Business Model Choice Matters: How Business Models Impact Different Performance Measures of Startups

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Abstract. Determining the influencing factors of business performance is an important topic in theory and practice. This applies especially to the entrepreneurship context, characterized by extreme uncertainty and high failure rates. Existing research, which is mainly qualitative, has identified business models (BM) as a performance determinant. This paper empirically examines the relationship between BMs and startup performance. The analysis follows an industry- and region-independent approach and is based on a dataset of 121 startups. The findings reveal that some BM patterns outperform others, but on different performance measures. More specifically, the contractor pattern enhances revenue, add-on highly influences growth, customer lock-in boosts valuation, and advertising enhances funding. On the theoretical level, this paper enriches the qualitative research with statistical evidence. On the practical level, it adds value to both entrepreneurs and investors by identifying successful patterns. The findings guide entrepreneurs in BM design and support investors when considering potential investment opportunities.

Keywords: Business model, business model pattern, startup performance, survey, quantitative research

1 Introduction

Startups are crucial economic participants, because they boost economic growth [1], create most new jobs [2], and drive innovation [3]. Nevertheless, startups are characterized by high failure rates, estimated to reach 90% [4]. It is, therefore, essential to investigate the reasons for startup success and failure to improve their chances of success. Some scholars have already explained the high failure rate by financial factors [4], entrepreneurial talent [5], "entry mistakes," industry-specific conditions [6], etc. Others have linked venture performance to the employed business model (BM) and have explored the association between these two constructs [7, 8].

Previous studies have shown that the BM indeed matters for performance and can enhance the competitive advantage [9, 10]. Nevertheless, most studies are qualitative or conceptual [8, 11], lacking statistical evidence to prove the correlation between

BMs and business performance. Other studies are quantitative or empirical, but, they focus on certain industries [12, 13] or regions [14], restricting the generalizability of the results. To the best of our knowledge, no study has quantitatively examined the correlation between BMs and business performance based on large-scale data with a region- and industry-independent focus. Our study bridges this research gap by empirically examining the BM as an influencing factor for startup performance while adopting an industry- and region-independent approach. We address the following research question: *How do applied BM patterns (BMP) correlate with startup success?*

Our research follows three-phases. First, we gathered relevant literature handling the influence of BMs on venture performance to build a foundation for presenting new results. Second, we developed a survey to capture data on applied business model patterns (BMP) and startup performance. Our survey reached 121 startups from Europe, Asia, and America. Third, we performed a contingency analysis on four models related to performance measures, i.e., revenue, growth, valuation, and funding.

This study has valuable contributions on theoretical and practical levels. It accentuates the role of the BM as a theoretical unit of analysis in entrepreneurship and strategy and addresses its importance as a determinant for startup performance. Furthermore, our findings support entrepreneurs through the process of BM design by providing clear guidance on BMPs with higher success potential. Our results also help investors when assessing potential investment opportunities.

2   Theoretical Background

The BM describes how an organization creates, delivers, and captures value [15] and enables a business to successfully develop its strategy [16]. Related literature that has tackled the BM as an influencing factor for firm performance can be structured into two main categories: qualitative (i.e., conceptual) or quantitative (i.e., empirical). Qualitative research has shown that the BM matters for business performance [17-19]. BM innovation can represent a powerful competitive tool [7, 20] that enables companies to gain competitive advantage [21-23]. Firms compete not only via their products or processes but also through their BMs [9]. The BM is as, or even more, important than the product [20], meaning that it has a considerable impact on performance. The economic value of a given technology can only be revealed when it is put to use via a BM [24]. To conclude, qualitative studies have conceptually addressed the BM as a determinant for business performance.

Quantitative research further corroborates the existence of an association between BMs and firm success and reveals that some BMPs perform better than others [25-29]. For example, the advertising pattern has been proven to have a high success chance [25]; the premium pattern has been shown to enhance the success of e-businesses [27]; and multi-sided markets have been shown to empower the performance of "big-bang disruptors" [26]. However, these results suffer one major limitation: they are limited in terms of generalizability because the studies focus on a

certain region or industry. Businesses, like Amazon, expand in new industries and need successful and generally applicable BMPs to further enhance their performance.

To summarize, a large part of the BM literature is qualitative [8, 11, 30] and does not present statistical evidence on the BM as a determinant for business performance. Yet, extant empirical studies are non-generalizable, because they have a limited geographical or industrial scope [8]. We bridge this research gap by carrying out a quantitative analysis with an industry- and region-independent scope. This research is of special theoretical and practical relevance in the entrepreneurship context.

