Dosi and Nelson, 2010), we control for the initial AR (t=1). This variable can also capture firm-specific effects and was measured using the same six-item scale as the dependent variable.

Resource acquisition. Because resources impact a venture's ability to grow and develop, we determine the venture's progress in acquiring customers, employees, or investors; lacking these resources heavily challenges entrepreneurial ventures in their survival (Zott and Huy, 2007). The variable ranges from 0-3 and captures the venture's success in acquiring these key resources, with 0 = none acquired; 3 = all acquired; and intermediate levels indicate an acquisition of one or two of these resources.

Venture age. We control for the venture's age at the time the dependent variable was measured (t=2) because older ventures will likely have made more progress (Delmar and Shane, 2006).

Elapsed time. This variable captures the amount of time between a respondent's first- and second-round surveys and is included as a control since it could influence a firm's advancements in AR.

Sector. Since technology type may influence application readiness, we used robust standard errors clustered on sector in our analyses. Our sector categories comprise life sciences (34% of firms), engineering (19%), software/data sciences (25%), and other (22%).

Statistical Estimation

Our application readiness variable has six outcomes that represent increasing degrees of AR, forming an ordinal dependent variable. The appropriate regression technique for such ordinal dependent variables depends on (1) the parallel lines assumption; and (2) the evaluation of probabilities (Bauldry et al., 2018). First, a Brant test (e.g., Brant, 1990; Protogerou et al., 2017) established that the parallel lines assumption is not violated in these data. Second, the AR variable as a scale represents an underlying continuous distribution, which means that the standard cumulative approach modeling the probability of being at or below a given value m [$\Pr(y \leq m)$] is suitable (Bauldry et al., 2018). Based on these two determinations, we used an ordered probit model to test our hypotheses (Bauldry et al., 2018).

EMPIRICAL RESULTS

Table 1 shows the descriptive statistics and correlations of our study's variables. The average AR in our sample is 3.30, corresponding to a level between "technology and application validated in laboratory environments" and "technology and application validated in relevant environments". This indicates that the SBVs, on average, had already identified a potential market for their technologies by the time of our second survey. On average, firms had 2.53 founders (including the lead founder), 1.61 advisors providing business advice, 1.32 advisors providing technology advice, and a somewhat developed business model (13.48 on a 16-point scale). Founders had 2.89, 5.98 and 5.04 years of entrepreneurial, technology, and industry experience, respectively, and a master's degree (education=9); females represent 27% of the sample. The maximum VIF in our models was 2.62, well below the suggested cut-off of 10 (Ryan, 1997), thereby suggesting that multicollinearity is not likely to be a problem in this study.

--Insert Tables 1-3 about here--

Table 2 shows the results of our ordered probit regressions, while Table 3 reports the estimated marginal effects at the means (m.e.m.). In Table 2, Model 1 only uses the control variables as regressors and indicates that as expected, a higher initial AR (t=1) leads to a higher AR at t=2 ($p<0.001$), as does venture age ($p<0.01$) and having raised more external resources ($p<0.05$). Model 2 estimates the effects of business advice and technology advice as predictors, and Model 3 estimates the interaction terms with entrepreneurial and technology experience. For business advice, the coefficient in Model 2 is significant and positive ($p<0.05$), suggesting a positive effect on AR. Evaluating the marginal effects of the nonlinear models (Hoetker, 2007) in Table 3 confirms this positive effect: on average, one additional individual providing business advice will decrease the likelihood of a science-based venture having an AR of level 1 or 2 by 3 and 2 percentage points respectively ($p<0.05$ for both). In contrast, one additional unit of business advice will increase the likelihood of having a high AR=4 by 1 percentage point ($p<0.10$) and AR=5 by 4 percentage points ($p<0.05$). These findings are in line with our Hypothesis 1a.

Model 2 estimates an insignificant coefficient for technology advice. In Model 3, the coefficient of technology advice is significant and negative, however. Likewise, the associated marginal effects indicate that technology advice positively contributes to the likelihood of having a low AR (AR=2, $p<0.10$) and negatively to a high AR (AR=5, $p<0.10$), but again only when interaction effects are included. Overall, we thus find tentative, albeit weak, support for a negative relation between technology advice and AR, and thus, for Hypothesis 1b. We also make note of the significant, negative effect of technology experience on AR in Tables 2 and 3.

Hypothesis 2 argued that overlapping advice-experience combinations would negatively moderate the effect of advice on AR. Model 3 estimates a significant and negative coefficient ($p<0.10$) for an overlap in technology advice-technology experience. This is echoed by the estimated marginal effects of Table 3: an increase by one unit lowers the probability of having an AR=5 by 7 percentage points ($p<0.10$). The negative effect of technology advice is thus especially strong for entrepreneurs high in technology experience (as shown in Figure 3)[2]. The results for the technology advice-technology experience combination are aligned with Hypothesis 2. On the other hand, the hypothesized negative effect for the business advice-entrepreneurial experience combination is not seen in our results.

