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Article

Operationalizing Business Model Innovation through Big Data Analytics for Sustainable Organizations

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Abstract: Business model innovation is considered key for organizations to achieve sustainability. However, there are many problems involving the operationalization of business model innovation. We used a design science methodology to develop an artifact to assist business model innovation efforts. The artifact uses performance measurement indicators of the company's business model, which are powered by Big Data analytics to endow customer-driven business model innovation. Then, we applied the artifact in a critical case study. The selected company is a fashion ecommerce that proposes a vegan and sustainable value using recycled plastic bottle yarn as raw material, and ensures that no material with animal origin is used. Our findings show that the artifact successfully assists a proactive and continuous effort towards business model innovation. Although based on technical concepts, the artifact is accessible to the context of small businesses, which helps to democratize the practices of business model innovation and Big Data analytics beyond large organizations. We contribute to the business model innovation literature by connecting it to performance management and Big Data and providing paths for its operationalization. Consequently, in practice, the proposed artifact can assist managers dealing with business model as a dynamic element towards a sustainable company.

Keywords: business model innovation; big data analytics; sustainability; design science; performance management

1. Introduction

The success of companies that introduce new business models (BMs) into their industries has increased academic attention to this area [1–5]. Accordingly, business literature is showing discussions on business model innovation (BMI); meanwhile, conceptual reviews have been carried out. However, proposals relating management approaches to BMI are still scarce [6]. Kijl and Boersma [7] highlight the fact that most of the literature focuses on business model design, while there is little contribution to its validation and testing. Recent literature highlights the fact that fail fast and trial-and-error are leading

to frequent unsuccessful results about the underlying business logic and, therefore, perpetuating failures that slow down the process of knowledge creation and, thus, undermining possibilities for growth. In this regard, there is a gap between what has been studied in academia and what can be potentially useful for managers willing to innovate their BM [8,9].

Thus, BM innovation, validation, and experimentation processes need to be structured and implemented. This is relevant in several industries as the greater frequency of disruption and dislocation are shortening business model life cycles and the sustainability of any specific business model is unclear [10,11]. In a scenario of constant change and need for a better structured management process for BMI, it is important to consider alternatives for testing and experimenting with new alternatives of BM. However, it is not clear in the BMI literature how to do this in the face of the recognized complexity of this process [12,13].

Christensen, Bartman, and van Bever [14] argue that there is the need for a systematic mechanism to evaluate the relationship between opportunities and BM. Besides, it is necessary to consider that innovation in BM cannot be generated randomly through guesswork. Nonetheless, Laudien and Daxböck [15] show that, in many cases, innovations in BM are not deliberate strategic options but rather a result of an emergent process, often unplanned. Strategic options, however, are usually related to a company's performance management which means the measurement of a set of indicators on various perspectives of the company [16,17]. In this sense, it seems natural that a proposition for the purpose of operationalizing BMI should be based on performance management.

The evaluation of enterprise performance management, however, requires actual data from which valuable information can be extracted to enable changes in organizational culture, systems, and processes [16,18]. Consequently, managing the performance of a BM also has to be grounded in data so that its actual conditions can be measured as well as the conditions of new hypothetical choices. Moreover, data orientation today requires the consideration off the context of big data due to the fact of its capability to provide information that can help in the development of customer-driven products and services [19].

Big data refers to data sets that, due to the fact of their size, disorder, and complexity, require special approaches to be viewed, stored, managed, and analyzed [20–24]. Among the types of companies most affected by such large volumes of data are those in the e-business sector, which, due to the fact of their digital nature, encompass large volumes of data from different sources [25–27]. At the same time, although research on BMs has devoted attention to these types of companies, there is still room for the evolution of BMs for e-business [5].

Despite the growing body of knowledge on BMI, there is a lack of proper methods to assist managers to systematically conduct well-structured experiments for BMI while, at the same time, sustaining and improving current business performance. Based on this literature gap, this study's research addressed the question of how to operationalize a process to assist management's decision making for guiding BMI efforts while sustaining performance. Bearing this in mind, the present work was based on an exploratory study with a novel approach to design and apply a systematic methodology for BMI. For this, a design science approach was proposed to build an artifact able to assist managers in real-world configurations. To this end, we first developed a method for BMI. Then, we defined the class of problems to which this method could be applicable to and then chose a specific real-world configuration that fit the class of problems to test and verify/assess/analyze the method through an in-depth longitudinal case study.

The paper presents, as a result, given its methodological nature, a theoretical construction that also provides important managerial implications. On a theoretical basis, the presented artifact contributes to an important gap in the literature regarding BMI by connecting it with performance management and big data theories which has been poorly explored. This is particularly relevant, because it provides a practical connection between BMI and strategy theories. Not only was a proposition created, but it was tested and evaluated in a business environment, achieving satisfactory results. Although this does not validate the theory or allow generalization, it does bring an important contribution, especially

considering that we sought a critical case study configuration. As practical implications, managers can understand how BM can be operationalized as a dynamic element of the company, using big data analytics. The proposed artifact can assist a company in understanding which alternatives work well and what needs to be improved or changed to innovate its BM.

The paper is organized as follows. Section 2 presents the theoretical background for BMI and big data. Section 3 presents the proposed methodology and the design and development of the artifact. Section 4 covers the case study and the evaluation of the artifact. Finally, Section 5 presents the conclusions, practical and theoretical implications, and future work.

2. Theoretical Background

2.1. Business Models and Sustainability

Discussions on BMs gained prominence in the early 2000s, in the wake of the “dotcom bubble” burst [28]. The concept emerged with the understanding that new technologies, such as the internet, multiply the possibilities for designing the business architecture beyond common sense (which is the conventional manufacturing industry business model) [29]. Thus, the idea that it is important to systematically think about the business logic, create experiments to test this logic, and understand how it fits into reality are the key ingredients in this research line. As Magretta [28] has put it, simply proposing to sell vegetables online is insufficient to be successful. There is a need to understand the customer’s journey, their preferences, their habits, and culture in order to design a successful business architecture and to accordingly develop the associated value chain. Therefore, a BM can be defined as the representation of the company’s “design or architecture of the value creation, delivery, and capture mechanisms it employs” [30] (p. 172). The concept of a BM allows for understanding that there are different forms of doing business to be considered in the route to being successful in the market.

Moreover, the search for sustainability broadens and reinforces the idea that new technologies are responsible for enabling new BMs. Since sustainability encompasses process and value chain restructuring, the use of new raw materials, the development of new suppliers, etc., the challenge of tuning the most adequate BM is even harder [31]. In face of the difficulties of conducting sustainable business, BM design is a conductor to innovation, a path to search for sustainability while securing business performance and competitiveness [32]. A good case in point, which is connected to the concept of a sharing economy, is the progressive inroad of the automotive industry towards the business of vehicle sharing. Such a move shows that sharing vehicles, maximizing resource utilization, reducing full demand size, and shifting from product to a service-oriented business has positive impacts on environment sustainability [33,34]. This changes the very nature of the business paradigm, for example, the notion of programmed obsolescence, as the shift to a service-oriented BM means that the longer the vehicle platform endures and the better suited the design is for recycling, the better the BM works.

The contextual aspects that surround both research lines, that of the BM and organizational sustainability, have a strong complementary fit. While there is a call for more sustainable ways of doing business, there is also the need for restructuring BMs in order to reach these goals. Thus, there is a strong challenge for organizations to be sustainable and rethink their BMs at once, testing different approaches in the search for sustainable BMs. This idea has been addressed by recent literature, showing that, indeed, BMI is key for achieving sustainability, even though it is not trivial to put this idea into practice. Weissbrod and Bocken [9] show how hard it can be for companies to experiment with new ideas for sustainability while conducting BM innovation. In this regard, it is important for us to better understand how to pursue BMI in a systematic manner. This means not only searching for BMI that will, in the future, create a sustainable business. It also means that current business performance in the market, its competitiveness, and its survival is also important for the transition to happen.

2.2. Business Model Innovation: The Need for a Systematic Process

The importance of BMI has been a matter of recent discussion. Business model innovation assists companies in dealing with environmental changes and in creating competitive advantages. Sometimes BMI is more important than the company's product or service innovation [35,36]. Additionally, it plays an important strategic role due to the fact of its potential to identify "new sources of value creation, based on innovations in the different components of a business model and/or the interactions between these components" [28] (p. 499).

Extant literature highlights the relevance of BMI in improving the performance of organizations in general [13,37]. The increasing interest in this topic among companies is due to the constant need for sustaining competitive advantages and as BMI is considered an important approach on achieving sustainability. Different studies point out that product and process innovations, alone, are often insufficient for achieving sustainable goals [9,38,39]. Thus, despite all innovations being important, when considering the necessary changes at the systemic level, BMI is of particular interest. The difference among distinct value chains means that not only new products and/or new processes are required, but also there is a need to adjust and eventually create an adequate BM to fit in different markets, developing novel resources and capabilities [11,40,41].

However, recognition of BMI's importance alone is not enough for a company to achieve success; it is necessary to be able to implement an innovative BM as well [42]. Implementation, however, is no trivial task. Cognitive barriers have been identified as important causes of BMI constraints [37,43–45]. Chesbrough [37] explores these barriers in his study and highlights the conflict between the certainty of maintaining the current BM and the uncertainty of implementing innovation in a new BM.

Thus, despite the known increase in sustainability stemming from BMI, a paradigm may persist in a manager's mentality that includes an aversion to implementing BMI. Some authors define such behavior as cognitive inertia [45,46]. However, this is not only a cultural or cognitive challenge that is difficult to overcome. Christensen et al. [14] points out the high volume of initiatives related to BMI that fail. In other words, even if these initiatives are in an ideal scenario, with no cultural restrictions at all, it would still be difficult to achieve success in the implementation of such new BMs.

Studies that search for solutions for companies which are developing innovative BMs have focused their efforts on cognitive issues. Thus, these works have presented proposals that address, for example, ideation [45], design [47], and visual tools [46]. Nonetheless, there is a lack of practical application approaches in the literature that allow for repeatability of a systematic process for BMI that could enable further advancement in this topic. In other words, the theory for management's empirical analysis applied to innovative BM is widely neglected [6,13]. In practice, organizational processes also need to change in order to lead companies to adopt positive attitudes towards experimenting with their BM in the search for sustainability.

