UNIVERSIDADE ESTADUAL DE CAMPINAS
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Managing business model innovation: measuring capabilities, and structuring and strategizing efforts

Gestão da inovação em modelo de negócios: medindo capacidades, formatando estrutura e estratégias

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MATHEUS FRANCO

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Campinas, 03 de agosto de 2023.

DEDICATÓRIA

Dedico esse trabalho à minha esposa, Bruna Karadi, que esteve comigo em todos os momentos. Seu apoio, carinho, companheirismo são imprescindíveis. Dedico à minha filha Anna Júlia, que nasceu ao longo do percurso, e desde então traz uma alegria infinita a nós. Dedico aos meus pais, Flávia e José Francisco que sempre me apoiam e estão sempre conosco.

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Em 2015, meu último ano na graduação, estava indeciso sobre os próximos passos em minha carreira. Ainda não havia descoberto uma paixão. Minha esposa, ainda namorávamos na época, em contrapartida, estava decidida a trilhar carreira acadêmica. Decidi acompanhá-la. Mesmo com receio, já que escrita nunca havia sido meu forte, mergulhamos no mestrado em 2016. Optei pela engenharia mecânica, com o Professor Antonio Batocchio, já que eu havia me interessado em suas linhas de pesquisa sobre gestão da produção. Me surpreendi ao conversar com ele. A oferta seria estudar algo sobre o qual nunca havia ouvido falar: Modelo de Negócios. E agora? Bom, meu primeiro agradecimento, certamente, é ao professor Antonio Batocchio. Além de ter sido um mentor e amigo, me apresentou ao tema pelo qual me apaixonei.

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RESUMO

Gestão da inovação do modelo de negócios tornou-se uma capacidade crítica para as empresas no atual ambiente acelerado e dinâmico. A literatura sobre modelos de negócios e suas inovações cresceu desde o surgimento do conceito no final da década de 1990. Apesar dos avanços, no entanto, lacunas críticas permanecem. O objetivo desta tese de doutorado é abordar lacunas relacionadas às capacidades dinâmicas, a estruturação de unidades de inovação de modelos de negócios e a digitalização de seu processo. Nossas descobertas são separadas em quatro capítulos interconectados. O Capítulo 1 mostra que, ao contrário da literatura que sugere uma relação unidirecional e recursiva entre capacidades dinâmicas e inovação do modelo de negócios, ela é de fato bidirecional e não recursiva. Por meio da *Design Science Research*, propomos um conjunto de 18 indicadores para medir capacidades dinâmicas e mostramos sua aplicabilidade em um estudo de caso único. O Capítulo 2 mergulha nas estratégias e na estruturação de unidades para a inovação do modelo de negócios. A literatura controversa favorece as unidades separadas como superiores às unidades integradas, ao mesmo tempo em que argumenta contra a estratégia. Ao contrário dessa sabedoria, o Capítulo 2 mostra que as unidades integradas podem ser de fato funcionais, explicando como e por que funcionam. Os capítulos 3 e 4 concentram-se no processo de inovação do modelo de negócios, reunindo engenharia e administração. Com base em uma abordagem teórica, o Capítulo 3 propõe o conceito de "*Business Model Innovation Analytics*", um processo orientado por dados que contrasta com a visão experimental dominante. Aplicamos essas recomendações no Capítulo 4, cujas descobertas mostram que a avaliação da literatura científica por meio do aprendizado de máquina é comparável à análise tradicional baseada em humanos e ambas se reforçam. Portanto, uma abordagem promissora para melhorar a reduzida taxa de sucesso do processo.

Palavras-chave: Inovação em modelos de negócios; Capacidades dinâmicas; inovação disruptiva; analítica de inovação; Digitalização; Gestão da Inovação

ABSTRACT

Managing business model innovation has become a critical capability for companies in today's fast-paced and dynamic environment. Literature on business models and their innovations has grown since the concept's emergence in the late 1990s. Despite advancements, however, critical gaps remain. This doctoral thesis' purpose is to address gaps related to dynamic capabilities, structuring business model innovation units, and the process' digitalization. Our findings are separated into four interconnected chapters. Chapter 1 shows that, contrary to the literature that suggests a unidirectional and recursive relationship between dynamic capabilities and business model innovation, it is in fact bidirectional and non-recursive. Through design science research we propose a set of 18 indicators to measure dynamic capabilities and show its applicability in a single case study. Chapter 2 dives into strategizing and structuring units for business model innovation. Controversial literature favors separated units as superior to integrated units, while simultaneously arguing against the strategy. Contrary to this wisdom, Chapter 2 shows that integrated units may be in fact functional, explaining how and why they work. Chapters 3 and 4 focus on the business model innovation process, bringing engineering and management together. Based on a theoretical approach, Chapter 3 proposes the concept of "Business Model Innovation Analytics," a collaborative intelligence process that contrasts to the dominant experimental view. We apply these recommendations in Chapter 4, whose findings show that machine learning appraisal of scientific literature is comparable to the traditional, human-based analysis and both are mutual reinforcing. Hence, a promising approach to improve the process' success rate.

Keywords: Innovation in business models; Dynamic capabilities; disruptive innovation; innovation analytics; Digitalization; Innovation Management

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SUMMARY

Introduction[1]

"*The key is to embrace disruption and change early. Don't react to it decades later. You can't fight innovation.*"—Ryan Kavanaugh

"*Innovators need a heavy dose of faith. They need to trust their intuition that they are working on a big idea. That faith need not be blind."*– Clayton Christensen

Blockbuster fell to Netflix. Nokia suffered with the software industry's emergence and growth. Airbnb struggled with COVID-19's social distancing. Encyclopædia Britannica was hit hard by Microsoft's Encarta. Why did these companies struggle? What did they have in common? For starters, they were well-managed companies, like those described by Clayton Christensen (2000). So, what was the problem? Odds are, they failed in conducting Business Model Innovation (BMI). Blockbuster attempted to fit new paradigms into its existing Business Model (BM) (AHUJA; NOVELLI, 2016). Nokia tried to create parallel software-based BMs instead of renewing its obsolete BM (HACKLIN; BJÖRKDAHL; WALLIN, 2018). Airbnb placed all efforts into a single BM (KOLOMATSKY, 2021; LEÓN, 2022), and although Encyclopædia Britannica recognized its BM's obsolescence and sought to renew it, the company struggled with BMI for 15 years (CAUZ, 2013; GREENSTEIN, 2017).

These cases evidence the plurality of challenges surrounding BMI management. Blockbuster is an example of organizational inertia and path dependency, Nokia of poor strategizing and decision making, Airbnb exemplifies the pitfalls of putting all efforts into a single BM, and Encyclopædia Britannica highlights the need for BMI capabilities to overcome BM rigidity. And these are only examples inside a much larger sample of BMI failure cases (SABARUDDIN; MACBRYDE; IPPOLITO, 2023), which is not all surprising as BMs are not

[1] This PhD thesis was conducted in alternative format, as a collection of published works according to the norm No. 14/2021 from the University of Campinas, Geosciences Institute, Department of Science and Technology Policy.

built to change, but to replicate (CHRISTENSEN; BARTMAN; VAN BEVER, 2016) which makes them rigid to change (DOZ; KOSONEN, 2010).

Despite these challenges, as Kavanaugh argues, you cannot fight innovation. Change is the only certainty in life. Although change and disruption have always been there, as remarked by Schumpeter’s (1947) Creative Destruction cycles, it is intensifying because of an increasing pace of social and technological shifts (SCHOEMAKER; HEATON; TEECE, 2018), in which digitalization plays a major role. After all, digital technologies’ general-purpose character (GAMBARDELLA; MCGAHAN, 2010) and their enabling capability for new products, processes, and BMs (TEECE, 2018a) are accelerating existing BMs’ obsolescence speed. Hence, escalating the need for managing BMI.

Digitalization also enables opportunities for exploring new BMs (BERMAN, 2012a; KLOS et al., 2021). Evidence for this claim is abundant. For example Netflix’s emergence from scratch to overcome a reigning giant, and digital startups threatening long living giants, such as FinTechs and incumbent banks (ANAGNOSTOPOULOS, 2018). Another example is Uber, which contrary to Airbnb, has pursued opportunistic BMI, creating Uber Eats and Uber Freight. Despite its core BM suffering from social distancing, its parallel BMs sustained the company’s health. In fact, Uber grew during the crisis (RICHTER, 2022). Thus, the same aspects underlying digitalization’s role in reducing BMs life cycles and urging the need for BMI, promote opportunities for companies to explore through BMI.

Business model innovation has, therefore, a bright and a dark side. While it is necessary to overcome turbulence (HABTAY; HOLMÉN, 2014; TONGUR; ENGWALL, 2014) and a source of competitiveness and resilience (BENSON-REA; BRODIE; SIMA, 2013; SNIHUR; TARZIJAN, 2018) it displays high failure rates and significant barriers that can lead companies to catastrophic outcomes and even threaten their lives (SABARUDDIN; MACBRYDE; IPPOLITO, 2023). Such characteristics highlight the need to investigate BMI management, to assist companies in making informed strategic decisions, building necessary capabilities, and improving the underlying process effectiveness.

During the past 23 years, since the dotcom bubble burst that gave origin to the BM concept (MAGRETTA, 2002), academics and practitioners have made significant advancements regarding BMI management. In the first 10 years of research, the focus was on attempting to clearly define the BM concept and its significance for companies (FOSS; SAEBI, 2016). After 2008, when research on BMI intensified, research switched focus to the BMI process, proposing numerous tools for BM design (e.g., CASADESUS-MASANELL; ZHU, 2013; JOHNSON; CHRISTENSEN; KAGERMANN, 2008; OSTERWALDER; PIGNEUR, 2010; TÄUSCHER; ABDELKAFI, 2017), ideation (FRANKENBERGER et al., 2013; WIRTZ; DAISER, 2018), and suggested trial-and-error (SOSNA; TREVINYO-RODRÍGUEZ; VELAMURI, 2010) and experimentation (CHESBROUGH, 2010) as underlying techniques.

After 2014, in contrast to the previous focus on definition, design and tools, literature turned attention to BMI antecedents. Inside this vein, scholars proposed the capability view of BMI (MEZGER, 2014; TEECE, 2018b), suggesting the Dynamic Capabilities (DC) of sensing, seizing, and transforming (TEECE, 2007) as the core BMI antecedent. In parallel, literature advanced on uncovering aspects that lead to the development of these capabilities. In particular, the revealing the role of top management team's cognition (FOSS; SAEBI, 2016; VOLBERDA et al., 2021), their perception of opportunities (e.g., MARTINS; RINDOVA; GREENBAUM, 2015), their diversity and background (e.g., GUO; PANG; LI, 2017) and how they influence companies BMI management.

Moreover, there have also been significant advances in strategizing for BMI. Findings appraise when and how incumbents benefit from exploring new, parallel BMs (BENSON-REA; BRODIE; SIMA, 2013; KIM; MIN, 2015; SNIHUR; TARZIJAN, 2018) and highlight the adequacy of strategies – renewing a threatened BMs or creating new BMs – considering the environmental dynamics (HACKLIN; BJÖRKDAHL; WALLIN, 2018). Studies also suggested that, for radical BMI (e.g., those necessary for Blockbuster and Encyclopædia Britannica), companies should deploy separate, dedicated units (CHESBROUGH; ROSENBLOOM, 2002; HABTAY; HOLMÉN, 2014; KUHLMANN; BENING; HOFFMANN, 2022; TONGUR; ENGWALL, 2014), and pinpointed key barriers to this strategy and the associated problems

(EGFJORD; SUND, 2020; RENNINGS; WUSTMANS; KUPP, 2022; SUND; BOGERS; SAHRAMAA, 2021).

Despite these advancements, there are still open debates in the BMI management literature, needing further clarification. One of the problems is that, even though DCs are recognized as the core BMI antecedent, its translation to practice is still underdeveloped. The organizational phenomena that build DC remains a black box. That is because the extant measurements for DC depict solely each capability's presence or absence. For example, two frequently used questions to measure DC are "We devote a lot of time implementing ideas for new products and improving our existing products." (PAVLOU; SAWY, 2011) and "The resource reconfiguration capability of our firm is strong" (YUAN; XUE; HE, 2021). The subjectivity in how much is "a lot of time" and what it means to have a "strong" capability leads to biases and confusion. The consequence is that they are interpretive and carry little (or no) information about "how" to develop the capability and "why" the DC is weak or strong.

Chapter 1[2] seeks to address this gap by creating a set of measurements that represent the organizational phenomena behind DC. Contrary to the literature, that suggests a direct relationship from DC to BMI, we show that the relationship is mutual and bidirectional. Thus, emphasizing that the BM shapes DC, and that BMI has the power to reframe DC. Based on this notion, we followed design science research, first conducting a systematic literature review to build the measurements followed by a single case study to evaluate the tool. We propose 18 measurements, six for each capability of sensing, seizing, and transforming. Then, we employ the indicators to diagnose the current BM state and then to guide BMI focused on improving DC. We show that this approach led the company to evolve its capabilities through time, offering evidence that DC and BMI share a mutual, non-recursive relationship.

The case presented in chapter 1 provided revealing evidence that to develop DC, the studied company needed to deploy a dedicated structure as owner of the BMI efforts. Such finding is aligned with another open debate in BMI research: structural configuration and

[2] Originally published in 2021 IEE Access: FRANCO, M. et al. Opening the Dynamic Capability Black Box: An Approach to Business Model Innovation Management in the Digital Era. IEEE Access, v. 9, p. 69189–69209, 2021. https://doi.org/10.1109/ACCESS.2021.3077849 (JCR: 3,476; Quali Capes: A1)

strategies to balance BM renewal, radical innovation, and exploration. Literature in this regard has been, so far, controversial. While research argues in favor of separate, dedicated units (e.g., CHESBROUGH; ROSENBLOOM, 2002; KUHLMANN; BENING; HOFFMANN, 2022), others highlight this strategy's barriers, challenges and problems (EGFJORD; SUND, 2020; SUND; BOGERS; SAHRAMAA, 2021) promoting arguments against it.

Despite the controversy, literature seems to agree that integrated structures are ineffective to conduct radical BMI and exploratory BMI (e.g., HABTAY; HOLMÉN, 2014; KHANAGHA; VOLBERDA; OSHRI, 2014). There is, however, a lack of evidence on this assumption, as studies focus on separated structures, their functions, and problems. Chapter 2[3] targets this issue, investigating the effectiveness of integrated BMI structures. We deploy a multiple case study with three large Brazilian incumbents and leverage systems dynamics as the analytical lens to evaluate the results. Our findings offer evidence that contradicts literature, showing that integrated structures may be in fact functional. Underlying its functionality is strategizing, as we suggest that combining renewal and exploration plays a major role in the effectiveness. We show that a future-oriented and transformative BMI, focusing on renewing the core BM is crucial for the long-term success of integrated BMI units. Our findings highlight that integrated structures should play a major role in the core BM, creating a "buffer" that sustains exploratory and radical innovation efforts.

Chapters 1 and 2 focus on strategic aspects regarding BMI management, while overlooking the BMI process. As suggested in BMI literature, the main approaches to conduct the process are effectuation (FUTTERER; SCHMIDT; HEIDENREICH, 2018; HARMS et al., 2021) through experimentation (CHESBROUGH, 2010; SILVA et al., 2019) and trial-and-error (DOZ; KOSONEN, 2010; SOSNA; TREVINYO-RODRÍGUEZ; VELAMURI, 2010). The major problem with this is that the process still has high failure rates and high associated costs, which are often taken for granted as part of BMI.

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[3] Originally published in Systems (MDPI): FRANCO, M.; MINATOGAWA, V.; QUADROS, R. How Transformative Business Model Renewal Leads to Sustained Exploratory Business Model innovation in Incumbents: Insights from a System Dynamics Analysis of Case Studies. Systems 2023, 11, 2. https://doi.org/10.3390/systems11020060 (JCR: 2,895; Quali capes: A3)

One of the reasons for that may be due to a dominance of management approaches, needing a deeper integration to engineering and other disciplines. Evidence for this assumption is the growth in studies investigating the impacts of digitalization on companies' BMs (e.g., BERMAN, 2012; IBARRA; GANZARAIN; IGARTUA, 2018; LATILLA et al., 2020), whereas the digitalization of the BMI process, through an interdisciplinary approach, remains underdeveloped. In this regard, literature has advanced notions of data-driven approaches for BMI, particularly attempting to reduce uncertainty and failure rates (e.g., MINATOGAWA et al, 2019). Nevertheless, we see both poles as problematic. On the one hand, relying on experimentation and trial-and-error alone may be misleading and inefficient. Conversely, eliminating uncertainty and automating the BMI process seems impossible and prone to creativity problems. Despite advancements in attempts to build artificial creativity, it is considered to be a weak spot and largely neglected (SCHULLER; SCHULLER, 2018).

Chapters 3 and 4 are result of a cooperation project of Unicamp with the Construction Engineering School, PUCV, Chile. The project's core is to advance the knowledge on collaborative human and artificial intelligence for innovation. Inside this project, Chapter 3[4]'s study seeks to combine management science and data science engineering to propose the concept of BMI analytics, in which machine and humans work collaboratively. Hence, we theorize that analytics and artificial intelligence can cope with knowledge intensive activities (e.g., screening large patent datasets) which can augment human creativity and cognitive processes (e.g., ideation and pattern recognition). We propose a theoretical framework depicting the BMI process as a double diamond, with creative divergent stages followed by knowledge intensive convergent parts underlying the DC of sensing, seizing, and transforming. We then propose that the knowledge intensive parts can be largely boosted by analytics, suggesting techniques and guiding questions. Finally, we suggest a roadmap for implementing BMI analytics, the teams' configurations, and the need to fit this into BMI dedicated structures.

[4] Originally published in the book "Innovation analytics: Tools for Competitive Advantage): FRANCO, M. et al. Business Model Innovation Analytics for Small to Medium Enterprises. In: Innovation Analytics: Tools for Competitive Advantage, eds. Subramanian, N., and Ponnambalam S. G., World Scientific, ISBN: 978-1-80061-000-2.

In Chapter 4[5] we dive deeper into the engineering part of BMI analytics. Working together with the Chilean Ministry of Public Works (MOP), the study applies a technique for scanning large amounts of academic publications, through a hybrid methodology. As such, we built an interdisciplinary team, composed of management and engineering scholars. The central idea is that the technique works as a complementary activity to screen for innovation opportunities in a specific field. In particular, the technique is adequate for the fuzzy front end of innovation. Given the partnership with MOP and the Construction Engineering School, the target industry selected was the construction sector.

We applied Natural Language Processing (BERT-Topics) to map the application of Machine Learning techniques in the construction sector. The major challenge with BERT-Topic technique, as with other machine learning techniques, is that data outputs may be hard to decipher, needing treatment and expert interpretation. Although so far it has resulted in hard-to-interpret results and a poor complement to mainstream approaches. Our findings show that its results are in fact similar and complementary, as Chapter 4 combines and compares both traditional and machine learning analysis, thus emphasizing the need for collaborative intelligence research for innovation. The study shows promising results for such an integration, and the results offer a basis for expanding to other sectors and other databases, such as patent databases.

In all, this Doctoral Thesis can be summarized into 2 parts. Part 1 targets BMI strategic level, in which Chapter 1 maps and measures the DC for BM and Chapter 2 investigates integrated BMI units and moves forward the discussion on strategizing and structuring for BMI. Part 2 turns attention to the BMI process, particularly bringing an engineering perspective to propose the concept of BMI analytics. Then, it dives deeper into the technical feasibility of these analytics with an application to the construction field. Figure 1 provides an overview of this thesis' chapters and parts.

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[5] Originally published Automation in Construction: GARCIA, J. et al. "Machine learning techniques applied to construction: A hybrid bibliometric analysis of advances and future directions," Automation in Construction, 142, October, p. 104532, 2022 https://doi.org/10.1016/j.autcon.2022.104532.

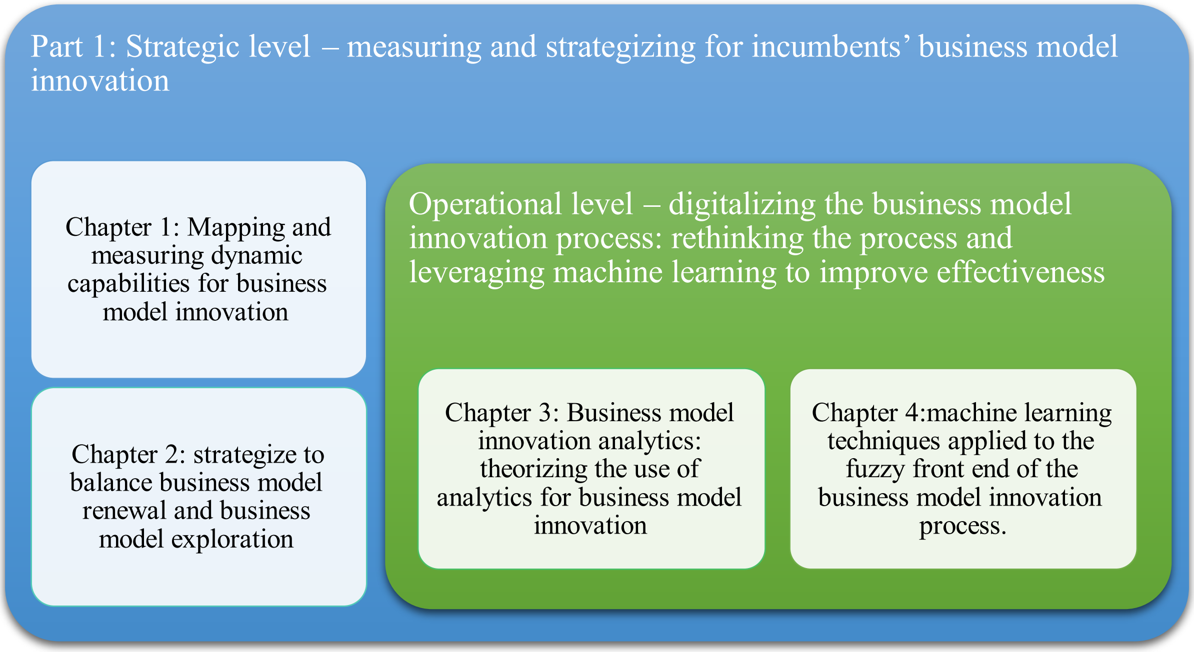

Figure 1. The structure and logic of the thesis and the overall organization of the chapters.

Chapter 1

Opening the dynamic capability black box: an approach to business model innovation management in the digital era

Franco, M., Minatogawa, V. Durán, O., Batocchio, A., and Quadros, R.

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Abstract

The digital era is reshaping the competitive landscape, creating a more turbulent environment where digital technologies play a significant role in enabling innovative business models. Companies need to promote business model innovations, readapting their business models, and create new digital business models to thrive in this scenario. The literature emphasizes that dynamic capabilities are the main antecedent to business model innovation. However, the dynamic capabilities construct is poorly operationalized, lacking proper measurements that effectively translate them to practice, remaining a black box. This paper aims to further understand, operationalize and measure the distinctive dimensions of dynamic capabilities for business model innovation. To this end, we follow the design science research methodology, building a tool for dynamic capabilities evaluation through a systematic literature review. We then evaluate the tool based on a three-year, in-depth case study of a software company. Our findings show that the current business model has a central role in shaping dynamic capabilities for business model innovation. The proposed measures encompass activities and practices and business model structure, highlighting the relevance of the co-evolution between business model and dynamic capabilities. Thus, we propose creating what we call a “business model innovation engine” as a function that reshapes the business model to incorporate dynamic capabilities as part of the value creation architecture. We contribute to theory by better translating dynamic capabilities for business model innovation to observable (and measurable) organizational phenomena, linking it to the extant strategic management literature, and elucidating how to measure and guide the build-up of such capabilities. We also add to practice by developing a practical tool for management to use as a means to evaluate their current dynamic capabilities state, therefore guiding for informed strategic action.

Keywords: Business model innovation; design science research; digital economy; dynamic capabilities; innovation management.

1. Introduction

This paper aims to further understand, operationalize and measure the distinctive dimensions of Dynamic Capabilities (DC) for Business Model Innovation (BMI). The focus is on assisting management in evaluating their company's DC for BMI, following the logic of responsiveness in management. It is necessary to better understand and measure the problem in order to be able to solve it. Thus, understanding the connection between DC, BM, and BMI is key to finding ways to manage DC's creation for BMI. Hence, this study seeks to answer the following research question: What are the main DC dimensions and how to measure DC for BMI management, leading to the build-up of such capabilities?

Research on BMI advanced fast in the past years, improving our understanding of designing and implementing novel BM. Recent literature reviews and studies aiming at framing the big picture of BMI have proposed similar ideas. Teece (TEECE, 2018a) argues that Dynamic Capabilities (DC) are necessary for BMI, accounting for the search, design, and implementation of novel BMs exploring technological opportunities. Foss and Saebi (FOSS; SAEBI, 2016, 2018) suggest that the theory is still fragmented because publications follow specific aspects of specific industries' particular cases, leading to an apparent conceptual divergence. However, the authors suggest that they may be closer than it seems and that the Open Innovation (OI) paradigm and DC are the core BMI antecedents. Wirtz and Daiser (BERND W. WIRTZ, 2016) suggest that knowledge management improves DC for BMI.

Despite the convergence in the literature towards emphasizing DC as the main road to BMI, the remaining issue is that reaching out to this conclusion is not enough. DC remains poorly operationalized because, in attempting to measure DC, extant research has not gone much beyond the quite abstract concepts of sensing, seizing and transforming (TEECE, 2018a), which are hardly translated to observable (and measurable) organizational phenomena. For instance, Yuan et al. (YUAN; XUE; HE, 2021) have asked the question “The resource reconfiguration capability of our firm is strong” in a questionnaire aimed at measuring DC (YUAN; XUE; HE, 2021). Yet, it is arguable whether managers answering such questions share the same understanding of reconfiguration capability. Moreno et al. (MORENO; CAVAZOTTE; DE SOUZA CARVALHO, 2020) adopt Pavlou and El Sawy’s (PAVLOU; SAWY, 2011) proposal for operationalization of DC, which is based on Teece’s early formulation of DC theory (TEECE; PISANO; SHUEN, 1997) and comprises the following categories to be measured in scale: environment understanding, learning ability, integration ability, and coordination ability. Again, such categories are at a very high level of abstraction, which is not easily identifiable with measurable organizational indicators. In this regard, how to translate sensing, seizing and transforming capabilities into measurable routines, practices and assets, which could consistently inform managerial action, remains a significant gap.

To answer this study’s research question, we choose to conduct the study under the Design Science Research (DSR) approach. First, we conducted a systematic literature review to extract and group the major organizational practices, resources and tools associated with the building up each of the three major DC for BMI: sensing, seizing and transforming. Then we created a measurement, an indicator for each group to construct a tool for evaluating DC for BMI. Finally, we conducted a longitudinal in-depth case study with a Brazilian medium-sized software company to evaluate the tool for three years.

Our findings indicate that the current BM plays a central role in shaping DC for BMI. Our evaluation tool and our case study show that the build-up of DC depends on specific activities and practices. Moreover, reshaping the current BM also helps in promoting DC in a company; that is, BM structure and its evolution path are significant for building DC. Hence, each company will likely need to deploy different strategies, activities, and practices for developing DC considering their BM characteristics. This finding highlights the tool's effectiveness once its indicators scores helped the company build-up DC for BMI by creating what we call a BMI engine function. Thus, our contributions to the literature are on advancing DC's theoretical construct, positioning it as a co-evolution with BMI and advancing the notion of BMI management. Finally, we also contribute to practice by providing management with a potential tool to map its BM current state in terms of DC and guide its development to create a BMI engine while also sustaining the BM performance.

The paper's structure is as follows. Section 2 presents the theoretical background, guiding the reader to our proposition's logic, and showing the main concepts. Section 3 presents the research methodology. Section 4 contains the tool design and presentation, and section 5 depicts its evaluation through a deep dive case study. We discuss the findings and put forth the final considerations in Section 6.

2. Theoretical Background

2.1. Dynamic Capabilities, Innovation, And Strategy

The achievement of sustainable competitive advantages is the primary goal in the strategy literature. To sustain competitive advantages, firms need to differentiate themselves, both by strategic positioning in the market and by leveraging complex, rare, difficult to imitate resources. However, the competitive positioning fades out in the presence of innovation (LINTON, 2009; TEECE; PISANO; SHUEN, 1997), which leads to the need for the company to build DC for sustaining its innovation performance and competitiveness (SCHOEMAKER; HEATON; TEECE, 2018). A good example is Kodak's creation (and failure to exploit) of digital photography, creating new dynamics in the industry that led Kodak to bankruptcy, destroying their value and competitiveness sources (LUCAS; GOH, 2009).

DC is defined as a firm's capability to sense new opportunities, mobilize resources to seize such opportunities, and transform/reconfigure key organizational aspects to implement the necessary changes (TEECE; PISANO; SHUEN, 1997). Therefore, DC is strongly associated with innovation and represents the exploration of both technological and market-oriented opportunities to profit from innovation (LIN et al., 2018). It means the company's capability to innovate at the strategic level.