[2] For simplicity, graphs were made using linear regression specifications.

Hypothesis 3 suggested that complementary advice-experience combinations would be associated with higher AR. Model 3 (Table 2) indeed shows a significant, positive interaction effect between business advice and technology experience, and the associated marginal effects in Table 3 are significant and positive for a high AR=5 ($p<0.05$) and significant and negative for a low AR=2 ($p<0.05$) Figure 4a shows this graphically: high business advice combined with high technology experience is associated with the highest AR, validating Hypothesis 3. Model 3 further suggests a significant, negative impact of the technology advice-entrepreneurial experience interaction, giving an estimated marginal effect (Table 3) for both AR=1 and AR=2 of 5 percentage points ($p<0.001$ and $p<0.10$, respectively) and lowering the likelihood of AR=5 by 8 points ($p<0.10$). In contrast to the prediction of H3, entrepreneurial experience amplifies the negative effect of technology advice on AR (Figure 4b). In summary, we find mixed support for Hypothesis 3 in that the two complementary advice-experience combinations do not show equivalent effects on AR.

--Insert Figures 3 and 4 about here--

Robustness checks and additional analyses[3]

Endogeneity. It is possible that less advanced ventures would seek more or different advisors than their more mature counterparts, and that this unobserved heterogeneity – rather than business or technology advice – would predict application readiness. We therefore examined the extent to which potential endogeneity impacts the two main variables, business and technology advice, with two instrumental variables: the lead founders' industry experience; and the advisor search intensity, measured as the total number of advisors (beyond our cap of 5). We used the Conditional Mixed Process (CMP) model developed by Roodman (2011) to predict the potentially endogenous

[3] All robustness tests and additional analyses are available from the authors on request.

variables business and technology advice first, allowing inclusion of instrumented estimates in our ordered probit model. The estimates obtained with these instrumental variables are consistent with the main model's result: we find a positive effect of business advice on AR ($p<0.10$) and a negative effect for technology advice ($p<0.05$). This suggests that our results were not driven by endogeneity.

Alternative model specifications. In the main analysis, we estimated an ordered dependent variable's probabilities with the standard cumulative approach. As a robustness check, we used a continuation-ratio model instead (Bauldry et al., 2018; Hayter, 2016a). Furthermore, we also used an OLS estimation because it may be used for ordinal dependent variables with at least five categories (Rhee and Leonardi, 2018). While the results showed lower statistical significance, our results remained substantially the same.

"Multiplex" advisors as predictors. We differentiated between business and technology advice, but one advisor can offer both types as so-called "multiplex" advisors, who may be more useful (Grossman et al., 2012). To test this effect, we created an explicit predictor variable for advisors offering both business and technology advice. This new variable did not impact AR nor alter the main results.

Source of AR assessment. Because AR is a self-reported variable, a potential overestimation of AR could influence our results. We therefore included a question in our survey that asked: "On which of the following sources is the above assessment of AR based?" Respondents could answer "personal experience", "co-founder experience", "potential partners/customers", "industry/technology experts", or "other". We created a dummy variable based on this response with 1 = "AR assessment based on an external source" (i.e., potential partners/customers or industry/technology experts), and with 0 = "AR assessment based on personal/co-founder experience" and included this in our analyses. This predictor did not affect the results, indicating that AR overestimation by founders was unlikely to bias the analysis.

Advisor closeness. The effectiveness of advice may depend on the tie strength between the advisor and the advice-taker, and a tie's perceived usefulness can depend on the closeness with the focal entrepreneur (Grossman et al., 2012; Kuhn et al., 2016). Since closeness is one of the strongest unidimensional measures of tie strength (Marsden and Campbell, 1984; Perry-Smith, 2006), we controlled for the perceived closeness using the measure of Zhang et al. (2010): "To what extent do you agree that you kept a close relationship with each other prior to starting the advisor relationship?" ranging from 1= "do not agree" to 7= "completely agree". Our results were not affected by including this additional variable.

Possibility of non-linear relationships. The main model focused on the five most important advisors. Given this relatively low number, we did not expect a(n inverted) U-shaped relation between the number of advisors and AR. Nonetheless, we tested the squared terms of business and technology advice in our regressions and found that the associated coefficient for technology advice was positive and moderately significant ($p<0.10$), thereby pointing towards a potential U-shaped relation between technology advice and application readiness. However, the squared term of business advice did not have a significant coefficient or impact on our results.