New studies that explore this area in more depth, demonstrating factors that make BM success viable, are also necessary [5,48]. This is important because trial and error is the normal option when a company pursues BMI [49]; that is, it is essential for companies to be capable of experimenting with their BM [37]. According to Sosna et al. [3] (p. 386), "the iterative nature of the trial-and-error process allows the organization to introduce variations that produce results that converge with goals, and also fosters collective/organizational learning about both exploration and exploitation streams, promoting organizational change or stability at different times".

Chesbrough [37] demonstrates that, although BM experimentation trials may fail, they provide new understanding and approaches that allow a company to continue to evolve such experiments. In this respect, Ehrenhard et al. [50] point out that business innovation requires that companies understand and use learning processes in order to create value in their business. Christensen et al. [14] reinforces this argument, defending the establishment of a business creation mechanism capable of constructing a steady flow of new BM. In Sosna et al. [3], a case study demonstrates the evolution of an organization that explores the trial and error process to innovate in its BM. However, the literature fails to show

how an organization can perform such experiments, create this mechanism, or replicate success cases through trial and error.

In this perspective, Batocchio, Minatogawa, and Anholon [51] provide an attempt to support this experimentation process, searching to create a mechanism to induce continual improvement on the company BM. The proposition is that organizations would be able to test hypotheses, check performance, and, thus, add or eliminate choices for the company's BM. When a satisfactory performance is verified, the choice could be added to the BM. Otherwise, the test could be used as generated knowledge for the organization.

This assertion is in line with the learning characteristic that experiments provide, since the performance measurement's main goal is change, reducing emphasis on control and increasing emphasis on learning [52–54]. This also aligns with the BMI definition by Eppler and Hoffmann [36] (p. 27); they state that, "[...] business model innovation is a multi-stage process whereby organizations transform new ideas into improved business models in order to advance, compete and differentiate themselves successfully in their marketplace." In other words, in BMI, new ideas should be tested to help in the decision making around business model improvement.

The definition of BMI may also include specificities, depending on the analyzed spectrum. The concept of sustainable business model innovation (SBMI), for example, can be observed in other studies. Based on Morioka, Evans, and Carvalho's [55] study, Hu et al. [56] (p. 3) defines SBMI as "[...] the conceptualization and implementation of new solutions for products, processes, marketing, and/or organization that are embedded in the firm's core business model (the firm's configuration to propose, create, deliver and capture value), in order to improve corporate sustainability performance".

In this connection, the orientation of experiments of a BM based on performance data, using a systematic, repeatable BM performance process can overcome some of the barriers regarding BMI. These are mainly cultural barriers, such as actions that have led to failure in the past, and, therefore, are assumed to be dangerous and provoke aversion [57] and cognitive inertia [58]. At the same time, using data to support performance management process, improving performance in an observable manner, can help reduce such barriers. Thus, leveraging the context of big data can not only help measuring specific indicators, but also support the reduction of inertia and change aversion.

2.3. Big Data

Understanding the proposition of using performance data to achieve BMI requires understanding data-based decision making. This concept can be defined as the use of data analysis to inform the course of an action involving politics and procedures rather than the use of pure intuition [59,60]. Still, it is important to highlight that the use of data analysis supplements and does not substitute for decision making [61], which, in addition to data, requires leadership and a clear and shared vision of reality [62,63].

This consideration is critical, particularly within the current context of big data which is driving the recognition of the importance of data [64–66]. Data are being generated, collected, and analyzed on an unprecedented scale, and this fact is influencing data-based decision making in all aspects of society [67].

Big data has become the main technology for utilizing data at the maximum possible level. Its importance is increasing due to the growing volume of data available from the Internet. The increased response speed in analyzing data can yield an important advantage. However, it is noteworthy that big data is not a solution but a means to use to reach a solution [20,24,68]. Therefore, when using such data, the intention is not to determine the decisions related to the BM of the companies, but rather that organizations can use data as a basis of their decisions and, thus, benefit from the current context of big data to innovate in their business models through the verification of their choices' performance.

The largest difference between using big data versus traditional information management is the capability provided to develop customer-driven products and services [19]. Thus, big data can be used to improve the relationship between companies and customers and, for example, to enable a company

to make decisions supported by real-time information [20,24]. In this context, Erevelles et al. [21] and Wang et al. [68] emphasize that big data can be used to gather information regarding the market and customer behavior. Analytics, on the other hand, are tools used to understand what the collected data mean [21]. Due to the immense capacity of computer systems to monitor a range of digital streams, it is possible through big data to collect, and through analytics, to interpret and analyze the data, generating relevant insights. The aim of big data is to find effective correlations among the information [19].

According to Rodríguez-Mazahua et al. [21] (p. 3078), “timely and cost-effective analytics over Big Data is now a key ingredient for success in many businesses”. The need to extract useful knowledge from an increasing volume of data has led to the development of data mining techniques. Furthermore, there is a need for new ways to make internal company decisions, especially in order to promote conditions that ensure its sustainability.

The main problem with big data is its composition. Big data is composed of a fast-flowing stream and it demands continuous management of the data gathered [19,69]. This can be done through the use of analytics. The aim of analytics, most of the time, is to provide simple statistics about the data from a website such as the number of visitors and the most requested pages [70]. However, more complex analysis can be done as well such as allowing a manager to understand why visitors placed goods in their shopping carts but left the site without buying anything [71].

The data collected through web analytics can be helpful in better understanding how visitors use the site. Through web analytics, managers can improve their sites, making them better for customers and increasing their site revenue [71,72]. In Google Analytics, for example, the traffic source overview shows where the traffic comes from (e.g., percentage of direct traffic, search engines, referring sites) [70].

Thus, as big data can support customer-driven products and services development, it is argued that it should be possible to elaborate on choices for a BM under the same circumstances. In particular, bearing in mind that analytics, as mentioned, can make the data collection analysis feasible, big data and analytics are tools that can provide “customer-driven” data to create hypotheses for new choices for a BM to leverage a more sustainable organization. Moreover, subsequent performance verification can demonstrate if it is feasible to implement such new choices, helping BMI.

The potential and need for data-driven BMs have been observed in other studies [73–76]. Some of the literature has sought out data-driven BM approaches, trying to contribute through proposals for frameworks and taxonomy studies [77,78]. However, most of the data-driven business modelling studies are still on the theoretical level [79], lacking proper transcription to real-world management reality.

Thus, this study aimed at the development of a method and tool that fits management reality and, thus, contributes to data-driven business modelling, bridging the gap between theory and practice. This proposal provides academic and managerial insights, first, because data-driven BMs are still undergoing development [80], and, second, because successful cases in data-based business models are largely anecdotal [78,81]. The next section details the methodological procedures used to conduct this research.

3. Method

3.1. Research Methodology

The theory of BMs and related innovation has improved significantly in the past fifteen years [82,83]. In this period, the sophistication of the BMI construct increased both the awareness of how it is an important unit of analysis for management and also improved the process regarding how it can be pursued by different companies. Also, several business modeling tools have been proposed, and a recent literature review captured the dimensions of those advancements [46]. Nevertheless, when looking at the practice, there still remain several gaps and confusions when trying to translate theory to practice, a fact that is reflected in recent data regarding start-up mortalities [8] and the high rates of BMI attempts that failed [9,14].

In this connection, there is a need to develop artifacts able to assist management in overcoming such barriers to successfully build capabilities for BMI. According to Hevner et al. [84], when dealing with problems that require building human-made artifacts for problem-solving-oriented purposes, by creating innovative solutions, the design science approach is particularly relevant. Whereas the prime goal of traditional research methods applied to management and engineering, such as case studies, surveys, and action research, is to explore, describe, explain, and predict [85,86], the goal of design science research (DSR) is to solve practical problems by technological rule-based evaluation [85–87]. Thus, according to Dresch et al. [86], DSR has an important abduction phase, where a creative process occurs to design proper artifacts capable of solving different practical problems aimed at satisfactory results. Additionally, it is relevant to state that design science and traditional research methods are not exclusive, rather, they are complementary [86]. Therefore, applying a combination of different methods under the design science paradigm is important, since the last phases of DSR comprises real-world experiments to validate the designed artifact in a real setting [87].

Considering that the aim of this study was to provide an artifact to support management BMI efforts, by means of problem-solving-oriented research, DSR is considered an appropriate approach [84]. Thus, we followed the four-step DSR proposed by Hevner et al. [84] and also by connecting the evaluation phase by a practical intervention as suggested by Cole et al. [88]. The first step is to identify the problem to be solved, deepening the understanding about the problem and also taking into consideration the interests of the main people involved with the problem. Here, it is recommended a special focus on the practical relevance and the potential implications of a solution. In this step, we defined the class of problems and the main target populations. The second step was to build the artifact. In this step, we gathered the state-of-the-art literature and also had an abduction phase to allow for the creativity necessary to build the artifact. The third step was the evaluation, in which the case study or the action research took place, and, therefore, the artifact's capability to solve the problem and its performance were considered. In this phase, an intervention was made in the selected organization to prepare for the artifact's application. Thus, in this step, we defined the specific characteristic of the real setting organizations and found an organization that fit this population to conduct a case study to see how the artifact worked in practice. Finally, the fourth step was to reflect and learn to understand both the practical and academic implications of the work and draw conclusions. In the last two steps, the evaluation and the reflection and learning can be iterative, since flaws in the artifact may be detected and modifications may need to be made to reach the objectives.

According to Dresch et al. [86], Hevner et al. [84], and Holmström et al. [87], the case study approach is suitable for the evaluation phase in the design science paradigm when the goal is to observe how the artifact works in a real setting and if it is able to solve the problem with satisfactory results, improving the performance of the business. Thus, in the following subsections, we will represent the first three steps while we present the case study in Section 4 as well as the discussion of the applicability of the artifact by means of a calibration mechanism.