To survive in today's "Digital Economy," companies need to build strong DC to sustain (and create) competitive advantages (TEECE, 2018b). The increasing technological progress pace, the organizations' digital transformation, the changes in the social and cultural spheres, and the rising environmental and social-related regulatory pressures are all ingredients to a more turbulent and uncertain environment. Uncertainty and risk are essential variables to understand the relevance of DC at the BM level. The former are "unknown unknowns," a terrain where there is simply no way of predicting the future. In turn, risks are "known unknowns," as they are predictable, measurable, and often manageable (TEECE; LINDEN, 2017a). In an uncertain digital world, there are increasing threats to a BM's health while opening the possibilities for new BM, emphasizing the relevance of developing strong DC for BMI.

The persisting challenge is that developing a strong DC is not trivial, and the distinction between Ordinary Capabilities (OC) and DC is essential to understand this issue. The former comprises the current routines, the cumulative learning by doing, and "best practices" underpinning the current BM (TEECE; PETERAF; LEIH, 2016). The latter searches for opportunities beyond the current BM designs new BM to seize those opportunities and implement a new BM by transforming and escalating (TEECE, 2018a). Christensen's (CHRISTENSEN, 2000) innovator's Dilemma and Levinthal's (LEVINTHAL, 1996) competence trap provide us with illustrations of how hard it is balancing between strengthening OC and developing DC. The odds that companies will focus on enhancing OC are much higher (CHRISTENSEN; BARTMAN; VAN BEVER, 2016).

The challenge is that improving the current BM performance is more straightforward and often more comfortable than developing DC. It may look even more challenging considering the difficulties to operationalize DC's, creating further barriers. To search for a potential solution to these limitations, we will further explore BM and BMI theories. Every company needs an adequate BM to be successful, strengthening it to improve performance. This leads to a side effect: the more effective the BM grows; generally, the more rigid it gets (FOSS; SAEBI, 2018). Additionally, to explore novel opportunities, especially those not aligned with the current BM, companies will have to design and implement new BM.

2.2. Business Models and Business Model Innovation

According to Teece (TEECE, 2010, p. 172), a BM "describes the design or architecture of the value creation, delivery, and capture mechanisms it employs." It represents the underlying logic of the business and how the different strategic components relate to each other. The literature suggests different BM dimensions and components (MASSA; TUCCI; AFUAH, 2017; ZOTT; AMIT; MASSA, 2011). DaSilva and Trkman (DASILVA; TRKMAN, 2014) define BM as a combination of the resource-based view with the Transaction Cost Economics and the market positioning literature. However, the point is that if it is only a combination of well-defined strategy theories, how does the BM literature add value to the strategic management literature? According to Foss and Saebi (FOSS; SAEBI, 2018), BM and BMI's core contribution is systemic, placing complementarities as the main BM component. Strategic management focuses on setting goals and objectives and defining key BM components, such as resources, capabilities, and market positioning (DASILVA; TRKMAN, 2014). The BM literature, in turn, focuses on how such components should be interconnected, amplifying the value chain by creating virtuous value cycles, translating the strategic plans into a logical and coherent architecture (CASADESUS-MASANELL; RICART, 2010).

Understanding BM as a system has significant conceptual consequences, such as that internal consistency alone is not sufficient since the relationship with the external environment is also relevant. Different countries and regions have different cultures, institutional rules of the game (i.e., regulatory scenario, Intellectual Property Rights laws, and human resources characteristics), and specific problems to solve. The fit between the value proposition to the customer will vary, and the value creation and delivery architecture will need to adapt. Analysis of Uber's BM transfer to South Africa shows us how environmental features, such as the high unemployment rates, lead to different value creation dynamics. Dreyer et al. (DREYER et al., 2017) show that the value to Uber's drivers is lower in South Africa because there are many more drivers available than in the USA, leading to problems with assigning runs and harming the BM's long-term health.

Considering complementarities as the key BM component has implications on the definition of BMI itself. We follow Foss and Saebi (FOSS; SAEBI, 2016, p. 216) definition of BMI as "designed, novel, and nontrivial changes to the key elements of a firm's BM and/or the architecture linking these elements," understanding BMI in terms of novelty and scope. Scope follows from modular to architectural. Modular indicates low complementarities level, meaning that it is possible to change a few components keeping the others intact. Architectural means that changing one component calls for a total BM reconfiguration. Novelty ranges from new to the company to new to the world.

Thus, both components and their interactions matter for BMI, leading to different degrees of change. For companies to survive, they need to understand those challenges to innovate their BM and answer to the changes resultant from both technological and non-technological innovations. However, the challenge is that this notion also has a side effect: the company's BM evolution shapes the company's capability to innovate the current BM (BERENDS et al., 2016). It leads to a seeming paradoxical nature that the company needs DC to innovate the BM, which could, in turn, reduce its DC in the long run. Therefore, it seems that while literature emphasizes DC as the primary BMI antecedent, the relationship does not seem to be unidirectional, simply because a BMI could lead to a reduction in the company's future capability for BMI. Christensen's (CHRISTENSEN, 2000) Innovator's Dilemma provides us several examples of this feature, with new entrants disrupting old markets by introducing novel BMs but failing to answer the next wave of disruption.

2.3. The Challenge Ahead

Considering the bidirectional relationship between DC and BMI, the challenge is how both literature strands can be combined to understand these dynamics better and tackle this issue. Recent literature suggests that similar to product innovation, BMI should also rely on understanding the BM lifecycle, with the possibility to manage more than one BM simultaneously (LAUDIEN; DAXBÖCK, 2017). Others suggest the organizational ambidexterity as a solution (MARKIDES, 2014), which is in fact considered an important dynamic capability (WIRATMADJA; PROFITYO; RUMANTI, 2020). Some specificities make sense in theory, but it is hard to translate to the practice. As we argue, this is due to the systemic character of BMs, which means that each company deploys different BM in different contexts, demanding different strategies. Therefore, one size does not fit all. A technology-intensive firm with low entrepreneurial orientation is more likely to have a hard time sensing opportunities. In turn, a market-oriented one may struggle to provide technological solutions to external opportunities. We argue that each company's BM reflects specific DC characteristics, having strengths in some DC facets while weaknesses in others. As such, strategic action for developing DC in the first example will be significantly different than to the second. While the first may focus on deploying open innovation to find market partners to sense opportunities, the second may focus on finding technical partners to develop solutions or leveraging a startup network to seize sensed opportunities. Thus, assessing DC's reality by understanding the BM is a means to understand strengths and weaknesses and map the necessary capabilities to build and create adequate strategic action plans.

3. Method

3.1. Research Methodology

We chose to conduct this study under the Design Science Research (DSR) approach. We justify this decision by the mixed theoretical and practical goals of this research. While contributing to BMI and DC literature, we address the need to create innovative “artifacts” (i.e., methods, tools, roadmaps, etc.) to tackle a problem-oriented issue (HOLMSTRÖM; KETOKIVI; HAMERI, 2009). Given such objectives, DSR is considered an appropriate approach (DRESCH; LACERDA; ANTUNES-JR., 2015). We adapted Hevner et al.'s (HEVNER et al., 2004) four-step methodological procedure, using Cole et al. (COLE et al., 2005) for managerial applications and Van Aken and Romme's (VAN AKEN; ROMME, 2009) for using systematic literature review to build the artifact as a tool for the evaluation of DC for BMI.

The resulting four-step methodology is as follows: (1) define the class of problems based on problem-oriented issues. In this study, the class of problem is that of the measurement of DC for BMI as observable organizational phenomena; (2) conduct a systematic literature review to build an “artifact” to solve the defined problem. Following the DSR literature, “artifact” represents any human-made artificial solution (DRESCH; LACERDA; ANTUNES-JR., 2015; MINATOGAWA et al., 2020). We used the systematic literature review to clarify different facets of the DC for BMI, organizing the literature into clusters and transforming such clusters into a set of indicators to measure DC for BMI. The set of indicators is the basis for designing a tool (artifact) to measure DC for BMI; (3) evaluate the artifact either in practice, through a case study, for example, or artificially through simulation. We chose to conduct an in-depth case study since our tool targets understanding DC as observable organizational phenomena; (4) draw conclusions, fine-tune the "artifact," and derive theoretical and practical implications. To fine-tune the tool, we conducted the literature review before and after the evaluation, as the practical application provides important inputs for the tool. To draw conclusions and implications, we considered the DC and BMI literature and the capacity to solve the practical problem of measuring DC.

3.2. DC For BMI Evaluation Tool Design Methodology

We conducted a systematic literature review to design the tool (VAN AKEN; ROMME, 2009). For the publications' search, we used Scopus and Web of Science databases. For the keywords' selection, we began by selecting influential articles and searching for representative keywords aligned with the guiding question of how to manage DC for BMI. Then, we conducted a pre-analysis to evaluate the search term's quality and fit the guiding question. The investigation was initially conducted in June 2017 and repeated in November-2020 to update and fine-tune previous results. Figure 3.1 summarizes the process.

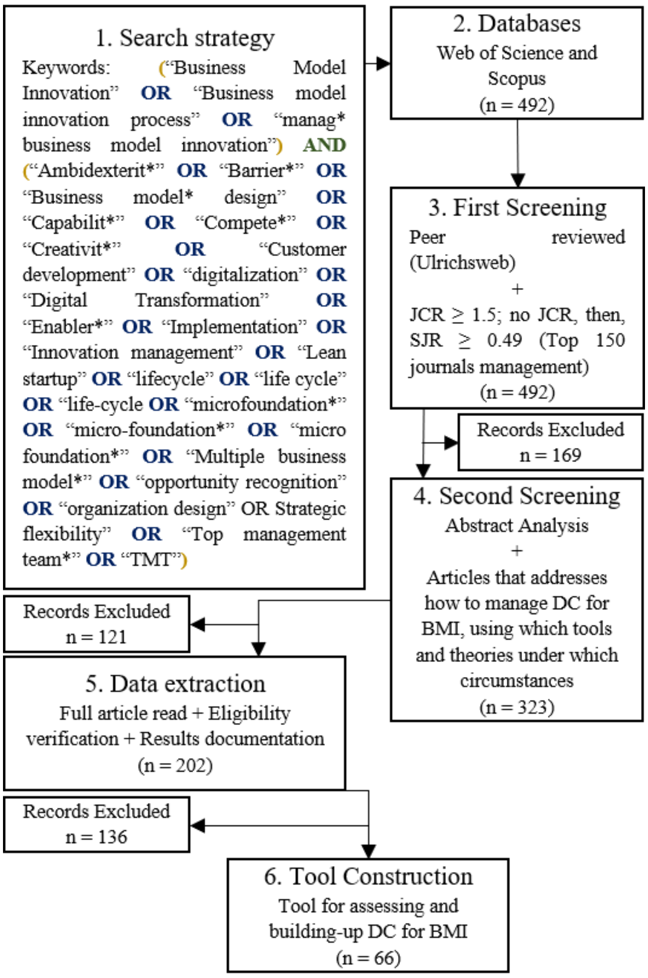

Figure 3.1 The systematic literature review process

3.2.1. Tool Construction

Operationalization is the act of translating an abstract construct to observable organizational phenomena, creating measurable indicators (BRYMAN; BELL, 2010). The main idea is to attempt to cover every facet of a given construct (DIAMANTOPOULOS; SIGUAW, 2006; DIAMANTOPOULOS; WINKLHOFER, 2001). Bearing this in mind, we organized the literature review into clusters that translate each DC of sensing seizing and transforming into a broad set of tractable and measurable indicators. We extracted six significant indicators for each capability (a total of 18 indicators) from the 66 literature review publications. To access each indicator, we created a worst and a best-case scenario as a method (Figs. 1.5 – 1.7). Attached to each indicator is a 6-point scale to attribute a score for each indicator, allowing for diagnosis and action. Also, it serves as a base to create an index that can be used for data visualization and future studies using the indicators for measuring DC for BMI in quantitative studies.

Our focus is on securing solid theory-driven indicators and qualitatively accessing their practical value through an in-depth case study to check their adequacy to reality. This is relevant considering that systematic literature reviews and practical evaluation are essential phases of building indicators for constructs (BROD; TESLER; CHRISTENSEN, 2009; ROSSITER, 2002).

Thus, to test the indicators, we apply the case study methodology. Thus, based on interviews and documentation, we assign scores to each indicator. To gather data, we designed a data collection strategy specific for each indicator. Then, we triangulate relevant data to access the necessary information and attribute an adequate score for the company's evaluation.

3.3. Tool Evaluation Methodology

The case selection is essential for the evaluation phase of the DSR method (HOLMSTRÖM; KETOKIVI; HAMERI, 2009), once it should involve the main targeted company population and critically assess the ones facing the defined class of problem.

We chose a critical, longitudinal, and revealing case study with exploratory goals (YIN, 2014). It is a critical case because it represents a company with weak DC for BMI, displaying rigidity to change given a successful BM with complementarities. To this end, we evaluated the company's history of not creating significant different BMs nor substantially changing its current BM. It is a revealing case because the authors had total access to relevant information, bringing forward knowledge that is otherwise hardly accessible. Finally, the longitudinal nature, showing a "before" and "after" situation, allows us to explore in-depth and detailed information regarding the case.

The selected company, which we will call "Alpha," is a medium-sized software company with approximately 300 employees and a revenue of about US$ 8 million per year (in 2020 values). The company's core competencies are related to digital technologies. The company provides services for large multinationals that outsource part of their R&D and software development. Since its founding, the company had not substantially changed its BM and has not created any significant new BM, evidencing weak DC.

3.3.1. Data Collection And Analysis

The data collection and analysis followed three years, from 2017 – 2020. We used the tool to diagnose the initial state and then as a means to re-evaluate after each of the company's interventions and compare it with the company's DC for BMI. We used different data sources to secure triangulation, such as semi-structured interviews, non-participant observations, company documents and artifacts, and other file registers.

The interviews were all semi-structured, allowing most of the conversation to be open for the interviewee to express freely. It is semi-structured since we used the DC indicators from the tool as an interview guide but did not limit the worst and best-case scenarios. Keeping the dialogue is relevant to capture significant facets of each measurement, which, combined with other data sources, allowed us to reduce biases and better depict each indicator. The interviews were not recorded to reduce informant biases (SCHEIN, 2010; WEI; MIRAGLIA, 2017), allowing the interviewee to express his/her opinion freely. We interviewed different company members to reduce biases since our key informants are all from the company's Top Management Team (TMT) (EISENHARDT; GRÄBNER, 2007; YIN, 2014). Thus, we interviewed middle managers and operations employees to confront the TMT's interviews and assess potential inconsistencies in their arguments. On average, interviews with key informants took from 60 to 90 minutes, considering that they are from the TMT and had a maximum of 90 minutes available for each interview without disrupting their agenda. The interviews with other company members had a maximum of 15 minutes. We took less time with other members to interview more people, gather different opinions, and improve the research's reliability (BRYMAN; BELL, 2010). During two weeks in the first year, one of the authors went to the company daily to gather local data and conduct additional interviews with different company members and specific observations for data triangulation. We repeatedly interviewed the key informants over the three years (on average, one interview every two months) and revisited company internal and public documents to understand DC's evolution. Table 3.1 summarizes each data source, the goal, and specific aspects for each evaluation lens.

Table 3.1.
Data collection sources and strategy

Data source	DC evaluation	BMI outputs
Interviews	Key informants: CEO, Innovation director. Additional: HR manager, project managers, and employees. Total of 19 people.	Key informants: CEO, Innovation director. Additional: HR manager, project managers, and employees.
Interview strategy	Semi-structured: the tool as an interview guide.	Semi-structured: focus on the current BM changes, its performance, and new digital BM developed
Observations	Routine activities, project dynamics and informal conversation dynamics.	-
Documents	Company's vision, mission, and values; Balanced scorecard, job satisfaction, leadership style, and strategy communication documents	Strategy communication presentations: balanced scorecard, changes in the company's current BM, performance data and new BM data.
Files	Public data: company website, and magazine and TV news.	Public data: magazine and TV news

We tabulated the documents to analyze the data, organized the interviews in a timeline, and analyzed each indicator. We revisited the data multiple times, conducting the "before" and "after" evaluation, trying to connect the DC evaluation to the practical results. We qualitatively analyzed every data and discussed between the authors, confronting the company in interviews when seemingly confusing or inconclusive data. We organized into cycles of DC evaluation, designing strategic action and implementation. We considered that a cycle was over when the designed strategic action plans led to significant (nontrivial) changes in its BM. Then, we re-evaluated the DC through the tool. We used the empirical results data as a control variable to the tool's indicators to validate its applicability.

4. Building the Tool For DC Evaluation

4.1. Opening the DC Black Box: The Tool For Evaluation of DC For BMI

We synthetized the BMI literature into the DC framework, considering the current BM as the central analysis unit, contemplating the different facets of each DC. Hence, we understand that the indicators should represent structural aspects and strategic and decision-making aspects. Current BM creates barriers and enablers for BMI, derived from path-dependency (DASILVA; TRKMAN, 2014). Strategy and decision-making aspects play an essential role in relevant DC facets. Some examples are: defining how to protect a new BM, secure sound implementation of BMI projects, execute experiments, and deploy adequate tools necessary to create and implement new BM. Thus, structure and strategy walk hand in hand when translating sensing, seizing, and transforming capabilities into observable organizational phenomena.

To build the DC evaluation tool, we organized the literature into "clusters" that translate parts of each dynamic capability of sensing, seizing, and transforming. We then created an indicator from each cluster and synthesized the central idea into a worst-best case scenario to guide DC for BMI evaluation.

The next sections present the indicators for each core DC – sensing, seizing, and transforming. We summarize each capability and deliver the tool in three separate parts, one for each DC. The organization of the literature into each DC dimension is in the Appendix.

4.1.1. Sensing Capability For BMI

Sensing for BMI means the capability to search for new business opportunities, both internally and externally (MEZGER, 2014). Monitoring the changing environmental conditions, such as new technological regimes, societal and regulatory pressures, and potential current and new competitor threats, also fit inside this capability (TEECE, 2018a). We organized the publications considering similar sensing opportunities and found supporting evidence to create six sensing capability indicators:

Managerial complexity represents the extent to which the organization's structure consumes managerial attention (LASZCZUK; MEYER, 2020) and is built to support the search for new opportunities with activities, resources, and processes (BOCK et al., 2012). Overly complex structures fill up management time, limiting search strategies (BOCK et al., 2012; BOCKEN; GERADTS, 2019).

Knowledge configuration represents the existing combination levels of technological and marketing knowledge (DENICOLAI; RAMIREZ; TIDD, 2014; EGFJORD; SUND, 2020). High technological knowledge and low marketing knowledge, for example, is not optimal since for better opportunity recognition, a balance between both is desirable (BERENDS et al., 2016; DENICOLAI; RAMIREZ; TIDD, 2014). The company's path-dependent learning and its members' experience and mental models are relevant. They are part of the "dominant logic" (CHESBROUGH, 2010). In the BMI case, the excessive experience could be harmful (MATEU; MARCH-CHORDA, 2016).

Network relationships represent the extent to which the company's partners and stakeholders (i.e., suppliers, clients, other organizations in the same industry, or other industries) improve knowledge deepness and broadness. Strong ties mean knowledge redundancy and deepness, whereas diverse ties mean knowledge broadness (MICHELI; BERCHICCI; JANSEN, 2020). Usually, this is a side-effect of the current BM evolution and is path-dependant (SNIHUR; WIKLUND, 2019). Having a diverse network is relevant to improving knowledge configuration, creativity, and broadness opportunities (CHESBROUGH; SCHWARTZ, 2007).

Top management team measures the board’s knowledge characteristics through diversity (tenure and functional) (GUO; PANG; LI, 2017) and their strategic orientation (GUO; SU; AHLSTROM, 2016b). It is particularly relevant because the TMT drives the strategic orientation, search activities and guides management's attention (BOCK et al., 2012; GUO; SU; AHLSTROM, 2016a). The functional diversity influences their view of the world (i.e., a board full of engineers is more prone to a "technocracy" than a board of marketers) (GUO; PANG; LI, 2017). This also applies to their experience in different industries, their tenure diversity. A long experience in the same industry may prevent the TMT from recognizing opportunities beyond dominant logic (DE SILVA; AL-TABBAA; KHAN, 2019; MATEU; MARCH-CHORDA, 2016). The TMT’s strategic orientation largely shapes the BM configuration and directs managerial attention and effort (SCHINDEHUTTE; MORRIS; KOCAK, 2019). Focus on large projects and only improving current BM performance creates unbalance in the portfolio (YAN et al., 2020; ZHAO et al., 2020), both because resources are directed to these projects and because managerial attention will also be focused on fulfilling this goal (VON KROGH; NONAKA; RECHSTEINER, 2012).

Teams' learning capability evaluates the teams' diversity, creativity, methodological approach, and efficacy. Hence, it captures the ability to conduct experiments, learn and pivot opportunities (BALDASSARRE et al., 2017; WEST; WIND, 2007). Experimentation capability is essential to extract valuable knowledge from BMI tools and practices (BOCKEN; SCHUIT; KRAAIJENHAGEN, 2018; GANGULY; EUCHNER, 2018; WEISSBROD; BOCKEN, 2017). Fitting the methodological approach for coping with uncertainty surrounding BMI efforts is relevant to secure better alignment between resources mobilized and achieved results (KOEN et al., 2010). Some authors (FUTTERER; SCHMIDT; HEIDENREICH, 2018) suggest screening and selecting a continuum between causation (FRANÇA et al., 2017) for less uncertain environments and effectuation for high uncertain environments (BRENK et al., 2019; CHESBROUGH, 2010). Hence the BMI context influences the tools' selection and application. It shapes the application success and secures the quality of sensed opportunities (SNIHUR; WIKLUND, 2019; TRIMI; BERBEGAL-MIRABENT, 2012).

Tools for sensing capture the existing tools applied for sensing new opportunities. The main tools are Lean Startup (GHEZZI; CAVALLO, 2020; SILVA et al., 2019; TRIMI; BERBEGAL-MIRABENT, 2012; WEISSBROD; BOCKEN, 2017), Customer Development (SILVA et al., 2019; TRIMI; BERBEGAL-MIRABENT, 2012), Validation board (MINATOGAWA et al., 2020, 2019), stakeholders value mapping (BALDASSARRE et al., 2017), BMI processes tools (GEISSDOERFER; SAVAGET; EVANS, 2017), BM visual tool

Canvas (TRIMI; BERBEGAL-MIRABENT, 2012), and agile methods crafted for testing hypothesis and refining it ("pivoting" is the word for changing the basic assumptions of the hypothesis) (GARCÍA-GUTIÉRREZ; MARTÍNEZ-BORREGUERO, 2016; SILVA et al., 2019). Figure 0.1 depicts the method guide for measuring the sensing indicators in practice.

4.1.2. Seizing Capability For BMI

Seizing is the capability to mobilize the necessary resources to design new BM for sensed opportunities (TEECE, 2018a), including designing a new BM to substitute a declining existing BM (LAUDIEN; DAXBÖCK, 2017). Additionally, there is a need to strategize how to protect new BM to secure a competitive advantage over potential imitators (CASADESUS-MASANELL; ZHU, 2013). Naturally, startups and new ventures do not face the issue of substituting a prior BM, but they will need to protect the BM from retaliation (SCHINDEHUTTE; MORRIS; KOCAK, 2008). When considering an existing BM, and not only startups and new ventures, it is crucial to have a balanced BM innovation portfolio (BOSBACH; BRILLINGER; SCHÄFER, 2020), not only for the evolution of the current BM, re-aligning to the contextual reality, but also to create new and parallel BM (KHANAGHA; VOLBERDA; OSHRI, 2014). We organized the publications considering similarities between the publications into six seizing capability indicators:

Technological capabilities evaluate a company’s ability to design and implement technological solutions to problems (BELTAGUI, 2018). It is key for coupling value proposition to customer segments and for improving the offering (BASHIR; VERMA, 2019). This dimension also regards the correlation between a company's innovation strategy and its technological base and industry (DENICOLAI; RAMIREZ; TIDD, 2014).

Resource mobilization indicates the quantity and quality of resources devoted to designing and experimenting with new BMs (KOEN et al., 2010; TEECE, 2018a). Every new BM demands resources, being it human (ARBUSSA; BIKFALVI; MARQUÈS, 2017; BURTON; O’CONNOR; ROOS, 2013), financial (KOEN et al., 2010), organizational (BOHNSACK; PINKSE; KOLK, 2014), or relational (BOCKEN; SCHUIT; KRAAIJENHAGEN, 2018; CHESBROUGH; SCHWARTZ, 2007; SJÖDIN et al., 2020). Securing these resources allows teams to build the BM, test and validate, and introduce it to the market (SILVA et al., 2019). The size of the company, existing slack resources, organizational structure, complexity, and BMI portfolio management all play a role in shaping the extent to which resources will be mobilized to different BMI projects (BOUNCKEN; FREDRICH, 2016).

BMI portfolio management evaluates the structure deployed to select BMI projects and the balance between improving the current BM and creating new BM (KHANAGHA;

VOLBERDA; OSHRI, 2014). Hence, it relates to how the company allocates time and effort for BMI (BOSBACH; BRILLINGER; SCHÄFER, 2020) and how it is structured to pursue BMI (GUO; PANG; LI, 2017).

Creativity evaluates the teams' knowledge diversity, intrinsic motivation, and openness to ideas (WEST; WIND, 2007). It depends on skills for designing new BMs and on the leadership style and culture (GANGULY; EUCHNER, 2018; WEISSBROD; BOCKEN, 2017). Engaging different stakeholders and supporting diverse teams are also relevant (BALDASSARRE et al., 2017).

BM protection strategies assess the existence of strategic actions to protect newly developed BM and evaluate these strategies' quality and suitability. Designing a potentially suitable BM is insufficient for its success in the market (BROEKHUIZEN; BAKKER; POSTMA, 2018; CORALLO et al., 2019). It is essential to protect it from retaliation (CASADESUS-MASANELL; ZHU, 2013), safeguarding against inconsistent regulatory pressures (ERNKVIST, 2015), and imitability (MARTIN-RIOS; PARGA-DANS, 2016). Possible paths are creating imitation barriers (BOHNSACK; PINKSE; KOLK, 2014), intellectual property rights management (ERICKSON, 2018), building complementary assets (and complexity) (SCHINDEHUTTE; MORRIS; KOCAK, 2008), and choosing the right time to introduce the BM to the market (CASADESUS-MASANELL; ZHU, 2013).

Tools for designing new BM evaluates the company's usage of tools, which are: Design thinking and design tools (AMIT; ZOTT, 2012; GEISSDOERFER; BOCKEN; HULTINK, 2016), BM visual tool Canvas and its variations (BALDASSARRE et al., 2020; TRIMI; BERBEGAL-MIRABENT, 2012), tools to support experimentation (BOCKEN; SCHUIT; KRAAIJENHAGEN, 2018; COSENZ; BIVONA, 2020; MINATOGAWA et al., 2019; TRAPP; VOIGT; BREM, 2018), agile methods, such as Lean Startup and customer development (CARROLL; CASSELMAN, 2019; GHEZZI; CAVALLO, 2020; SILVA et al., 2019; TRIMI; BERBEGAL-MIRABENT, 2012), business modeling processes (GEISSDOERFER; SAVAGET; EVANS, 2017), customer experience journey modeling (KEININGHAM et al., 2019). Figure 0.2 depicts the guiding worst and best-case scenarios for evaluating seizing capability.

4.1.3. Transforming Capability For BMI

The transforming capability relates to managing implementation and scaling new BMs' growth, moving forward in the BMI process. It is mainly associated with constructing the value creation architecture, fine-tuning every BM element to build complementarities (SOSNA;

TREVINYO-RODRÍGUEZ; VELAMURI, 2010). The literature supported evidence for creating six transforming capability indicators:

Organizational culture evaluates the existence of a learning culture, such as openness to ideas and communication, management by commitment, shared vision, and trust, which is critical for considering a changing environment (BOCK et al., 2012; MALIK; PEREIRA; TARBA, 2017). It is part of the company's BM, and leadership plays a significant role in enabling or hindering change management and learning (BASHIR; VERMA, 2019; WEST; WIND, 2007). Even though this seems more applicable to existing companies, startups also display a culture from their founders, which largely shapes their capability to change the main idea as new learnings come (GARCÍA-GUTIÉRREZ; MARTÍNEZ-BORREGUERO, 2016; MINATOGAWA et al., 2019).

Resources and capability building are the extent to which the company is capable of creating new resources and capabilities. In practice, this can be done by developing internally, creating new business functions, and training people (LOON; OTAYE-EBEDE; STEWART, 2020) or externally by leveraging strategic partners (OGILVIE, 2015). It is a necessary dimension to scale a BM growth. It enables value creation and value delivery architectures (ARBUSSA; BIKFALVI; MARQUÈS, 2017).

Strategic human resources management refers to evaluating the company's practices for hiring, deploying, and training people (LOON; OTAYE-EBEDE; STEWART, 2020). It means bringing new people in, moving people for acting on different BMs, correctly assigning people based on skills, cultural background, and interests (BOSBACH; BRILLINGER; SCHÄFER, 2020; MALIK; PEREIRA; TARBA, 2017; MARKIDES, 2013a).