DISCUSSION

Science-based ventures play a crucial role in converting basic research into outcomes such as innovations and economic value (Fini et al., 2019; George et al., 2016). Academic work on SBVs has grown over the last decade (Fini et al., 2019; Tartari et al., 2014) and has increasingly focused on the technology-market linking process (Danneels, 2002; Molner et al., 2019; Rotolo et al., 2015). However, our understanding of how inventions are transformed into commercial applications is still limited by both the paucity of data at the earliest stages of ventures' coalescence and the lack of a valid construct to capture progress prior to traditional economic outcomes. To address this gap, we introduced and defined application readiness to capture a venture's progress in transforming its technological discovery into a commercial solution. This measure synthesizes the increased tendency to manage market elements early (Blank, 2013; Ries, 2011) with standardized technology readiness tools for private and public investors (Conti et al., 2013; Magnaye et al., 2010; Ward et al., 2012). We anticipate that this measure can contribute to comparative studies of processes and factors driving technology translation.

Our findings show that advice impacts an SBV's application readiness. Many new ventures rely on external advice (Robson and Bennett, 2000), and entrepreneurial support organizations such as incubators, accelerators, and publicly funded programs encourage the use of external advice or even require it (Huang-Saad et al., 2017; Leatherbee and Katila, 2020; NSF, 2017; Pauwels et al., 2016) Despite this trend, our previous understanding of whether and when advice actually helps new ventures was mixed at best (Chrisman et al., 2005; Chrisman and McMullan, 2004; Rotger et al., 2012). This work directly speaks to this divide by disentangling business and technology advice in emerging science-based ventures (Clayton et al., 2018; Markman et al., 2008). Our findings show which type of advice matters: business advice advances SBV application readiness, while technology advice retards it.

Early-stage technology commercialization involves bridging unconnected scientific fields to create radical discovery and innovation (Rosenkopf and Nerkar, 2001). In that sense, connecting technology advisors to science-based ventures seems reasonable to support design and prototyping (Ahsan et al., 2018), but our findings do not support this. It seems more beneficial – at least with regard to advancing application readiness - to connect emerging science-based ventures to business advisors than with technology advisors.

Moreover, advice is most helpful when it complements, rather than reinforces the lead founder's experience, consistent with studies on knowledge diversity in entrepreneurial teams (Fern et al., 2012; Gruber, 2010; Gruber et al., 2012), novel framing (Furr et al., 2012) and experimentation during technology venturing (Patel et al., 2015). The beneficial business advice-technology experience combination supports the importance of a holistic perspective common in other humanistic disciplines to bridge the technology-market gap of science-based venturing (Smith et al., 2010). On the other hand, the detrimental effect of the overlapping technology experience-technology advice combination resonates with evidence that participants in a technology entrepreneurship program benefit less if they already have the skill set (Lyons and Zhang, 2018) and that specialist knowledge flows may not contribute to firm and technology evolution (Furr, 2019). When the founder and advisor have high knowledge overlaps in the technology domain, the technology may advance but at the expense of market insight, and thus, at the expense of application readiness. It is clear that the relationship between advice and SBV application readiness is complex and depends on multiple factors, such as the type of advice, the number of advisors, and the knowledge base of the entrepreneur.

Our study also offers a broader perspective to the literature on human capital in SBVs that to date has mostly focused on key founding team members, their commercial motivations (Jain et al., 2009), status (Stuart and Ding, 2006), career levels (Ding and Choi, 2011; Tartari et al., 2014) and composition (Knockaert et al., 2011). Emerging ventures have fluid identities and unclear boundaries (Rindova and Kotha, 2001; Santos and Eisenhardt, 2009); evidently, the knowledge imparted at the venture's boundaries influences SBVs' initial progress and commercial outcomes.

This analysis thereby adds to a growing literature stream demonstrating how success in the firm's earliest stages may depend on actors beyond the key founders (Choi et al., 2019; Nair et al., 2020).

In the context of policies supporting university spinoffs, this study has critical implications. These findings suggest that institutionalized advisory roles – especially in business – supporting the coalescence of deep technology startups (Cohen et al., 2019; Huang-Saad et al., 2017; Leatherbee and Katila, 2020; NSF, 2017) can perhaps lead to better outcomes. Following venture launch, a second important setting is the subsequent phase in which young firms are publicly supported through technology development programs, such as the Small Business Innovation Research (SBIR) program. In the SBIR context, experience has a direct effect on selection for the award and progress (Link and Wright, 2015) – presumably posing a barrier for university spinoffs led by early-career scientists. The support of advisors can potentially help mitigate these effects. Finally, smaller firms (1-5 employees) yield a larger variation in programmatic outcomes in SBIR, producing both the lowest and highest values (Belz et al., 2019). Perhaps embedding business advisors in that program would facilitate more consistent progress.

Limitations and Future Research Avenues

Technology commercialization is an iterative process and requires revisions of and iterations between multiple technology-market configurations. This revisiting process is non-linear and a firm may regress back to lower levels of application readiness as it re-engages in discovery (Ambos and Birkinshaw, 2010). Nonetheless, high levels of AR are correlated with having sales, and investors and governments look at readiness as an important signal of emerging SBV quality (Brush et al., 2012; Conti et al., 2013; Magnaye et al., 2010). Therefore, gaining a better understanding of the factors that accelerate AR is important.