3.2. Class of Problems

Defining the class of problems within which the artifact is suitable is a crucial step during DSR [86,87]. This is so because, even though most of method or instantiation validation occurs inside a single setting, there is a need to be able to generalize, not to every other company, but to a specific set of problems faced by specific organizations [86]. Moreover, there is a need to adapt the artifact to the specific local conditions [85]. Nevertheless, the artifact remains applicable if the class of problems is adequate, despite adaptation needs. Therefore, since the class of problems has been thoroughly described herein, we will provide only a brief summary.

Recent assessments on new companies and trials for new sustainable business model creation, both from new companies and incumbents, report a certain difficulty in putting theory into practice [8,9,89]. The main problem is that testing different business hypotheses is more complicated than thought, leading to a misunderstanding about the central business logic and not ensuring there is a match

between the customer segment and the value proposition. Meanwhile, the literature points out that, considering uncertain environments, the failure rate should be higher than the success rate. Thus, there is a gap regarding how to improve this rate, leading to a superior success rate during BMI efforts [14].

With that said, we emphasize that the class of problems is the operationalization of the BMI process and involves activities such as developing new business models; changing the current business model; and improving performance of the current business model by evaluating its consistency and the complementarities among its components. Considering this spectrum, we consider that engineers and managers can use this artifact to improve their BMI effort's success rate.

With this in mind, the aimed object was the process of BMI, that is, how to improve each stage ensuring the better information collection possible, supporting management's decision making and also contributing to a good experiment design and learning during the process. In this regard, new companies seeking new BMs while assuring performance and working capital from the current business are the affected population to which this study aims.

3.3. The Method for Data-Driven Business Modeling

The second step of the DSR method is to design and develop the artifact. The proposed artifact was aligned with the points highlighted in the literature review section. That is, the process will be based on common performance management practices such as a cause-and-effect relationship, selection and measurement of indicators, and data analysis. The initial concept of the artifact starts with Batocchio, Minatogawa, and Anholon's [51] proposition, because it gives a starting point to discussing the performance measurement of a BM. The authors assume that the Canvas business modeling visual tool [90] derives from the Balanced Scorecard perspective [17]. Thus, it would be possible to manage and improve BM choices through performance indicators. From this starting point, and because it focusses on BM improvement and not on BM Innovation, we aggregated several points of the literature to form the artifact. Examples included learning from performance management [16], experimentation through trial-and-error [3,9], understanding the value of web analytics [91], and leveraging the big data context for customer-driven orientation [19].

Thus, unlike the strategic performance management process [16,17,92], the artifact focuses on measuring BM components and architecture choices instead of the strategic objectives. This perspective will open room for the creation and testing of new BM hypothetical choices, in order to verify if its performance sustains its implementation in the company's business model. In addition, also in line with the literature, the data collected will be coming from web analytics, seeking the concept of making customer-oriented changes. In line with current big data theories, this was conducted to bring about not only accuracy from data—which data to collect, how and why, the veracity and the value dimensions of big data [22]—but also to leverage the proactive character of the artifact.

In the sequence, Figure 1 demonstrates the designed artifact that was applied in the case study for evaluation. For a better understanding of the method's instantiation elements, a numbering was provided to each box which composes this structure in order to guide a brief detailing.

In Figure 1, Box 1 is the identification of the initial organizational knowledge about the BM and the representation of the company's current BM, as this is a representation of the company's value stream [89,90,93,94]. Box 2 consists of the reorganization of the BM choices collected in the previous step by identifying how the customer segment interacts with the value proposition through the channels. The result of this flow analysis is a representation of the cause and effect relationships involved in the current business model. Box 3 is the data collection to measure the indicators' values. The proposed method uses data (such as bounce rate, visitor traffic source, etc.) provided by the web analytics (see Box 4) to feed these indicators. Since the selected company uses Google Analytics, we used this specific tool in this research, but other analytics tools can also be used for this purpose.

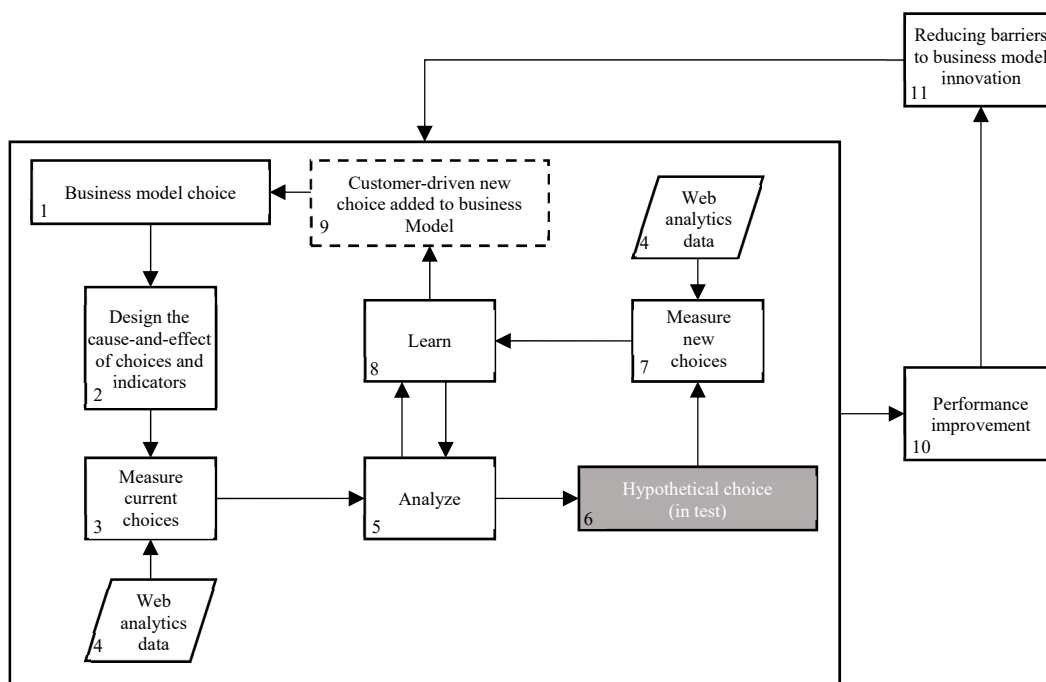


Figure 1. Proposed method for data-driven business modelling, the step roadmap for application, and the learning loops.

At this point, the leading and lagging indicators for each step in the cause and effect diagram can be identified considering how each can be used as an accurate index for the company. Box 5 is to analyze the data in order to ideate and determine hypothetical new choices (as is seen in Box 6). Box 7 consists of the measurements of the impact of the implementation and learning (Box 8) of the new choices. Box 9 represents the addition of a customer-driven new choice to the business model, and then the cycle returns to Box 1 of the next loop with the representation of the changes in the model.

It is also possible to migrate directly from Box 5 (Analyze) to Box 8 (Learn), because there are different degrees of uncertainty associated with different BMI efforts. Considering the existing literature, it is possible to notice that higher degrees of uncertainty calls for trial-and-error approaches based on hypothesis formulation and testing, pursuing low resource usage to fail fast and learn. In other words, learning is the main goal of high uncertainty hypothetical choices to innovate BMs; usually this approach is called exploratory. On the other hand, there are instances where the uncertainty is low, and the outcome of the changes are mostly predictable. Under these conditions, the main goal is improvement in the performance, and usually this involves more resources and implementation directly without experimenting in test conditions. This approach is usually called exploitative. Using this contingency approach to solve different problems with different goals, we followed the logic proposed by Futterer, Schmidt, and Heidenreich [95] which associates entrepreneurial theory of causation and effectuation to improve the effectivity of BMI efforts. The authors correlate strategic reasoning with deductive thinking to solve exploitative BMI efforts while connecting action and experimentation with low resource usage to test and validate hypotheses for exploration goals.

Therefore, there are two possible paths to follow using the application artifact (Figure 1): the short loop, which has exploitative goals and reduced uncertainty, and the long loop, which presents high uncertainty and has exploratory goals. Figure 2 demonstrates the possibilities of these loops.

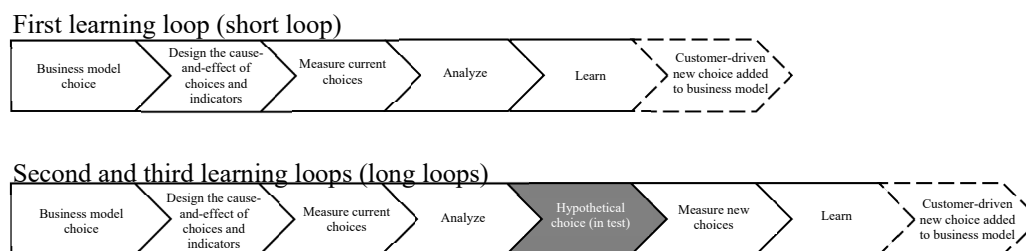


Figure 2. Possible tracks for the learning loops while applying the proposed artifact.

The artifact is a knowledge creation cycle in which, after each loop completes, the learned experiences are embedded in the organizational knowledge assets. The evolution of the changes in the business model and in the cultural issues are registered after each step of the new choices proposal to illustrate both the business model dynamics and the steady overcome of cultural barriers as can be seen in Boxes 10 and 11, also considered the main constructs addressed by the artifact, its external environment. Based on the characteristics of the procedure and the applied nature of the research, the approach follows the proposed artifact. Thus, it is possible to analyze how the business model interacts with the competitive environment in an ordered way.

Finally, we note that the purpose of this research was not to focus on any specific meta-business model, but rather on the choices present in the business model and the dynamics during this process, regardless of the meta-business model considered [3,96]. Thus, the choices can be measured so that decision making around the BM can be based on the data gathered. However, it was necessary to adopt a meta-business model to make it possible to design the BM for the case study. On the first evaluation of the company's knowledge about the BM, familiarity with the business model visual tool "Canvas" was identified. The tool is thoroughly described in Osterwalder and Pigneur [90], so only a brief explanation is provided. In general, it is a nine-block frame that presents some, although not every possible, key components of a BM (see Foss and Saebi [83] for a deep explanation).