Change management assesses the existence of good practices of building a shared vision to create commitment and be transparent while implementing practices (BASHIR; VERMA, 2019; LOON; OTAYE-EBEDE; STEWART, 2020; MITCHELL; BRUCKNER COLES, 2004). It is influenced by the leadership style and organizational culture as structural constraints (CHESBROUGH, 2010; NAOR; DRUEHL; BERNARDES, 2018).

Organizational design indicates the quality of practices for creating the value creation and delivery architecture for newly developed BM. Some practices are developing strategic capabilities internally or externally (OGILVIE, 2015), creating structures to protect from imitation, such as creating complex distribution channels (NIELSEN; LUND, 2018), creating complementarities with other BMs to build complexity (MARKIDES, 2013a) and imperfect imitability (SCHINDEHUTTE; MORRIS; KOCAK, 2008), and creating a constellation of startups as partners to execute new BMs (BOUNCKEN; FREDRICH, 2016). Thus, it relates to decisions surrounding new BMs' structure (LATILLA et al., 2020; TEECE; LINDEN, 2017b).

Organizational Ambidexterity assesses the application of adequate strategies to manage multiple BMs. Exploring complementarities with other BMs while separating potential conflicts are key ambidexterity practices (MARKIDES, 2013b). It is directly related to the business model innovation portfolio (BOSBACH; BRILLINGER; SCHÄFER, 2020; KIM; MIN, 2015), but designing new BM is different from managing and scaling them (NIELSEN; LUND, 2018). The tools for sensing and seizing focus on BM design, but these tools usually do not cover when reaching out the point of scaling or defining how to explore synergies between an existing BM and a new BM while avoiding pitfalls that destroy value (KHANAGHA; VOLBERDA; OSHRI, 2014). Figure 0.3 depicts the guide for measuring transforming capability indicators.

5. Tool Evaluation: Results of the Case Study

5.1. First Evaluation-Design-Implementation Cycle

5.1.1. Presenting the BM context and initial state evaluation

Alpha was a project-based organization whose value proposition was to provide software solutions for different Multinational ICT players. Alpha optimized its value creation through total quality management and focused on operations management to be attractive in a competitive environment. The idea was to keep costs low while securing high quality and on-time delivery to leverage customer satisfaction. The higher the satisfaction was, the better the company reputation and the greater demand for projects. Being knowledge-intensive, Alpha relies mainly on human resources as the foundation of value creation. Therefore, keeping up a high project demand also means increasing its HR retention and reducing turnover.

A critical problem with Alpha's BM was its context. The external environment, more precisely the broader economic cycles, plays a major role in shaping customers' budgets, affecting demand for projects. Sales downturns or performance losses by its main clients caused a reduction in their R&D budget, leading to a drop in project demand, directly impacting its BM, since the decline in project demand entailed severe drawbacks. First, Alpha assigned specific personnel for specific projects. Hence, when there was a reduction in project demand, it also implied laying off unassigned personnel. Second, since experience and knowledge accumulation were relevant for securing project quality and delivery time, layoffs meant a loss of technological capabilities and performance. Figure 5.1 contains Alpha initial state DC evaluation.

In aggregate, it is possible to notice that Alpha had an overall low score in the initial state DC evaluation. The strongest points were especially those related to the current BM path dependency, such as technological knowledge and strategic human resources management. We also noticed a good overall organizational culture and propensity to change, considering its leadership style. This aspect would facilitate the implementation of necessary changes in the current BM to develop DC. Figure 5.3 shows the initial state scores in blue.

5.1.2. Strategic Action Plans Design

Alpha designed an innovation program focusing on sensing and seizing capabilities. Such a program was pointed to leverage synergies between the innovation program and the current BM, building complementarities and improving performance. In the long-term, the company expected to begin performing BMI through these new value creation activities. Besides, such activities were associated with the innovation program, leading to a diversification of business activities. Initially, the key selected dimensions for change were Managerial Complexity, Knowledge Configuration and Absorptive Capacity, management Team’s tenure diversity, Network Relationship, Business model innovation protection strategy, Resources Mobilization, Tools for sensing opportunities, and Business model design tools. Table 5.1. depicts the key strategic action plans, the description, the affected DC dimensions, and how it changes Alpha's BM.

Table 5.1.
Summary of the first cycle strategic action plans, the affected DC dimensions and the impacted BM dimensions

Strategic Action Plans	Affected DC dimensions	Impacted BM dimensions
Change in the company's structure.	Sensing: TMT. Seizing: BMI portfolio management.	Value creation: structure
Design and implement OI funnel.	Sensing: Managerial complexity; Knowledge configuration; Network relations. Seizing: BM design tools;	Value creation: key resources and partners
New technological learning groups	Sensing: Managerial complexity and Knowledge configuration Seizing: Technological capabilities	Value creation: key activities and resources
Explore external non-refundable financing	Seizing: Resources Mobilization	Value creation: key resources.

For better clarifying strategic action plans, we provide a brief description of its objectives in sequence.

Change in the company's structure: (1) Decouple the innovation program from the quality branch to directly reporting to the CEO as a new "innovation function," and (2) Hire an innovation director with different backgrounds and experiences.

Design and implement OI funnel: (1) Focus on outside-in open innovation to leverage marketing knowledge by searching for marketing-oriented external partners. At that moment, it was not designed as an inside-out OI strategy, considering that no technology was idle to license, and it had not created any significant new venture to spin-off. (2) Target partners: universities, companies, startups, public organizations, research institutes, and social organizations. Also, different people with experience in key selected market areas, such as health, finance, and agribusiness, are needed; (3) Create internal technological platforms: Data science, Internet of Things (IoT), Computational Vision, Cognitive computing, and Artificial Intelligence (AI).

New technological learning groups: Solidify its technological capabilities by creating new activities (learning groups) for the personnel engaged with specific technologies.

Explore external non-refundable financing: (1) Explore the regional public policy regarding non-refundable financing for innovation projects; (2) Design of a training process to develop the necessary skills to formulate projects in order to be successful in obtaining funding;

Implement BMI tools for sensing and seizing: (1) Design of the "futures lab," an event-based program where the company's members and the external OI partners ideate potential problem-solution fit to begin the BM design process; (2) Coupling marketing and technology knowledge; (3) Apply BM design tools: Design Thinking, Lean Startup, and BM Canvas.; (4) Create Minimum Viable Products (MVPs) and Proof of Concepts (PoCs) (for more details on MVPs and PoCs definitions, please refer to (BLANK, 2007; RIES, 2011).

5.1.3. Implement and Monitor

The first important thing in implementation was Alpha's recognition of the need to proceed through the BM change process, leveraging its existing transforming capability. In practice, it followed the change management practices (LONG; LOOIJEN; BLOK, 2018; WEINER, 2009) of building a shared vision, sending strategic signals from the TMT, including the new activities into its strategic map and the employee's functions, and using its established strategic human resources management capability. The procedure designed by Alpha has the following four steps: Build shared vision, Build informal leadership, Create technological platforms, and Experiment with “Futures lab.”

Build shared vision: TMT’s engagement and active communication with employees to transmit the future state and the innovation program’s vision. The TMT also participated in the search for OI partners.

Build informal leadership: engage influential volunteers to spread the innovation program’s vision and gather volunteers to learn writing innovation projects for non-refundable financing.

Create technological platforms: solidify the new technological learning activity and increase motivation.

Experiment with "Futures lab": demonstrate that OI is not easy and that not all good ideas are inside the company. Find weak spots and induce learn-by-doing.

We notice that the tool's evaluation of its transforming capability was in line with its practical results. The average high scores on change management, organizational culture, and strategic human resources management reflect real-world evidence. Alpha successfully implemented these first changes in the BM, overcoming barriers such as inertia and the dominant logic by inducing change and securing their employees' support. The high rates of volunteers, the goodwill of employees to spend overtime in the initial phases of technological research groups, the engagement and motivation during the "futures lab," and their engagement in the search for external partners are all evidence supporting the success of the implementation. Alpha experimented with the designed innovation program for a year before assessing whether the evolved BM would have improved its DC. Figure 5.3 depicts Alpha DC scores evolution after implementation in orange.

5.2. Second Cycle

5.2.1. Strategic Action Plans Design

The second cycle action plan's target was the transforming capability, emphasizing organizational ambidexterity and organizational design, seeking to move a step forward on new BM development. The already implemented changes targeting sensing and seizing would be further improved, especially searching to improve BM knowledge (for enhancing BMI tools and practices). Alpha could reach the MVP and PoC point of BM design but still struggled with the revenue model and value creation architecture for the new potential BMs. According to the evaluation, there was an improvement. Still, there remained a learning curve, and low BM knowledge hindered the quality of the opportunities and the capability to design novel BM effectively.

		Evaluation	Evidence	Score
Sensing	1. MC	Alpha did not have any specific activities for searching for new opportunities. Also, its management keeps attention filled with hiring new people, given the high turnover rates, and the commercial also had overlapping activities with operations, which also increases managerial complexity.	Interviews: CEO and Innovation director; Documents: functions description and organogram.	1 2 3 4 5 6
	2. KC	Alpha is a knowledge-intensive firm, focusing on Information and Communication Technology (ICT), making it more technology-oriented than market-oriented. There was an unbalance of knowledge configuration with technological knowledge more prominent than market knowledge. Additionally, the high turnover meant a loss of previously accumulated knowledge and technological capabilities. Due to its market positioning to assist in conducting Software Development projects for different customers, the focus was more on software development than on researching. Finally, Alpha did not have any technological research activity.	Interviews: CEO, Innovation director and HR manager; Documents: balanced scorecard	1 2 3 4 5 6
	3. NR	Alpha's partner relations were mostly strong, long-term ties. The contacts to universities and other stakeholders were limited to Human Resources and projects' co-production. Thus, partners were very stable and, hence, limited the search for new partnerships.	Interviews: CEO, commercial director and commercial employees	1 2 3 4 5 6
	4. TMT	Alpha's TMT was composed of the CEO, the quality director, the operations management director, the commercial director, and the HRM director. The CEO came from an engineering background and had previous experience was in a Brazilian Research Technology Organization (RTO). The commercial director has a marketing background and experience in different industries and has been in the past years inside RTOs. Overall, this points to a relatively high functional diversity while medium to low tenure diversity.	Interviews: CEO, HR manager and different company's employees	1 2 3 4 5 6
	5. TS	Alpha did not apply any specific tool for sensing novel opportunities, nor did it build specific teams to this end.	Interviews: Innovation director; Documents: balanced scorecard	1 2 3 4 5 6
	6. TLC	There were some aspects related to the existence of a relatively good learning culture. As evidence, we noted openness to communication between members during the teams' observations on regular projects, combined with interviews with different company's members that point to medium-high motivational levels and the overall high project performance.	Interviews: Innovation director, CEO, HR director, and employees; Observation: Participation in day-to-day activities; Documents: Vision, mission, and company values.	1 2 3 4 5 6
Seizing	7. PM	Alpha did not conduct R&D, and its "innovation" program was inside its operations management division, under the quality branch. This points towards a significant focus on improving current BM rather than searching for new BM.	Interviews: TMT and employees; Documents: balanced scorecard and Organogram	1 2 3 4 5 6
	8. CR	Alpha's hiring policy focused on commitment and cultural alignment more than skills, searching for high motivational levels, and understanding that hired people to grow their skills. It had a resilient leadership style, preoccupied with motivational levels, and openness to communication. Overall, Alpha displayed relevant aspects of creativity, namely intrinsic motivation, diversity, and openness to communication. The narrow technological base, no R&D lowers the knowledge diversity and this dimension's score.	Interviews: HR director; project managers and employees; Documents: leadership style, job satisfaction; Observation: Day-to-day activities	1 2 3 4 5 6
	9. PS	There were no specific tools for BMI, as already mentioned in the previous section. Because of software development projects and no associated R&D, Alpha's current practices demand no attention to IPRM. Furthermore, considering that it did not create new BM, it did not need protection strategies	Interviews: Innovation director, CEO and project managers	1 2 3 4 5 6
	10. TC	This may be one of Alpha's core capabilities since its BM focused on creating digital technology solutions to different problems. Hence, pointing to a relatively medium-high score on this dimension; however, the high turnover rates, with the eventual knowledge loss and shifts in capabilities over time, and the non-existence of an R&D department, reduce this score.	Interviews: CEO, innovation director and project managers; Documents: balanced scorecard	1 2 3 4 5 6
	11. RM	Alpha had significant financial limitations, which was a key obstacle to including innovation at the core of its future vision. Thus, mobilizing resources (financial, human, organizational, and relational) for different innovation projects was limited by the current BM mechanism for capturing value.	Interviews: CEO and innovation director; Documents: Company's finance sheets	1 2 3 4 5 6
	12. DT	There were no specific BMI tools at this moment for seizing new BM opportunities.	Interviews: Innovation director	1 2 3 4 5 6
Transforming	13. OA	Alpha did not pursue ambidextrous goals. Its innovation portfolio management focused on exploiting the current BM rather than creating a new BM. Therefore, the score is minimal.	Interview: CEO, innovation director and employees	1 2 3 4 5 6
	14. CM	Considering key cultural elements for change, Alpha had a good base and showed experience in change management practices. The leadership style was flexible and resilient, in which the employee's motivation and autonomy are central elements of its project management guidelines. These aspects set out the trust between employees and the company, aiding the building of shared vision, reducing fears of losing their positions, and sustaining the necessary motivation to endure the change process.	Interviews: HR management, CEO, and employees; Documents: Vision and mission, leadership style, HR blueprint	1 2 3 4 5 6
	15. OC	Alpha's culture fostered learning and building trust between its personnel and had an openness to communication. As abovementioned in the previous dimension evaluation, overall, the employees were satisfied with the company and were motivated. The flexible work hours and vestment rules, working at home also helped increase motivation. A high motivational level is critical for both learning and creative outcomes. Given the absence of an R&D and no new BM creation, the score was reduced.	Interviews: HR manager, project managers, CEO; Documents: Vision, Mission, and exposed values; Observation: day-to-day activities	1 2 3 4 5 6
	16. OD	Alpha's BM and structure followed standard practices in its industry, suffering almost no significant changes since its founding. It also fosters long term strong ties and has no R&D. Hence, company A is not structured for BMI.	Interviews: CEO and innovation director; Documents: Balanced scorecard	1 2 3 4 5 6
	17. RB	Alpha needed to re-shape its technological capability base due to fluctuations in the project demand. Thus, the company demonstrated an average capability to develop new technological capabilities and new resources. However, creating well-known capabilities and resources differs from building new capabilities and resources novel BM. Alpha did not show the need for developing new managerial capabilities, which also hinders this dimension's score.	Interviews: TMT, project managers Documents: projects technological base over time	1 2 3 4 5 6
	18. HR	The bright side of Alpha's BM weaknesses was that the high turnover also led the company to develop strong SHRM practices. As history matters, this means that the company does have a fair evaluation in this dimension.	Interviews: HR manager, and employees; Documents: Job satisfaction, hiring policy	1 2 3 4 5 6

MC = Managerial Complexity; KC = Knowledge Configuration and Absorptive Capacity; NR = Network Relationship; TMT = Top Management Team; TS = BMI tools for sensing; TLC = Teams learning capacity; PM = Business model innovation portfolio management; CR = Creativity; PS = Business model protection strategies; TC = Technological capability; RM = Resources mobilization; DT = BM design and validation tools; OA = Organizational ambidexterity; CM = Change management; OC = Organizational culture; OD = Organizational design; RB = Resources and capability building; HR = Strategic human resources management.

Figure 5.1. Alpha initial state DC evaluation, the description of the company state, the evidence, and the scores

Another problem was that merely looking outside for partners was not enough to engage with the right partners. However, Alpha's image was evolving as innovative, successfully attracting higher-quality partners willing to share the venturing risk. Table 5.2. summarizes the strategic action plans, the affected DC dimensions, and the consequent BM changes.

Table 5.2.
Summary of the first cycle strategic action plans, the effects on the DC dimensions, and its BM changes.

Strategic Action Plans	Affected DC dimensions	Impacted BM dimensions
Deepen learning by doing with BMI tools	Sensing: Knowledge configuration, Network relations, and Tools for sensing Seizing: BM design tools	No changes.
Improve the brand's image as an innovator to attract more reliable external partners	Sensing: Knowledge configuration and network relations. Seizing: Creativity, Resource mobilization, and BM design tools;	Value creation: key activities Value delivery: channels
Build complementarities between technological learning groups and current BM	Sensing: Knowledge configuration. Seizing: Technological capabilities, Resource mobilization.	Value creation: key activities and resources Value capture: customer segmentation
Stimulate intrapreneurship and build new venture teams to launch new BM to market	Sensing: Network relations Transforming: Organizational ambidexterity, Organizational design, and Resources and capability building	Value capture: Revenue stream
Take the first steps towards organizational ambidexterity	Transforming: Organizational design and Organizational ambidexterity	Value creation: cost structure Value capture: revenue stream

To better clarify each strategic action, we provide below a brief description of each action.

Deepen learning by doing with BMI tools: (1) Employees were trained on lean startup, customer development, and business model canvas; (2) Participation of employees in events, such as lean startup machine and hackathons.

Improve the brand's image as an innovator to attract more reliable external partners: (1) Build synergies between the innovation program and the current BM; (2) Use MVPs and PoCs as assets to leverage the brand's image; (3) Demonstrate the capability to solve problems and resilience.

Build complementarities between technological learning groups and current BM: (1) Technological learning groups began to research potential customers' problems and develop solutions; (2) Instead of being found by clients, proactively propose projects to clients.

Stimulate intrapreneurship and build new venture teams to launch new BM to market: (1) Increase motivational levels and stimulate employees to transform MVPs into potential BM design; (2) Create a bridge between new BM and Alpha's BM through the employees.

Take the first steps towards organizational ambidexterity: (1) Improve complementarities and conflicts analysis to build new BM launching to market strategies; (2) Learn about the key issues surrounding designing and implementing novel BMs into the market; (3) Explore potential partners to participate in the new BM design, create adequate teams, and secure Alpha's support.

5.2.2. Implementation and DC Re-Evaluation

Alpha's approach to design and test the actions to improve exploratory transforming capability was to experiment. The idea was to deploy organizational ambidexterity through conflicts and complementarities analysis, seeking to understand how to take new BMs to market, if completely separated or partially united or completely united. Finally, to increase the BM escalation, the idea was to leverage organizational design by finding adequate partners to develop the new BMs' resources and capabilities. Leadership and strategic human resources management were vital in this process, identifying key personnel with an entrepreneurial orientation to create functional teams by coupling with external partners to design new BM and experiment in practice. The goal was to make diversified and complementary teams capable of building new BMs to escalate and spinning-off the most successful ones. This action walked hand in hand with the efforts to continue improving sensing and seizing because improving the sensed opportunities and the BM design process quality increased the new BM's success chances. Figure 5.3 depicts Alpha's DC evolution after the second cycle implementation in green.

5.3. Evaluating the Tool: Alpha BMI Outcomes

5.3.1. Alpha’s Current BM Changes

Alpha’s BM suffered nontrivial changes. As shown in Table 5.1 and Table 5.2, there were changes related to value creation, delivery, and capture. Before the first cycle, Alpha had a passive tailored software development BM. This means that the source for new projects was through referrals from other satisfied customers. Clients were responsible for contacting Alpha and requesting specific software solutions. After the first and second cycles, Alpha solidified the execution of a technological research activity, which served as the base for a BM's change to an active tailored software development BM. Through the technological learning teams, Alpha searches key ICT players' core technological developments. Instead of waiting for customer’s demands (passive), Alpha actively suggests software developments that would assist these players, focusing on solutions through its competence. This change significantly impacted the company’s performance after implementing the innovation management program. As reported by Alpha's CEO and by its Innovation Director, the innovation program accounted for around

54% of 2020 revenue (around US$ 8 million). Alpha's financial performance before the innovation program shows a pattern of resistance of around US$ 9 million in sales revenue (in 2020 values). However, it evolves to a consistent growth pattern after 2017, surpassing the previous barrier (Figure 5.2). Furthermore, the technological research activity became an R&D department, which led Alpha to leverage technological innovation performance in its new BM configuration.

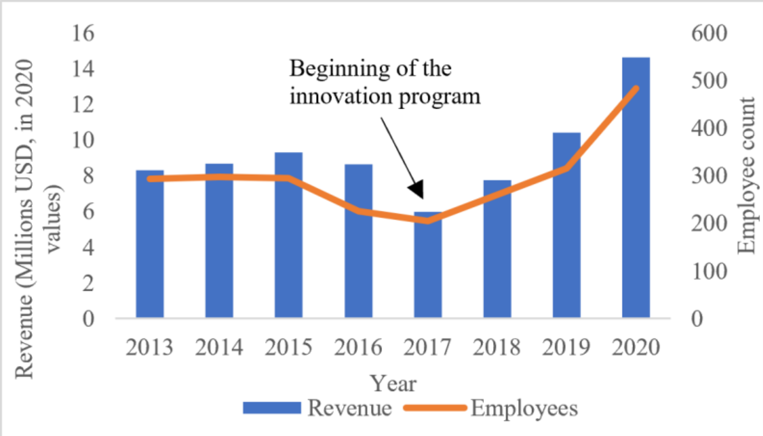

Figure 5.2. Alpha annual sales revenue in 2020 values and employee count (2013/2020)

Inside this new BM paradigm, the developed MVPs and PoC's role is twofold. First, it works as a showcase allowing the ICT players to observe Alpha's capability to carry out innovative software projects. Second, it creates complementarities by promoting Alpha's image as innovative, enhancing its reputation, attracting new customers and strengthening the relationship network.

Thus, Alpha's open innovation funnel engages relevant stakeholders, supporting and building a strong brand image. The open innovation funnel and the "futures lab" events support the technological research activity. Through that, it was possible to raise funding for projects to create MVPs and PoCs, reducing the cost structure and legitimizing this new key activity.

5.3.2. Alpha's Spin-Offs

Alpha's innovation program had an ultimate goal creating new digital BMs, developing, through the open innovation funnel and the technological research activity, new companies as spin-offs. After the second cycle, Alpha began to create its first new BM through the open innovation funnel and the technological research activity, executed through the "futures lab." In the first stage, Alpha used the MVPs and PoC as showcases to improve its current BM. However, after consolidation, Alpha started to explore them to create new digital BMs and start introducing them into the market. Alpha had to design an inside-out open innovation activity.

This was made by coupling a co-acceleration process for the new Digital BM, building complementary assets with partners, engaging with startups, and exploiting its technological capability.

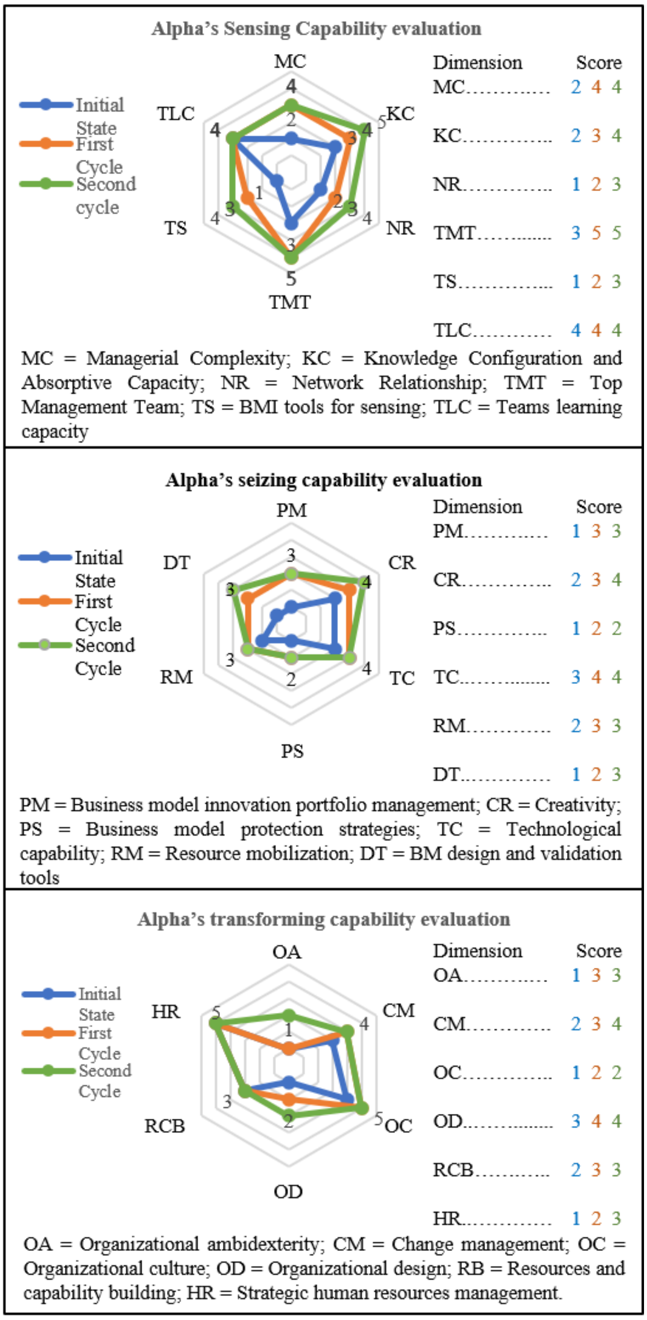

Figure 5.3. Alpha's DC evaluation evolution from the initial state to the second cycle

Alpha also performed a prospecting process looking for entrepreneurs inside the company to embrace MVPs and PoCs as the starting point to create new BMs. The first experimentation with this new strategic action plan led Alpha to create the first four startups, Beta, Gama, Delta and Epsilon (Table 5.3.).

Table 5.3.
A summary of Alpha's developed startups, its descriptions, base technology, and market area

Startup	Market area	Technological base
Beta	Finance	Artificial intelligence, Cognitive computing
Gama	Finance	Blockchain, Artificial intelligence
Delta	Finance	Social media, Blockchain, e-commerce, and Artificial Intelligence
Epsilon	Finance	Data Science

Beta BM focuses on debt paying, connecting debtors and creditors, using Artificial Intelligence. It contacts both sides through an avatar with voice and video (deep fake techniques) to create an AI with empathy, improving customer experience through a more humane machine, promoting negotiation. To protect this BM, Alpha explored one large partner to be Beta's core first customer. Beta had its first monetization in January 2021.

Gama deploys a platform-based BM. It is an app to facilitate money transfer in markets, considering people without access to the banking systems and pays cash only. It creates a safe environment through blockchain technology that converts change into digital money, creating a digital wallet for customers. The app keeps track of its customers' expenses, helping them to manage their money better. Currently, the startup is validating its BM inside a medium-sized supermarket chain in Ceara, Brazil.

Delta is a platform BM specialized in creating e-commerce for digital influencers. It has two primary value propositions. First, it creates safe micro e-commerces to sell their products using blockchain. Second, it applies Artificial Intelligence to profile the influencers' followers for effective digital marketing strategies. Delta's app is available on both Google Play and Apple store. It has more than five thousand downloads.

Epsilon BM's focus is on facilitating opening new companies in Brazil. The Brazilian regulatory issues and associated costs of opening new companies are very high, leading to a problem that hinders the entrepreneurs' impetus to open new companies. Epsilon's app simplifies this process and creates new companies in 10 minutes. It also has a consultancy program in which it helps startups to grow. Epsilon has been launched into the market and has a number of clients in its portfolio.

6. Discussion and Conclusion

This study aims to understand, operationalize and measure the distinctive dimensions of DC for BMI. Our findings of the systematic literature review show that extant BM plays a major role in shaping DC for BMI. This notion allowed us to build the tool by combining BMI and DC theories and organizing them inside the BM concept, making the build-up of DC for BMI measurable and manageable. Our findings from the longitudinal in-depth case study show that the tool seems to reach satisfactory results, contributing to the company developing DC for BMI over three years. The practical results show evidence supporting the idea that DC and BMI co-evolve and have mutual influences. To develop DC coherently, Alpha needed to deploy specific activities and practices supporting DC, reshaping its BM to foster DC inside its value creation architecture logic, moving from a passive to an active tailored software development BM. This finding highlights the proposed tool's relevance in capturing the structural dimensions, coupled with human and tools dimensions.

Therefore, we propose that companies should create what we call a BMI engine, complementary to the dominant BM, advancing the discussion on BMI for incumbents. Alpha successfully designed an innovation program by decoupling the innovation direction from other divisions. This new division had the utmost goal of creating new BM, developing new solutions to existing problems, which called for new technological developments. Nevertheless, it also had significant synergies to Alpha's current BM, effectively improving its performance while legitimizing its position to manage BMI. The BMI engine consisted of innovating Alpha's current BM, creating new activities, resources, and building complementarities between existing BM components. There were attractive architectural gains, such as technological research contributing to the commercial, proactively proposing solutions to customers, and improving operations by improving technological capabilities. Furthermore, it created a new key resource, namely the brand's image in the market, consequently improving the project demand and monetization. This coherence in the BMI engine structure was responsible for the build-up of DC and successfully embedding DC into the BM logic, sustaining the engine's persistence until reaching out to the point of creating new BMs.