We report the intriguing finding that ventures led by female founders have a lower application readiness than those led by their male counterparts, even when controlling for advisors, founder education and experience, resource acquisition and venture age. In line with past research (Smith et al., 2020), this finding indicates that entrepreneurial support systems should specifically pay attention to women in supporting entrepreneurs, and should take care when matching female entrepreneurs with advisors.

Our post-hoc analyses suggest a non-linear, U-shaped relationship between the number of technology advisors and AR; future research could explore optimizing the number of advisors. Another potentially important factor is variation in advisor quality, function, affiliation or experience. This unobserved heterogeneity could impact our outcome variable or others. Future research could investigate this further.

Finally, we focused on two knowledge domains – business and technology – because an SBV fundamentally operates at an equilibrium optimizing both. However, the domains could be reorganized in other ways, such as operational or strategic background, industry, or along other dimensions. It would be interesting to understand more broadly which domains affect outcomes.

CONCLUSION

Our study explored the impact of advice on application readiness – a novel construct capturing the transition of a technological discovery to the marketplace. We found that advice can accelerate application readiness, particularly advice on business matters. Moreover, advice that complements an entrepreneur's knowledge base rather than overlaps with it is generally more beneficial. This work extends ongoing discussions in scholarship regarding technology entrepreneurship, innovation and advice, and has actionable implications for public and private entrepreneurial support organizations.

Table 1 – Descriptive statistics and correlations

	Mean	Std. dev.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. Application readiness (t=2)	3.30	1.58	1.00													
2. Gender (female)	0.27	0.44	-0.10	1.00												
3. Education	8.99	1.28	-0.11	0.05	1.00											
4. Industry experience	5.04	8.07	0.07	-0.10	0.02	1.00										
5. Number of founders	2.53	1.29	0.00	0.02	0.11	-0.02	1.00									
6. Business model development	13.48	2.85	0.25**	-0.15	-0.11	0.08	-0.09	1.00								
7. Initial application readiness	3.19	1.56	0.54**	-0.07	-0.15	0.17	-0.08	0.22*	1.00							
8. Resource acquisition	0.41	0.72	0.31**	0.13	-0.16	-0.07	-0.17	0.25**	0.24*	1.00						
9. Venture age	1.20	1.57	0.23*	0.05	0.04	0.23*	0.14	0.03	0.28**	0.14	1.00					
10. Elapsed time	0.97	0.50	0.07	0.14	-0.01	0.03	0.02	-0.06	-0.01	-0.09	-0.01	1.00				
11. Entrepreneurial experience	2.89	5.12	0.11	0.04	-0.08	0.55**	-0.02	0.22*	0.06	0.01	0.33**	-0.10	1.00			
12. Technology experience	5.98	6.56	-0.01	0.06	0.29**	0.51**	0.16	-0.04	0.14	-0.02	0.33**	0.12	0.36**	1.00		
13. Business advice	1.61	1.37	0.17	0.20*	-0.09	0.16	0.12	0.18	0.13	0.24*	0.30**	-0.14	0.25**	0.01	1.00	
14. Technology advice	1.32	1.20	-0.00	0.19*	0.08	0.34**	0.23*	0.01	0.00	0.12	0.20*	0.11	0.17	0.20*	0.52**	1.00

n = 112

*p<0.05, **p<0.01

All independent and control variables were measured at the time of the first survey, while the dependent variable AR was measured at the time of the second survey, and the variable "Elapsed time" captures the time between the first and the second survey.

Table 2 – Ordered probit regressions: Dependent variable = Application readiness (*t*=2)

	Model 1		Model 2		Model 3	
	Coeff.	*Std. error*	*Coeff.*	*Std. error*	*Coeff.*	*Std. error*
Gender (female)	-0.26	0.20	-0.30†	0.17	-0.37**	0.12
Education	-0.01	0.04	0.06	0.07	0.05	0.11
Industry experience	-0.00	0.01	0.00	0.01	0.02	0.02
Number of founders	0.06*	0.02	0.09*	0.04	0.09**	0.03
Business model development	0.04	0.05	0.02	0.05	-0.00	0.05
Initial application readiness	0.37***	0.07	0.39***	0.07	0.39***	0.07
Resource acquisition	0.36*	0.15	0.39***	0.11	0.47***	0.11
Venture age	0.06**	0.02	0.05*	0.03	0.03	0.04
Elapsed time	0.25*	0.12	0.41*	0.17	0.43**	0.16
Entrepreneurial experience			0.14	0.10	0.15	0.09
Technology experience			-0.22*	0.11	-0.09	0.19
Business advice			0.14*	0.06	0.16**	0.05
Technology advice			-0.14	0.16	-0.18†	0.10
Business advice x Entrepreneurial experience					0.11	0.13
Technology advice x Technology experience					-0.24†	0.12
Business advice x Technology experience					0.21†	0.11
Technology advice x Entrepreneurial experience					-0.27*	0.12
McFadden's Pseudo R^2	0.12		0.14		0.15	
AIC	334.93		329.76		322.93	

n = 112

***p≤0.001, **p≤0.01, *p≤0.05, † p≤.10 Two-tailed significance tests reported.

All standard errors are robust standard errors, clustered on industry sector.