This visual tool can be separated into two main major parts: the front-end and the back-end. The former is the portion of the business that has direct contact with the market, meaning the value proposition, the value delivery, and the mechanisms to capture value. The back-end represents the underlying value creation architecture; it represents the company side. Thus, the front-end comprises the fit between customer segment and the value proposition, as well as the adequate channels used to deliver the value and the designed relationship to the customer(s) segment(s), specifically for acquiring and retaining them, and, lastly, the revenue stream which means the mechanisms applied by the company to make money (direct sales, licensing, sponsor-based, leasing, etc.). The back-end, in turn, comprises the key activities and the underlying key resources, alongside the definition of who executes each activity and provides the resources or, in other words, the partner network associated with the business that is necessary to create the value and, finally, the cost structure associated with the value creation and delivery. Considering that this visual tool is the most used for this purpose [2,97], we decided to use it. Nevertheless, we focused on its front-end in order to provide a more in-depth analysis of the proposal's indicators, given the particular problems faced by the target in the BM case study; these were value proposition, channels, customer segmentation, and revenue stream.

3.4. Evaluation: Case Study—Data Collection and Analysis

3.4.1. Case Selection

The case selection was very important for evaluating the artifact in real-life conditions during the last stage of DSR [86,87,98]. This was of particular relevance, because the aim was to draw generalizations not for every case but for the ones that fit the class of problems thus making contributions not only to practice but also for the literature [84,86]. In this respect, we sought to select a case that

could be considered a critical case, in which the contextual conditions were close to the less favorable as possible to allow making these generalizations [86,99,100].

Considering the abovementioned class of problems, organizations that represented critical conditions were ones that fit into five conditions: (1) had high technical knowledge and a technical background, lacking managerial and marketing capabilities: one of the main failure causes were related to a mismatch between the value proposition and the customer needs, which was strongly related to a lack of marketing and managerial background [101]; (2) had low IT capabilities, considering that the proposed solution should be simple enough to leverage big data in every context, especially considering the importance of BMI studies not only in large enterprises [102]; (3) had low resource availability and, therefore, could not simply reach out through the market and needed to cope with what they already had: this was important, especially because the literature points to the importance of slack resources for BMI and how restricted resources can hinder BMI efforts [103]; (4) had a potential product that was recognized by outsiders; however, they had not yet been able to achieve success with this product, lacking a proper BM and struggling to survive: this directly relates to the class of problems proposed in the sense that there was still a need to couple the product's value proposition to a market need through a customer segment and, therefore, there was an evident business modeling problem; and (5) had the minimal analytics infrastructure, most desirable of a free option in the market and also had a low skill level with using the interface.

3.4.2. The Selected Company

The selected company is a fashion e-commerce business. Founded in 2014, the company aims to become a major fashion accessory player, but with the differential of being a vegan and sustainable brand. It is widely believed today that vegan diets have a positive impact on the environment [104]. However, despite the vegan world being well known in the food industry, it is still emerging and not well understood by the general population in other segments such as the clothing and accessories industries. That is because it is still not straightforward to comprehend the true meaning of which specific piece is vegan and why the other one is not. The vegan characteristic is embedded in each piece but is, nevertheless, mostly invisible to the end customer—the vegan and the non-vegan piece may look very similar, unlike the food which is most obvious.

The company's main products are fashion accessories such as handbags, purses, passport holders, footwear, and thermal handbags. All products use recycled plastic bottle yarn as raw material, and the suppliers are carefully selected in the sense that they should have a sustainable orientation. Thus, as a small company, supplier development and product development are the core value creation activities. Finally, there is the challenge to not only embed sustainability in the product and in the company's value chain but also in creating a brand image and a niche in the market to overcome the industry's entrance barrier. In Section 4, we further detail the company's BM.

In 2015, the company founder was invited by Facebook to speak about social media's role in the business' growth in an event for entrepreneurs. The speech was a practical case of social media use. Nevertheless, despite having a considerable number of followers and a potential impact on the market, this apparent success was not reflected in the company's balance sheet. Thus, even though the company has a solid base of potential customers and a seemingly good product, since its background is an exclusively technical one, the company still struggles to find a suitable BM and achieve success in the market. The task is not trivial at all, since the fashion industry is well established and one that has a significant brand-related entrance barrier. Therefore, to overcome these issues, there is a need for strong innovation capabilities and high entrepreneurial skills to be able to couple technical solution to a market's need, if a new business model is to be successfully introduced to this market.

The overall evaluation of the company points out that its founder's structure is technical oriented, a fact highlighted by its manager in the initial screening. Low entrepreneurial and managerial skills were also highlighted by the top management, meaning that it has training in standard management but without entrepreneurial skills necessary to build novel BMs. Additionally, the company lacks

IT capabilities (for this evaluation, we used Mao's et al. [105] IT capability framework) and has few resources, since it has low working capital.

Given this background, the overall problem can be linked to the fact that the company had not clearly found an adequate BM. The lack of entrepreneurial capabilities for BMI made it hard for the company to overcome the challenges of entering in this competitive market and to fulfil its aim of becoming a major player. Thus, there is a match between the firm's problem and the purpose of this study for the artifact evaluation. As it will be demonstrated through the results, during the application, it was possible to record the evolution of the company, not only by the means of its BM performance, but also the steady overcoming of the main identified problems, namely, finding a fit between the value proposition and the customer segment and building the necessary capabilities.

3.4.3. Data Collection and Analysis

The data sources were semi-structured interviews, participant observation, and analysis of documents for data triangulation and proposition veracity checking [100,106]. Interviews with the company owner (one interview every two weeks during a two-year period, for a total of 48 interviews) were conducted during the application of the artifact. Interviews had an approximately one-hour duration and were not recorded. In turn, real-time notes were taken by one of the researchers. The decision not to record the interviews was to reduce key informant biases, especially considering that cognitive and cultural related aspects were also evaluated [57,107]. As documents, we used the company's analytics tools (in this case, Google Analytics) and its enterprise resource planning (ERP). Finally, we observed several working meetings and day-to-day business activities to evaluate the routines during the BMI efforts. We compiled the collected data into short field reports which were qualitatively analyzed to understand the evolution of the artifact testing.

During this stage, information was gathered about the current BM of the company as well as the management's evaluation of the success and adequacy of the BM. Data collection also addressed resistance to change or, in other words, the central logic barrier [37,58]. Interviews were also conducted longitudinally in order to produce evidence on how the proposed artifact was working and to document changes in cognition; even though the cognitive dimension was the most exploited, it remained an important barrier to BMI; thus, the artifact application should also consider this dimension to be successful. Document analysis was done based on data collected from Google Analytics. This analysis enabled the evaluation of customer behavior and the consequent focus on customer-driven choices for the BM. Additionally, these data were used for BM performance evaluation. Participant observation was carried out through direct observations of what should be the hypothetical new choices of the BMI to be implemented and the resistance to change in terms of cultural behaviors. Secondary data from commercial articles available online, regarding practices and procedures performed by large companies were also used as data sources by the company's manager.

In summary, interviews, observations, and document analyses were conducted during a two-year period with the company (from November 2016 to October 2018). Thus, initially, we made a first evaluation of the company to make an assessment of the current state. Then, we made an intervention by teaching and showing the method for the company members and also how to apply it. During this period, several week-length evaluations (at least one per month) using interviews, observations, and document analyses were conducted to calibrate and evaluate how the method works in practice, searching for potential improvement points, and also to analyze its performance and if satisfactory results were being obtained. This two-year period with frequent interactions and observations of the artifact in practice was crucial for methodological consistency, because conducting a longitudinal in-depth case study assures that every detail of the artifact is considered and documented. Also, it is an important step for allowing future tests with multiple case studies. The results were recorded in the form of learning loops which captured several dimensions of interactions between the method and the practice and its impacts on the firm's performance. The results of this study are presented in Section 4.

4. Results of Case Study

This section brings forward the case study, designed to evaluate the artifact, presenting the learning loops that occurred while implementing the proposal's instantiation in the selected company. The cyclic nature of the proposed approach provides several iterations during this process, impacting on the business model's configuration. As a consequence, the cause-and-effect relationships will also suffer impacts, changing the business model value stream.

4.1. First Learning Loop

4.1.1. Business Model Choices

Following the artifact, the first step was to evaluate the average knowledge about the BM and to teach the employees about the subject. An interview was conducted, and it was identified that the manager had had contact with the BM visual tool Canvas but no application or use of it was reported. Thus, in this first stage, the business model of the company was represented partially using the Canvas in Loco according to the employees' view. The resulting business model choices were adapted to a simplified version and are represented in Figure 3.

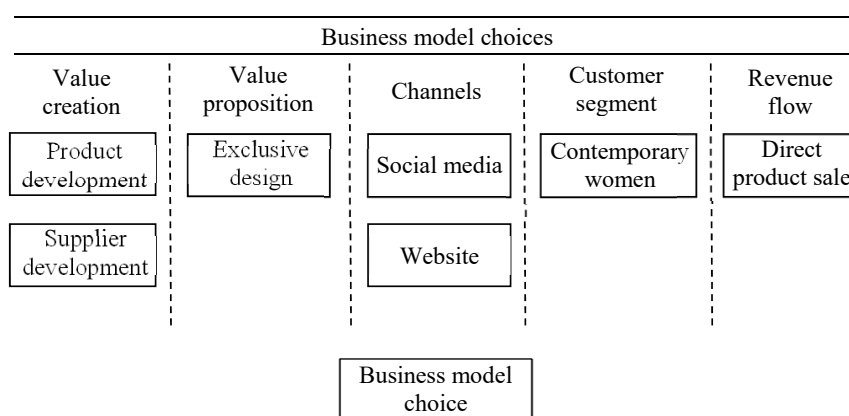


Figure 3. Initial BM choices representation.