3 Data and Methods

3.1 Sample and Data Collection

We conducted this empirical research focusing on startups founded in 2015. We considered startup age the determining criterion in the sample definition process because the age reveals whether a startup is mature enough to be evaluated. In accordance with many previous studies, we argued that a 4-year period is sufficient for an entrepreneur to fully establish a business [31]. Some entrepreneurship experts have argued that a product needs about 3 years to become profitable [32]. In a 4-year period, a startup becomes mature enough to be evaluated. Additionally, practitioners suggest that the greatest competitive pressures appear 4–6 years after founding [33]. These results support our choice of 4-year-old startups as a proper sample.

To ensure that the sample is representative for many regions and industries, we used a stratified sampling method [34]. The startup population included in the CrunchBase[1] database was segmented into mutually exclusive strata depending on the headquarter region. Startups from each subgroup were randomly selected to support many represented regions in the sample. We sent the survey invitations to the participants via email. The invitations were guided by the following items. First, the purpose and the context of the survey were explained. Second, the participation was voluntary. Third, answers were to remain confidential and anonymous, and only an aggregated total result would be reported. Finally, the participation incentive (i.e., providing the participants with a BM benchmarking) was communicated.

We applied a methodological, between-method triangulation [35] using primary and secondary data to validate the performance measures. Secondary data about revenue, funding and valuation were drawn from CrunchBase whereas primary data were measured by the survey. We compared primary and secondary data and validated the correctness of revenue, funding and valuation measures from the survey. Growth data were not validated as the growth rates were not available in Crunchbase. We did not find inconsistencies in the data.

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[1] https://www.crunchbase.com/

3.2 Survey Development

In agreement with the research question and the survey objectives, the questionnaire included three parts. The first section comprised questions about BMPs to evaluate the extent to which the startups relied on a certain BMP. The second section gathered information about startup performance regarding its current valuation, funding, annual revenue, and expected revenue growth. We mainly opted for closed questions with interval categories. Asking for exact numbers about profitability may result in many respondents refusing to answer. Therefore, the performance section consisted of closed questions followed by a free-text field, in case the participants wished to convey exact numbers. We included a "No answer/ I do not know" option in the response alternatives to eliminate potential bias and to reduce noise in the data. The third section was the feedback section. The questionnaire used the LimeSurvey software.

The questionnaire was evaluated with multi-method testing [36] and endured several feedback loops. First, the authors performed an initial assessment of the questions and went through many improvement iterations among themselves. Second, multiple experts and researchers reviewed the questionnaire. Their feedback led to some modifications of the scale points and the BM definitions. Third, we used the card-sorting technique to validate the understandability of the questions. As part of an online exercise[2], 16 participants with a BM background were asked to assign every item to one of the following categories: revenue streams and payment/ pricing models; value proposition; and channels and relations to external actors. Obtained clusters are illustrated in Table 1. The card-sorting exercise had an average completion rate of 89%, explaining why some percentages in a row did not add up to 100%. Here we only report the names of the BMPs; the actual exercise also contained BMP definitions/ the items.

Table 1. Card-sorting results

Business Model Pattern	Revenue streams and payment/ pricing models	Value proposition	Channels and relations to external actors
Freemium	**93%**	0%	7%
Subscription	**93%**	0%	7%
Pay-per-use/ pay as you go	**93%**	0%	7%
Advertising model	**79%**	14%	7%
Add-on	**71%**	29%	0%
Cross-selling	7%	**86%**	0%
Data-as-a-service	7%	**86%**	7%
Long tail	7%	**71%**	21%
Premium	36%	**64%**	0%
Contractor	7%	**64%**	29%

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[2] https://www.usabilitest.com/

Crowdsourcing	14%	14%	**71%**
Multi-sided platform	0%	29%	**71%**
E-shop	0%	21%	**71%**
Customer lock-in	14%	14%	**64%**
Ultimate luxury	14%	36%	**50%**

The existence of clear majority patterns validates the understandability of most pattern definitions. Nevertheless, the classification of some BMPs, such as *ultimate luxury* or *customer lock-in*, was not explicitly unique. After obtaining feedback from the participants, we confirmed that the classification was not due to a lack of understandability or to confusion, but rather to the nature of these patterns that incorporate multiple BM elements. Finally, we conducted a pilot-test among 21 startups. This number measures up to the suggested number from the literature (i.e., 10 to 30 participants) [37, 38]. Participants could provide feedback after completing the questionnaire. Answers from the feedback section were continuously checked. Owing to the positive and neutral feedback, no modifications were made at this stage.