AIC = Akaike information criterion. Models with lower values of AIC are preferred.

All independent and control variables were measured at the time of the first survey, while the dependent variable AR was measured at the time of the second survey, and the variable "Elapsed time" captures the time between the first and the second survey.

Table 3 – Marginal effects from the ordered probit estimations

	AR = 1		AR = 2		AR = 3		AR = 4		AR = 5		AR = 6	
	m.e.m.	*Std. error*	*m.e.m.*	*Std. error*	*m.e.m.*	*Std. error*	*m.e.m.*	*Std. error*	*m.e.m.*	*Std. error*	*m.e.m.*	*Std. error*
Model 1 (Controls only)												
Gender (female)	0.06	0.05	0.04	0.03	0.01	0.01	-0.02*	0.01	-0.08	0.06	-0.01	0.01
Education	0.00	0.01	0.00	0.01	0.00	0.00	-0.00	0.00	-0.00	0.01	-0.00	0.00
Industry experience	0.00	0.00	0.00	0.00	0.00	0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00
Number of founders	-0.01**	0.00	-0.01†	0.00	-0.00	0.00	0.00†	0.00	0.02†	0.01	0.00	0.00
Business model development	-0.01	0.01	-0.01	0.01	-0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00
Initial application readiness	-0.07**	0.02	-0.06***	0.01	-0.02	0.01	0.02	0.02	0.11***	0.02	0.01	0.01
Resource acquisition	-0.07**	0.03	-0.06*	0.03	-0.02	0.01	0.02	0.02	0.11*	0.05	0.01	0.01
Venture age	-0.01*	0.01	-0.01***	0.00	-0.00	0.00	0.00	0.00	0.02***	0.01	0.00†	0.00
Elapsed time	-0.05	0.03	-0.04*	0.02	-0.01†	0.01	0.02	0.02	0.08**	0.03	0.01	0.01
Model 2 (Main effects model)												
Entrepreneurial experience	-0.03	0.02	-0.02	0.02	-0.01*	0.00	0.01	0.01	0.04	0.03	0.00	0.01
Technology experience	0.04†	0.02	0.04†	0.02	0.01	0.01	-0.01	0.01	-0.07†	0.04	-0.01	0.01
Business advice	-0.03*	0.01	-0.02*	0.01	-0.01†	0.00	0.01†	0.01	0.04*	0.02	0.00	0.00
Technology advice	0.03	0.03	0.02	0.03	0.01	0.01	-0.01	0.01	-0.04	0.05	-0.00	0.01
Model 3 (Full model)												
Entrepreneurial experience	-0.03	0.02	-0.03	0.02	-0.01	0.00	0.01	0.01	0.05	0.03	0.00	0.01
Technology experience	0.02	0.03	0.01	0.03	0.00	0.01	-0.01	0.01	-0.03	0.06	-0.00	0.01
Business advice	-0.03*	0.02	-0.03**	0.01	-0.01	0.00	0.01	0.01	0.05**	0.02	0.00	0.00
Technology advice	0.03	0.02	0.03†	0.02	0.01	0.01	-0.01	0.01	-0.06†	0.03	-0.00	0.01
Business advice X Entrepreneurial experience	-0.02	0.02	-0.02	0.02	-0.00	0.01	0.01	0.01	0.03	0.04	0.00	0.00
Technology advice X Technology experience	0.04†	0.02	0.04*	0.02	0.01	0.01	-0.02	0.02	-0.07†	0.04	-0.01	0.00
Business advice X Technology experience	-0.04	0.03	-0.04*	0.02	-0.01	0.01	0.01	0.02	0.06*	0.03	0.00	0.00
Technology advice X Entrepreneurial experience	0.05***	0.01	0.05†	0.02	0.01	0.01	-0.02*	0.01	-0.08†	0.05	-0.01	0.01

Marginal effects (m.e.m.) of the control variables are only shown for the controls model because of space considerations.

Marginal effects for independent variables, moderators, and interaction variables are shown for the main effects and full models.

Marginal effects are computed at the means.

***p≤0.001, **p≤0.01, *p≤0.05, † p≤.10 Two-tailed significance tests reported.

Figure 1 – Conceptual model of application readiness in science-based ventures.