In the following subsection, we provide a brief description of each choice to better understand the analysis:

- **Value Creation:** The main value creation activities were related to product development. This is mainly because the company has its own brand, and exclusive design is an important element of its value proposition. Moreover, as the business does not produce its own materials, a key activity is the development of the appropriate suppliers (partners) to manufacture the goods.
- **Value Proposition:** An internal team develops the design of clothing and accessories. It has trained professionals from the fashion industry, which pursue activities ranging from the search for trends in design for each product. This choice was identified as the value proposition because, in the perception of the manager, this is what the company's customers valued the most.
- **Channels:** The manager chose social media as the main channel for knowledge and disclosure of the company's brand and products. The most used tool in this respect was its Facebook fan-page. As the purchasing channel and service, the company selected its own website.
- **Customer Segment:** The company focuses particularly on women aged 25 to 50 who are located throughout Brazil as the customer segment.
- **Revenue Flow:** The revenue stream is from directly selling products, which is traditionally how an e-commerce business operates.

At this point, the manager also brought up the fact that, although the company had Google Analytics installed and working since its beginning, it had barely been used. This was because, according to the manager, although there were a lot of data available, its use was confusing and very difficult to explore.

4.1.2. Design of the Cause-and-Effect of Choices and Indicators

In order to observe the cause-and-effect relationships around the value delivery process, the BM components were organized by the order in which the customers flow through the process, as shown in Figure 4. The value proposition reaches existing and potential customers through social media, the company website, and word of mouth. If it meets the need of its visitors, the visitors stay on the website, and then they evaluate the product and decide whether or not to buy it.

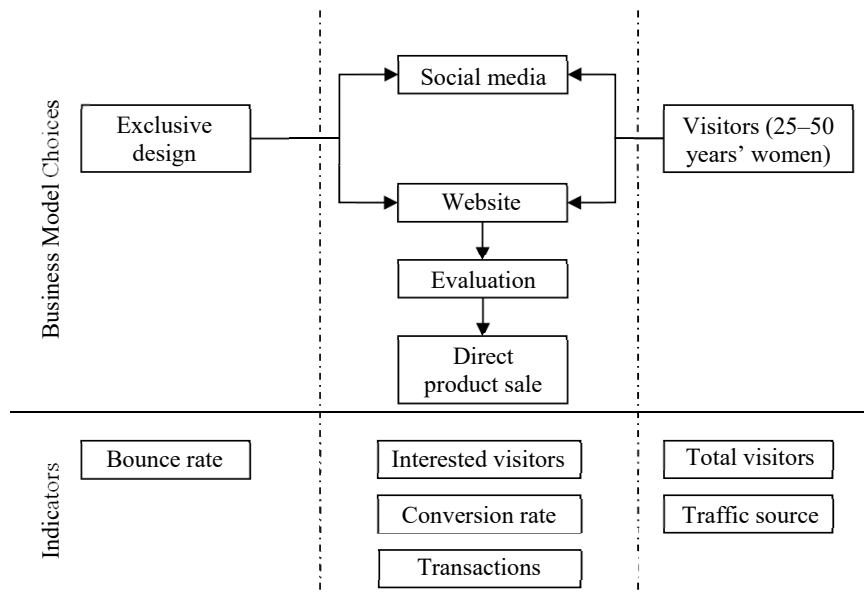


Figure 4. Initial cause-and-effect representation of the BM choices and the selected indicators.

The next step was to translate this flow into measures that could be fed into the analytics. Starting with the value proposition, if it is not what the visitors want, they instantly leave the page (in Google Analytics, is called bounce rate); thus, the first measure selected was one minus the bounce rate, which shows the rate of people that were at least slightly interested in the value proposition. This percentage multiplied by the total visitors leads to the number of interested visitors. The interested visitors, depending on its conversion rate, which represents the transactions per visitors (transactions divided by the visitors), lead to more transactions (Figure 5).

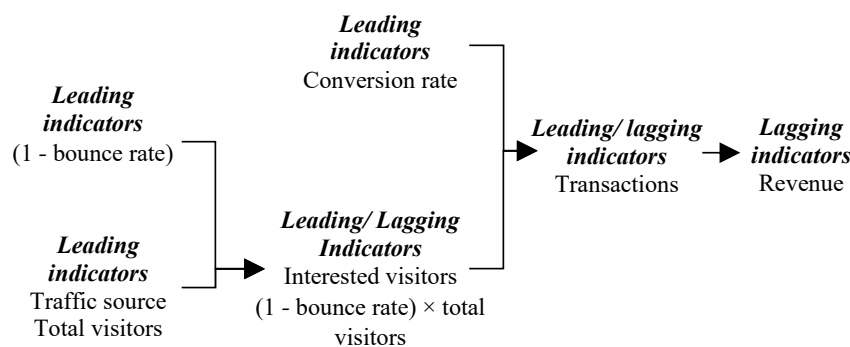


Figure 5. Selected leading and lagging indicators' cause-and-effect relationship.

4.1.3. Measure and Analysis

In order to obtain accurate information about the selected measures, analytic data on the measures were collected from the launch of the e-commerce website (a period of two years) and compared with financial results (represented by the company’s revenues). The first measure for the value proposition was collected and, as shown in Figure 6, the higher the bounce rate, the lower the conversion rate, confirming the relationship among these measures as shown in Figure 5. The second indicator, interested visitors, was calculated by multiplying one minus the bounce rate—representing the percentage of visitors that stayed on the site—by the total number of visitors. This measure was plotted alongside the transactions (Figure 7) and, except for the period of September–October 2015, the higher the number of interested visitors, the higher the number of transactions. These data taken from the analytics were all weighted and multiplied by a factor to hide the actual value due to the confidentiality agreement; however, the necessary proportion was maintained.

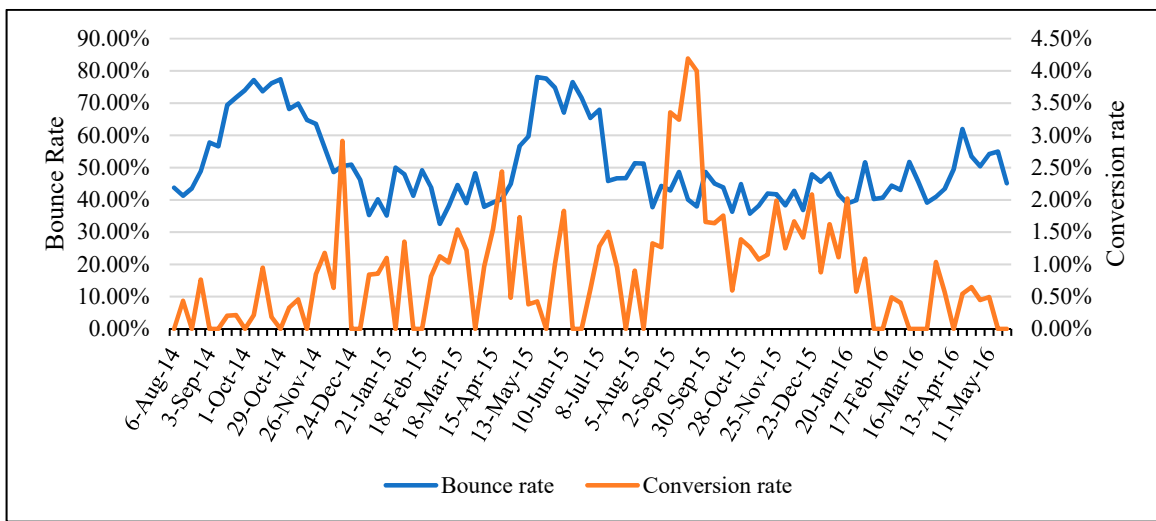


Figure 6. Value proposition: bounce rate × conversion rate.

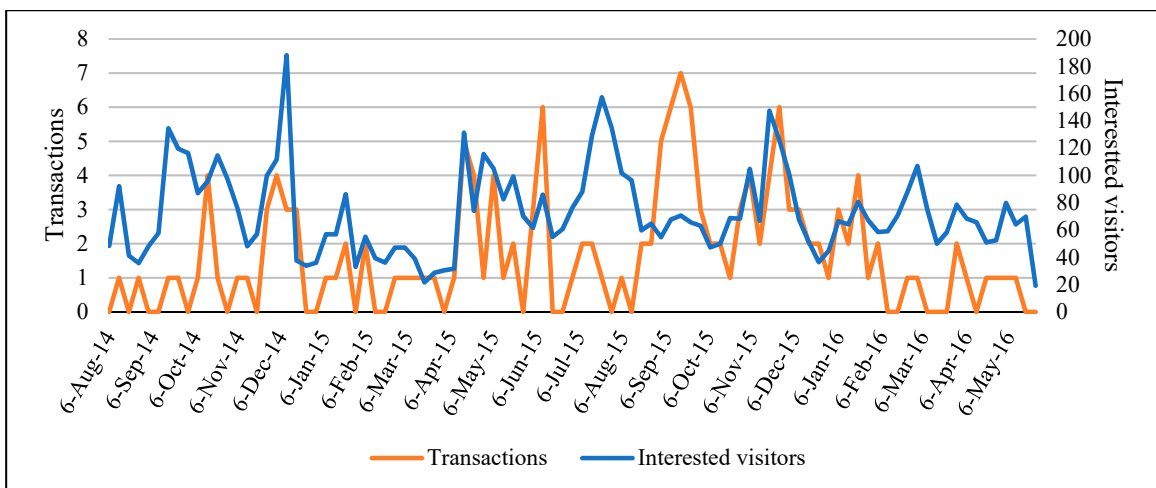


Figure 7. Channels × revenue streams: interested visitors × transactions, the leading/lagging indicator.

Based on the observed data, it was possible to affirm that the hypothetical cause and effect was correct but also that there were some data that needed more in-depth analysis in order to be accurately understood. To that end, in Figure 8, the traffic sources of where visitors were coming from was plotted in relation to the transactions and an event analysis to observe external associations with direct impact

on sales. The considered events were holidays, to check seasonal influence; purchase of marketing media, such as Google AdWords; and new collections of products launched.