3.3 Measures

Table 2. Operationalization of the BMPs.

Dim.	BMP	Operationalization / survey item
Revenue streams and payment/ pricing model	Subscription	We follow a subscription model where we regularly charge upfront fees.
	Advertising	We mix our product or service with advertising.
	Pay per use/ Pay as you go	We charge for the duration or intensity of the usage of our product or service.
	Freemium	We offer basic services or a trial for free and charge for a premium version or a special feature.
	Add-on	We offer a basic product at a competitive price and charge for several extras.
Value proposition	Premium	Compared to our competitors, our offering has a higher price and is superior in terms of product, service, experience, or brand.
	Contractor	We sell services provided primarily by people, such as consulting, construction, education, personal care, package delivery, live entertainment, or healthcare.
	Long tail	We focus on selling a large number of niche products, each of which sells relatively infrequently.
	Data as a Service	We offer information as a core value proposition. Our key resource is data.
	Cross selling	We offer complementary products or services in addition to standard ones. Thus, single-product buyers become multi-product buyers.
Ch	E-shop	We have a web shop where we sell our products or services online.

Crowd-sourcing	We outsource activities to the crowd (e.g., an internet community).
Multi-sided platform	We bring together two or more groups of customers, where the presence of each group creates value for the others.
Ultimate luxury	We focus on selling our products or services to the top-tier customers of the income pyramid.
Customer lock-in	Our customers are bound to our ecosystem and have high switching costs.

Independent Variable: BMP. BMPs are reusable, general, and abstract BM elements with similar characteristics, behaviors or building blocks [9, 15, 39]. Based on the 55 BMPs collection elaborated by Gassmann (2017) [9], we derived a core selection of 15 patterns to keep the survey short and motivate startups to participate [36]. The operationalization of the chosen BMPs is depicted in Table 2.To validate that our core selection is representative and collectively exhaustive, we structured it along the following three dimensions: revenue streams and payment/ pricing model (How? Value?); value proposition (What?); and channels and relations to external actors (Who?) [9]. Each BMP is operationalized via a Likert scale ranging from 1 (core of our business), 2 (part of our business), to 3 (not part of our business) to evaluate the extent to which the startups relied on a certain BMP.

Dependent Variable: Startup Performance. When capturing startup performance, it is essential to perceive the complex and multidimensional nature of this construct [40-43]. Some business activities may have a positive effect on one performance dimension and a negative effect on another [43]. Thus, we measured performance by using multiple key performance indicators (KPI), such as total revenue in the last financial year, annual total revenue growth, current valuation, and total funding amount.

Financial indicators are important performance measures [40, 44, 45]. In line with the results of the German Startup Monitor of KPMG (2017)[3], we used the following two important metrics that reflect the financial performance of a startup: total revenue in the last financial year and total funding amount. The valuation of early-stage ventures is an integral part of the entrepreneurial journey [46] that reveals startup performance, because the valuation can be adjusted in each investment round, depending on the performance [47]. Growth is an important KPI [40, 43, 48-50] that can be more meaningful and representative than short-term profitability because some businesses prioritize long-term growth over temporary profit [40, 51].

3.4   Validity of the Performance Construct

Evaluation of Internal Consistency. Using R, we computed Cronbach's alpha, to evaluate how closely related the KPIs are. Cronbach's alpha was equal 0.70, suggesting that the performance items had good internal consistency [52]. The

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[3] https://deutscherstartupmonitor.de/fileadmin/dsm/dsm-17/daten/dsm_2017.pdf

composite reliability was equal to 0.80, a value well above the 0.70 threshold, emphasizing good internal consistency [53].

Investigation of Dimensionality. To rigorously verify the validity of the performance construct, we also evaluated its dimensionality by performing an exploratory factor analysis [50, 54]. We first determined the optimal number of factors to be extracted. Both the Kaiser criterion (analytical method) and the scree test (graphical method) suggested the optimal number of factors as "2". Then, we executed the EFA and opted for an oblique rotation, because the correlation matrix (not reported) shows an obvious correlation within the four KPIs [54]. The EFA results reveal that *revenue*, *valuation*, and *funding* load on the one factor with factor loadings of 0.65, 0.93, and 0.68, respectively; whereas *growth* loads on the other factor with a loading of 0.98. This finding was quite expected when considering the difference between short- and long-term performances. We further discuss these findings in the discussion section.