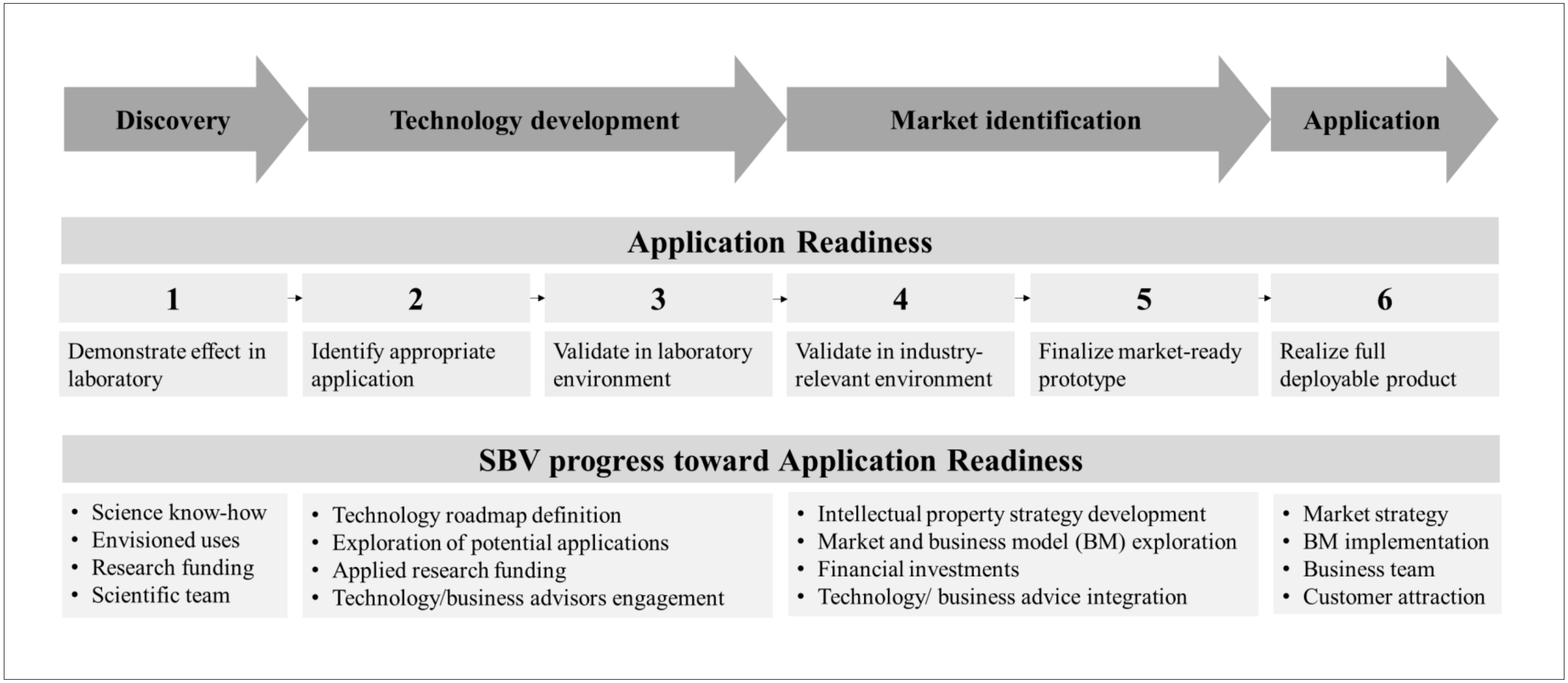
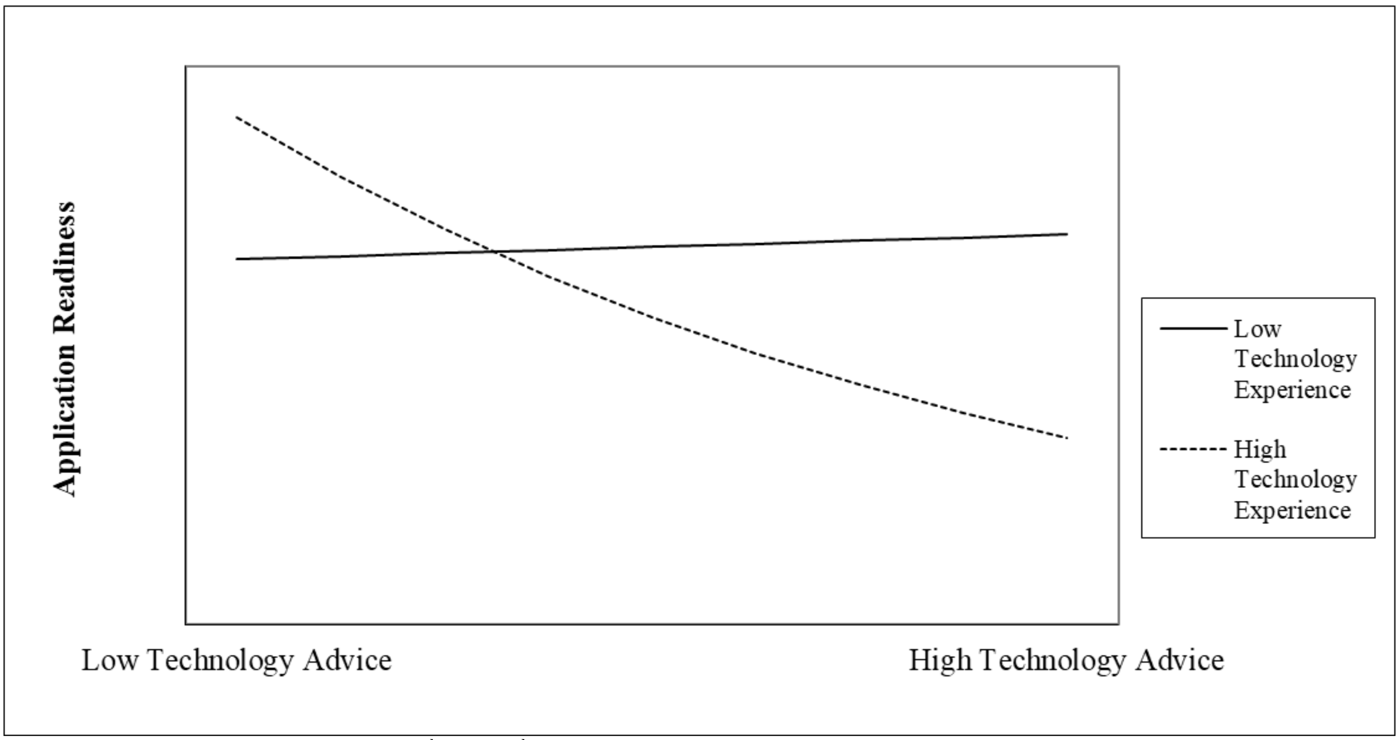