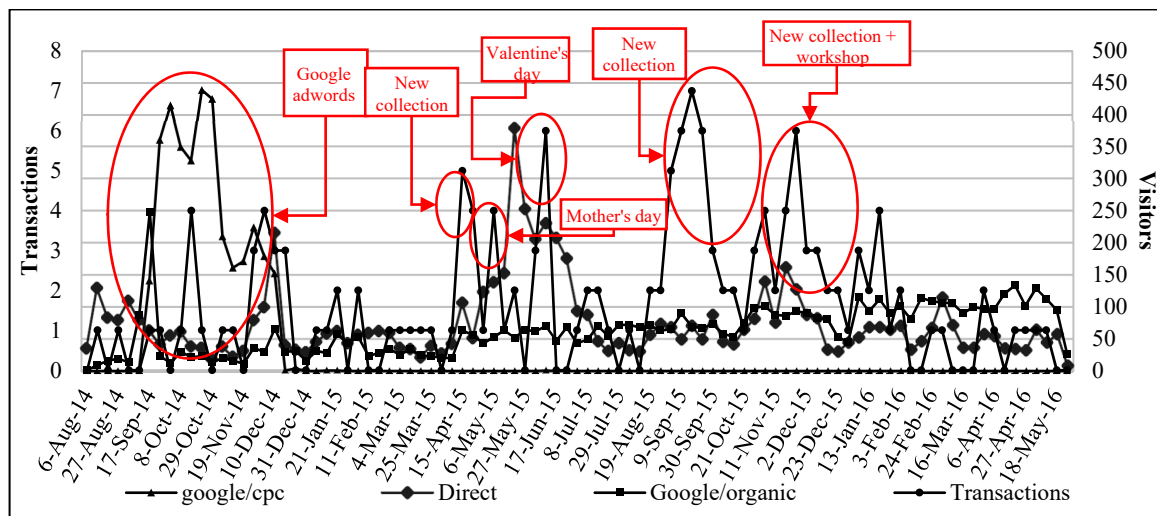


Figure 8. Channels × revenue streams: visitor traffic source × transactions, with event comparison for analysis.

Based on this data, it was observed that at the beginning of the e-commerce phase, merchandising with Google AdWords (Google cost per click) had a strong impact on the number of visitors that came to the website. However, this period also had the highest bounce rate and the consequence was no substantial increase in sales. Therefore, there was a negative return on investment.

The next point to discuss was that the transaction peak between April and June 2015 began with a new collection launch, followed by two important commercial dates, Mother's Day (May) and Valentine's Day in Brazil (June). Such data would have pointed to important seasonality but data from September and November 2015 and May 2016 explained these results otherwise. The first time period related to a large new collection and very high conversion rates that, even with a similar average number of interested visitors, led to the highest revenue period. The explanation was that the value proposition met visitors' expectations. The second time period had both a new collection and a workshop (event where it was possible to present the company's products and the brand's values) which effectively increased the number of interested visitors and the conversion rate. The last time period, relative to Mother's Day 2016, had no new collection and generated no further sales.

The deduction from these data was that the main issue regards the value proposition. That is, what empowers the business is the presence of new products. When merchandising is done, without any changes to the product, there is no return on the investment. The same is true on holidays; if specific products are released for these dates, then the result is positive; if not, there is no change in sales.

4.1.4. Learn and Customer-Driven New Choices

Based on the analysis of the historical data (Figure 8), the first two new business model choices were based on actions already performed in the past and, thus, it was possible to evaluate the results generated by these initiatives using historical data. Following Yin's [100] recommendations, we triangulated the historical data with interviews to understand the context of each situation, to confirm the potential success of the actions. The first two choices are summarized as follows:

- Based on the data, the duration of the sales of a new collection was around two to three months; thus, the first initiative was to launch a new collection every two to three months. A few weeks before the new collection is launched, there is a decrease in sales (after the transactions peak).

Therefore, in order to keep sales active between new collections and reduce stock, a sale should also be instituted;

- Moreover, from the analysis of the same data, the manager decided that the new collections would have a predetermined number of items, as the value proposition is based on the company’s differentiation and exclusive design.

During the first learning loop, interviews were used to analyze the resistance to the implementation of initiatives to improve the BM. The main issue raised in this phase was that the data could be used as a good means to support the application of the new choices, because, as pointed out by the manager, these data demonstrate a clear and explicit relation with the improvements obtained and they also show the efforts that worked, providing elements for data-driven performance management. At the beginning, the manager was not sure about changing the BM; however, after the historical data analysis, she was confident to make the changes and to invest in the novelty, and, it was demonstrated later, it constituted an important value proposition with low associated risk.

In addition, it was observed that the organization of the indicators in a cause-and-effect relationship gave relevance to which data to mine. This shows how one approach complements the other. That is, as one of the greatest difficulties of performance management is to have available and accurate information about selected indicators, and, additionally, to select the desired organizational indicators, the artifact also helps to surpass the difficulties related to analytics previously exposed by the manager, namely, the question of which data to gather and how this data can help.

4.2. Second Learning Loop

4.2.1. Business Model Choice Representation and the Cause-and-Effect Diagram

The resultant business model is represented in Figure 9. Considering the new knowledge created through the first learning loop, the novelty was added to the business model as a choice for the value proposition. The new flow of the cause and effect relationship is also represented. The leading and lagging sequence of indicators remains the same.

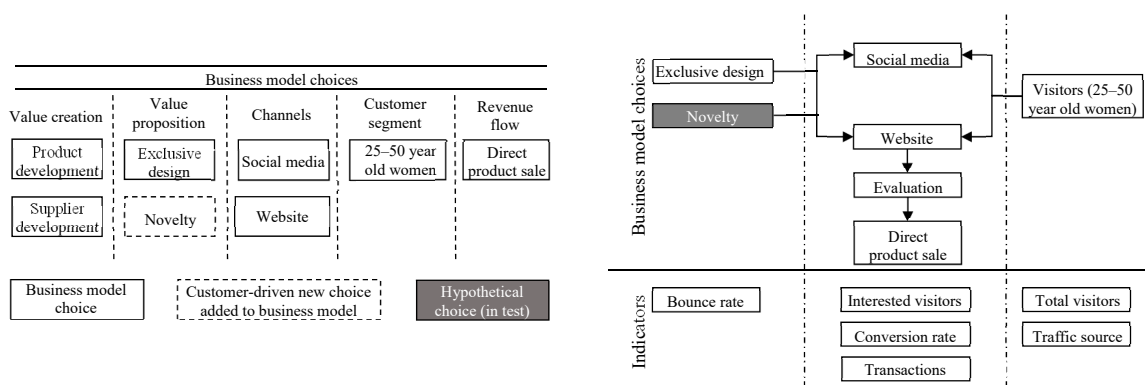


Figure 9. Second learning loop BM choices representation and cause-and-effect diagram with the selected indicators.

4.2.2. Measure and Analysis

Based on the indicator measurements from the data analysis (Figures 6 and 7) and the cause-and-effect relationship, there appears to be a potential leverage point in business performance through the improvement in both total visitors and the bounce rate. To accomplish this, two new hypothetical choices were proposed, and as they were never explored in the e-commerce situation in the past, they required validation:

- A co-creation competition for a new collection would be launched. The people in the brand’s Facebook network of fans and friends would be invited to participate in a competition where

they could be the brand’s designers and draw a set of products; from this, the winners would be announced as the new collection creators. The winners would also receive a prize, yet to be decided. This initiative had two objectives: The first was to engage the users of the brand in interactions and, consequently, to increase their connection with the brand. The consequence was also to enhance word of mouth which could provide free marketing and will increase the number of visitors. The second objective was to evaluate what the visitors really like, what they expect the brand to offer and, in this way, better understand the visitors’ needs and improve the value proposition. The two objectives combined had the goal to increase both the value proposition and number of visitors, which would also increase the number of interested visitors and, therefore, the transactions;

- The traffic source data showed that some visitors came from another fashion website and from fashion blogger posts. Based on this, the manager decided to establish partnerships with these fashion channels and observe if they were valuable and could become possible key elements in the business model.

The implementation of these four new choices was done at the same time and for four months, that is, from June to September of 2016. To analyze the impacts of these changes on the business model, a longitudinal analysis was conducted comparing the periods before (from October 2015 to April 2016) and after the application (from October 2016 to April 2017). Figure 10 shows the company’s business model after the new choices, considering the hypothetical ones that would need to be tested.

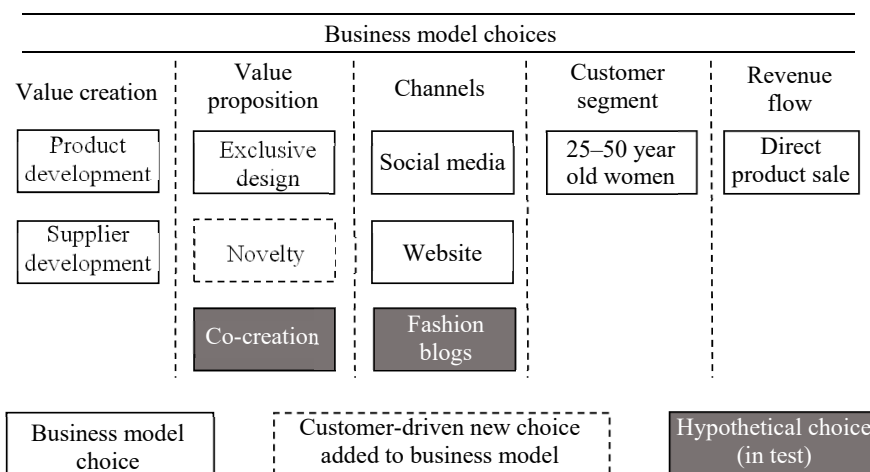


Figure 10. Business model choice representation after the new hypothetical choice creation in the second learning loop.

4.2.3. Longitudinal Analysis (Measure and Learn)

The new choices from both learning loops generated action plans for implementation. The first two involved studies about the ABC curve of the profit and stock, followed by the BCG (Boston Consulting Group) matrix in order to determine the products with the highest sale levels and, thus, the creation of content focusing on the core business of the company. The blogging initiative was also applied as a new channel to attract a greater flow of customers to e-commerce.