6.1. Theoretical Contributions

The theoretical contribution of this paper is the operationalization of DC for BMI. One of the key critiques on the DC literature is that it only addresses the empirical world at a quite abstract level. Therefore, there is a substantial challenge to translate it into practice (KUMP et al., 2019). This problem is even more relevant since much advancement and recent literature point towards DC as the primary BMI antecedent (FOSS; SAEBI, 2018). Some studies show how companies successfully achieved BMI deploying different DC (RICCIARDI; ZARDINI; ROSSIGNOLI, 2016; SCHNEIDER; SPIETH, 2014; ZHAO; WEI; YANG, 2019). In our study, we open the DC black-box by deliberately connecting the DC and BMI literature, focusing on producing indicators for the distinctive DC of sensing, seizing, and transforming. We also promote a measure translating DC for BMI into observable organizational phenomena by creating an evaluation tool capable of detecting why each DC is present or not and which facets are well or badly implemented. Hence, it helps to identify how the current BM is structured to support DC. Thus, our tool assists strategic action for building-up DC for BMI. Therefore, we sustain BMI as a continuous effort and not a solution for a specific problem. Hence, to operationalize DC, we suggest creating the BMI engine as a function analogous to what R&D is for technological innovation. Alpha shows that the innovation program sought to create a continual BMI management capability that should remain after implementing the new model. Such capability may be a path to overcome the BMI side-effect of reducing DC in the long term. This finding is relevant once the literature on BMI suggests that usually, a BM's evolution accompanies an increase in its rigidity to change (CHRISTENSEN, 2000; FOSS; SAEBI, 2018; LEVINTHAL, 1996). As Christensen et al. (CHRISTENSEN; BARTMAN; VAN BEVER, 2016, p. 33) put it, "Business models by their very nature are designed not to change, and they become less flexible and more resistant to change as they develop over time." Our findings show a potential path for reaching the opposite effect, improving the BM while increasing the capability for BMI.

The literature strand that tries to measure DC shows significant problems (KUMP et al., 2019). First, overall, DC measurement scales are somewhat diffuse, pointing towards DC for different activities (such as product development) or, more generally, to a few selected capabilities. Most of these measures do not consider higher-order DC linked to BMI, a relatively new proposition (FOSS; SAEBI, 2018; TEECE, 2018a). As our DC indicators show, the TMT is critical when considering the BM level. The changes encompass several divisions, changes in the overall business logic, entrance into different markets, and exploration of synergies between current BM and newly created BM. Hence, DC for BMI is much more related to the TMT and often relies on the strategic level. The DC measures usually focus on practices (i.e., market search, competitiveness analysis, etc.) at the operational level, often neglecting the TMT's level.

Our findings suggest a relevant dialogue between the DC for BMI literature with the innovation management literature. This is aligned with Tidd and Bessant (TIDD; BESSANT, 2018) criticism of the disconnection between BMI theory and the Innovation Management research field. Many of the measurement dimensions do not seem to be specific to BMI and overlap with technological innovation management capabilities, such as those defined by Francis and Bessant (FRANCIS; BESSANT, 2005). Setting a balanced innovation management portfolio, securing the TMT's participation in all stages of the innovation process, recognizing new opportunities, designing technical solutions, and the overall sensing and seizing capabilities have a significant match. The most distinct DC for BMI is transforming capability. One interpretation may be that traditional innovation management practices usually focus on sustaining business performance and not changing the BM (CHRISTENSEN; BARTMAN; VAN BEVER, 2016; QUADROS et al., 2017). One explanation is that DC for BMI expands traditional innovation management to embrace creating new BM and following different technological strands that do not fit the current BM. Our findings, therefore, match the notion of better grounding BMI in the consolidated innovation management field.

The discussion about the relationship between BMI and technological innovation theories is relevant, and it still needs further clarification (BEREZNOY, 2019). To date, literature has mostly developed the idea of BMI as a conduit to market new technologies, especially technologies that do not fit its creator's current BM (FERREIRA; COELHO; MOUTINHO, 2018). It is also the OI's central idea, which places new BM development to explore unused patents and monetize from intellectual property rights (CHESBROUGH; VANHAVERBEKE; WEST, 2006). Therefore, there is a strong suggestion that technological innovation precedes BMI. In our case, Alpha revealed the opposite. BMI led to the creation of R&D and pulled the need to conduct technological innovations. Thus, we advance this discussion by taking the first steps in understanding this opposite relation between BMI and technological innovation. Is BMI a path to build technological innovation capabilities? It is a question that we did not have the ambition to answer in this paper. However, our results display potential baby steps in such a direction.

6.2. Managerial Implications

The increasing turbulence and uncertainty in the business environment brought about by the digital era are reshaping companies' strategic reality. This increases the pressure to innovate the BM as new competitors arise and distinctive industries' boundaries dissolve. One good example is that digital players, such as Google and Apple, span the traditional automotive industry's boundaries as the digital and electric paradigm gain strength (ROGERS, 2016; TEECE, 2018b). This change in the business landscape means that the very base of companies BM is under threat, which pushes management towards trying to find means to develop capabilities to consistently manage BMI, targeting the digital transformation of their current BM and creating new digital BM (SCHALLMO; WILLIAMS, 2018; VERHOEF et al., 2019). Thus, there is an increasing urge to elucidate and measure the organizational phenomena behind the effective management and development of capabilities for BMI. We believe that we contribute to this issue by taking steps into better understanding the organizational phenomena behind the DC for BMI, reducing failure rates of strategies deployed, and increasing the quality of actions considering each company's BM particularities.

This study targets this issue by proposing a tool to help managers measure their current BM state regarding DC and design strategies for BMI. Therefore, management should focus mainly on understanding their current BM. How could cutting-edge BMI practices, such as open innovation, engagement with startups, Lean Startup, be better-applied, building complementarities and virtuous value creation cycles to the company's current BM. We think it would be possible to reduce failure rates during the implementation phase by following this direction. This will improve companies' innovation performance and enhance the BM performance. Thus, creating a favorable environment to move forward with innovation strategies, improve the company members' overall buy-in, and create virtuous cycles.

We also propose a potential roadmap to develop DC. First, begin with an in-depth BM analysis. Then, follow to create a new function for placing innovation at the TMT's level and design the sensing and seizing capability. Before creating new BM, one should have a good antenna for sensing opportunities and quality for designing, testing, and validating solutions. Then there is an important step of connecting this initial stage BMI engine to the current business, exploring complementarities to strengthen the main BM. Finally, target the remaining DC to create the capability to design complete BM and introduce it to the market.

6.3. Limitations and Future Research

It is important to highlight that the tool evaluation is based on a single case study setting, which provides limitations regarding drawing generalizations. Thus, evaluating the current BM and the associated DC in Alpha may not necessarily lead to similar results in other companies. Some idiosyncrasies will certainly vary for each case, and, consequently, the strategies to build-up DC in different conditions will probably differ. However, we focus on the tool's capability to operationalize DC in practice, showing in detail how it happened. This approach is essential for learning and allowing future research. Moreover, although our indicators show theoretical consistency and a positive practical application, they should still undergo full validation, evaluating their content validity, collinearity, and convergent validity using other reflective DC measurements (DIAMANTOPOULOS; SIGUAW, 2006; DIAMANTOPOULOS; WINKLHOFER, 2001; HAIR JR et al., 2016).

We argue that because our tool has its roots at the BM level, it should help capture each case specificity, deploying specific strategies aligned with these variations. This is in line with the DSR methods' propositions, in which the focus is to be the most applicable as possible, considering a set of organizations that face similar problems. Thus, we believe that a multiple case study setting should further enhance the tool, fine-tuning it, and increase its applicability across different industries. Moreover, a multiple case study setting can help better understand potential macro archetypes of existing BM, providing the possibility to search for similarities that lead to similar approaches to build DC. Hence, leaving the adaptation to each company BM specificities to tactical actions.

Another limitation is that our study focused on BM as the central analysis unit. In this respect, we also chose a case study based on a high degree of accessibility to information and weak overall DC while having a successful BM. However, we did not directly consider how the external dynamics variations and how the external environment impacts and shapes each DC dimension's relevance over time. It seems that completion, sectorial conditions, and external dynamics, such as regulatory and social pressures, may affect the extent to which a company must develop and explore each of the DC dimensions. Thus, combining our tool with elements such as level of industry opportunities, cumulativeness of knowledge, and appropriability levels (MALERBA; ORSENIGO, 1996), for instance, could be interesting to further continue the research on the operationalization of DC for BMI.

Appendix

Figure 0.1. The tool for measuring sensing capability for BMI and its core dimensions.

Seizing capability evaluation guide

	Worst-case scenario		Best-case scenario
1. PM	We focus on improving the current business model process and products, seeking to sustain the current competitive position.	1 2 3 4 5 6	We balance our innovation portfolio to search for new markets and new business models to bring our new technology to market and/or we balance our innovation portfolio to include the search for new business opportunities through open innovation activities
2. CR	Creativity is fostered only in the context of improving current business model performance.	1 2 3 4 5 6	We combine market, technology, and business model knowledge through diverse teams and engaging different stakeholders in the process of designing new business models in all its stages (problem-solution fit, product-market-fit, and escalation)
2.1. TN	We do not build specific teams for business model innovation projects.	1 2 3 4 5 6	We build teams based on each business model innovation project's specificities and idiosyncrasies, leveraging diversity. We pursue a psychological safety environment where everyone respects each other's opinion
2.2. LM	Our leadership's most important element is to control.	1 2 3 4 5 6	We foster a relational leadership style, trying to keep maximum motivation considering each one separately. Our leadership focuses on resilience, cultural alignment, and open communication
3. PS	We do not use any specific strategy to deploy new business models into the market.	1 2 3 4 5 6	We evaluate different contextual reality, such as levels of investment, easiness to imitate, regulatory reality, and the potential response of competitors while strategizing an immersion of new business models into the market
3.1. IP	Our business model competitiveness does not has intellectual property rights management as a key activity	1 2 3 4 5 6	Our business model depends on IPR management, and we coordinate with partners of the open innovation process to create and capture value from IP
3.2. TM	Our company do not distinguish new BM from the current BM.	1 2 3 4 5 6	We strategize different business models, considering when it is better to introduce them to the market given their particular technological and market aspects.
3.3. CA	Business model innovations are usually organic and emergent, without a specific entry strategy.	1 2 3 4 5 6	We build complementarities and complementary assets between our current business models and new business models, seeking to create barriers to imitation and entry, securing its performance
4.TC	Our business model does not include technological research, and our core innovation strategy is on the acquisition of specific assets and licensing from technical leaders.	1 2 3 4 5 6	Our business model includes technological research and development, and the business model also has an open innovation strategy to receive externally developed technologies.
5. RM	We do not explore significant strategies to orchestrate the necessary resources for business model innovation projects.	1 2 3 4 5 6	We follow different strategies to mobilize resources for the different business model innovation strategies, leveraging both internal and external resources, escalating expenditure as levels of uncertainty falls.
6. DT	We do not apply any specific stage process for business model innovation projects	1 2 3 4 5 6	We use different tools and follow a business model innovation stage's process, validating the different components until we reach the escalation and fine-tuning stage.

PM = Business model innovation portfolio management; CR = Creativity; TN = Teams diversity and norms; LM = Leadership and motivational levels; PS = Business model protection strategies; IP = Intellectual property; TM = Business model immersion in market; CA = Complementarities and co-specialized assets; TC = Technological capability; RM = Resources mobilization; DT = BM design and validation tools

Figure 0.2. The tool for measuring seizing capability for BMI and its core dimensions.

Transforming capability evaluation guide

	Worst-case scenario		Best-case scenario
1. OA	We do not analyze the systemic complementary or conflicting forces of new business models on the current business model and do not explore different strategies to develop these business models based on this contingency	1 2 3 4 5 6	We evaluate the complementarities and conflicts between new and existing business model systemically to derive adequate strategies while developing the new business models, exploring potential synergies between the business models, and avoiding potential value-destroying conflicts during the process
2. CM	We do not have a specific process to conduct structural business changes, and every change demands significant effort to reach satisfactory results	1 2 3 4 5 6	Our leadership and organizational culture are taken into consideration while conducting different organizational change activities. We follow the best-practices process to conduce changes.
3. OC	Our leadership focuses on the current business model, with an efficiency-oriented culture.	1 2 3 4 5 6	Our leadership focuses on learning and exploration besides efficiency, fostering a creative and innovative culture. Changes are usually welcome, and the resistance is low.
4. OD	We conduct all activities internally and usually explore new business opportunities through the current business model logic.	1 2 3 4 5 6	We follow a different strategy to exploit/explore different business opportunities, engaging a set of partners seemingly pertinent to exploit/explore new business models.
5. RB	Building new routines and capabilities are strictly connected to current business model performance	1 2 3 4 5 6	We derive strategic activities through organization design and engage other partners to build new capabilities and resources while exploiting new business models or changing the current business model. We align with our strategic human resources management to timely deploy necessary people for new routines
6. HR	We follow human resources management based on knowledge and capability to conduct specific tasks and job descriptions.	1 2 3 4 5 6	We follow a strategic human resources management based on commitment in the first place, aligning the culture and securing high motivational levels

OA = Organizational ambidexterity; CM = Change management; OC = Organizational culture; OD = Organizational design; RB = Resources and capability building; HR = Strategic human resources management.

Figure 0.3. The tool for measuring transforming capability for BMI and its core dimensions.

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Chapter 2

How Transformative Business Model Renewal Leads to Sustained Exploratory Business Model innovation in Incumbents: Insights from a System Dynamics Analysis of Case Studies

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Abstract

The digital era and mounting sustainability pressures have reinforced incumbents' need to respond to radical innovation through business model innovation. Despite advancements in the literature on incumbent business model innovation, there are still open debates regarding strategies for achieving systematic innovation and poor integration between the literature on managing multiple business models and the strategic management of business model innovation. To address these gaps, we investigated three Brazilian incumbents that developed systematic business model innovation processes and analyzed their evolution. We followed a multiple case study methodology, deploying system dynamics as an analytical lens. Our findings showed that the evolution of innovation departments from business model renewal to exploration is based on a systemic tension between solving the core problems of the business and creating openness to innovation, innovation capabilities, and resources. By assigning the innovation departments a vital role in the renewed business model and exploring synergies to manage multiple business models, the companies create a "buffer" to sustain exploratory business model innovation. We suggest that the strategy for conducting business model renewal matters, especially when the renewal is transformative, aiming to shape the future. We contribute to incumbent business model innovation theory by showing the system dynamics behind the evolution from business model renewal to exploration and by connecting the management of parallel business models to the strategic management of business model innovation.

Keywords business model innovation; system dynamics; incumbents; innovation management; exploration; renewal.

1. Introduction

The need for incumbents to respond to radical innovation through business model innovation (BMI) acquired momentum in the last 20 years. This was mainly because of digital technologies (e.g., the internet, big data analytics, cloud computing, mobile phones, the internet of things, and artificial intelligence) and mounting sustainability pressures (e.g., circular economy, grand challenges, sustainable development goals, and societal and regulatory demands), which created multiple possibilities for designing and proposing new BMs (FRANCO et al., 2021; GEISSDOERFER; VLADIMIROVA; EVANS, 2018; TEECE; LINDEN, 2017) as well as instability in competitive environments, thus reducing BMs' lifecycles (LAUDIEN; DAXBÖCK, 2017; MINATOGAWA et al., 2019; SCHOEMAKER; HEATON; TEECE, 2018). Under such a context, the literature concluded that incumbents need BM renewal and BM exploration capabilities to build long-term resilience (HACKLIN; BJÖRKDAHL; WALLIN, 2018; SCHAFFER et al., 2022), highlighting the relevance of balancing exploitative and exploratory BMI (KIM; MIN, 2015; OSIYEVSKYY; DEWALD, 2015; SUND; BOGERS; SAHRAMAA, 2021).

The literature on achieving such a balance is still rather controversial, with ongoing debates on how to structure the configuration of "BMI engines". Chesbrough and Rosenbloom's (CHESBROUGH; ROSENBLOOM, 2002) study of Xerox's spin-offs provided evidence that incumbents' dominant logic operates against exploratory behavior, though structural separation helps to avoid such pitfalls. This study had its roots in the interaction between radical technological innovation and BMI (e.g., Tongur and Engwall (TONGUR; ENGWALL, 2014); Kaulio et al. (KAULIO; THORÉN; ROHRBECK, 2017)), showing that technological incompatibilities favor structural separation. Similarly, Kuhlmann et al. (KUHLMANN; BENING; HOFFMANN, 2022) found that separation is fruitful with paradigmatic changes, such as moving towards circular BMs. Habtay and Holmén's (HABTAY; HOLMÉN, 2014) study provided empirical evidence that in cases of a combination of radical technological innovation and BMI, a separation seems superior, while under other conditions, an integrative strategy should be applied.

Despite research partially supporting the separation strategy, it does not come without challenges. Egfjord and Sund (EGFJORD; SUND, 2020), for instance, investigated how separation generates a misalignment of perceptions among those responsible for the current BM and those responsible for the exploration of new BMs. Likewise, Sund et al. (SUND; BOGERS;

SAHRAMAA, 2021) investigated the barriers to exploring BMI. Their study showed that BMI engines have limited resources and capabilities, experiencing control pressures from the dominant BM to obtain results. Thus, integration mechanisms and balancing incremental and radical innovation might be needed. Another relevant barrier is the notion that adding a new BM is not always beneficial (KIM; MIN, 2015). Besides the possible creation of unwanted complexity by adding new BMs, Hacklin et al. (HACKLIN; BJÖRKDAHL; WALLIN, 2018) showed that when the core BM is under threat, searching for new BMs draws attention away from saving the former, leading to catastrophic results. Thus, exploratory BMI is a sound strategy under stable environments, not only because it creates new revenue streams, but also because the proactive search for new BMs plays a major role in the ability to respond when the time of obsolescence arrives. Thus, the exploration of new BMs benefits incumbents' ability to respond to radical innovation (HACKLIN; BJÖRKDAHL; WALLIN, 2018; SCHAFFER et al., 2022; TEECE, 2018a, 2018b).

These contributions, therefore, advocate against a separation strategy, reinforcing the significance of managing BM renewal and exploration in parallel and creating a portfolio of multiple BMs (BOSBACH; BRILLINGER; SCHÄFER, 2020; LI, 2018), whereby incumbents benefit from deliberately exploiting complementarities between parallel BMs (BENSON-REA; BRODIE; SIMA, 2013), even under the existence of partial cannibalizations (VELU; STILES, 2013). Markides' (MARKIDES, 2014) seminal account provided a theoretical basis for understanding the exploration of such complementarities through degrees of integration between co-existing BMs while managing specific conflicts through partial separation. In line with this view, Khanaga et al. (KHANAGHA; VOLBERDA; OSHRI, 2014) showed that exploring touch points and integration between the obsolete BM and the substitute BM is beneficial for accelerating change while reducing organizational inertia.

Thus, the notion of incumbents benefitting from multiple BMs is rather contradictory to the idea of structurally separating the BMI engines to provide isolation from the influence of the core BM. The barriers to radical BMI also provide conflicting evidence, considering that the key barriers primarily stem from such a separation. Therefore, the literature focusses on understanding separated approaches and informing the need for integration mechanisms (EGFJORD; SUND, 2020; HABTAY; HOLMÉN, 2014; KUHLMANN; BENING; HOFFMANN, 2022; RENNINGS; WUSTMANS; KUPP, 2022; SUND; BOGERS; SAHRAMAA, 2021). There are, however, fewer studies exploring in-depth cases aiming at understanding how the creation of integrated innovation departments can work to overcome existing barriers (SUND; BOGERS; SAHRAMAA, 2021). Moreover, despite the contradictory findings between both research streams, the literature on incumbent BMI has, to the best of the authors' knowledge, neglected the bidirectional impacts of managing parallel BMs on the degree of exploratory BMI by incumbents.

To contribute to filling these gaps, our study's objectives were to:

1. Investigate incumbent companies that have developed systematic BMI processes through an integrated approach.
2. Analyze the evolution of the investigated incumbents' BMI process.

As a methodological approach, we conducted a multiple-case study involving three large Brazilian incumbents and adopted a system dynamics analytical lens to develop our theories. Our findings showed that a structured approach to achieving BM renewal with positive outcomes leads incumbents to pursue exploratory BMI. This structured search, besides achieving BM renewal, generates, as relevant outcomes, an increase in the openness to innovation, the buildup of innovation capabilities, and the greater availability of resources. The systemic consequence is a tension that pushes companies towards exploratory behavior to harness the favorable conditions. We also found that this evolution from BM renewal to exploration is insufficient because of the significant time delays between deciding to explore new BMs and achieving significant returns. Hence, the systemic forces push in the other direction: the lack of (short-term) results reduces the openness to change and increases control. To prevent this, our findings encourage the creation of a "buffer" that consists of: (1) the assignment of a vital role in the renewed BM to the innovation departments; and (2) the exploration of synergies between the core BM and new BMs. Our cases suggested that the type of BM renewal matters for the creation of the "buffer". In particular, transformative BM renewal leads to the creation of white spaces inside novel paradigms, which the company can explore through new BMs, and tends to connect the innovation departments to the renewed BM`s value proposition.

This study's contributions to the BMI literature are threefold. First, we contribute to the ongoing debate on the degrees of separation between BMI engines and the existing BM by providing evidence to suggest that integrated BMI engines that evolve from a transformative BM renewal strategy have positive impacts on solving potential barriers to exploratory BMI in incumbents. Second, we take the first steps in understanding how the management of multiple BMs through the deliberate pursuit of complementary new BMs as part of the renewed BM core logic plays a significant role as a "buffer" to support the longevity and the health of exploratory BMI. Third, we contribute to incumbent BMI theory by implementing the system dynamics lens to explain the key forces behind balancing BM renewal and exploration. Finally, our study contributes to practice by describing a process that can be followed by incumbent managers when creating their BMI engines.

The next section describes the theoretical background, including the business model and business model innovation concepts, the challenges and opportunities for incumbent BMI, and the bases for our analytical lens of systems thinking. Section 3 explains the methodological approach as well as the strategies for case selection, data collection, and analysis. In Section 4, we present our core findings from the case studies. Finally, we discuss this study’s key contributions to the literature and implications for practice and suggest some future research avenues in Section 5.

2. Theoretical Background

2.1. Business Model Innovation in Incumbents

A business model is a dynamic concept encompassing a combination of internal components, often referred to as the value proposition, value capture, and value delivery (TEECE, 2010), and their evolution to adapt to and anticipate external environmental changes (DEMIL; LECOCQ, 2010). As such, the BM, as a non-static concept, is a complex system in constant evolution. Its architecture builds internal consistency between components (FOSS; SAEBI, 2018), which must be aligned to the external environment under continuous change.

As a complex system, the power of the BM concept lies in the interactions between its components (FOSS; SAEBI, 2018), as the whole is greater (or smaller) than the sum of its parts (BERTALANFFY, 1968). Casadesus-Masanell and Ricart (CASADESUS-MASANELL; RICART, 2010) referred to the components as choices directed by the strategy, leading to several consequences that should create complementarities and sensemaking, ultimately generating competitive advantages. The evaluation of the Ryanair case showed that every BM part was aligned with the value proposition of offering low-fare flights. Similarly, by explaining the concept of business models as models, Baden-Fuller and Morgan’s (BADEN-FULLER; MORGAN, 2010) seminal account improved the understanding that BMs can be scale models, scientific models, and recipes. Condensing a complex system into a scale model, such as “the Ryanair model”, “Rolls Royce’s power-by-the-hour model”, and “the McDonald’s model”, represents it as a (well-understood) coherent system, which can be, of course, broken down into more detailed parts for analysis as a scientific model and then represented as a recipe of ingredients (components) and preparation modes (their interrelations).

This notion is particularly relevant, as BMI is a result of not only deliberate design practices (RIES, 2011; SILVA et al., 2019; TEECE, 2010) but also organic evolution, often with less-extensive design processes, in the pursuit of competitive advantages (CHRISTENSEN; BARTMAN; VAN BEVER, 2016; DOZ; KOSONEN, 2010; FOSS; SAEBI, 2018; GIROTRA; NETESSINE, 2013). In connection with this, it is worth differentiating the development of a startup, i.e., a new BM from scratch, and the innovation of existing BMs, as in the case of incumbents. For the former, there is no previous system, as the BM does not yet exist, and it is, therefore, often an outcome of design (SILVA et al., 2019). For the latter, the BM evolves and creates complementarities that strengthen its market position over time. Such conditions generate not only structural but also cognitive forces around a system that already works that tend to create rigidity and inertia to change (AHUJA; NOVELLI, 2016; CHRISTENSEN, 2000; CHRISTENSEN; BARTMAN; VAN BEVER, 2016; DOZ; KOSONEN, 2010; KOEN; BERTELS; ELSUM, 2011; LUCAS; GOH, 2009). Understanding the nuances inside the umbrella term BMI is crucial because, as Casadesus-Masanell and Zhu (CASADESUS-MASANELL; ZHU, 2013, p. 480) argued, BMI is a "slippery construct to study." Thus, the particularities of each type of BMI lead to not only very different outcomes but also different managerial processes, capabilities, and challenges.

In a recent literature review, Foss and Saebi (FOSS; SAEBI, 2016) created a typology for BMI by separating changes in the components (modular) and changes in the complex system (architectural), which could be new to the firm or the industry. However, it is still hard to grasp the differences between types of incumbent BMI based on such definitions. Volberda et al. (VOLBERDA et al., 2021) proposed a detailed typology considering the type of change, either transformative or evolutionary, and the strategic orientation in the ecosystem, either responding or shaping. As such, they provided a more fine-grained analysis of the possibilities of BMI by incumbents. For evolutionary changes, the BM renewal proceeds with no fundamental change in the BM logic. In cases of innovations (or societal changes) that dislocate the tight coupling between an incumbent's BM and the environmental conditions (e.g., customer behavior, technology, changing society, and customer needs), transformative changes in the BM are called for, demanding different approaches (HACKLIN; BJÖRKDAHL; WALLIN, 2018; KHANAGHA; VOLBERDA; OSHRI, 2014; SCHAFFER et al., 2022). Responding and shaping refer, respectively, to the strategic positioning of adaptations to changes as they come and the attempt to induce the changes themselves, pioneering and creating the future.

Additionally, incumbents can explore new BMs, creating new ventures (CHESBROUGH; ROSENBLOOM, 2002; CHESBROUGH, 2003; DOZ; KOSONEN, 2010;

FUTTERER; SCHMIDT; HEIDENREICH, 2018; HACKLIN; BJÖRKDAHL; WALLIN, 2018; RENNINGS; WUSTMANS; KUPP, 2022; SUND; BOGERS; SAHRAMAA, 2021). Finally, incumbents can also explore both paths, targeting ambidextrous behavior conducive to BM renewal and exploration (BENSON-REA; BRODIE; SIMA, 2013; HACKLIN; BJÖRKDAHL; WALLIN, 2018; MARKIDES, 2014; SCHAFFER et al., 2022). Thus, for incumbents, the concept of BMI can represent different things, ranging from incremental changes to transformative changes, coupled with the possibility of creating new BMs from scratch. Bearing this in mind, we differentiate the various types of incumbent BMI as incremental BM renewal, transformative BM renewal, and BM exploration:

- Incremental business model renewal

This type of BMI may be an outcome of both diagnosis and design activities and evolutionary, less deliberate changes that occur during a company's search for increasing performance. In terms of the degree of change, it can be modular and/or architectural, but the core notion is that there is no radical change in the underlying BM logic, i.e., the changes tend to rely on additional value creation and delivery as means to increase the value flow and potentialize the value proposition already in place. As such, the core idea is to strengthen the position in the market, which is often represented by a greater willingness to change in order to obtain short-term results and is broadly supported by top management teams, considered the path-dependent solution (KHANAGHA; VOLBERDA; OSHRI, 2014; SCHREYÖGG; SYDOW, 2011). A good example is the optimization of an existing BM by making it digital, i.e., through an online channel, to increase its reach and automate the value creation activities and its underlying business processes. In terms of challenges, naturally, any changes display inertia, but as the resulting changes fit the dominant logic (CHESBROUGH, 2010), the barriers are lower and there is a reduced need for structured approaches to conduct (KHANAGHA; VOLBERDA; OSHRI, 2014).

- Transformative business model renewal

This type of BMI involves in-depth changes to the BMI logic, broadening or altering the customer bases, supply network position, and overall value proposition alongside value creation, delivery, and capture, i.e., a deep change in the organization's capabilities. As such, the value proposition is reconceived, which calls for the rethinking of the creation, delivery, and capture. Illustrations of transformative BMI are Rolls Royce's power-by-the-hour model (JOVANOVIC; ENGWALL; JERBRANT, 2016) and the *Encyclopaedia Britannica* adaptation. The literature stresses that inertia (BASHIR; VERMA, 2019; HUANG et al., 2013; TONGUR; ENGWALL, 2014), path dependency (BOHNSACK; PINKSE; KOLK, 2014; GÄRTNER; SCHÖN, 2016;

REUVER; BOUWMAN; HAAKER, 2013; TEECE; PISANO; SHUEN, 1997), and the potential cannibalization (KHANAGHA; VOLBERDA; OSHRI, 2014; VELU; STILES, 2013) of the business works against transformative BMI. Accordingly, the recommendation is for a separated, focused structure (CHRISTENSEN; BARTMAN; VAN BEVER, 2016; TUSHMAN; O'REILLY, 1996). This type of BMI is often linked to a survival threat whereby the organization faces a situation in which the BM change is inevitable. However, the literature highlights the importance of proactivity and the realistic prognosis of the relevance of conducting transformative BMI as an opportunity to shape the future and improve an incumbent's capacity to respond to radical innovation (HACKLIN; BJÖRKDAHL; WALLIN, 2018; VOLBERDA et al., 2021).