Evaluation of Common Method Bias (CMB). To test whether CMB is a concern, we used Harman's one-factor test, in which all items were loaded into one factor using an EFA to determine whether the majority of the variance could be accounted for by only one factor [55]. The Harman's one-factor test revealed that one general factor explained only 11% of the variance, which is obviously less than 50%, suggesting the absence of one dominant factor. Therefore, it can be concluded that CMB is very unlikely to exist and that the data are not affected.

4 Data Analysis

4.1 Contingency Analysis

We chose contingency analysis as the method to examine the dependency between the applied BMPs and performance because the two variables were on a nominal scale [54]. We applied a contingency analysis on four models. Each model tested the association between the BMPs and a respective KPI (i.e., revenue, growth, valuation, and funding). We structured our analysis in two steps. First, the existence of a systematic dependency between each BMP and the respective KPI was examined by performing a Yates corrected Chi-square (χ^2) test and an exact Fisher test [54]. Second, the dependency's direction and strength were determined by computing the contingency coefficient and the Cramer's V for each model [54].

Table 3. Statistically significant results of the contingency analysis

Model	Significant BMPs	χ^2 value	χ^2 p-value	Fisher p-value	Contingency coef.	Cramer's V
Revenue	Contractor	23.08	0.02706	0.03048	0.422851	0.32995
	Advertising	20.035	0.06643	0.05697	0.395573	0.30455
Growth	Add-on	26.275	0.02388	0.01499	0.447387	0.35372
	Lock-in	22.052	0.07756	0.09595	0.421617	0.32878

Valuation	Lock-in	25.543	0.001257	0.00050	0.474302	0.38096
	Crowdsrc.	14.192	0.07689	0.06647	0.367310	0.27925
Funding	Advertising	16.336	0.03782	0.02349	0.369985	0.28160
	Lock-in	15.793	0.04545	0.06697	0.367722	0.27961
	Multi-sided platform	14.019	0.08128	0.08196	0.349116	0.26344
	Ultimate luxury	13.672	0.09073	0.07696	0.345290	0.26016
	Add-on	13.633	0.09186	0.07146	0.341885	0.25725

Table 3 summarizes results[4] of the contingency analysis. The table includes the χ^2 value, the χ^2 p-value, and the Fisher p-value used to test the null hypothesis (H_0: the considered BMP and KPI are not dependent). It also includes the contingency coefficients and the Cramer's V values, which reveal the strength of the dependency between each two variables. Only BMPs meeting the following condition are reported: both the χ^2 test and the Fisher test should deliver p-values smaller than 0.1, given the significance of 10%.

4.2 Robustness Tests

To test the robustness of the results, we executed an additional contingency analysis on only European startups. Because 87% of the startup sample were from Europe, it was essential to check whether the startups from the other regions biased the results.

We computed the same key figures as for the first contingency analysis. We report the results in Table 4, which focuses on BMPs demonstrating a strong association with the respective KPI and having a χ^2 p-value and a Fisher p-value lower than 0.1 according to the statistical level of significance of 1%. The contingency analysis performed exclusively on European startups shows the same results as the analysis performed on the whole sample in terms of most successful BMPs. More specifically, results reveal that the contractor pattern had the strongest association with revenue, add-on with growth, lock-in with valuation and advertising with startup funding.

Table 4. Statistically significant results of the contingency analysis on European startups

Model	Significant BMPs	χ^2 value	χ^2 p-value	Fisher p-value	Contingency coefficient	Cramer's V
Revenue	Contractor	18.7670	0.09431	0.09345	0.4134874	0.3211165
Growth	Add-on	21.4290	0.09113	0.04648	0.4365804	0.3431376
Valuation	Lock-in	25.60900	0.00123	0.0004637	0.5020305	0.4104633
Funding	Advertising	15.8120	0.0452	0.03918	0.3847503	0.2947492
	Ultimate luxury	14.1700	0.0774	0.06047	0.3706017	0.282146

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[4] The χ^2 test was conducted according to the Yates correction (i.e., the χ^2 value and the χ^2 p-value are Yates corrected)

5   Discussion

Understanding the reasons behind the high failure rates among startups remains a serious topic in entrepreneurship research and in practice [11, 56]. Based on our empirical research on 121 startups, we show that some BMPs were strongly associated with different variables of startup success, i.e., revenue, growth, valuation, and funding.