The co-creation choice had not yet been implemented. It some resistance to implementing this choice was observed. During a conversation with the manager, it was notable that this choice represented bigger changes and greater leaps in comparison with the other choices selected for implementation and, thus, insecurity around its application was clearly visible, even though this new choice was seen as promising during the idealization for new hypothetical choices.

The measurements of each cause-and-effect indicator before and after implementation are shown in Figure 11.

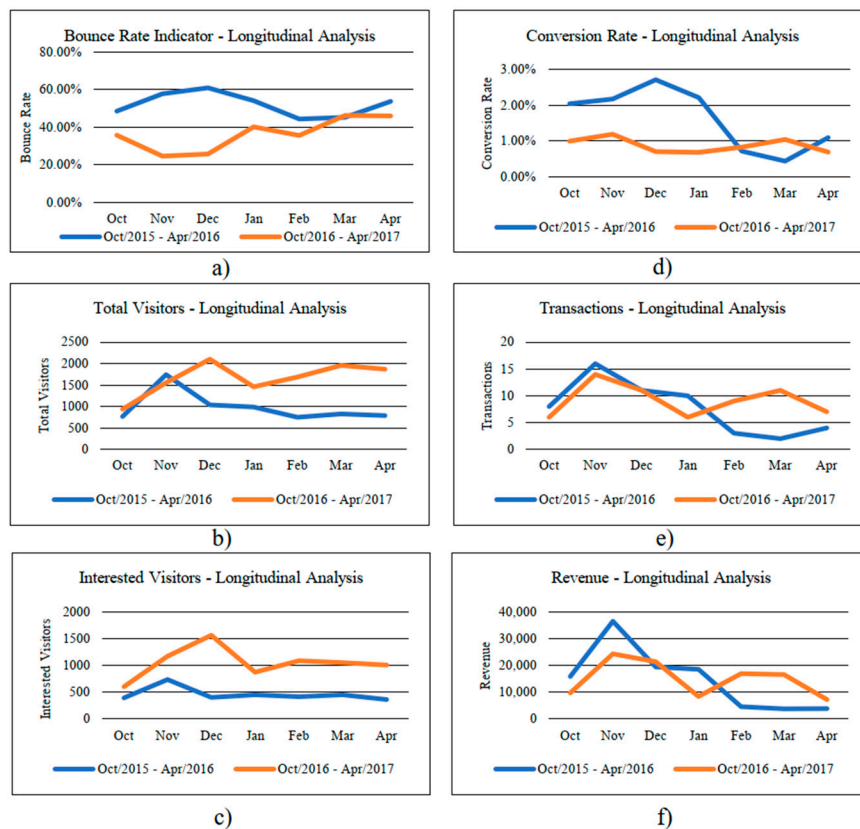


Figure 11. Longitudinal analysis of the selected indicators based on Figure 5.

The actions that were taken led to an improvement in sales distribution with smaller discrepancies between different periods as can be seen in the data in Figure 11e,f. Additionally, there was an overall increase in revenue of 2% when the two periods were compared; moreover, from February to April, when the sales were significantly lower before, there was an improvement of 231% in revenue for these periods.

This better distribution of sales was a very positive phenomenon for the organization, as it could now sustain a profit margin due to the associated fixed costs. In addition, an important caveat was the fact that during 10 days in January 2017, there was a problem with the payment process in the checkout phase (the final stage of revenue in which the client finishes the purchase in the website). Thus, during this period it was impossible to complete any sale and, therefore, no revenue could be registered. It is also relevant to highlight that the two periods analyzed covered November 2015 which had previously been the month with the highest revenue.

In relation to the new channel, the fashion blogs, there was a significant improvement in the indicators of total visitors (Figure 11b) and in the bounce rate (Figure 11a) which resulted in a larger number of interested visitors (Figure 11c) as proposed by the cause-and-effect diagram (Figure 5). However, it was also possible to detect a decrease in the conversion rate (Figure 11d) which meant that the increased volume of interested visitors did not result in a proportional increase in the number of transactions. This implies that the customer segment may not have been clearly and well defined.

In the interview conducted after the new choice implementation, even with an overall improvement in revenue of 2%, the manager was satisfied with the results. That is, as revenue was now more evenly distributed, this allowed for more working capital. In consequence, the manager showed willingness to keep working to improve the business model and the overall business performance.

The lesson learned at this stage of the application was that the level of change proposed by new choices, to steadily overcome cultural barriers, should be done incrementally. This means starting with more secure and smaller changes in the business model, seeking performance improvement,

and small innovation at first. This is because, as observed, the increase in morale can be important fuel for the paradigm shift regarding new choice selection and can lead to bigger innovations. To this end, the performance management of the business model, alongside reliable data, proved to this point to be a strong incentive.

4.3. Third Learning Loop

4.3.1. Hypothetical Choice

In the second learning loop, it became clear that the hypothetical choices proposed were proven correct; however, the customer segment, which was assumed as a correct and taken for granted choice, changed its status to hypothetical. Thus, a resulting BM is represented in Figure 12, containing the fashion blog as a new channel, the co-creation not yet implemented, and the customer segment hypothetical choice yet to be tested. Customer flow is also represented in Figure 12. In the flow, the conversion rate indicator is also utilized as a customer segment indicator, as the new knowledge obtained from the second learning loop suggested.

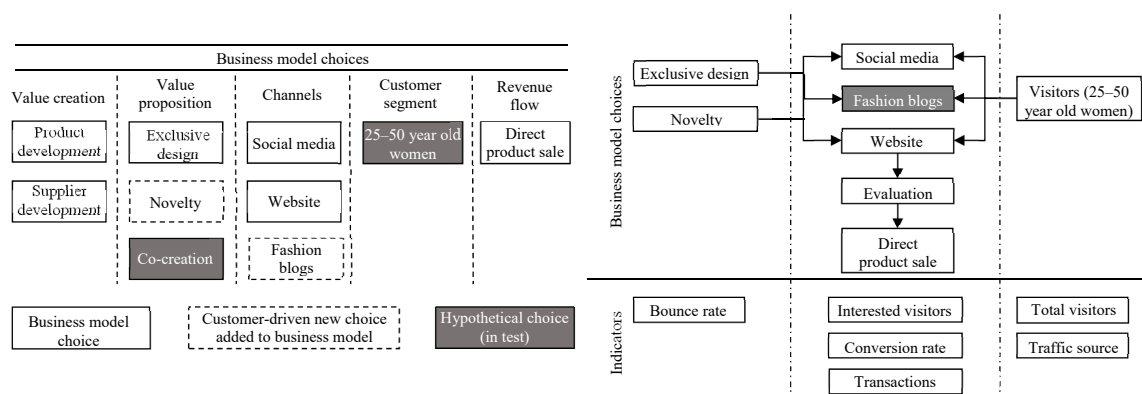


Figure 12. Third learning loop hypothetical BM choices and cause-and-effect diagram representation.

4.3.2. Measure and Analysis

After the representation of the resulting BM from the second loop, as the web analytics provided real-time data and following the artifact, the third learning loop started with the analysis of the new data in hand. Considering the cause-and-effect chain (Figure 5) and the new knowledge from the second learning loop, transactions and revenue were shown not to increase in the same proportion as the volume of visitors to the site. In addition, data on devices used by the visitors were also included. An increase in visitors coming mainly from mobile devices was observed and the conversion rate for such devices was much lower. The company’s e-commerce was not responsive for mobile devices and there was no mobile version. Therefore, the navigation on the website from mobile devices was difficult and not optimized. Consequently, the conversion rate on this device tended to be lower, as confirmed in Tables 1 and 2.

Table 1. Comparison between devices used and selected indicators: October 2015 to April 2016.

| Device | Total Visitors (Number) | Bounce Rate (%) | Interested Visitors (Number) | Conversion Rate (%) | Transactions (Number) | Revenue (Monetary Units) |
|---------|-------------------------|-----------------|------------------------------|---------------------|-----------------------|--------------------------|
| Desktop | 4550 | 55.87% | 2008 | 1.01% | 46 | 90,163.56 |
| Mobile | 2173 | 49.10% | 1106 | 0.32% | 7 | 11,262.12 |
| Tablet | 186 | 43.01% | 106 | 0.54% | 1 | 1155.24 |
| Totals | 6909 | 53.39% | 3220 | 0.78% | 54 | 102,580.92 |

Table 2. Comparison between devices used and selected indicators: October 2015 to April 2016.

| Device | Total Visitors (Number) | Bounce Rate (%) | Interested Visitors (Number) | Conversion Rate (%) | Transactions (Number) | Revenue (Monetary Units) |
|---------|-------------------------|-----------------|------------------------------|---------------------|-----------------------|--------------------------|
| Mobile | 5807 | 35.46% | 3748 | 0.26% | 15 | 24,679.08 |
| Desktop | 5475 | 36.99% | 3450 | 0.86% | 47 | 75,704.28 |
| Tablet | 293 | 47.10% | 155 | 0.68% | 2 | 4332.84 |
| Totals | 11,575 | 36.48% | 7353 | 0.55% | 64 | 104,716.20 |

Based on the results from the implementation of the first and second loops of new choices, a third set of hypothetical new choices were generated, seeking to improve the conversion rate. Included in this analysis was the fact that the previously taken for granted choice, the customer segment, was transformed into a hypothetical choice. This was based on the fact that expected results pertaining to new visitors to the website were not realized.

As the data indicated, the conversion rate decreased due to the lack of proper targeting of the company's customer segment. Thus, the results indicated that within the increase in the flow of visitors, there was also an increase in visitors outside the company's core segment of customers. As the company's products have higher quality and higher prices, a portion of visitors may show interest but do not purchase the products. In addition, an analysis was conducted of the conversion rates achieved by big companies in the fashion industry. During this analysis, the need to create a sales funnel in Google Analytics was identified, as it analyzes customer flow within the website and points out where customers abandon their purchases. This analysis can lead to insights around new ideas for improvements, since it is possible to identify the best leverage point.