- Business model exploration: corporate entrepreneurship

This type of BMI refers to entrepreneurial activities undertaken by incumbents to create and explore new BMs, such as startups, either to open new markets and create new revenue sources or to accelerate current BM performance (FUTTERER; SCHMIDT; HEIDENREICH, 2018; KARIMI; WALTER, 2016). This involves exploring new knowledge, resources, and partnerships to develop innovative value propositions and seize new business opportunities. It requires entrepreneurial vision from a company's board and top management, as its development is realized through corporate entrepreneurship or corporate venturing initiatives (URBANO et al., 2022; ZAHRA, 1993). A good example is the undergoing strategic transformation of Bosch from a B2B manufacturing leader based on outstanding product innovation to a B2B leading provider of technological solutions based on internet of things and artificial intelligence (RENNINGS; WUSTMANS; KUPP, 2022). As illustrated in the Bosch case, companies that pursue venturing BMI are primarily exploring the frontier of opportunities opened up by the digital economy and digital transformation. Moreover, as much as innovation itself has moved from the closed paradigm based primarily on internal R&D to open innovation based on interorganizational collaboration and access to external knowledge, venturing BMI has been characterized by strong external partnerships, particularly through corporate engagement with startups, i.e., incubation (FORD; GARNSEY; PROBERT, 2010), acceleration (URBANIEC; ŻUR, 2021), venture building, and corporate venture capital (COVIN; MORGAN P. MILES, 2007). However, this BMI type presents barriers to incumbents, and many initiatives tend to collapse with time (SUND; BOGERS; SAHRAMAA, 2021). The first barrier is that experimentation and trial and error (CHESBROUGH, 2010; SOSNA; TREVINYO-RODRÍGUEZ; VELAMURI, 2010) are the underlying processes for BM exploration. This results in a resource-intensive process that takes a long time to achieve returns, depending on strong commitment. Startup founders, for example, depend on their entrepreneurial activities' success, and the literature shows that commitment is crucial (VIVARELLI, 2004). This is not true for incumbents, as they already have a successful BM that they can easily turn to if the endeavors fail. Thus, issues such as goal incompatibility (BRENK et al., 2019; CHESBROUGH, 2010), managerial complexity (HACKLIN; BJÖRKDAHL; WALLIN, 2018), and a loss of focus (EGFJORD; SUND, 2020) play a role in shaping the tendency to return to incrementalism.

Therefore, in the literature and in practice, attempts are being made to uncover ways of overcoming such barriers and determine the most suitable organizational structure for pursuing lasting BM exploration that allows companies to seize "white spaces" (JOHNSON, 2010) for business opportunities. Moreover, the relationship between BM renewal and exploration needs further clarification, especially considering the literature's emphasis on both being vital for incumbents. This relationship can be either positive or negative. An excessive focus on BM renewal with an incremental goal, i.e., extrapolating from the current BM perspective, can hinder the ability to respond to discontinuities and constrain exploration (DOZ; KOSONEN, 2010; KHANAGHA; VOLBERDA; OSHRI, 2014). The random exploration of new BMs can bring complexity, i.e., too many technological bases, high rates of cannibalization, and conflicts, leading to suboptimal BM management and consuming managerial attention (HACKLIN; BJÖRKDAHL; WALLIN, 2018). Moreover, the challenges of generating relevant returns through new BMs (SUND; BOGERS; SAHRAMAA, 2021) and the cognitive barriers relating a departure from the dominant logic (CHESBROUGH; ROSENBLOOM, 2002; EGFJORD; SUND, 2020; RENNINGS; WUSTMANS; KUPP, 2022) can induce barriers to exploratory BM, thus limiting future exploratory efforts. On the other hand, BM exploration is regarded as relevant to fostering experiments that can improve future envisioning, reduce dominant logic, and enhance BM renewal activity (DOZ; KOSONEN, 2010; FRANCO et al., 2021; HACKLIN; BJÖRKDAHL; WALLIN, 2018; SCHAFFER et al., 2022; SOSNA; TREVINYO-RODRÍGUEZ; VELAMURI, 2010). In this regard, the dynamics behind incumbent BMI and the relationship between BM renewal and BM exploration needs to be further studied. In particular, the balancing of renewal and exploration and the impacts of the various BMI types on each other remain understudied. To tackle these issues, we deployed systems thinking lens to better understand the dynamics behind incumbent BMI.

2.2. Systems Thinking and Business Model Innovation

Systems thinking is a manner of understanding complex systems as a whole instead of looking at their parts individually (BEHL; FERREIRA, 2014). The underlying notion is that the different parts of a system (e.g., businesses, ecosystems, or groups of people) are connected and that it is vital to understand how these parts affect one another. As such, it can be understood as a framework for analyzing and evaluating the interrelation between a system's parts rather than listing its parts, i.e., it helps uncover patterns of change rather than taking static snapshots. Senge (SENGE, 2006) highlights how, for example, short-term solutions to business problems represent a remedy that can, although improving performance, worsen the root problem that caused the issue in the first place. One of the reasons for this is that alleviating the problem's symptoms works against setting up means to effectively solve the problem (LEVESON, 2011; SENGE, 2006). Furthermore, small changes in one part of a system can greatly affect the whole system (SENGE, 2006).

In this regard, the literature provides a plethora of studies that have investigated the impacts of systems thinking on performance under different settings, such as sustainability (MARTÍNEZ LEÓN; CALVO-AMODIO, 2017), design thinking (BUCHANAN, 2019), public health and healthcare (LEISCHOW et al., 2008; LINNÉUSSON et al., 2022), and business performance (SCHIUMA; CARLUCCI; SOLE, 2012). The search for efficiency can begin by analyzing each member of an organization, with the goal of improving their individual performance. However, it is necessary to understand the mechanisms in place to determine how individual improvement affects performance—for example, the organizational processes, culture, and teamwork norms. For example, Cady's (CADY, 2021) study showed that interventions at the system level can significantly improve teams' performance when aligned with systems thinking concepts, i.e., the invisible (sometimes visible) mechanisms in which the individuals are embedded affect their mental models, thus shaping their interaction dynamics (BLOKLAND; RENIERS, 2021), highlighting the power of systems thinking for businesses.

3. Method

3.1. Research Methodology

As a research methodology, we conducted a multiple-case study, as this is considered a suitable research approach when the subject involves complex systems and organizational phenomena about which there is little knowledge (EISENHARDT, 1989; YIN, 2018). In line with this study's objectives, multiple-case studies allow an in-depth and longitudinal analysis of cases, which could help us uncover and establish theories by assessing the similarities and differences between various companies, ensuring the reliability, validity, and relevance of the research (EISENHARDT, 2021; EISENHARDT; GRÄBNER, 2007). Additionally, case studies provide a richness of data that is supportive of exploratory studies aiming at the creation of new theories, as was the case with this study (YIN, 2018).

3.2. Case Selection

Following Eisenhardt and Gräbner's (EISENHARDT; GRÄBNER, 2007) guidelines, we sought to build a theoretical sample. Moreover, we followed recommendations for critical (FLYVBJERG, 2006; RUDDIN, 2006) and longitudinal cases (YIN, 2018). We delineated the following criteria: (1) we selected cases at least in the stage of pursuing the creation of new BMs through a BMI engine; (2) the selected companies displayed resilience and longevity in their BMI engines; (3) we selected large incumbents that were leading companies in their market segments; (4) the sample comprised at least one company in the manufacturing industry, one company in the ICT industry, and one company in the services industry; (5) the cases were not born digital and had existed for at least 20 years. The focus on large companies was based on the notion that larger and older companies tend to display a higher degree of systemic complementarity in their BMs (CHRISTENSEN; BARTMAN; VAN BEVER, 2016; FOSS; SAEBI, 2016), which leads to greater rigidity. This criterion rounded up our focus on critical cases, as the BMI literature highlights the challenge of changing existing BMs and moving from traditional business-as-usual to agile and exploratory organizations (for more details on agile organizations, see (ANNOSI et al., 2020)).

3.2.1. The Selected Cases

Alpha is a 96-year-old leading incumbent in the Brazilian health diagnosis industry, offering a broad range of services. In 2014, the company started its renewal, in particular by reshaping and intensifying innovation activities, moving from traditional reactive medicine with diagnostic services to precision medicine. In the last three years, the company has created its first new BM and has been pursuing the creation of new startups to fill in the predictive and precision medicine value chain.

Beta is a global player and a leading incumbent in the personal care and cosmetics industry, with a long and successful history. The company was born with innovation at its core, as it is one of the only players in the world to leverage Brazil's extensive flora and fauna. The uniqueness of the products has placed R&D at the core of the company since its founding. Since 2012, the company has been rethinking its BM, especially due to digital transformation. In the last three years, it has been attempting to create new startups with a strong merger and acquisition strategy.

Gama is one of the ten largest incumbents in the field of R&D outsourcing in the Brazilian ICT industry, and recently it has become an international player with projects in North America and other countries in South America. Despite the company's core activity of operationalizing third-party R&D projects, it has displayed poor innovation performance since its founding. Considering its basis in information technology, the company had no specific technological focus, executing almost any kind of project. To tackle this issue, the company began its BMI journey in 2017 by narrowing its technological focuses to the most promising future technologies according to a foresight study (including 3D printing, data science, cognitive computing, industry 4.0, cybersecurity, and blockchain) and creating new BMs based on these technologies. In 2020, the company launched its first new startup, and it launched two more in 2021. Table 3.1 summarizes the cases in terms of their size, revenue, and employee count.

Table 3.1.
A brief description of the cases, including the country of origin, age, industry, size, employee count, and revenue.

Case	Age (Years in 2021)	BMI Journey Beginning	Industry	Employee Count	Revenues (USD)
Alpha	96	2014	Health services	~13.000	>1 billion
Beta	53	2012	Personal care and cosmetics manufacturing	~17.500	>22 billion
Gama	21	2017	Software	~700	>100 million

* We followed the Eurostat classification of company size based on persons employed: micro-enterprises with less than 10 persons, small enterprises with more than 10 and less than 49 persons, medium enterprises with 50 or more and less than 249 persons, and large companies with more than 249 persons.

3.3. Data Collection

For the data collection, we followed the literature's directives for multiple-case studies (EISENHARDT, 1989, 2021; YIN, 2018). We developed a case-study protocol, considering data from semi-structured interviews with key informants and a longitudinal analysis of annual reports and public documents as secondary data. To ensure reliability and validity, we deployed triangulation techniques to cope with possible informant biases, especially stemming from the characteristics and judgments of our interviewees that may have led to a distortion of reality (GIBBERT; RUIGROK; WICKI, 2008). Considering the different realities of our case companies, we followed different triangulation and data-collection strategies. For Alpha and Beta, which are public companies, we took advantage of the availability of a large amount of documentary data, extensively using reports and documents to triangulate with the interviews. Thus, we first conducted an in-depth documentary analysis and then proceeded to the interviews. This allowed us to confront interviewees from Alpha and Beta with documentary data when contradicting information arose. For Gama, which is not public and thus did not provide such a richness of documentary data, we broadened the demographics of our interviewees by including persons from different backgrounds and managerial layers and conducted an internal document analysis.

We conducted 14 semi-structured interviews, with an average duration of 60 min, ranging from 15 to 75 min. We created transcripts of the interviews immediately following their completion. Considering the goal of understanding the systemic complementarities between the BMI engine and the current BM, focusing on the structural and strategic levels, we chose our key informants from the top management team of the companies, preferably at the CXO level and directly connected to the BMI engines. In the case of Gama, we included interviewees from other departments and levels, such as R&D and human resources, to make up for the lower amount of available data and facilitate a deeper analysis. Table 3.2 depicts the demographic data of the key informants in each case, the supplementary material used to triangulate, the number of interviews per case, and the duration of the interviews.

Table 3.2
Key informants, number of interviews, average duration, annual and managerial reports, and additional documents.

Case	Key Informants	Number of Interviews (Average Duration)	Managerial Reports Analyzed	Additional Sources
Alpha	CTO and innovation manager	3 (60 min)	7, from 2015 to 2021 (~200 pages)	Public data from social media, website, and informative documents.
Beta	Executive business director and CEO	2 (63 min)	7, from 2015 to 2021 (~750 pages)	Public data from website, social media, news, and mergers and acquisitions.
Gama	CEO, innovation director, HR director, R&D personnel	9 (15–75 min)	Not available	Internal strategic documents (strategic map evolution, strategic communication); public data from website, social media, and news.

3.4. Data Analysis

For the data analysis, we filed and documented the data into tables and revisited the interview transcriptions multiple times to analyze the gathered data. Then, we followed Strauss and Corbin’s (STRAUSS; CORBIN, 1998) recommendations. First, we conducted open coding, focusing on first analyzing each case separately. After understanding each case, we moved to axial coding, looking for similarities and differences between the cases and considering how they contributed to answering our research question. Finally, we conducted selective coding to derive relevant constructs and concepts from the cases (EISENHARDT, 1989). We also employed one of the researchers as a devil's advocate to help reduce potential biases in the analysis (NEMETH; BROWN; ROGERS, 2001). Finally, the authors conducted data ideation and representation processes, contrasting the available data sources as the underlying triangulation method (HOLLOWAY, 1997; MILES; HUBERMAN, 1994).

4. Results of the Case Studies

In this section, we present our study's core findings. First, we briefly present the BM of each of the studied cases, highlighting how it co-evolved with their BMI engines from the beginning of our analysis. Then, we investigate the system dynamics through which their structured approach to pursuing BM renewal led them to begin exploring more radical BMI. We then show how our case studies created integration mechanisms between their BMI engines and the core business model to sustain their exploratory efforts. Hence, through a system dynamics analytical lens, we present the inducted theory of how incumbents can create BMI capabilities to prepare themselves to respond to radical BMI.

4.1. Presentation of the Cases

4.1.1. Alpha

Alpha's initial BM was that of a health diagnostics service, operating via intermediates, in the B2B2C model or directly via the B2C model. The core value proposition was centered on high-quality tests and sample collection. Its value creation architecture was based on deploying a technical-oriented staff responsible for conducting R&D to create new tests or improve the existing ones. Alpha's position in the market was to attend all patient classes, with different layers of tests and exams and through different channels, focusing on service excellence to acquire and retain customers. Thus, innovation until 2015 was mostly directed toward technological advancements in medical techniques and analysis.

The BMI efforts in the company began in 2017 with the "genomic project", an initiative that aimed to leverage the power of digital technologies, particularly artificial intelligence, to pioneer predictive and precision medicine in the future (Alpha's annual reports, 2017, 2018, 2019, 2020; CEO interview). Alpha's modular BMI process was based on reframing its value proposition to focus on predictive and precision medicine, i.e., patient well-being. This materialized as modular differentiation from the reactive medicine practiced so far via the exams and tests offered by the company, based in discrete product innovations inside the BM (Alpha's new business director).

The evolution of such a practice led Alpha to a transformative change in its BM, rethinking its business model from a diagnostic services provider to a healthcare platform (Alpha's annual reports, 2020 and 2021). The value creation element of the new BM changed to incorporate the exploration of new businesses that could play a role in the predictive medicine ecosystem. In 2019, Alpha launched its first spin-off, a B2C BM platform that performed the functions of telemedicine marketing, genetic and lifestyle conditions monitoring, treatment and exam scheduling, and so on (Alpha's annual report, 2019 and 2020).

4.1.2. Beta

Beta's initial BM followed the traditional personal care and cosmetics manufacturing model. The company delivered value by deploying a large force of sales representatives that increased its sales and created value through R&D to provide product and process innovations that sustained the value proposition of well-being through differentiation. The company differentiated itself within the market by positioning itself as a sustainability-oriented company, exploiting the country's vast plant diversity without depleting it and creating value for neglected populations living in underexplored areas. In a manner, the company's demand was driven by its network of representatives, which sold the products through personal contacts to end customers. Thus, it could be understood as a B2B2C model.

Naturally, this network of representatives played a major role by shaping Beta's product mix, obtaining customer feedback that could inform R&D, and creating bonds with end customers to transmit the company's core values to society. This was, however, a largely analogical process that relied on suboptimal information flow and emphasized mouth-to-mouth mechanisms. Thus, Beta depended on its representatives' knowledge creation and sharing, whose effectiveness was perceived as low due to information loss (interviews with Beta's CIO and innovation manager). As such, Beta's BMI journey began by focusing on how to digitalize this highly analogical process, therefore improving its effectiveness. It is safe to say that this represented modular and incremental BM renewal.

The evolution of Beta's BMI journey followed the digitalization of its entire BM, with the precise goal of becoming a digital company (interview with Beta's CIO). For Beta, this meant implementing an agile culture to reduce lead times from innovation processes, and therefore the company moved forward to renew its value creation mechanisms through digitalizing the R&D process. Finally, Beta decided to explore the addition of new BMs, especially a service BM, to reinforce its value proposition through a BM exploration strategy. The company mainly adopted an acquisitions strategy to purchase fast-growing startups with BMs that were seen as complementary to the company's vision in order to create a well-being platform around its core BM.

4.1.3. Gama

As described by its CEO, Gama's initial BM was that of a "passive outsourcing of Information technology R&D" (interview with Gama's CEO). In this regard, Gama's value propositions were information technology competency and knowledge, with its value creation process being the application of knowledge to solve customers' problems. Under the initial model, the value delivery was achieved through the company's commercial department. Large IT companies found Gama due to its market reputation and asked for potential solutions to well-defined projects, which the companies were unwilling to conduct internally. Although offering R&D outsourcing solutions, Gama did not have its own R&D department and hired people ad hoc to solve demands as they arose (interviews with Gama's operations manager and CEO).

Gama's BMI journey began in 2017, when macroeconomic problems in Brazil led major IT companies to cut their R&D budgets, which had drastic consequences for Gama (interview with Gama's innovation director, internal strategic documents). The company needed new revenue sources to complement its main BM, as it was too dependent upon the external economic conditions. Gama first changed its value proposition by proactively searching for market problems and creating potential solutions in the form of minimum viable products (MVPs) or proofs of concepts (PoCs), which were implemented to improve the company's reputation in the market and gain a competitive advantage.

Following this, Gama created an R&D department responsible for anticipating the problems faced by large IT companies and building MVPs and PoCs encapsulating the resources needed to solve such problems. In doing so, the company transformed its BM from a passive R&D outsourcing BM to an active R&D outsourcing BM. The accumulation of such MVPs and PoCs, considered assets by the company, led it to explore novel BMs, launching its first startup in 2020 and three more in 2021. Gama's startups are still in the market creation stage

4.2. From Business Model Renewal to Business Model Exploration

The BMI efforts of our studied cases arose due to the perceived threats stemming from digitalization, which created a feeling of needing to act among the companies' management. Alpha's journey began by repositioning its services toward high-end customer segments, with the focus of the improvements being on the value proposition (Alpha's annual report, 2015 and 2016). Then, it coupled this action with the genomic project, which combined the company's medical capabilities with novel bioinformatic and digital capabilities, targeting the creation of new business strands through novel service offerings complementary to the existing BM (annual reports, 2018 and 2019; CEO interview). Beta focused on its sales representatives network, which was highly personal and analogical, targeting its value delivery architecture to improve performance while creating means to extract value from customer data (CTO interview, Beta's annual report). Gama's target was the creation of new assets, such as prototypes, that could support its reputation and image in the market, thus reshaping its value proposition and value delivery by better segmenting its customers and sharpening its offerings (interviews with the CEO and innovation director).

The first step to achieving the outlined goals was to deploy a structured approach, changing the organization's design by: (1) either creating an innovation department at the top management level (Beta and Gama) or reframing a top-management-level department's role to focus on innovation (Alpha) and (2) assigning a champion to the innovation departments at an executive position. Alpha's choice was to reframe its new business department to embed digitalization at the core of the business (Alpha's annual report) through the deployment of IT personnel in the leadership:

> "*We are an organization that we had a medical and technical board, and I was also part of it, where there is an R&D with all the doctors conducting innovation in tests and innovation in services. The doctor with the R&D team sets up this test. Now we have a new arm in business innovation. [...] And there is the whole IT part that has the traditional, infrastructure and systems and there is the all-digital part that looks after squads, whether in the traditional or in the new businesses.*" (Alpha's CEO)

Relevant to the evolution dynamics of the BMI efforts by the studied cases was the provision of limited resources coupled with a high degree of control and a need for results. Alpha had the most significant resources for its innovation department, as it reassigned part of the new business department, providing a dedicated innovation personnel and budget. However, the company understood the need to keep the department lean by building the innovation team transversal to the company, with employees from different departments participating in the innovation squads (CEO interview). Beta assigned to its newly created vice presidency of the business platform (Beta's annual report) a team of five members (interview with Beta's CIO). These groups were also deployed transversal to the organization through a matrixial structure, in which the projects were managed through squads (interviews with Beta's CIO and innovation manager).

"*In 2012, when digitalization actions began, the goal was the digitalization of the business, and not of internal specific departments. Hence, the challenge was to digitalize our representatives' network in the society.*" (Beta's innovation manager)

Similarly, Gama's approach was to entrust its innovation direction to its innovation director, with other team members being volunteers taking part in the innovation projects (interviews with CEO, innovation director, and R&D manager).

"*We had limited resources, and the department was comprised only by me. So, I had to create engagement and gather volunteers, which worked outside their hours.*" (Gama's innovation director)

Due to the combination of limited resources, a high degree of control, and the need to change, the innovation department focused on renewing the current BM, targeting solutions that consumed fewer resources and delivered more significant results. The innovation departments' actions grew from small modular changes in specific parts of the BM, i.e., digitalization, to architectural changes across the whole BM. In doing so, the companies experienced an increase in the performance of their current BMs. Alpha's revenue grew from around USD 500 million in 2015 to USD 1 billion in 2021 (Alpha's financial reports). Beta grew 175% from 2016 to 2021, along with an increase in net profits, in comparison to its growth of 43% in the period from 2011 to 2015, during which Beta shrunk its margins and net profits (Beta's financial reports). Gama's income grew 250% in the period between 2017 and 2021, and it swelled from around 250 employees in 2017 to more than 600 in 2021, again in high contrast to the period between 2014 to 2017, when the company reduced its size from around 300 to less than 200 employees and struggled to maintain its revenue size (Gama's internal documents). Table 4.1 provides more details on the companies' performance.

Table 4.1
Performance of Alpha, Beta, and Gama by year.

	Alpha		**Beta**		**Gama**	
Year	**Revenue Growth (% Compared to Previous Year)**	**Head Count**	**Revenue Growth (% Compared to Previous Year)**	**Head Count**	**Revenue Growth (% Compared to Previous Year)**	**Head Count**
2015	11.60%	8600	8.60%	6591	7.20%	291
2016	9.70%	8400	1.73%	6397	−5.91%	229
2017	12.40%	8700	25.09%	6311	−29.11%	181
2018	11.30%	9400	34.99%	6635	32.80%	188
2019	9.10%	10,000	6.17%	6820	36.53%	227
2020	2.10%	11,200	39.97%	6920	40.86%	399
2021	30.10%	13,000	7.64%	17,672	116.59%	600

Interestingly, whereas Alpha and Gama's growth was steady during the considered periods, Beta displayed an "accordion effect", whereby it recorded high growth in one year, followed by a stagnant period the next year. This phenomenon, which can be interpreted as a consequence of the company's acquisitions strategy, will be explored further below. Although limited, these performance indicators help partially translate the BM renewal in terms of the company's growth rate and employee count.

Despite the main result being a reduction in the need to change the current BMs, this growing evolutionary approach led to a set of relevant additional outcomes that we will explore in the next subsections: (1) increased openness to innovation among both the top management and the wider employee bases of the companies; (2) enhanced resource mobilization (human, budgetary, relational) and availability for innovation departments; and (3) an increase in BMI capabilities, with the teams focusing their learning efforts in this direction, enjoying greater freedom and growing resources.

This subsection examined how the conditions surrounding the emergence of BMI efforts in the incumbents played a vital role in the evolutionary dynamics of their BMI capabilities. This was because such conditions led the companies to deploy creative methods for gathering resources, coupled with an incremental and more chirurgical focus on Pareto solutions that consumed the least resources but led to higher returns. The achievement of performance gains through the renewal of the current BMs reduced the need to change the current BMs while creating a latent stock of BMI capabilities. We observed a growing set of resources for innovation departments and cultural changes related to increased openness to innovation. This created a tension (i.e., between growing BMI capabilities, openness to innovation, and available resources and a diminishing need to change the current BM) that led to a shift in focus from BM renewal to the exploration of new BMs. Figure 4.1 summarizes the system dynamics surmised from the multiple case studies, which we will explore further in the next subsections.

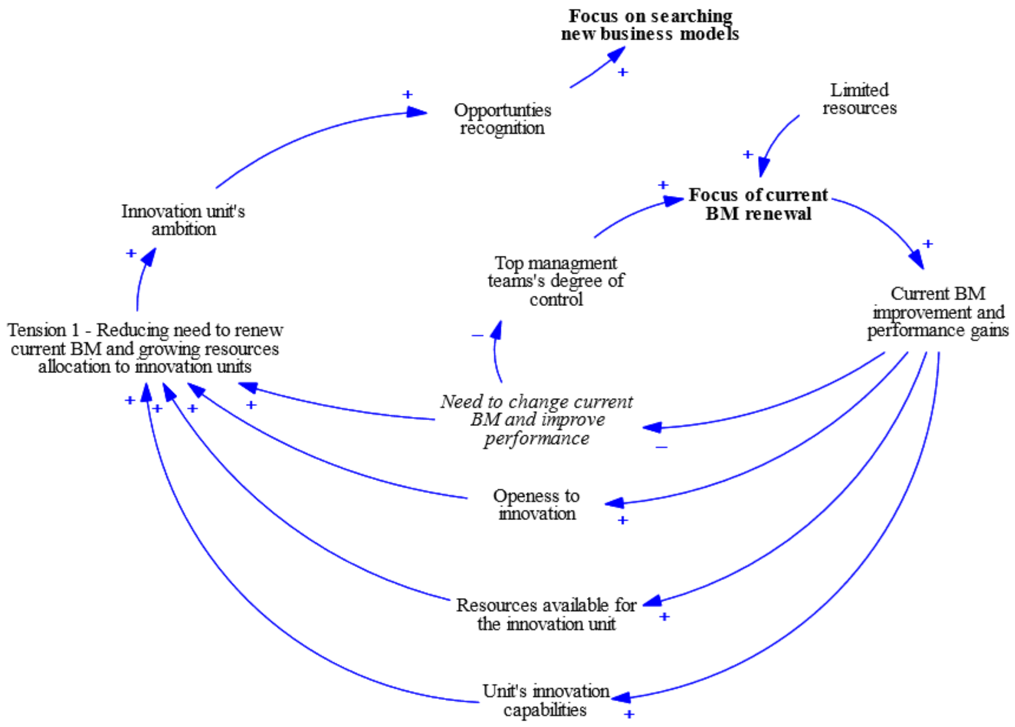

Figure 4.1. The system dynamics behind the evolution from BM renewal to BM exploration

4.2.1. Openness to Innovation

We found that openness to innovation had its roots in three different mechanisms. The first was the integration mechanism of creating transversal agile teams, in which members from different departments took part. To unfreeze and change the organizational culture towards innovation, the companies chose the strategy of introducing BMI techniques and creating an innovation-friendly atmosphere to motivate and capacitate their personnel. Alpha and Beta introduced Spotify squads (Alpha's innovation manager; Beta's CIO) led by IT experts, with the particular aim of helping disseminate agile techniques. This action was conducive to engaging interested employees to take part in Hackathons, design thinking (DORST, 2011), and lean startup (BOCKEN; SNIHUR, 2020) events (Alpha CEO interview, Beta innovation manager interview, Gama CEO interview). One essential element cited in the interviews was the acceptance of failure, which was accompanied by events and a secure space to think outside the box.