Contractor is the most successful pattern that enhances revenue. It involves selling services "provided primarily by people, such as consulting, construction, education, personal care, package delivery, live entertainment or healthcare" [57]. Literature confirms that the *contractor* is one of the most successful pattern in terms of cash flow on assets [57]. In an entrepreneurial context, the strategy of startups that offer human-intensive services might be very different from startups that provide a digital product. Startups that provide digital products (e.g. a mobile app) might aim for a rapidly increasing number of users with free products or a freemium model. Whereas, human-intensive services are not scalable. Hence, freemium BMs are typically not reasonable for human-intensive services. However, with human-intensive services, startups can directly generate revenues. Thus, the *contractor* pattern is suitable if revenues are needed in very early stages.

Add-on is the most successful pattern related to revenue growth. *Add-on* entails offering the core product at a competitive price, while selling extras (e.g., extra services, extensions, or customizations) at high prices. The pattern is in particular suitable when a market does not follow clear customer segments. Customers can customize a product with extras that have a higher margin [9]. On the other hand, the aggressive pricing strategy of the basic product can lead to rapid growth. An example is the low-cost airline Ryanair. Supported by the transparent online flight market, Ryanair used the *add-on* pattern for an aggressive pricing strategy and became one of the biggest airlines in the world in terms of passengers. Our findings quantitatively support this example.

Customer lock-in highly correlates with startup valuation. The lock-in BMP imposes high switching costs [9, 58]. Customers are bounded to the firm's ecosystem. An example is the Nestlé-Nespresso system [9]. Customers had to buy patented Nestlé capsules and were bound to the ecosystem, what reduces their exposure to competitors. This strengthens customer loyalty and encourages future purchases. Recurrent transactions increase transaction volume [59] and, therefore, the valuation. Additionally, switching costs are not necessarily monetary, but can also refer to time and effort. *Customer lock-in* can manifest as network externalities [59], meaning that the value of a product increases as the number of users increases [60]. This raises the barriers to entry for competitors, which again increases valuation. Summarizing, a lock-in is hard to establish. But if a startup already established a *customer lock-in*, it indicates a form of maturity, which clearly supports its valuation.

Advertising has the strongest association with funding. The pattern "provide[s] a product or service and mix[es] it with advertising" [61]. Thus, it describes an additional source of revenue, next to product or service sales. It is considered as the main revenue stream of internet businesses [62]. *Advertising* earnings enable a startup

to offer its core product or service at a very low cost or even for free, making its value proposition very attractive to customers, which indicates growth potential [9]. Moreover, online marketplaces use their increasing customer data to offer targeted advertising and recommendations [63]. Thus, advertising can be considerably more effective than traditional banner advertising and can still be the most important revenue stream, as we see in various internet platforms. These factors may encourage investors to invest in startups with advertising revenue streams.

The EFA results in Section 3.4 corroborate previous findings on the multidimensionality of the performance construct [40-43]. The KPIs defined in this paper load on two different factors. First, revenue, valuation, and funding load on one factor. All three performance indicators describe an absolute performance of current state of a startup. Hence, the first factor is about absolute performance. Revenue growth loads on the second factor. It describes the relative performance compared to the past.

5.1   Theoretical contributions

On the theoretical level, this study contributes to two research streams. It contributes to the BM literature by reinforcing the theoretical perception of the BM concept as a unit of analysis [64, 65]. Moreover, it empirically supports the correlation of BMs and performance and enriches qualitative studies in this research area [10, 66]. The results statistically corroborate the finding that the BM choice can increase competitive advantage [19]. The results show that businesses compete through their BMs and not only through their products or processes [9] and that BMs matter for firm performance.

Further, this study contributes to entrepreneurship research by identifying four BMPs that have a correlation with different measures of startup performance, i.e., revenue, growth, valuation, and funding. The findings indicate why some startups perform better than others in different performance measures by considering the BM as an influencing factor. Results show that the BM matters also for startup performance.