4.3.3. Learn and Customer-Driven New Choice

The third set of hypothetical choices aimed at refining and/or redefining the company's customer segment. Since the customer segment largely influences channel and value proposition choices and also the BM overall performance, improving the knowledge about exactly who is the customer segment is of great importance. Besides, previous learning loops provided significant evidence to question if the initial customer segmentation was, indeed, accurate enough. To sum up, the main goal was to improve product/market fit—a condition considered crucial for any BM to be successful. These choices were:

- Conduct a study to identify the customer segment. In order to accomplish this, the e-commerce manager would carry out a study on age group, interests, and average income of the brand's customers. To this end, the manager would initially conduct a data analysis of Google Analytics in regard to the age range and interests of those who already purchased products. These data would serve as the basis for the formulation of a survey of the e-commerce clients, seeking to identify congruence among the data;
- Conduct a study about blog performance as well as the target audience of each blog in order to correlate the results of each blog with its respective target audience. The goal of this would be to triangulate with Google Analytics and survey data to define the business customer segment;
- Create various segments to boost the marketing in social networks to increase the number of brand users and verify which segments bring more revenue;
- Implement a sales funnel to generate data about customer flow within the site in order to identify how many visitors abandon their shopping carts with products and how many visitors reach the checkout stage. In sequence, identify how many visitors finish the checkout process and how many visitors abandon their purchases. According to an analysis of big company records, the manager pointed out that for fashion e-commerce in Brazil, the average abandon rate of a cart is 50%. This initiative sought to verify current state data to generate new platform improvement initiatives (creation of a new key activity);

- Analyze the feasibility of implementing responsiveness to the mobile device to improve navigation, improve the user experience and, hence, the conversion rate.

After the formulation of these new choices, a new interview with the manager was conducted to verify her resistance to the BM change process. As highlighted before, she expressed satisfaction with this process, and she felt that improvements had taken place and the overall performance of the business was also better. At this point, the subsequent visual representation of the BM, in addition to the fact that it integrated a more dynamic understanding of the concept, was also important in the idealization process. In other words, as was observed in this case, it led to a more holistic view of where improvements and new choices should be considered. During this phase, the manager showed a greater disposition to continue changing and improving the BM as it was also positively impacting on the overall business performance; thus, it was also possible to observe better morale and a better sense of security from the manager around the more venturous changes.

As an example, the manager intended to incorporate platform management as a new key activity of the company, even with little knowledge on the subject. Before the use of data analytics, the manager had not considered this activity due to the fact of its costs and the uncertainty about the need for it and the consequent impact on the business. After analyzing the data, she recognized platform management as an important activity for company growth. In other words, the use of big data through analytics allied with measurements of the business model choices gave the manager more confidence and understanding. Therefore, the barriers of BM trials (experimentation) were reduced.

The BM proposed after the second set of initiatives, that is, the future state to be implemented, is presented in Figure 13. The platform management was not part of the activities because, according to the manager, it was purchased from third parties and, therefore, not the core competence of the organization. Nevertheless, based on the data collected, it was demonstrated that even outsourced, platform service optimization would be interesting to develop through experimentation. In addition, the co-creation initiative was not yet tested and continued as a hypothetical choice, since it holds significant customer-driven value that should be investigated.

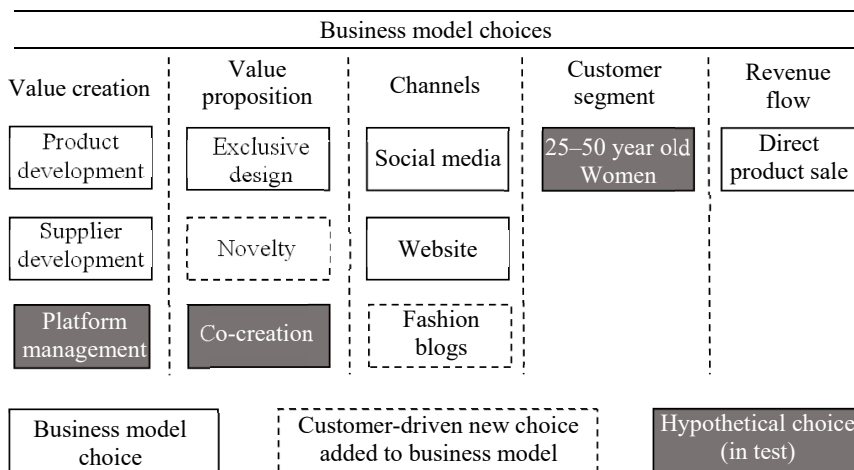


Figure 13. Business model choice representation after the new hypothetical choice creation in the third learning loop.

The customer segment that was previously considered a choice was now considered a hypothesis to be developed, since the data showed that there could be a misalignment between the audience reached by the channels and the audience that actually buys the company’s products. In addition, fashion blogs proved to be an effective channel requiring only optimization and, therefore, was incorporated into the BM as a new choice.

The results allowed to better understand the theoretical gap identified in Sections 2.1 and 2.2. That is, they explain how to develop a systematic process that allows a company to make decisions about

innovations in its BM guided by data. The application of the artifact resulted in a set of incremental BM changes, flowing from more secure ones in the beginning to more risky ones as the artifact cycled through more loops. This indicates that the risk minimization of the “error” part of the trial-and-error process based on accurate data about the business model performance played an important role in overcoming the initial cognitive inertia.

It is noticeable that given the nature of the study, keeping the exploratory focus, the research sought to present cycles of the application. However, as demonstrated by the results, this type of proposal is not a project with a start date and a deadline for closure. On the contrary, such an approach develops through cycles reinforcing learning within the company in each interaction. Thus, considering the work as exploratory, the focus of the study was to provide applications that demonstrate the accomplishment of these cycles so that other authors can use this as a starting point for future studies. The results presented here open opportunities for multiple case studies for external validation.

5. Conclusions and Future Research

As highlighted above, in this study, the focus was to provide an artifact for supporting decision making in the BMI process through the use of big data analytics. Therefore, a DSR was carried out to apply the proposed artifact and check the results obtained. As demonstrated in the previous section, the approach based on design science provided an in-depth analysis and investigation of the application over a period of time. That is, this study was conducted over a period of time to describe the consequences of the different learning loops presented. The choice for this methodological approach was to better describe how the organization became involved with the proposed artifact. Offering greater detail for future applications, thus operating as a reference guide.

The results collected present a valuable sample of how the analyzed e-commerce company made decisions about changes to its BM based on the methodology proposed, achieving, therefore, a better sustainable potential and making decisions about BMI. As an example, from the data obtained with analytics, it was possible to verify that customer segmentation of the BM was not well defined by the company. Even with some communication skills and influence on social networks, the company could be wasting resources when communicating with a segment which were not actually consumers. Thus, the results demonstrated that the ability of big data to deliver customer-driven products and services [19] can also be expanded to customer-driven BM. Hence, it is observed the relevance of a method that can manage BM choices and propose new alternatives with better performance intended to maintain a sustainable organization. Therefore, the results are aligned with the concepts of BMI and of SBMI [44,55,56].

The results show, as practical implications, how to deal with the BM as a dynamic element of company management, using big data analytics. That is, based on the analysis of data, the studied company was able to follow a guided search for innovations in its BM. From a theoretical point of view, the results analysis demonstrated that, in the case approached, even the most conservative tests, when successful, can help companies overcome cognitive barriers related to business model changes, contributing to the literature related to cognitive inertia [45,46]. This can be a starting point for other studies and based on the process, performance verification of experiments related to BM choices.

It is also important to highlight on a theoretical basis that the work contributed to an important gap in the literature. The study proposal indicated a way to operationalize BMI. Although there is a large body of research on the subject, there are few contributions as a practical approach on how to make this type of initiative feasible [6,13]. As recent literature shows, there are many problems when using the existing concepts and tools in practice [9,89]. In addition, we have also expanded the discussion to small businesses, not limiting the concept and operationalization of BMI to the spectrum of large companies that have a completely different context to address such practices. Which is important since the BMI literature is based on large corporations, with slack resources and sophisticated capabilities [1].

In short, this study proposes an opportunity to democratize the use of concepts such as BMI, big data, and web analytics that sometimes seem far from the reality of micro and small businesses.

The artifact is a low-cost tool, accessible to businesses of any size, and do not require a high degree of technician knowledge. Therefore, it provides a data-driven approach for companies seeking sustainability proactively.

As a limitation of this study, it should be noted that a single case study was used to conduct the research with an exploratory goal. This enabled researchers to follow the company closely in a longitudinal study and provided a deep analysis of the facts during the process. Nevertheless, as pointed out previously, the aim of this work was not to validate a theory or allow a generalization. Another important limitation to highlight is that the BMIs conducted were made according to the company's needs. In this sense, other organizations with other features may need different approaches or adaptations. In order to address more closely the conditions of the environment directly related to competitiveness, a study pointing out influencing factors for BMI correlated to this present work can be observed in Reference [58]. Nevertheless, the positive side of a single case study is that we could follow closely the problems associated with conducting the BMI process. Thus, our study provides an interesting view of the artifact functioning in practice and how it worked to support management decision making during a continual BMI effort which allows for further advancements on the topic.

For future research, it is important that the application in this study expands to other case studies that include other units of analysis in different contexts and sizes in order to evaluate the propositions in this research. In this sense, besides being of a theoretical contribution, its practical implications contribute to generating important innovation capabilities in business models through the linkage between a class of problems and an artifact. For this reason, the proposed application operates as a reference guide and may support future studies.

Furthermore, the use of analytics to evaluate business model performance can be expanded to other kinds of businesses beyond e-commerce. The challenge, in this case, is to find ways to collect data to use in the analysis. The prominent context of Industry 4.0 might provide an adequate ecosystem for BMI [108] once businesses become immersed in data.

Additionally, new studies are needed that contemplate BMs with dynamic characteristics that need to be simultaneously coordinated, combining existing choices with new choices to be experienced. The combination of exploratory and exploitative efforts with the same team, in the same location, despite working in the case here studied, also provided evidence for potential conflicts. In this sense, organizational ambidexterity should be explored as a mean to overcome this challenge and as a promising research path to follow to enrich the BMI theory and gain organizational sustainability.

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