> *"But new capabilities as professionals who think about User Experience, digital, platform solutions, we didn't have. We bought [a] primary care startup. We set up a digital team, a team with young people with these other capabilities. We were making a mix, because in our view these people with new capabilities cannot be left alone in the organization"* (Alpha's innovation director)

The second mechanism was the top management team's degree of control, the consequent autonomy of the innovation department, and the influential actions of the innovation department's leadership. The need to generate results with limited resources naturally pushed the leadership to act as a seller of ideas in pursuit of buy-in from the top management. The incremental growth from small wins to larger changes in the current BM increased the top management team's confidence in the department's ability to deliver results and make autonomous decisions for larger jumps. As Beta's CIO put it:

> "*The CEO and the chairman were the biggest sponsors' of the projects. As we had successful small wins, we earned top management's interest and that allowed us to reach the current stage. […]. So, we spent 2 years piloting a digital Business Model in which the digital was placed at the center. The first was in Campinas and ended up being rejected due to the view that the Value Proposition for consultants was still insufficient. The second pilot was in São José dos Campos, with adjustments to this value proposition, and already a slightly more open vision. This led to changes even in the organization's way of approving projects. In the past, to make a small change to the company's logo had to be approved by the Vice Presidents. In 2014, when the Business model was created, Natura started to provide a platform for the consultant, with all the necessary functionalities*" (Beta's CIO)

The third mechanism stemmed from the managerial point of view. The structural change induced by the top management teams through creating specialized innovation departments transmitted an important message across the organization regarding the company deemed relevant. This induced a shift in cognition, with personnel believing that to fit into the organization it was essential to embrace innovation, triggering an evolution in the culture to one more open to innovation:

> "*We transmitted a message for the employees that innovation was of utmost importance. We designed our open innovation funnel and how innovation would contribute for our core business, hired an experienced, yet forward thinking, innovation director.*" (Gama's CEO)

4.2.2. Resource Availability

We noticed a solid and constant growth in the number of employees involved in the innovation departments. Gama started with only the innovation director in 2017. In 2020, the company had more than 30 employees dedicated to the department, which increased to around

50 employees in 2022, accompanied by the creation of a formal R&D department (Gama's internal documents). Beta's vice presidency of business platforms started with five employees, i.e., the CIO, one product owner, one tech lead, one scrum master, and one user experience professional (Beta CIO interview). Subsequently, it grew and separated into two core subdivisions, the innovation lab and the business innovation department, and added a CTO to share the leadership with the CIO (interview with Beta's innovation manager). This represented an increase in resources and freedom to balance incremental and radical innovation. When asked about the size of the fixed team, the CIO answered as follows:

> "*(Today) 50, my team practically does the leadership, who does it in practice is consulting (partnerships). In our squads, the Product Owners, Tech leads, scrum master and User Experience are all [Beta] employees. The remainder of the development and quality force is outsourced. There are more than 50 [outsourced] consulting partners.*" (Beta's CIO)

4.2.3. Innovation Capabilities

The accumulation of innovation capabilities stemmed from the combination of learning activities conducted by the innovation departments and the strategic and structural approach followed by the studied cases. The guiding thread that allowed the associated activities to create BMI capabilities was the attention devoted to searching for opportunities, designing changes to gather necessary resources, and the cultural and transformational actions necessary for change. The efforts to create an innovative culture and improve the quality of solutions led to a learning curve regarding BMI in the studied cases. Alpha's attempts to combine digital competencies and innovation capabilities with their core competence in medicine through the squads led to knowledge sharing regarding BMI and the spread of knowledge about its tools, practices, and processes (Alpha CEO interview). In measurable terms, Alpha increased from 66 implemented product and process innovations in 2015 to 430 in 2021 (Alpha's annual reports, 2015 and 2021). Gama's approach was to encourage its employees to use their working hours to study innovation and engage in events, including their own BMI-oriented event, which combined theoretical and practical knowledge as the basis for their BMI capability evolution.

> "*In the first rounds of our open innovation event, we had many potential opportunities brought by our employees, but we noticed that they still lacked quality, and we could only create basic ideas that, despite serving our core BM well, had no potential to become new business models. After a few iterations we noticed an important improvement, and were able*

to create our first ideas that had true potential to become new BMs" (Gama's innovation director)

4.3. Sustaining Business Model Exploration through the Creation of a "Buffer"

Exploring new BMs is an uncertain and time-consuming activity, from initiation until the new BMs provide relevant returns to the incumbents. The exploration of new BMs is also a resource-intensive activity. This is further exacerbated for incumbents, which need to sustain growth to satisfy their shareholders' and stakeholders' interests. In systemic terms, this means that the resources committed lead to a momentaneous increase in exploratory behavior and experimentation to create novel BMs. Given the time and learning curves, such activity might lead to the generation of new business models. However, on the other hand, the time delay associated with this activity in terms of years tends to suppress the activities by unbalancing the resource allocation towards incremental BM renewal, suppressing radical BM exploration.

In our cases, Beta had the most significant barriers to the pursuit of exploratory BMI. Alpha and Gama followed a more organic and evolutionary path. One probable reason was that Beta, after achieving BM renewal and securing greater resources, attempted to separate its new business creation engine from the core business (interviews with Beta's CIO and innovation manager). Moreover, Beta's BM renewal was mostly incremental, with most innovation manifesting as a transformation from analogical to digital, but without changing the BM logic (Beta's reports, 2015–2021). On the other hand, Alpha and Gama pursued transformative BM renewal; Alpha rethought its business from a value proposition of diagnostic services towards fully predictive medicine (Alpha's reports, 2018–2021, and Alpha CEO interview), and Gama moved from responsively operating outsourced R&D activity to anticipating its customers' needs, offering projects with cutting-edge technology, coupled with the creation of innovative BMs based on digital technologies (interviews with Gama's innovation director, CEO, and R&D manager).

Such a situation emphasizes the need to create integration mechanisms between the exploratory BMI endeavors and the current BMs. Alpha and Gama took advantage of the evolutionary dynamics of their BMI engines to establish touchpoints between both. Hence, to avoid the suppression of exploratory behavior, it makes sense to create a "buffer" that sustains the long-term perspective. One possible path, followed by Alpha and Gama, was to assign to their BMI engine a significant role in the existing BM and to explore the creation of complementary parallel BMs. Figure 4.2 depicts the systemic model of the buffer as a bridge mechanism between the renewal of the current BM and the creation of a new business model in incumbents, allowing incumbents to develop the ability to respond to radical innovation. The next subsections explore the cases' "buffers".

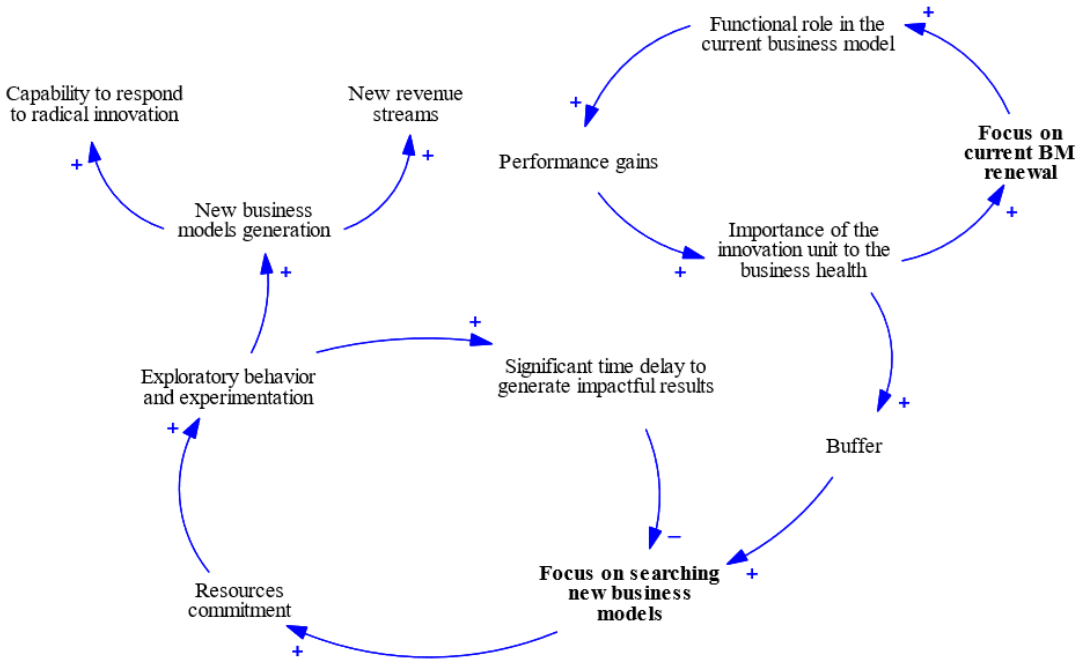

Figure 4.2. The "buffer" as a mechanism for sustaining exploratory BMI and bridging the dual goals of focusing on the core BM while exploring new BMs**.**

4.3.1. Alpha's Healthcare Platform Business Model as the Driver for Exploring New Business Models

Alpha had two core integration mechanisms. The first was the genomic project, in which the innovation department provided an inflow of high-value-added services for predictive and precision medicine to its customers, underpinning the company's differentiation strategy within the healthcare platform BM (annual report, 2021; CEO interview). This project formed the basis of mixing medical knowledge with data science and bioinformatics, comprising the core value proposition of the company's healthcare platform BM. The company defined this core as precision and predictive medicine based on patients' genomic, proteomic, and habit-related information, aimed at predicting future diseases and anticipating treatments.

> "*In fact, the potential of using genomic information, behavioral and biological data from exams, has enormous potential. You can make a more predictive medicine. So how can we reduce patient health risk, do better follow-up to make an individualized and personalized health journey. Predictive medicine, such as using genomic, behavioral, and environmental data. So, the potential is very large and goes into analytics*" (Alpha CEO interview)

Alpha promoted, through both mergers and acquisitions and internal startup development programs, the creation of new businesses that could orbit this central value proposition (Alpha's annual reports, 2019, 2020, 2021; CEO interview). Consequently, Alpha sought to fill multiple gaps in the predictive healthcare supply chain, delivering prediction services, treatment solutions, surgeries, habit and nutrition counseling, and services for digitalizing hospitals and nurseries. Therefore, although new businesses may take time to yield returns, Alpha's mixture of acquisitions and the creation of new BMs created a "constellation" of mutually reinforcing BMs. For example, its newly created BM, a B2C market platform, uses patients' data to promote their health and well-being. The platform has connections to the genomic project, as it provides predictive and preventive care for users, but it is also part of the marketplace for diagnosis, treatments, and so on, alongside Alpha's service and competitors. Additionally, Alpha took advantage of its access to data and large customer base to accelerate the growth of this new BM. The result is that this BM represents 5.2% of Alpha's revenue due to such linkages (Alpha's annual reports, 2020 and 2021).

4.3.2. Beta's Incremental Business Model Exploration to Improve Its Core Business Model

Beta rooted its BM exploration strategy in deploying startup challenges to (1) accelerate the resolution of current process bottlenecks and (2) solve large sustainability problems and, by exploring startups that offered services aligned with its core BM value proposition, strengthen its market position (interview with Beta's innovation manager). The idea was to create a BM constellation, to which the innovation department added, through acquisitions, fast-growing startups offering services that could potentialize their core business' product sales (CIO interview). Beta's innovation department, however, faced challenges when attempting to create its own new BMs:

> "*What we have is an innovation machine that is not yet fully tuned. An incremental H1 type innovation is super easy. Now a more disruptive innovation is much more complex. We identify a cool startup that can speed up a process, the squads go there and promise that it will impact a certain indicator within a period of 4 months. The new business team does this pre-sale a lot, to raise funds. Everything that talks about innovation that is not connected with the core of the current business model is more complex*" (Beta's CIO)

One explanation for Beta's struggle to sustain its BM exploration strategy lay in the fact that the company skipped radical (or transformative) BM renewal, moving directly to BM exploration. Despite the accumulation of favorable conditions, this did not create an effective buffer through renewing the company's value proposition, which remained the same after Beta's BM renewal. In this regard, Beta's deployment of acquisitions to accelerate the transformation and create new startups was conducted in order to gain buy-in from the top management and the company (Beta's CIO), leading to the observed accordion effect.

4.3.3. Gama's Competency "Encapsulation" and the Search for Pioneering Digital Technology Business Models

Gama's innovation department was at the root of their active R&D outsourcing BMs, whereby the R&D activity was focused on anticipating widespread customer trends and needs and creating highly customized and high-value-added offerings (interviews with Gama's CEO, innovation director, and R&D manager and Gama's strategic map). Similar to Alpha's approach, Gama's innovation department underlays the value creation at the core of its renewed BM's value proposition. To create the value of actively anticipating the widespread needs of IT customers, the company deployed its R&D team to explore well-defined technological platforms. This allowed them to play with novel solutions and create MVPs and PoCs (considered by the company as assets) that represented the cutting edge and tacit technological competencies in tangible terms (R&D manager interview).

> "*We are a competencies seller. To have a competitive advantage in this market, we need to prove our skill to the clients, which is challenging because competencies are not tangible. What we do is anticipate our customers' needs by deeply studying what they will do in the future, build our experiments, transform into MVPs and PoCs and then enchant our customer. This is what differentiates us from our competitors in the market*" (Gama's CEO)

As stressed by different members of the company (CEO, innovation director, R&D manager, new business manager) one of the greatest challenges for Gama when persuading customers to engage in R&D projects is to prove its competency. This is a task that the company is addressing through its innovation department in order to differentiate itself from other players in the market. The effective execution of plans and the achievement of meaningful results, such as growing from less than 200 employees in 2017 to more than 600 in 2021, were attributed by the company's management and employees to the innovation department (interviews with Gama's innovation director, CEO, R&D manager, and operations manager).

As a side-effect, Gama began accumulating such assets on its "shelf", which led the company to attempt to explore the natural creation of new BMs. Consequently, it was possible to observe a crescent-shaped growth in Gama's attempts to create new BMs. In 2019, Gama accumulated a set of 18 assets in the form of MVPs and PoCs, with no attempt to create a new BM. In 2020, Gama launched its first four startups in the market, and in 2021, two more were launched (Gama's internal documents).

In addition to the competency "encapsulation" integration mechanism, Gama has also followed the approach of linking the exploration of new BMs to a core strategic vision. Through this connection, the new BMs should follow the company's long-term goals regarding technological bases and market areas (Gama's internal documents). As such, the company can explore links between the core BM and newly created BMs by accelerating technological development and exploring its connections to facilitate market penetration (interviews with Gama's innovation director and new business manager). The impetus behind the technological alignment is not only the possibility for Gama to accelerate its nascent BMs' technological development and market penetration, but also the opportunity to create future clients who would also leverage Gama's R&D outsourcing BM.

> "*My dream for the future of our innovation department is, that we will be creating our future clients."* (Gama's innovation director)

5. Discussion and Conclusions

5.1. Theoretical Contributions

The innovator's dilemma (CHRISTENSEN, 2000) has provided a basis for understanding that well-managed and innovative incumbents tend to crumble in the face of radical innovation. This theory highlights the fact that incumbent BMs are structured not to promote innovation and the creation of novel BMs, but to be further improved (CHRISTENSEN; BARTMAN; VAN BEVER, 2016; DOZ; KOSONEN, 2010). However, incompatible with the current realities of businesses, digitalization, the increasing pace of technological development, and the growing pressures to achieve sustainable development goals have emphasized the need to solve this dilemma. The literature has reached a consensus that the ability to conduct core BM renewal and new BM exploration is vital (FRANCO et al., 2021; RENNINGS; WUSTMANS; KUPP, 2022; SCHOEMAKER; HEATON; TEECE, 2018; SUND; BOGERS; SAHRAMAA, 2021; TEECE, 2018a). Furthermore, creating parallel BMs is a potential path to building resilience and anticipating future disruptions (HACKLIN; BJÖRKDAHL; WALLIN, 2018; SCHAFFER et al., 2022). The development of such resilience is, however, a significant challenge considering path-dependency issues (BOHNSACK; PINKSE; KOLK, 2014; GÄRTNER; SCHÖN, 2016; REUVER; BOUWMAN; HAAKER, 2013; TEECE; PISANO; SHUEN, 1997), the cognitive and cultural barriers stemming from dominant logic and goal incompatibility (BRENK et al., 2019; CHESBROUGH, 2010; CHESBROUGH; ROSENBLOOM, 2002), the possible adverse effects of adding new BMs to a portfolio (HACKLIN; BJÖRKDAHL; WALLIN, 2018; KIM; MIN, 2015), the time delays and challenges presented by new BMs before they can generate relevant results for the company, and the high resource mobilization required (SUND; BOGERS; SAHRAMAA, 2021). Thus, despite the wide recognition of the relevance of conducting both exploitative and exploratory BMI, the attempts to achieve the latter still suffer from high failure rates and poor results (EGFJORD; SUND, 2020; HACKLIN; BJÖRKDAHL; WALLIN, 2018; SUND; BOGERS; SAHRAMAA, 2021). Our findings mirror exactly such phenomena, with the movement from BM renewal to BM exploration occurring in a semi-automatic fashion. The major problems arise when sustaining BM exploration efforts. We found that these are dependent upon a series of factors.

Bearing this in mind, by analyzing through a system dynamics lens the evolution over time of incumbents that developed systematic BMI processes though an integrated approach, we provided a series of contributions to understanding how incumbents can sustain their BM exploration efforts. More precisely, we depicted the existence of an evolutionary approach comprising a movement from BM renewal to the creation of favorable conditions for exploratory BMI. In line with the barriers identified by the literature (e.g., (SCHAFFER et al., 2022)), our findings also provide evidence that the discrepancy between the need to grow and the results obtained by BM exploration creates resistance from the top management and a tendency to move backwards to incrementalism. This vicious cycle has its roots in the fact that searching for new BMs is an activity that demands high resource allocation. Nevertheless, it presents long delays before providing noteworthy results, i.e., it is challenging and time-consuming to create a BM that generates results comparable to those achieved by incremental and short-term efforts. Thus, there is a paradoxical tension: exploring new BMs needs strategic alignment and a balance between incremental and radical innovations, which tends to favor incremental solutions over radical and exploratory ones. Our study, therefore, provides an initial contribution by showing that such a paradox is also a problem for integrated approaches. Beta’s case precisely illustrates this paradox.

In contrast, our findings also provide evidence to support the idea that the integrated approach may have advantages in overcoming these barriers, especially through the creation of a buffer. Alpha and Gama's approach was to strategically assign to the BMI engines a vital role in contributing to the renewed BMs' value proposition and creation architecture. The companies thus relied on their BMI engines to create value and returns that satisfied the top management's requirements while creating integration mechanisms such as the transversal participation of the organizations' members in innovative activities. This pertains to the continuous pursuit of innovations within the core BM. An additional mechanism identified was the exploration of new BMs that are somehow complementary to the core BM, in line with the ambidexterity theory (BENSON-REA; BRODIE; SIMA, 2013; BOSBACH; BRILLINGER; SCHÄFER, 2020; KHANAGHA; VOLBERDA; OSHRI, 2014; MARKIDES, 2014). In this regard, our results provide evidence that both agrees with and contradicts the literature. In Beta's case, the strategic alignment between the core and the exploratory endeavors favored path-dependent behavior, while we found contradictory results for Alpha and Gama, whose buffers worked to foster radical innovation.

One explanation for this contradiction is that the problem did not seem to lie in the attempt to align the strategy of the innovation departments and the core BM, which, as the literature has highlighted, tends to unbalance attempts in favor of incremental innovation (CHESBROUGH, 2010; CHESBROUGH; ROSENBLOOM, 2002; SUND; BOGERS; SAHRAMAA, 2021). We suggest that when BM renewal is carried out with a long-term perspective in anticipation of disruptive BMs in a particular industry, this problem becomes a potential solution. Alpha's BM renewal began with the understanding that their present BM, focused on reactive medicine, would become obsolete when predictive and precision medicine became the new paradigm. Such a strategic vision led the company to carry out its BM renewal within this new paradigm, changing its BMs to those of a healthcare platform. Considering the possibility of pioneering this new paradigm and the existence of many "white spaces" (JOHNSON, 2010; JOHNSON; CHRISTENSEN; KAGERMANN, 2008), the exploration of new BMs turned out to be aligned with the company's strategic orientation and complementary to its vision. Likewise, Gama envisioned the future of R&D-outsourcing BMs as more collaborative, working with customers to anticipate the future, i.e., generating the demand from customers, rather than the customers outsourcing whatever R&D projects they are unwilling to conduct internally. With this approach, the company also changed its core BM into a pool from which many new BMs could be derived, creating mutual complementarities.

On the other hand, Beta stuck to its current BM's core logic, focusing on the digitalization of its analogical processes and targeting performance gains. In this case, the alignment did not lead directly to creating opportunity spaces for developing new BMs. Likewise, many of the abovementioned barriers stemmed from a scenario whereby the innovation departments were seen as a panacea, with the exploratory BMI able to diversify the company's revenue streams and save the company. One explanation for this is that in cases where no future envisioning takes place during the BM renewal, the dominant logic, with strong roots in the present state of the BMs, tends to win out over the exploratory behavior.

This theory also helps explain why the issue of managing parallel BMs does not arise in some cases of radical BMI by incumbents. For example, the exploration is seen to be segregated from the incumbent's core BM (SUND; BOGERS; SAHRAMAA, 2021); attempts are made to fit it into the present state of the core BM, as in the case of the Xerox spin-off (CHESBROUGH; ROSENBLOOM, 2002); or the exploration is carried out in random directions, which negatively affects the incumbent by increasing its managerial complexity (HACKLIN; BJÖRKDAHL; WALLIN, 2018). It is reasonable to assume that diversifying the revenue stream through new BMs may be seen as unproductive in the short term by the top management, as the exploration takes time to produce results that represent significant returns. We argue that if this is the case, the tendency is for companies to attempt to gain buy-in by acquiring larger startups that can bring additional customers to the core BM, which can be understood as "incremental BM exploration".

Beta's example is particularly revealing. In the face of the top management team's reluctance to accept exploratory projects, the innovation department's managers began to map and purchase more mature startups to show the top management the power of adding novel BMs. The startups were aligned to the company's core BM, as they offered services that could encourage users to purchase Beta's products, thus improving the current BM and targeting lock-in effects. In sharp contrast, we observed that Alpha's spin-off encouraged patients to use not only Alpha's solution but also its competitors' solutions. Such a scenario highlights the fact that Alpha's buffer and BM constellation core were not aimed at further improving the initial BM but rather at contributing to the overarching future vision of predictive medicine benefiting patients' quality of life. Hence, with this case study, we provide the first evidence to complement the view presented in the literature that incumbents can sustain their exploratory BMI by following a transformative BM renewal strategy, attempting to anticipate possible disruptive paradigms for their respective BMs.

Finally, it is also noteworthy that of our three studied cases, the manufacturing company struggled the most to pursue transformative BM renewal. Although the focus of the study was not on conducting such a comparison, it should be mentioned. This difference may have been due to influences of higher sunk costs and a product-oriented mentality, which might have rendered the manufacturing company more rigid when it came to transformative BM renewal. Many cases presented in the literature, such as Kodak, Nokia, and Blockbuster, as well as those introduced by the innovator's dilemma, represent poor responses to radical innovation from manufacturing companies. Further investigation in this regard may be fruitful to broaden our understanding of the subject.

5.2. Managerial Implications

This study revealed relevant managerial implications. We sought to understand the process of BMI in incumbents, presenting a fine-grained consideration of different types of BM. Our results were in line with the literature's suggestion that incumbents should not abandon their focus on the core BM to explore new BMs randomly, and that a combination of both approaches can be fruitful for creating resilience when responding to radical innovation. In this regard, our system dynamics analysis of the evolution of BMI engines showed significant differences between the impacts of incremental and transformative BM renewal regarding the effectiveness of BM exploration, especially in relation to the creation of a strong "buffer". Thus, our study can assist the managerial audience in implementing BM renewal strategies that are future-oriented and transformative, targeting the anticipation of future disruptions. Although we recognize the challenges surrounding this process, innovation departments could assist in developing the necessary innovation capabilities to help overcome such issues. To this end, our studied cases followed the path of beginning with incremental changes, building capabilities, and advancing to a transformative BM renewal process. Then, leveraging conditions favorable to exploratory BMI, they moved forward to begin exploring new BMs in order to fill the gaps that existed inside the transformed value proposition.

5.3. Limitations

This study provided valuable insights into the system dynamics of BMI and the role of innovation departments in driving and managing this process. It is important to note that as qualitative research, this study's focus was not on validating or confirming a hypothesis. Instead, this paper offered important contributions to theory construction in the field of BMI. However, certain limitations of the present study should be pointed out. This research was based on multiple case studies, i.e., three Brazilian incumbents, which may not be representative of other companies or industries. We would have liked to address a wider range of technology and company types and, consequently, investigate different types of BMI. Comparing companies from different sectors could highlight the potential for cross-industry learning and the transferability of best practices. Nevertheless, comparing the BMI processes of similar companies, in terms of size and technology, could also lead us to new insights

5.4. Future Research

Considering the abovementioned limitations and the results of this study, future studies could explore different areas. First, conducting a multiple-case study with a more representative organizational sample would be interesting. This would help to expand our knowledge regarding BMI and BM renewal processes. Second, a comparative analysis between similar companies, as mentioned previously, could also help to enhance our theoretical and practical understanding of this matter.

Furthermore, quantitative studies are essential to the development of this field, especially as they allow researchers to test hypotheses and evaluate the strength of relationships between identified variables. For instance, a future study could explore structural equation modeling (SEM) to examine the relationships between different variables that impact the success of business model innovation processes in incumbents. SEM would help identify the drivers of business model innovation and renewal and the mechanisms through which they operate in incumbents. Such a study could test hypotheses regarding the factors influencing the ability of companies to implement BMI effectively. Furthermore, studies could be conducted to provide empirical evidence regarding the relationship between transformative BM renewal and the performance of BM exploration endeavors in incumbents. Likewise, the effects and characteristics of top management teams could also be assessed to further elucidate the conditions that facilitate the pursuit of BM exploration.

Our findings highlighted an interesting connection between transformative BM renewal, from a future-based perspective of shaping the market and building avenues for planned opportunism, and BM exploration, which seeks to fill the consequent “white spaces” that emerge from such behavior. Thus, there is an opportunity to combine future studies on topics such as corporate foresight and BMI in incumbents. Such studies could provide better evidence regarding how companies can benefit from foresight activities and investigate whether certain forecasting practices negatively affect transformative BMI, shedding light on its barriers and opportunities. An analysis of top management teams could also be revealing in this regard. Finally, future studies could also investigate the long-term results of BMI processes, considering the impact on organizational sustainability. A combination of qualitative and quantitative approaches could help with this task.

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Chapter 3

Business Model Innovation Analytics for Small to Medium Enterprises

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Abstract

Hypercompetition requires shorter life cycles for products, services, processes and business models. Innovation management aided by innovation analytics is helping companies to respond more precisely to such challenge. Business model innovation, yet, is poorly explored in combination with innovation analytics. The subject is even more neglected when approached under the SMEs perspective. This kind of company struggles dealing with scarce resources. Still, they are also exposed to hypercompetitive environments. A theoretical background covering the evolution of innovation management and the importance of business model innovation specific practices is provided. Thus, we will introduce a framework that enables SMEs on innovation analytics. Presenting a comprehensible process, we integrate dynamic capabilities activities and data analytics. The aim is a data-driven focused business model innovation. As theoretical implication, this is one of the first studies relating business model innovation and innovation analytics. In practice it will help managers to better understand innovation analytics for further application in SMEs.

1. Introduction

Hypercompetition (D'AVENI; GUNTHER, 2007) requires shorter product cycles, as it increases global competitiveness and the degree of uncertainty (KING, 2013). Sustainable competitive advantages become scarce and lag very quickly (MAHTO; AHLUWALIA; WALSH, 2018). Consequently, the same notion of fast change and the need to constantly innovate applies to products, services, processes, and Business Models (BM).

This hypercompetition phenomenon gained strength with Digital Transformation and the changes in the competitive business landscape (VERHOEF et al., 2019). The increase in uncertainty resulting from the digital transformation injected more turbulence in the business landscape (SCHOEMAKER; HEATON; TEECE, 2018a). Even though the effect of digital transformation is not homogeneous throughout different industries, it is safe to say that its pervasiveness impacted almost every economic activity (D'AVENI; DAGNINO; SMITH, 2010; WIGGINS; RUEFLI, 2005), pushing organizations towards the need to embrace digital transformation.

Digital transformation involves an organization's ability to adapt or promote new business models (SCHALLMO; WILLIAMS, 2018; VERHOEF et al., 2021), emphasizing the critical relevance of creating capabilities for Business Model Innovation (BMI) (FRANCO et al., 2021). BMI is a fundamental process on different spectrums. The literature refers to BMI as an essential mechanism for conferring organizational sustainability (MINATOGAWA et al., 2020) and increased performance (FRANCO et al., 2021; JOHNSON; CHRISTENSEN; KAGERMANN, 2008; TEECE, 2010). BMI is also an essential element for technology led innovations, such as the ones within the industry 4.0 (IBARRA; GANZARAIN; IGARTUA, 2018). In addition, its role has been discussed in industries strongly affected by the current covid-19 pandemic crisis (BREIER et al., 2021; HARMS et al., 2021; PRIYONO; MOIN, 2020).

Achieving BMI, however, is still a considerable challenge. Many BMI attempts fail (CHRISTENSEN; BARTMAN; VAN BEVER, 2016; GEISSDOERFER; VLADIMIROVA; EVANS, 2018), causing severe economic consequences for companies (CHESBROUGH, 2007), delaying, for example, the adoption of sustainable solutions (GEISSDOERFER et al., 2017). Large companies can use their slack resources to sense and seize opportunities for new business models. Cases like BASF (WINTERHALTER et al., 2017) demonstrate that such companies can allocate entire departments to innovation, impacting its BMI capabilities, being somewhat less sensible to economic drawbacks from failures and increasing the applicability of trial-and-error approaches for creating BMI capabilities.

Regarding Small and Medium Enterprises (SMEs), the challenge is more significant. Few SMEs make an effort for BMI and most of those fail to get expected results (LATIFI; NIKOU; BOUWMAN, 2021). Usually, SMEs are likely to focus in addressing current BM’s emerging issues, neglecting the exploration of new opportunities (KESTING; GÜNZEL-JENSEN, 2015). However, exploiting only their current BM to achieve economic effectiveness, which alone is challenging, presents a risk in the current hypercompetitive reality.