Figure 2 – Hypotheses

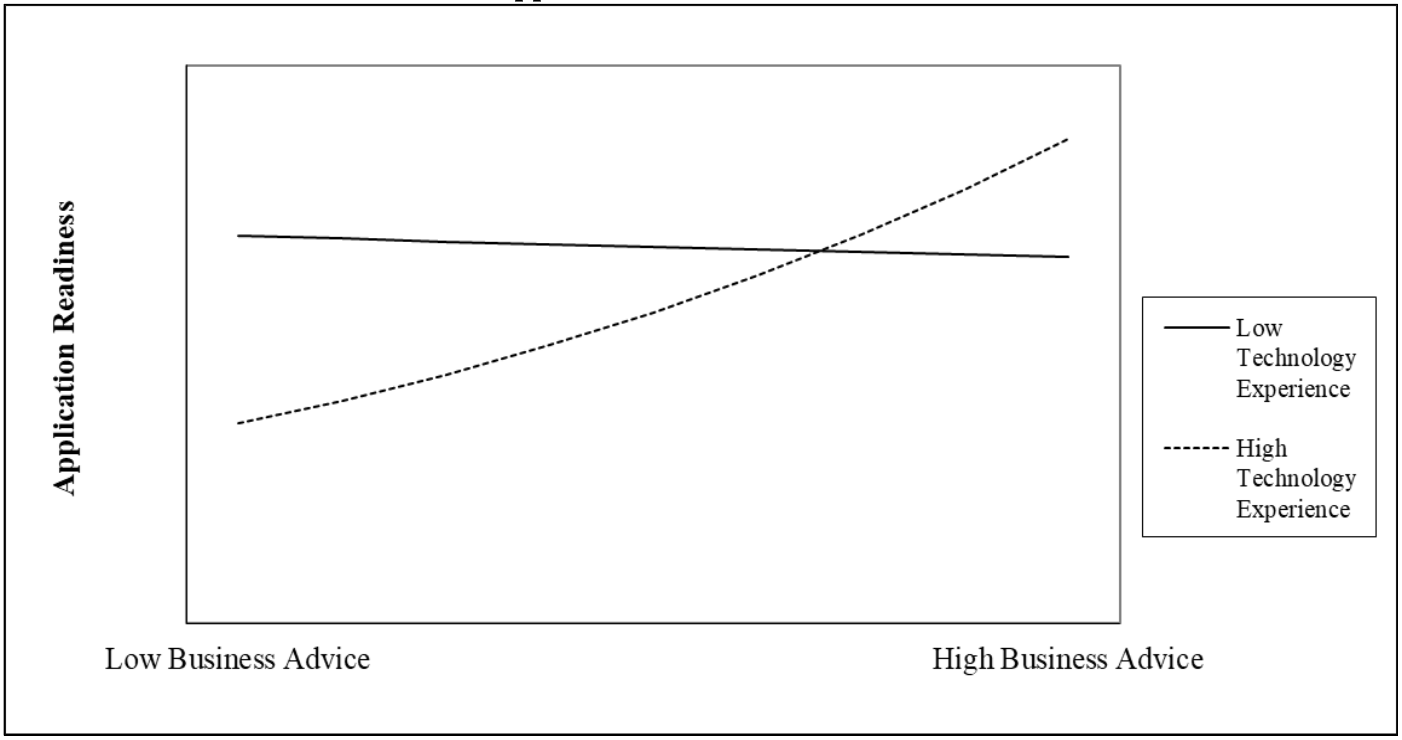
		Advice domain	
		Business *[H1a (+)]*	**Technology *[H1b (-)]***
SBV founder experience	**Entrepreneurial**	Overlapping *[H2 (-)]*	Complementary *[H3 (+)]*
	Technology	Complementary *[H3 (+)]*	Overlapping *[H2 (-)]*