5.2   Practical contributions

On a practical level, this study makes entrepreneurs aware of the BM as an essential factor for startup success. The study further shows that different BMs can lead to different performance outcomes. Results indicate four BMPs that correlate with increased performance measures. Initial recommendations can be derived to help startups boost their performance. Depending on their startup stage, entrepreneurs can adapt their BM to increase a certain performance measure. *Contractor* might help generate initial revenues. *Advertising* can help to increase chances of funding. *Add-on* can be used to aggressively gain customers and boost growth. *Customer lock-in*, if achieved, can increase valuation. Findings underline the significance of the BM development process. Indeed, entrepreneurs should recognize the importance of the BM choice and place much effort into its design. Combinations of patterns are of

course possible. The BMPs can further help entrepreneurs to think outside of the box challenge prevailing ways of doing business in certain industries. Moreover, the results support investors in their investment decisions and help them identify opportunities that are most attractive. The findings provide four BMPs that are likely to be successful and, therefore, potential profit-driving investments.

5.3   Limitations

Despite its contributions, this paper has limitations. First, we used a contingency analysis without control variables on a cross-sectional dataset. This analysis uses categorial performance measures and does not control for other success determinants, such as industry, region, founders' social capital [67], team composition, cognitive factors related to the entrepreneurs [68], market scope [69], or additional environmental characteristics [70, 71]. To provide startups with reliable guidance which BM to follow in which industry and state, a more in-depth econometric analysis is needed. More rigorous methods with ratio scaled performance measures can enrich this contingency analysis. Still, this paper indicates first descriptive results. Second, despite the stratified sampling method, the geographical distribution of the participating startups is not perfectly balanced. Most startups are based in Europe and only few in America or Asia, probably because the university is better known in Europe. Nevertheless, we performed a second analysis on a subsample composed only of European startups to confirm the robustness of the results. Third, this study does not consider BM changes over time when assessing firm performance. The startup context is characterized by high volatility and dynamism. Startups typically go through various phases and stages. They perform pivots to find their BM. Thus, it would be beneficial to adopt a dynamic perspective on the BM and examine its change. Nevertheless, this study is a first step towards more profound econometric analyses about BMs and startup performance. Findings show that different BMs correlate with different performance measures.

6   Conclusion and Future Research

In this study, we empirically examined the BM as an influencing factor for startup performance using a dataset of 121 startups from Europe, America, and Asia. Using contingency analysis, we analyzed the relationship between a core collection of 15 BMPs and startup performance, which was measured through revenue, growth, valuation, and funding. Results revealed that some BMPs performed better than others, but on different measures of performance. More specifically, we found that the *contractor* pattern had the strongest association with startup revenue, *add-on* highly influenced startup growth, *customer lock-in* had the strongest positive effect on startup valuation, and *advertising* notably enhanced funding. Because we adopted an industry- and region- independent approach and performed an additional contingency analysis on a subsample comprising only European startups to check for robustness,

the results are generalizable. The findings corroborate qualitative research proposing that the BM explains business success and enhances competitive advantage [7, 9, 10].

This study contributes to entrepreneurship and BM research and provides an empirical enrichment of qualitative studies. Results are a trigger for BM innovation. They guide entrepreneurs through the process of BM design by presenting a benchmark of 15 BMPs. The findings also help entrepreneurs position their businesses in the large startup ecosystem and, evaluate their performance. Furthermore, this study helps investors evaluate potential investments and assess attractive opportunities.

Future work can build upon our approach and investigate the most successful BMs with regard to the different phases that a startup goes through using panel analysis. BMs are of dynamic nature because they can change over time depending on technological and economic trends. Startups typically experiment in a complex domain where patterns emerge [72]. Future work can take a longitudinal perspective and assess changes over time and analyze emerging patterns. These analyses will help to better understand when BMPs impact which performance measure, how long the impact lasts and whether a positive impact might shift towards a negative impact and vice versa.

Furthermore, future research can enhance our contingency analysis by developing and testing more extensive models. While we have not investigated the impact of control variables or further explanatory variables for performance, this represents a fruitful avenue. Conducting for example econometric analysis will help to better isolate the effect of BMPs and assess its impact in relation to other performance antecedents. These analyses also provide the opportunity to investigate the interaction effects between BMPs and other antecedents. The relationship between BMPs and performance may for example be moderated by the team composition. The more interdisciplinary the team the better it might execute the BM, what increases its impact on performance. Future studies can also investigate incumbents and identify successful BMs in an incumbent context and, thus, further strengthen the BM as a unit of analysis and a driver of firm performance.

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