1.1. The need for a data-driven approach for BMI

Despite the growth in the BMI literature, the state-of-the-art approach for conducting the BMI process is through experimentation and trial-and-error (COSENZ; BIVONA, 2021; MINATOGAWA et al., 2019; SILVA et al., 2019). Many studies demonstrated the relevance of experimentation capability as a path to cope with uncertainty and increase the BMI process's effectiveness (BALDASSARRE et al., 2020; BOCKEN; GERADTS, 2019; BOCKEN; SNIHUR, 2020; KONIETZKO et al., 2020; MA; HU, 2021; WEISSBROD; BOCKEN, 2017). However, it is still an often-random process with many more failures than successes (CHRISTENSEN; BARTMAN; VAN BEVER, 2016; MINATOGAWA et al., 2019). This poses a significant problem for SMEs since every fail, besides inflicting costs, also might reduce the willingness for future BMI efforts, leading to risk aversion.

For SMEs the BMI experimentation process needs to be more assertive. It needs to be data driven, making decision as accurate as possible and reducing results randomness. As data science evolves, so does its contribution to improve innovation management processes, particularly in regard to sensing and seizing capabilities (LIN; KUNNATHUR, 2019). Netflix's

"House of Cards" series is a case in point, as it is an analytics-assisted project to define, for example, the cast and script (CARR, 2013; LIN; KUNNATHUR, 2019; MAZZEI; NOBLE, 2017).

As analytics are technological solutions for data-driven decision-making, it has recently been explicitly applied to innovation, creating the so-called "innovation analytics," with applications in the fuzzy front end of innovation (KAKATKAR; BILGRAM; FÜLLER, 2020). Innovation analytics is a recent approach with little literature basis. When considering BMI analytics specifically, there is no literature on the subject to the best of the authors' knowledge. As noted, however, this type of innovation can have a profound impact. Hence studies that aid companies, especially SMEs, with data-driven approaches, will reduce subjectivity and randomness, thus calling for a data-driven approach for SMEs developing BMI.

In this chapter, the authors will contribute by providing a framework that integrates data science aspects for decision-making in the business model innovation process. Such contribution will comprise data science approaches for leveraging the dynamic capabilities of a company.

This book chapter is subdivided into sections. In section 2, we offer a theoretical background that will support the construction of the framework, addressing the problem situation raised in the introduction. Section 3 designed the framework, dividing it into different parts of the process involving data science and business model innovations. Finally, section 4 presents our conclusions about this conceptual study.

2. Theoretical Background

2.1. The Evolution of Innovation Management

Innovation management as a research field has evolved alongside with the very theoretical knowledge in innovation studies. Thus, the emerging concern with the management of business model innovation and the digital transformation of business models mirrors the substantial growth in research and literature focusing business models and business model innovation. In this section, we present a concise overview of such evolution and argue that much of the blooming interest in business models stems in the ever-growing importance of (digital) services and the challenges posed to the conventional business models of manufacturing industries by digitalization.

Let us get inspiration from Rothwell's seminal account of generations innovation process models (ROTHWELL, 1994) for a brief synthesis of the evolution mentioned above. As the understanding of the innovation process leaves behind the linear model (KLINE; ROSENBERG, 1986; ROSENBERG, 1982) and the need for coupling technology and market (FREEMAN; SOETE, 2008) is largely accepted, the focus of innovation management moved from the dominant emphasis on invention and R&D management to the view of innovation management as a multifunctional process, integrating technology strategy and development strategy (WHEELWRIGHT; CLARK, 1993). As the innovation dilemma was made clear (CHRISTENSEN, 2000), that is, the problems posed by strongly distinctive capabilities and resources required from incremental and radical innovation, so has increased the understanding that external partners and networks are critical for successful innovation (ROTHWELL, 1994). In line, the literature on the management of innovation networks (POWELL; GRODAL, 2006) and later on Open Innovation (CHESBROUGH, 2003) has seen an enormous growth.

So far, the literature on innovation management as much as the most influential schools in innovation studies, namely the neo-Schumpeterian and the evolutionary approaches, had largely focused in the manufacturing industry and the corollary of its business model, technological innovation of product and process (OECD; EUROSTAT, 2018). Thus, the most disseminated ideas and authors dealing with models, process and tools concerned with innovation management focus on technological innovation. At this point, it is important to bring in the French and the Dutch school of studies on innovation in services (BETTENCOURT; BROWN; SIRIANNI, 2013; GALLOUJ; SAVONA, 2008; OLIVEIRA; VON HIPPEL, 2011), whose authors have early disputed the adequacy of the manufacturing industry inspired view of innovation to deal with services innovation. Perhaps their most relevant contribution is to put the client at the center of the innovation processes in services, as a critical actor. Moreover, some of their propositions for modeling innovation management in services deal with issues that are now explored in the literature on business model innovation such as value/service delivery and the modeling of services monetization (DEN HERTOG; VAN DER AA; DE JONG, 2010). Yet, so far the innovation in services literature has been quite limited in changing the received wisdom about innovation processes and innovation management.

However, technical change is full of paradoxes, and it was up to the latest wave of disruptive and general-purpose technologies, i.e., digital transformation, to make even clearer the perception that (digital) services have become central to growth in the manufacturing (and non-manufacturing) company and that innovation in business models assumed a central position in the debate on the innovation process. On the one hand, the potential scope for deep change in the current business model is vast, it may affect most, if not all functions in the firm. Digital transformation brings about potentially substantial change in products, internal business processes, channels and links with clients and providers, forms of monetization and in the value proposition. On the other hand, learning from digital transformation can facilitate the entry in new markets, with new value proposals and entirely new businesses. In this connection, we are dealing here with a focus change, from product/process innovation to (digital services) business innovation. Last, but not least, as argued in this chapter digital technologies have the potential to transform the very consolidated processes in innovation management such as technology and competitive intelligence and ideation.

To conclude, the emergence of business model innovation opens a large set of new opportunities, indeed, but as much as new, we are dealing in a terrain of limited experience, in which many of the new management practices will require trial-and-error attempts before being well understood and consolidated. Therefore, it is important to address and discuss the concept of business model innovation.

2.2. What is Business Model Innovation

Understanding the business model innovation concept is essential for the chapter's purposes. As important as getting a definition of the term, we need to understand what characterizes a business model innovation. What characteristics can one observe in a new business model that differentiates and makes it innovative? Although there may be some degree of subjectivity in such discussion, to later aggregate the idea of analytics will be essential to clarify these characteristics.

The concept of business model innovation has evolved considerably in the last 20 years (FOSS; SAEBI, 2016). Mitchell and Coles (2004) understood BMI as BM changes that provide product and service offerings to end customers that were not previously available. Gambardella and McGahan (2010) proposed the idea that business model innovations occur when a company takes a new approach to commercializing its assets. Yunus, Moingeon and Lehmann-Ortega (2010) argue that it is not only about creating new sources of revenue, but making new value propositions.

Other authors relate business models innovation with business logic issues. Bucherer, Eisert and Gassmann (2012) define the term as a process that deliberately alters the central elements of a company's logic and business logic. Along with the same idea, Casadesus-Masanell and Zhu (2013) understand that BMI refers to the companies' search for new logic and new alternatives to create and capture value for all the stakeholders, focusing mainly on finding new ways to generate revenue and defining value propositions for customers, suppliers and partners. Eppler and Hoffmann (2013) declare that BMI is a multiphase process by which organizations transform new ideas into improved business models, seeking to advance, compete and differentiate successfully in the market.

Thus, BMI is directly related to the systemic search for innovative ways of designing the flow of value. In this regard, two approaches may be considered. On the one hand, it considers an existing business model and innovation seeks to improve and increase its efficiency. On the other hand, completely new business model innovation seeks to create new markets. Examples cited by Johnson, Christensen and Kagermann (2008) illustrate these distinct processes well. There is the example of Hilti, a company that sells tools to the construction industry and whose business model consisted of products direct sales to its customers. However, the organization realized that its consumers generated value by delivering the contracts, not by owning the tools.

With this, a business model innovation process resulted in a service offering, with the proposal to rent the tools instead of selling them according to the customer's need. This change significantly increased the effectiveness of Hilti's Business Model.

According to Schneider and Spieth (2013), although highly relevant to companies, especially those operating in volatile environments, existing knowledge about how organizations prepare to explore opportunities through innovations in business models is limited. They also state that it is necessary to achieve a deeper understanding of the factors that lead to the opportunity to innovate in business models in response to this situation. Similarly, Foss and Saebi (2016) also point as an open field for research, studies that demonstrate the capability, leadership, and learning mechanisms necessary for successful innovations in business models to occur.

The creation of new business models, however, is a process surrounded by subjectivity. It is still conceived Adhoc in many instances (CHRISTENSEN; BARTMAN; VAN BEVER, 2016). Adopting the same product and service innovation processes does not necessarily result in new business models (FRANCO et al., 2021; TIDD; BESSANT, 2018). In this context, companies need to develop not only ordinary capabilities but also dynamic as a means to enable this type of innovation to emerge.

2.3. Dynamic Capabilities for BMI

Resources are the base for any successful process, and, when combined to make solid routines and capabilities, they create value (WINTER, 2003). Capabilities are defined as "high-level routine (or collection of routines) that together with its implementing input flows, confers upon an organization's management a set of decision options for producing significant outputs of a particular type."(WINTER, 2003). Routines have their roots in acquired and standardized knowledge, creating processes that are realized repetitively.

This definition of capabilities and routines places them both as the way a company generates profits at a specific time point (LAAKSONEN; PELTONIEMI, 2018). The digital technologies had their impact on competition dynamics, injecting turbulence and rendering many BM health uncertain. If innovation was a critical competitive element since the mid-XIX century

(NELSON, 2007), especially technological innovation, today the vast possibilities to propose a business around a value proposition and the ease in doing so in a low-cost way, it has gained even more momentum and became a must for almost every company. This increase in turbulence means that solid capabilities and routines that promote profit become obsolete faster and faster (SCHOEMAKER; HEATON; TEECE, 2018b).

How to live in a competitive world where capabilities and routines that underpins a BM can become obsolete at any time? The answer is: we need capabilities to change our mainstream capabilities, known as dynamic capabilities. With dynamic capabilities, a company can adapt and be mutable in a turbulent world. Hence, the conceptual distinction between dynamic capabilities and ordinary capabilities is relevant (LAAKSONEN; PELTONIEMI, 2018). Ordinary capabilities are responsible for the operational excellence of a current BM–how do we make money now. Dynamic capabilities are responsible for reshaping the ordinary ones–how do we keep making money in the future. Bringing this capability discussion into business model language, we have high-level ordinary capabilities as the pillars that sustain the value creation, delivery and capture architectures. Dynamic capabilities, by definition, change the value creation, delivery and capture architectures and are, hence, the primary BMI antecedent.

What are dynamic capabilities? As they are tailored for changing something, they look like any innovation or improvement process. They are separated into three major parts, sensing, seizing and transforming (TEECE, 2018). Sensing means to have antennas looking anywhere for opportunities. It can be a flaw in an existing process, new suppliers, new customers, new technologies, among others. The seizing capability means to translate opportunities into solutions that become products or services and new BM. Transforming capability means to escalate the BM to grow and compete in the market (TEECE, 2007). The analogy extends to also looks like a funnel: more opportunities are coming in than new BM coming out. Sensing, seizing and transforming are the capabilities that execute the BMI process and are, therefore, where one will look at when proposing innovation analytics for BMI. But first, authors will dive in a little into data analytics.

2.4. Data Analytics

Data science and the concept of analytics are gaining momentum in literature. Data analytics refers to technologies and processes of acquiring deep knowledge and extracting information from data (CAO, 2017). This topic is highlighted mainly due to some contemporary contexts and specific conditions. First, the condition of the great availability of data, bringing up the concept of big data (CHOI; WALLACE; WANG, 2018). Second, techniques development for exploring big data context. As new approaches emerged, such as machine learning, new opportunities have also arisen (AGARWAL; DHAR, 2014).

Data analytics allows latent information extraction from raw data (HADI et al., 2018). This has great value since it enables, for example, to identify trends. The combination of data analysis and IoT systems helps to understand didactically such reality. The main objective of data analytics in IoT systems is to interpret the data better and thus formulate effective decision-making (SALEEM; CHISHTI, 2019). As an example, sensors can provide a large amount of data about the behavior of structures such as bridges and buildings (KIM; QUEIROZ, 2017). From Data Analytics, monitoring this type of structure can change paradigms. Maintenance that was previously carried out preventively can now be done in a predictive or prescriptive way (ZONTA et al., 2020).

It is important to highlight that trends identification is only one example made possible by the advances in machine learning techniques. Other important decision-making can also be assisted by such resource. Illustrating another type of example, in manufacturing it is possible to use machine learning techniques for the detection of bottlenecks in the dynamics of a production system (SUBRAMANIYAN et al., 2020).

Thus, it is observed that structured data can foster analytics. That is, data that already has its content organized, usually by means of rows, columns and related tables for analysis. This structured nature facilitates search and storage, usually through relational database systems (BENNETT; PICKERING; SARGENT, 2019). Web Analytics, such as the Google Analytics tool, present features where structured data is presented regarding websites(LI et al., 2021). This type of analytics captures data that provides information such as demographics, location, devices, browsing behavior, consumption habits, among many other resources.

However, data can also be unstructured. That is specific resources that are not organized for data analysis and can be structured to extract information. These features can be characterized as text files, audio, videos (ZHANG et al., 2019). Thus, there is an even broader context of Analytics applications if we also consider the feasibility of using unstructured data (SUBRAMANIYASWAMY et al., 2015).

For instance, healthcare analytics has explored this wide variety of data (e.g., medical images, biomedical signals, audio transcripts, handwritten prescriptions) to become a data-driven industry. In a more specific way, these resources help the decision-maker in the health area answer various types of questions, depending on the type of analytics used. Thus, descriptive, diagnostic, predictive, prescriptive and discovery analytics can be presented (MOSAVI; SANTOS, 2020).

In addition, it is also essential to consider the velocity at which data is made available. Such a feature makes a difference, for example, for social media analytics. Analyzing social networks typically covers the idea of real-time data (GU; QIAN; CHEN, 2016). This is critical for entertainment decision-makers. In this industry, it is necessary to quickly understand your audience's reaction to a particular event and/or content.

Thus, three features can be highlighted, volume, variety and velocity. These are the characteristics that are commonly used to define the concept of Big Data Analytics (SAGGI; JAIN, 2018). The examples cited are didactic to exemplify each of the characteristics. However, it is important to note that volume, velocity and variety are inherent in all examples of analytics cited.

Nevertheless, something little explored in the literature is how analytics can be exploited for decision-making regarding business model innovation. As already discussed, this type of innovation is extremely relevant for different types of industries and companies. There may be the argument that this is simply a variation of innovation analytics. However, just as the processes of products and services innovation have already proved unsuitable for business models, the same could be argued for analytics.

Thus, it is relevant to discuss theoretical bases that allow establishing a clear analytics process for business model innovation. How could the business model innovation process be combined with this entire data context, which provides us with information and adds new knowledge? What approaches could be considered efficient, and at what stage of the process would it be more efficient? This discussion will lay the foundation for the proposition of a framework for Business Model Innovation Analytics.

3. Towards a Business Model Innovation Analytics

3.1. Framework Proposal

The BMI process can be understood as having four steps: (1) recognizing opportunities; (2) ideation and experimenting for refining opportunities and designing potential solutions; (3) design and experiment with a prototype BM; and (4) implement and refine the BM (FRANKENBERGER et al., 2013; GEISSDOERFER; SAVAGET; EVANS, 2017). The sound execution of the BMI process depends on a set of dynamic capabilities, which are idiosyncratic of each company, and are a consequence of their BM structure, their decision-making processes, the set of activities and practices deployed for BMI, and the resources the company has available (FRANCO et al., 2021).

SMEs have some advantages when we consider that their BM is considered more flexible than larger companies. Hence, they tend to display less friction and inertia for BMI (CHRISTENSEN; BARTMAN; VAN BEVER, 2016; FRANCO et al., 2021). Translating into the capability’s language, SMEs have fewer BM structural constraints, which is positive. However, SMEs do not enjoy abundant resources. Instead, they usually have limited human, financial, organizational, and relational resources (BOUNCKEN; FREDRICH, 2016; MINATOGAWA et al., 2020). Considering that the BMI process is resource-consuming and highly uncertain, it is understandable that SMEs show aversion to proactively pursuing BMI, if not necessary, due to threats to survival.

How can analytics help cope with uncertainty, reduce costs and increase the effectiveness of SMEs' BMI efforts without the need for highly specialized resources? As we know, analytics, machine learning, and algorithms are more effective in more knowledge-intensive activities than creative ones (KAKATKAR; BILGRAM; FÜLLER, 2020). Creative processes still depend on human activity, even with the advances in non-supervised machine learning and self-programming diverging algorithms. This notion is relevant for considering innovation analytics to improve the BMI process once knowledge-intensive parts are highly dependent on resources (BERENDS et al., 2016; DENICOLAI; RAMIREZ; TIDD, 2014).

With that said, before proposing BM innovation analytics, we need to break down the BMI process to understand which parts more knowledge-intensive and which ones are more creative-intensive. To this end, we combine the double-diamond innovation process with the abovementioned BMI process.

It initiates by identifying an opportunity, demanding deep knowledge about specific customer's needs, which are still unmet and maybe a latent or non-identified need. This process leads to the ideation and creative process of selecting and defining which opportunities have potential solutions, seeking to create the so-called problem-solution fit pairs (BLANK, 2007; JOHNSON, 2010; RIES, 2011), the very base of a new BM. This stage is a creative process in which activities are primarily deployed to improve creativity, which is also the core idea of the supporting tools and practices such as Design Thinking, ideation through business model visual tools, among others. After ideating, the outputs are potential problem-solution pairs, which call for experimentation to generate knowledge – another knowledge-intensive stage.

After validating the problem-solution pairs, the next step is to design potential BM, which also comprises the associated products and/or services, to which market. In this stage, several potential BM are designed, characterizing it as a creative-intensive process. Next, there is an experimentation process to validate the best BM design, testing the financial model, if it provides returns, how should the value creation and delivery architectures be. This is also a knowledge-intensive process.

Finally, one important highlight is that the process is not linear nor continual, as the experimentation stages often iterate with the creative design stages. Finally, when introducing the BM into the market, the process moves forward to traditional strategic management, focusing on creating efficiency and BM evolution. Figure 3.1 depicts the double-diamond BMI process, separated between creative and knowledge-intensive stages, indicating the innovation analytics role as potentializing the knowledge-intensive parts of the process. It is important to highlight is that every pair of knowledge-intensive and creative-intensive stages are iterative-the process is not linear and has many return points.

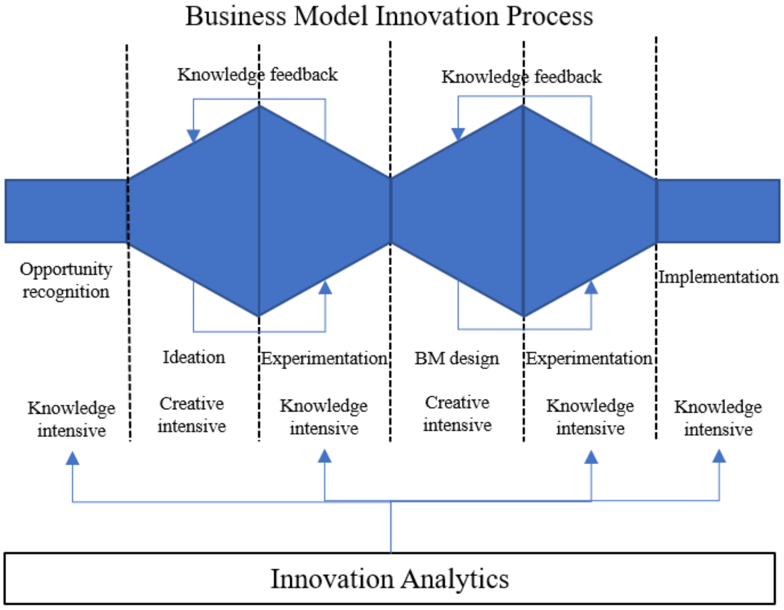


Figure 3.1. The Business Model innovation process and its key stages. The innovation analytics proposed to optimize the knowledge-intensive parts of the process.

In each knowledge-intensive stage, innovation analytics act as supporting activities to refine knowledge and lower the cost of access to knowledge. Hence, it has a data-driven decision-making aspect but does not replace human activity by any means. The effective deployment of innovation analytics for BMI depends on answering crucial questions:

- Data collection

  - Why collect data? (Improve performance, refine customer segmentation, discover new customers, explore new technologies, explore new markets, etc)
  - What data? (Customers, internal processes, other markets, new technologies, etc.)
  - Where to gather data? (Customers`, special purpose experiments, enterprise resources' planning systems, internal databases, internal spreadsheets, etc.)
  - Who will collect the data? (Which teams, formed by which members, with which skillsets)
  - How will we collect the data? (Leverage built-in analytics such as google analytics, Facebook data, design surveys, use data crawlers or natural language processing in social media, etc)
- Data storage:
  - Where to store the data? (Cloud, internal servers, special databases, SQL or NoSQL)
  - Who will store the data? (Internally develop resources, externally managed through partners)
  - Which data will be stored? (Filter the irrelevant from the relevant data – closely linked to the data collection strategy and strategic BMI goal)
  - How to store data? (Create database capabilities, delegate to external partners)
- Data analysis:
  - Who and how to explore the data? (Exploratory Data analysis techniques)
  - Which data analysis technique? (K-Nearest neighbors, Regressions, K-means-clustering, supervised or non-supervised machine learning, deep learning, etc.)
  - Who will analyze the data? (Data scientists, internally trained employees, external partners)
  - How to apply the data analysis into the BMI process? (Data visualization techniques and teams' dynamics)

3.2. Framework Usage

The core idea of applying innovation analytics to SMEs' BMI efforts is to reduce resource consumption while improving performance and allowing for ambidextrous behavior. The main drawback is that BMI efforts are highly context-dependent and specific to each company's problems. Searching for a plug-and-play solution is hardly a productive effort. We do not aim to provide such a solution. Instead, our goal is to help SMEs creating capabilities for successfully deciding how to apply innovation analytics to their BMI efforts.

Bearing this in mind, it is hard to foresee a scenario where SMEs will be able to deploy business model innovation analytics without at least a data scientist or a few data scientists, depending on the company's size. It means that some specialized human resources will be necessary. Even though it may sound costly, with the advancement of information and communication technology, computer power on the one hand, and on the evolution of programming languages such as Python and R, with sophisticated libraries for data collection, cleaning, and analysis on the other, this is increasingly feasible for SMEs with low resources.

Considering the challenges surrounding BMI, and the abovementioned issues, we propose three core recommendations. (1) it is important to move out of the inertia and begin experimenting with the BMI process. The best way of doing this is to begin with less uncertain efforts, focusing on the current BM issues that can provide good performance increase returns. This process is the base for evolving to more advanced BMI efforts, since it works as virtuous cycles by improving motivational levels and freeing resources. (2) integrate data scientists into the multidisciplinary BMI teams, thus not only enhancing creativity levels, but also sophisticating and improving the innovation analytics and the BMI process. (3) solidify capabilities for BMI, creating new organizational structures and processes as to make this activity a capability and not an isolated event.

3.2.1. Recommendation 1: start small, but start

Considering this need for specialized resources and the need to amplify existing resources, our roadmap for business model innovation analytics begins by focusing on gaining performance and developing digital capabilities. Hence, a good start is to diagnose the current business model stage to find its key weaknesses, which are the high leverage points. Deploy the first data scientists to assist in this diagnosis stage. Following the abovementioned questions, one can gather data from the company's customer segments, using social media, promoting surveys, and profiling their behavior for improving value proposition and increase the enticement to pay for the company's services and/or products. Second, use this stage as a growth spiral, as performance gains in the current BM create financial resources, through economic gains and human resources, through learning by doing and experience with digital capabilities, while also gaining experience with executing the BMI process.

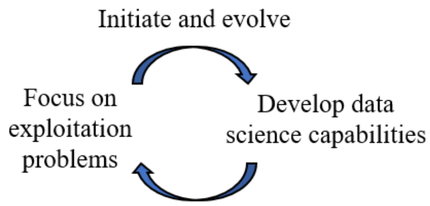
It is a co-evolution between learning and creating capabilities for executing the business model innovation process with the creation of digital innovation capabilities. Naturally, data science and innovation analytics alone will not lead to practical performance gain results. Data science and business model innovation management walk hand in hand together. Innovation management and business model innovation knowledge are essential for extracting success from BMI analytics. Therefore, patience and strategic focus may be the key elements for achieving success.

3.2.2. Recommendation 2: Build multidisciplinary teams

The BMI process alone relies upon multidisciplinary teams, working together to leverage creativity, and providing the technical and marketing bases of a BM. Usually, BMI efforts are conducted under a project management logic, following a more agile paradigm. Hence, the teams should include people with relevant expertise, building technical knowledge for building the new BM core value proposition, and marketing people, to couple the value proposition to a customer segment. Finally, dealing with novel BM means that many customers and markets are unknown, and integrating external stakeholders to the process helps the agile creation of knowledge to improve the BMI process.

The integration of innovation analytics means to add data scientists to the BMI teams. This integration requires constant knowledge exchange, since technical and marketing knowledge build the domain knowledge that surrounds BMI, which is key for deriving the right questions for data scientists to answer. Algorithms alone will certainly not deliver high performance results: they must follow the adequate questions to provide adequate answers.

Hence, it is particularly important to explore the recommendation 1, beginning with more feasible BMI, helps the teams` gaining knowledge and experience with the BMI process. With data scientists working together, this also improves the knowledge about how to use data, leading to more sophisticated data analysis further improving the effectivity of BMI. Partnership with data-oriented companies and universities may also help covering the gaps and weaknesses in data analytics without increasing costs as hiring many specialists. Figure 3.2 shows the co-evolution between recommendations 1 and 2, focusing on the interplay between BMI process knowledge and data science capabilities. Finally, it depicts the iterative nature between both recommendations.



Current BM diagnosis	**Identify data needs**
• Prioritize problems with most potential financial returns • Refine customer segmentation • Test different value capture mechanisms • Refine internal value creation processes • Understand core value proposition	• Hire/train data scientists • Explore data-oriented partners • Explore partnerships with universities • Identify infrastructural needs – servers, computers, among others.

Figure 3.2. Recommendation to begin applying the BMI process on current BM performance improvement and co-evolve the BMI capability with the digital innovation capability.

3.2.3. Recommendation 3: Rethink structure, solidify BMI analytics capability

BMI is costly, uncertain, and may be painful, but the rewards are equally substantial. Beginning and acquiring knowledge of how to execute the BMI process is very challenging. But by using innovation analytics on costly activities may help reduce these costs while also reducing uncertainty, which can have powerful effects on the acceptability for incorporating BMI efforts as a part of the business.

Similar mid-final XIX century, when innovation, particularly technological innovation, became part of the business to survive, today we have BMI as almost a must, given the new competitive dynamics brought about with the digital era. Thus, incorporating the BMI as a new business function is essential. In the first half of the XX century, companies created the R&D function, which was integrated into the overall BM. BMI changes the BM, affecting strategic elements, which may render problems when proposing a similar solution. We propose changing the company structure to include BMI as a new function at the higher level possible, such as on the C-Level.

Doing so allows for continual deployment of activities and practices for BMI and BMI analytics efforts. This leads to a positive learning curve to assist companies in incorporating this capability into their BM. Hence, we suggest focusing on how this should be done, considering each company's BM logic, as one size fits all solution may not work.

4. Concluding remarks

This chapter aims to provide a framework that integrates data science aspects for decision-making regarding the business model innovation process. Considering the incipience of the innovation analytics subject, there is a scarcity of literature that provides appropriate theoretical bases for business model innovation analytics.

Within such context, it was opportune to develop a framework that would be able to guide decision-making regarding business models innovation—especially considering SMEs and the characteristics inherent to this kind of organization. Large companies can use their slack resources to develop teams that integrate different data Science and innovation management skills. Even though the discussion on the potential rigidity differences between SMEs BMs and Large companies BMs may be somewhat advantageous for SMEs to embark in the BMI world.

To fulfill the objective of the book chapter, therefore, a theoretical construction was proposed. Initially, the concept and importance on the theme of innovation were discussed. The myriad of possibilities and innovation types enables a range of specific solutions. Innovation Analytics has a focus more centered on products, processes and services innovation. Business model innovation has different complexity comparing to these other types of innovation. Thus, just as innovation management processes needed to be adapted to business models, it is coherent to argue that innovation analytics also need to consider particular aspects for these archetypes.

An interesting opportunity is that the systematization of the business model innovation process remains a significant gap in the literature. Hence the emergence and need for understanding the subject related to dynamic capabilities. Such capabilities differ from routine activities, that is, ordinary capabilities. Dynamic capabilities are linked to activities such as sensing, seizing, and transforming.

The authors argue that dynamic capability can be combined with data analytics. The big data context and its volume, variety and velocity characteristics bring new possibilities for data-driven decision making, especially when combined with techniques developed for this context. Thus, interesting results are already presented in different areas of knowledge, branching out to descriptive, diagnostic, predictive and prescriptive analytics.