Figure 3 – Knowledge overlap as interaction effect: Impact of technology experience and number of technology advisors on application readiness



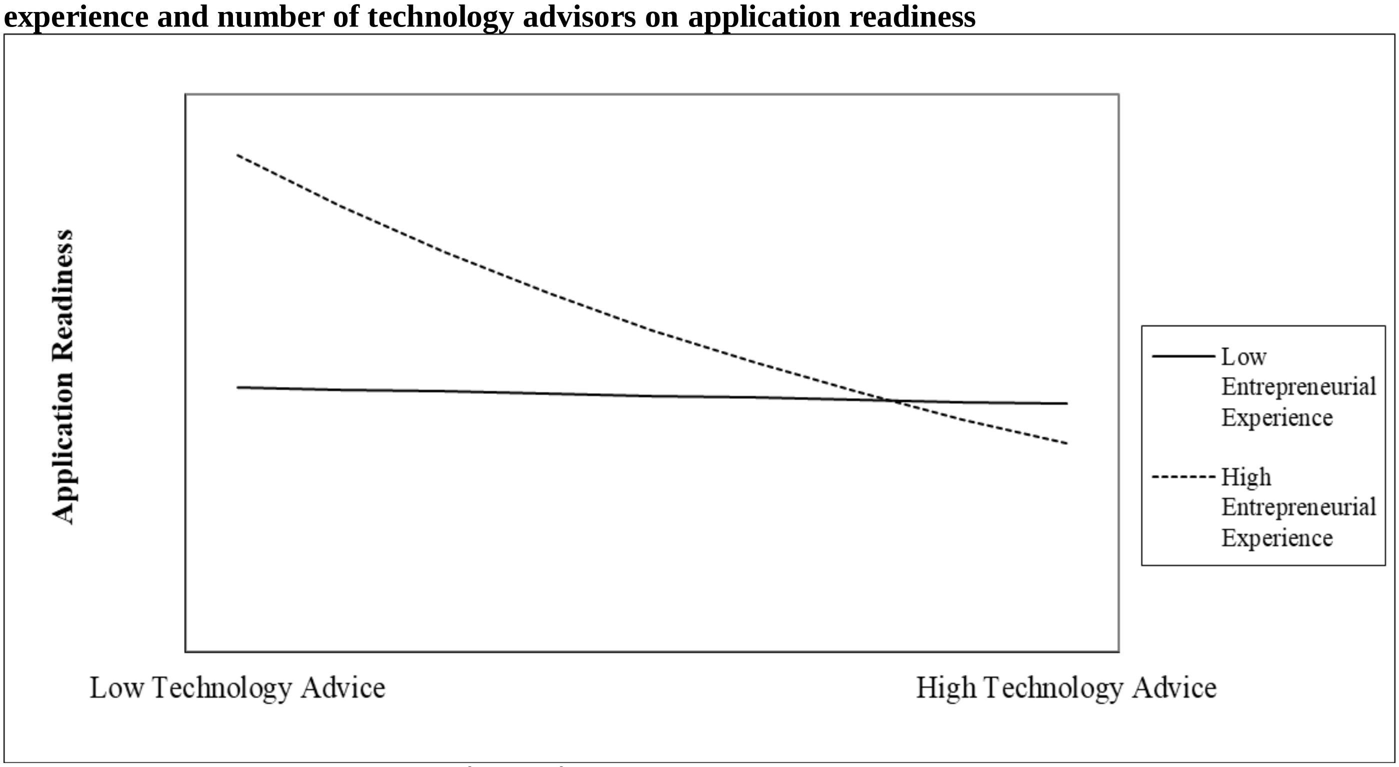
Low/High Technology experience = 10th and 90th percentile values of technology experience

Figure 4a – Complementary knowledge as interaction effect: Impact of technology experience and number of business advisors on application readiness



Low/High Technology experience = 10th and 90th percentile values of technology experience

Figure 4b – Complementary knowledge as interaction effect: Impact of entrepreneurial experience and number of technology advisors on application readiness



Low/High Entrepreneurial experience = 10th and 90th percentile values of technology experience

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