The chapter, therefore, presents a framework toward business model innovation analytics. Steps of the business model innovation process and activities of dynamic capabilities were merged. In the framework, important questions relevant to data collection, data storage, and data analysis were presented. Finally, the authors established recommendations on the use of the framework proposal considering the context of the SMEs.

It is not clear in the literature a framework with the characteristics and purpose as the one presented in this book chapter. As discussed in the previously BMI is a key factor for enabling digital transformation. This paper, however, brought the possibility that this relation may present a two-way street. Digital transformation enhances a company's ability to create and analyze data to make decisions about BMI.

Although it is a theoretical proposition, the presented study contributes to the literature by aggregating this combination of innovation, business models, dynamic capability and data analytics. From a practical point of view there is an interesting contribution for managers and decision-makers of SMEs, since the framework can operate as a support in the data-driven decision-making process for business model innovation.

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Chapter 4

Machine learning techniques applied to construction: A hybrid bibliometric analysis of advances and future directions

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Abstract

Complex industrial problems coupled with the availability of a more robust computing infrastructure presentmany challenges and opportunities for machine learning (ML) in the construction industry. This paper reviewsthe ML techniques applied to the construction industry, mainly to identify areas of application and futureprojection in this industry. Studies from 2015 to 2022 were analyzed to assess the latest applications of ML techniques in construction. A methodology was proposed that automatically identifies topics through the analysis of abstracts using the Bidirectional Encoder Representations from Transformers technique to select main topics manually subsequently. Relevant categories of machine learning applications in construction were identified and analyzed, including applications in concrete technology, retaining wall design, pavement engineering, tunneling, and construction management. Multiple techniques were discussed, including various supervised, deep, and evolutionary ML algorithms. This review study provides future guidelines to researchers regarding ML applications in construction.

Keywords: Machine learning; BERT; Construction; Concretes; Retaining walls; Tunnels; Pavements; Construction management;

1. Introduction

Nowadays, machine learning (ML) techniques are widely applied to multiple tasks and challenges. Herewith, the availability of a more powerful computing infrastructure provides the necessary tools for implementing advanced ML techniques to solve complex industrial problems. In this way, we can improve decision-making in industries, increasing their sustainability and productivity. The fourth industrial revolution (Industry 4.0) is changing all the industries in different aspects (DALLASEGA; RAUCH; LINDER, 2018). One of the industries that is expected to benefit significantly from ML implementation is the construction industry. Multiple articles raise the need to automate construction to improve the way this industry works, including the need to improve the construction supply chains (DALLASEGA; RAUCH; LINDER, 2018;

OSUNSANMI, TEMIDAYO; AIGBAVBOA; OKE, 2018; RAUCH; LINDER; DALLASEGA, 2020). In this work, a review of ML applications for smart construction was developed. Articles published in recent years that consider the concepts of ML and construction were analyzed. The initial database obtained was more than 5000 articles, so it was decided to use a methodology based on topic modeling, Section 2, to make an initial grouping of the most interesting topics to later delve into each of these.

The objective of topic modeling is to group documents and words that have similar meanings. It is widely used in a variety of domains, including natural language processing (NLP) and information retrieval (IR). It uses unsupervised ML algorithms to extract topics from document collections. There are several topic modeling approaches available, for example, Probabilistic Latent Semantic Analysis (PLSA) (HOFMANN, 2001), Latent Dirichlet Assignment (LDA) (BLEI; NG; JORDAN, 2003). Another interesting method, nonnegative matrix factorization (NMF), is an unsupervised technique for reducing the dimension of nonnegative matrices (LEE; SEUNG, 1999), which has been widely utilized to deduce underlying links between texts and to find latent themes (ARORA; GE; MOITRA, 2012). Although these approaches do not require labels to operate, they require specifying the number of categories to perform the grouping. However, a growing number of topic modeling systems are based on LDA and NMF, although they require considerable work in hyperparameter tuning to generate meaningful topics.

In general, the methods outlined above have some drawbacks. One of these limitations is that they ignore semantic relationships between words when using bag-of-words representations. These representations do not consider the context of words in a sentence, which may make it difficult for them to display documents correctly. This article uses a semi-automatic method to carry out a bibliographic analysis. In the first stage, a search is carried out on the Scopus database, and a set of abstracts related to the search is obtained. These abstracts are modeled across topics using BERTopic (GROOTENDORST, 2022). This method has been used to model topics and provides a better contextual perspective than previous methods.

Based on the latter, this article uses a semi-automatic method to carry out bibliographic searches. In the first stage, a search is carried out on the Scopus database, and a set of abstracts related to the search is obtained. These abstracts are modeled across topics using Bidirectional Encoder Representations from Transformers topis (BERTopic) (GROOTENDORST, 2022). Subsequently, the main topics are validated for consistency by an expert to select the relevant topics. Using the relevant terms of each of these topics, new Scopus queries are generated to finally carry out a traditional bibliographic analysis with the result of said queries and a clustering analysis based on bigrams.

This study aims to determine the latest applications of ML tools in the construction industry through a semi-automated method that integrates ML techniques and expert knowledge. The main objective is to determine in what areas and what ML techniques have been developed and implemented to solve problems in the construction industry. This state-of-the-art review includes articles from the last seven years, where the search focused on applications of machine learning in construction areas.

A brief summary of the structure of the content of the following sections: Throughout Section 2, the procedure used to carry out the bibliographic analysis is explained. In Sections 3 and 4, the bibliographical analysis of the selected articles is detailed. First, The BERT topics are selected, and a general scientometric analysis is carried out in 3. Later, for each selected topic, a bigram analysis is carried out in Section 4, plus the traditional bibliographic analysis. In Section 5, future directions are developed and finally in Section 6, develop the conclusions and the next steps.

2. Methodology

This section describes the proposed methodology. First, an overview of the method is given to later describe each of the stages. In Figure 2.1, the detail of the methodology used to carry out the review is shown. In the first stage, a search on Scopus is carried out using the concepts of "Machine Learning" and "Construction." Later these are filtered for articles in English retrieved in the last seven years. These results are analyzed using the methodology developed in Section 2.1. Each of the topics obtained is validated by experts in the area who determine validity, evaluating the coherence between the main terms obtained. For the topics that pass the expert criteria for each of them, a search is performed again based on the attributes obtained in the topic. With this new search, the selection of articles is carried out according to expert criteria again, and for this selected set, a bigram analysis is carried out on the one hand, which is detailed in Section 2.2, in addition to a traditional review that implies reading of the article and extraction of the main characteristics is realized.

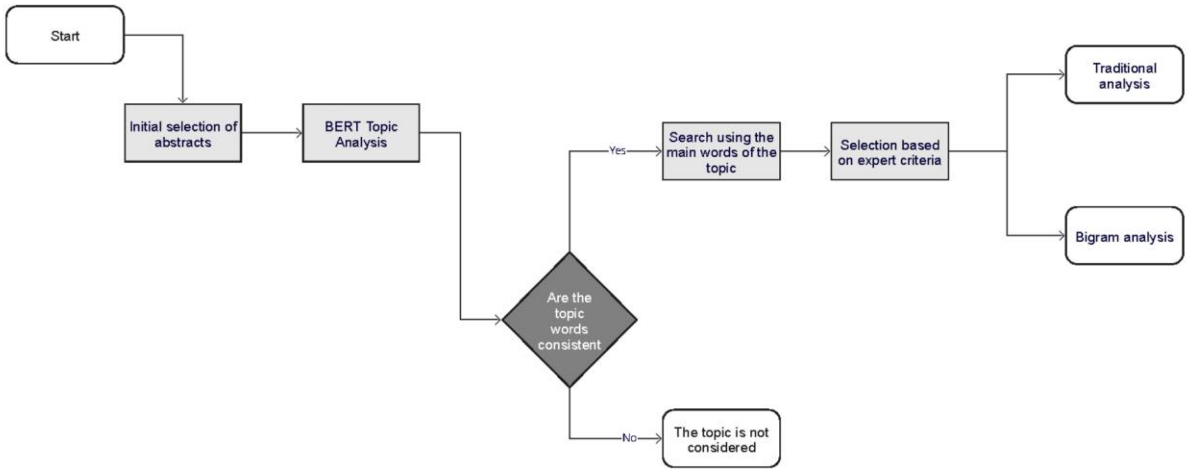

Figure 2.1. Flowchart of the semi-automated literature review methodology.

2.1. Topic Analysis

The selection of topics is made by analyzing the abstracts of all the retrieved documents. In order to make the selection of these, the process consists of three stages. In the first stage, a numerical and contextual representation of each of the terms is generated. To perform this representation, a pre-trained model of a neural network, Bidirectional Encoder Representations from Transformers (BERT) (DEVLIN et al., 2018), was used. This embedding is very powerful for language comprehension as it captures the semantic relationships between words. Once the words are embedded in a vector, in order to analyze and group the concepts in a meaningful way, a dimensionality reduction process must be carried out. Several techniques allow the reduction process to be carried out. In this case, as the reduction process requires preserving global and local components of the data space, the uniform manifold approximation and projection for dimension reduction (UMAP) technique (MCINNES; HEALY; MELVILLE, 2018) is used. This algorithm uses the concept of simplex obtained from algebraic topology in addition to manifold theory to be able to develop dimensionality reduction. Once the dimensionality reduction has been carried out, it is necessary to perform the groupings in order to find the similarities that allow us to obtain the topics. Following on from the work done in (GROOTENDORST, 2022), at this stage (HDBSCAN) (CAMPELLO; MOULAVI; SANDER, 2013) is used to generate the topics.

2.2. Bigram Analysis

A bigram is a sequence of two adjacent elements of a chain of tokens; in our specific case, they correspond to words. The objective is to carry out a statistical analysis of the frequency distribution of these bigrams in the different analyzed abstracts. To perform the analysis of each of the topics identified by BERT, the R-bibliometrix (ARIA; CUCCURULLO, 2017) package was used. Specifically, four visualizations were used. The first corresponds to the Treemap. This aims to identify the frequency of the main bigrams in each of the topics. Subsequently, the thematic map is used; this graph uses the concept of density (internal associations) together with that of centrality (external associations) (GRIVEL; MUTSCHKE; POLANCO, 1995; LÓPEZ-FERNÁNDEZ; SERRANO-BEDIA; PÉREZ-PÉREZ, 2019).

This visualization is divided into four quadrants; quadrant 1 identifies high density and high centrality. And the main topics that appear in the articles are considered. The second quadrant corresponds to high centrality and low density, which are basic and transversal topics. Quadrant 3 corresponds to high density and low centrality topics and is related to the niche or specialized topics. Finally, the fourth quadrant corresponds to emerging or poorly developed topics.

Finally, the last two visualizations correspond to conceptual maps and dendrograms. The conceptual structure visualization creates a conceptual structure map of each of the topics obtained by BERT. Specifically, multidimensional scaling (MDS) is performed on terms extracted from the abstracts of the documents. In addition to analyzing the relationship between the terms in a hierarchical way, the conceptual structure is also displayed through a dendrogram.

3. BERT topics and general bibliometrics

This section details the results obtained from the analysis of topics, and later with the selected articles of each topic, a general analysis of the journals, authors, and the thematic evolution of the main concepts is carried out. According to the methodology detailed in Section 2; The analysis begins with generating topics using BERT to later select the most important topics according to expert criteria. Figure 3.1 shows the selection made for the topics. In particular, five themes are selected. Concrete, retaining walls, pavements, tunnels, and construction management. With the keywords obtained in each topic, a manual selection of the articles to be analyzed was made. Figure 3.2 shows the main journals analyzed. Automation in construction, construction and building materials, and engineering with computers were the main sources of articles. Figure 3.3 shows an analysis of the contribution by country as well as an analysis of author networks. In the case of countries, in the upper right diagram of Figure, the country with the greatest contribution corresponds to the USA with a frequency of 91 author appearances, followed by China with 57 and further down Iran with 30, South Korea with 20 and Canada with 17. Additionally, the visualization represents a collaboration between countries, in which if the frequency of authors between countries with articles in common exceeds the value 5, a connection is drawn between them. At this point, the collaboration between the USA and China, the USA and Iran, and Spain and Chile stands out.

Concrete topic
- Concrete
- Structures
- Machine
- Learning
- Crack
- Model
- Columns
- stcc-columns
- compressive-strenght

Retaining Walls
- Retaining
- Machine
- Learning
- Embodied-energy
- Cost
- Compaction
- Optimization
- Load
- Geotechnical

Pavement topic
- Pavements
- Deep-learning
- Asphalt
- Learning
- Crack-Detection
- Cracknet
- Prediction
- Detection
- Distress

Tunnel topic
- Tunnels
- Boring
- Machine-Learning
- Crack
- Blasting
- CNN
- Health
- Monitoring
- Forecasting

Management topic
- Project management
- Decision-making
- Learning
- Classification
- Delivery
- Activity
- Recognition
- Contract
- Security

Figure 3.1. BERT topics selection results.

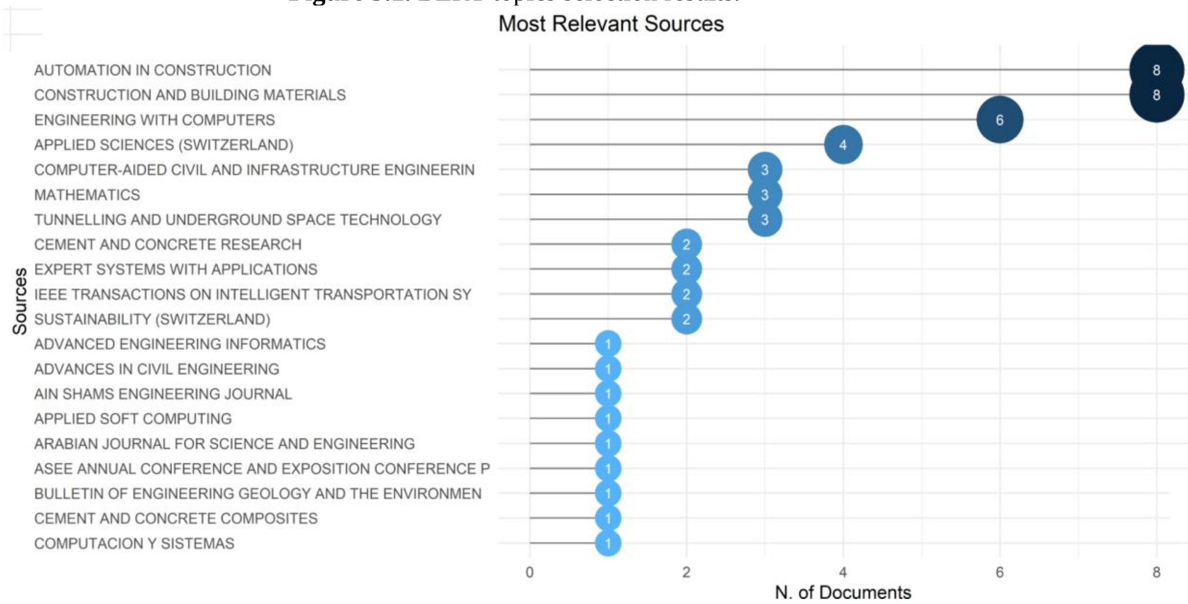

Figure 3.2. Most relevant sources.

The upper left diagram of Figure 3.3 shows a network analysis of the authors. There are seven main groups in the diagram. Where the most significant collaborative group is highlighted in red, the author's network, Zhang, A; from the USA; Fei, Y, from the USA; Chen, C, from the USA; Liu, Y; from the USA; and, Li, B, from China. The lower diagram highlights the publications with important impact factors in the red group between 2017 and 2020. Their publication area is related to the detection of cracks in the asphalt pavement area through the use of deep learning techniques. Another collaborative network of authors is the one led by

Koopialipoor, M; of Iran, which considers collaborations with the USA and Vietnam. In the lower diagram, they have had a significant number of publications in 2019 and 2020, in addition to a significant number of citations. The publication line is related to applying ML techniques such as deep learning to tunnels. The inspection and detection of cracks in tunnels have been addressed by Doulamis A; Protopadakis E ; Doulamis, N, and other collaborators. They stand out with publications and important impact factors in 2015 and 2017.

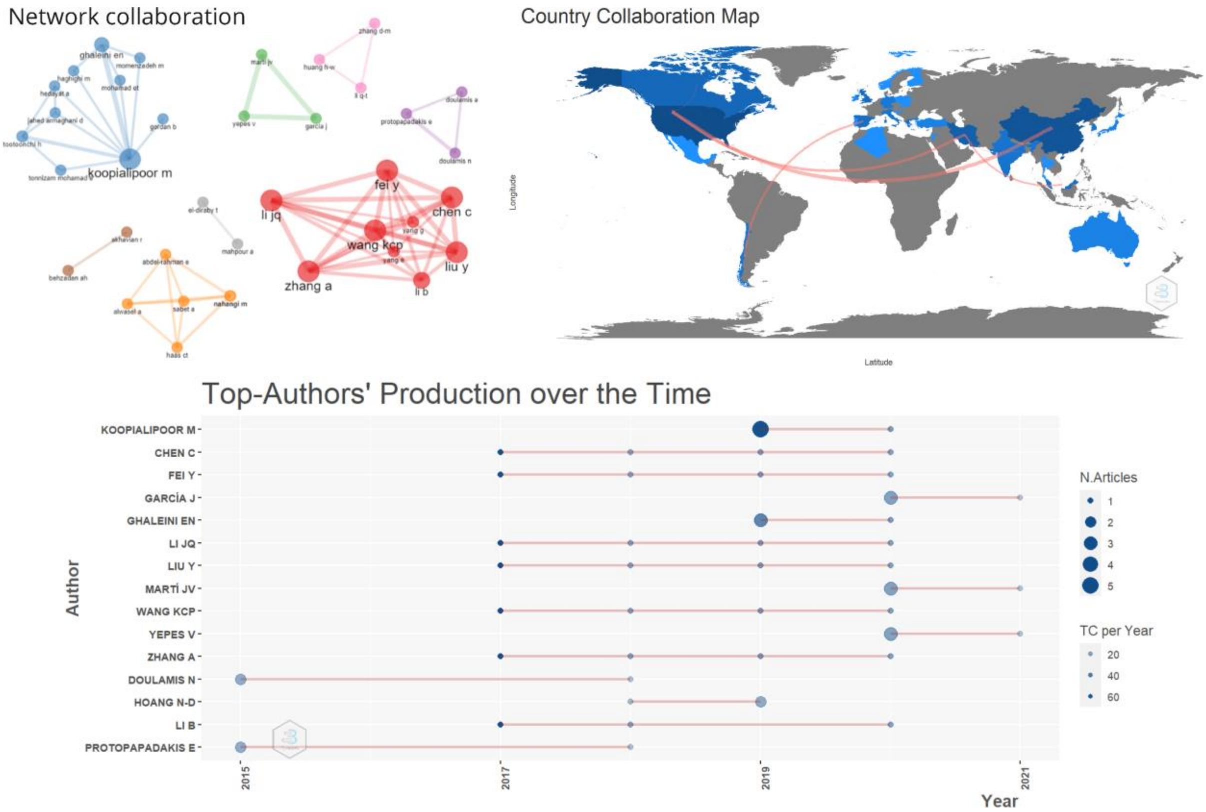

Figure 3.3. Country and author's collaboration map.

Figure 3.4 depicts a diagram for assessing the topic evolution of the articles under consideration. Combining performance analysis and scientific mapping, this method identifies and visualizes conceptual subdomains (COBO et al., 2011). Co-word analysis is utilized in a longitudinal context to identify the many study subjects covered during a specific time period. The Figure shows that machine learning and deep learning topics appear strongly in the first window of time. The above is quite natural since the review is focused on ML techniques. It is also observed that these concepts are maintained in the different time windows. Another interesting point in the first time window is crack detection. We see that already at this time, this concept was already addressed significantly through ML techniques. When we move to the second time window, we see that deep learning techniques are strongly related to Crack Detection applications, the construction industry and management, and health monitoring. Finally, two additional concepts appear in the last window of time; ML and deep learning techniques have been focused on and strongly converged into prediction models. On the other hand, a new area of application related to pavement conditions appears.

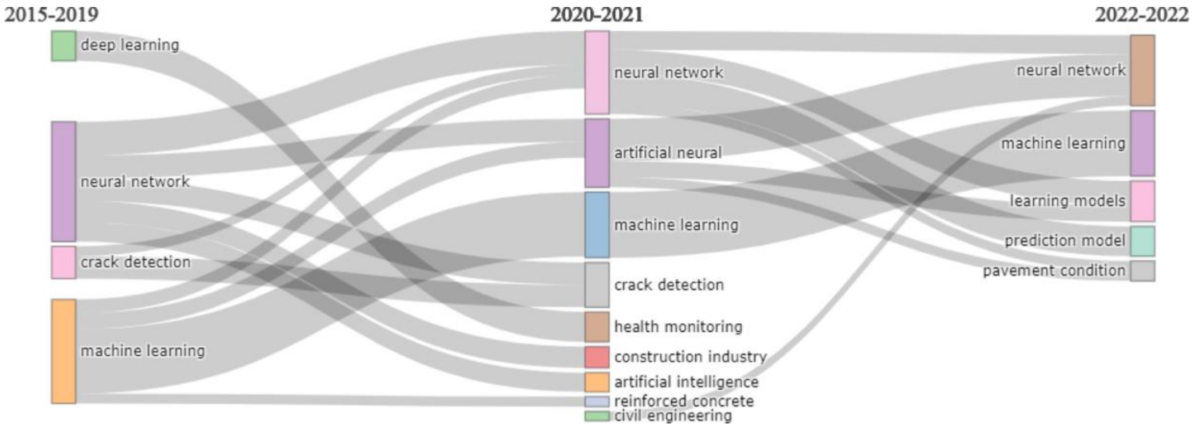

Figure 3.4. Thematic evolution map.

4. Bigram and traditional results

This section details the analysis for each of the five topics obtained in the previous section. The analysis, according to the methodology proposed in Section 2 consists of two parts. First, an analysis of bigrams is carried out, from which groups of related words are extracted to obtain an overview of the topic. Then a traditional analysis of the selected articles on each topic is developed.

4.1. Concrete structures

Concrete is the most widely used artificial material in buildings, pavements, and retaining walls. Concrete technology deals with the study of the properties of concrete and its practical applications. Concrete is used to construct foundations, columns, beams, slabs, and other load-bearing elements in building construction. The production of concrete requires large quantities of coarse and fine aggregates. To preserve natural resources, it is of the utmost importance to pay close attention to the use of waste materials and by-products in concrete mixes. For this purpose, predictive models based on ML have been used to determine the properties of concrete in order to save time, cost, and energy.

4.1.1. Bigram document analysis

When performing the bigram analysis and structuring the most relevant concepts, we see in the upper left graph in Figure 4.1 that the main concepts related to the artificial intelligence techniques appear: artificial neural networks (ANN), and support vector machines. When observing the concepts related to concrete techniques, reinforced concrete, concrete mix, retaining walls, and compressive strength, appear as the main concepts.

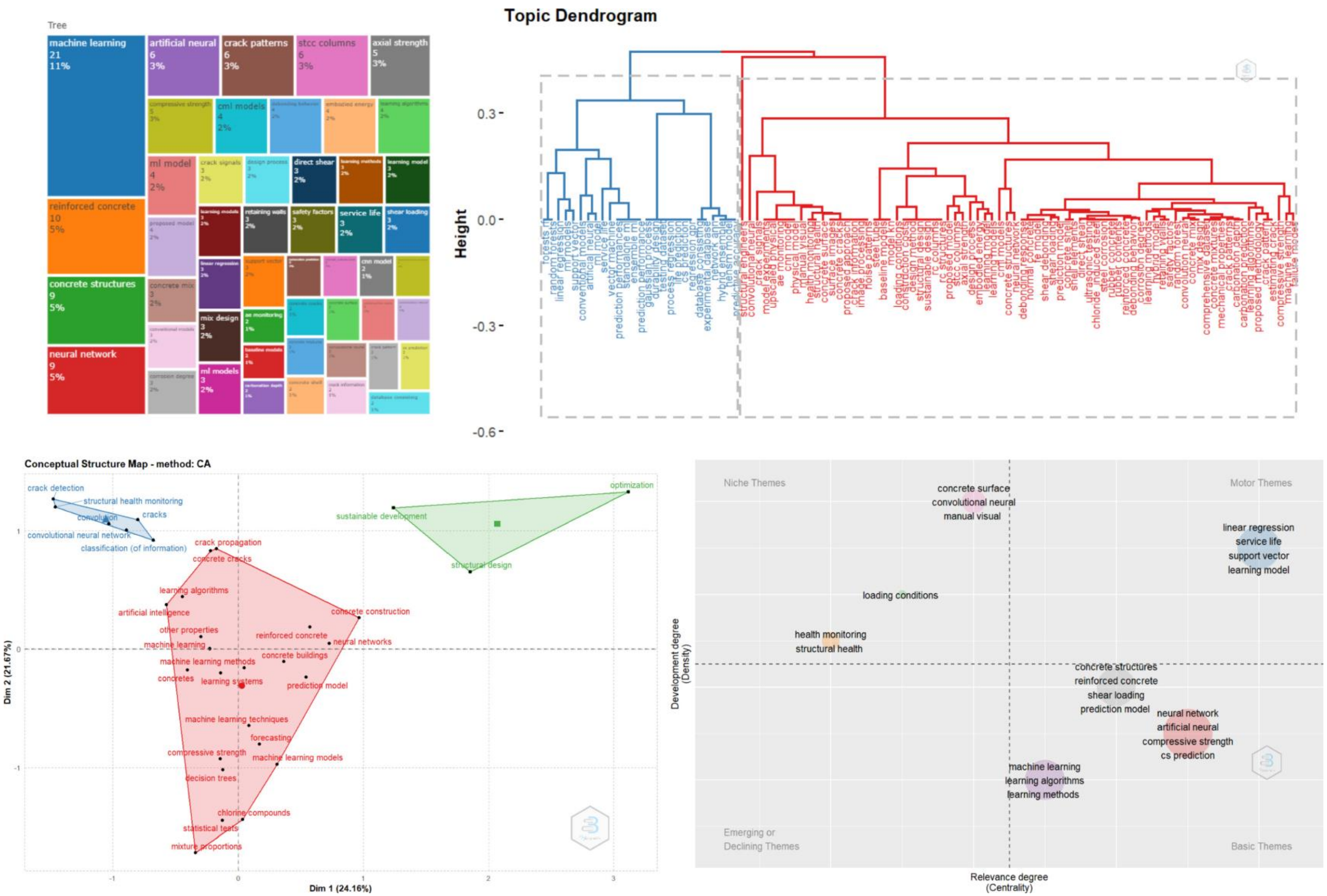

Figure 4.1. Tree, Thematic, conceptual and dendrogram maps applied a concrete dataset.

When the co-words analysis is applied, the concepts are later grouped. The result can be seen in the lower right Figure. In this Figure, it is observed that the concrete and reinforced concrete structures are related to prediction models. On the other hand, the study of compressive strength is in conjunction with neural networks. The part of crack detection and the concrete surface appears strongly related to convolutional neural networks. When the bigrams are grouped further, three clusters mainly stand out. These results are shown in the two figures below. In the lower-left Figure, we see that there is a cluster that is related to the structural, sustainable design and its optimization. On the other hand, there is a whole group related to crack detection, structure health monitoring, and convolutional neural networks. Finally, a large group relates a significant number of machine learning techniques to concrete design and production variables such as compressive strength of reinforced concrete, mixture proportions, and compressive strength.

4.1.2. Traditional analysis

In Table 4.1, a summary of the different articles selected for Concrete structures is shown. The table highlights the use of ANN, RF, and SVM techniques. On the other hand, applications for monitoring structures, crack and prediction of concrete properties appear more frequently. Following the groups found in the bigram analysis, the main group related to the design and production of concrete was found. Concrete is the most widely used artificial material in buildings, pavements, and dams. Concrete production requires large amounts of coarse and fine aggregates. To preserve natural resources, much attention has been paid to the use of waste materials and by-products in concrete mixes. The fresh and hardened properties of concrete mixes containing waste foundry sand (WFS) residues as a partial or total replacement for fine aggregate have been the focus of several recent studies. To manufacture molds and cores, the ferrous (iron and steel) and nonferrous (copper, aluminum, and brass) metal-casting industries discard WFS. Using predictive models for concrete properties can save time and energy and provide information on scheduling activities such as frame removal. In Behnood and Golafshani (2020), the M5P (decision tree) algorithm was used to model the strength, modulus of elasticity, strength, and tensile strength at the break of these concretes. A complete containing information on mixed proportions and mechanical property values at different ages was compiled using internationally published documents.

Table 4.1. Summary of applications and techniques in concrete structures.

Reference	Application	Techniques	Results	Data
(ZHANG et al., 2022a)	The effect of adding rubber to concrete on steel corrosion and concrete deterioration is studied.	1. Bayesian Ridge 2. K-nearest neighbors 3. RF	1) R2 = 0.87; MAE = 2.84; MSE = 12.73 2) R2 = 0.97; MAE =1.26; MSE = 2.88 3) R2 = 0.97; MAE = 1.22; MSE = 2.82	Data derived from ultrasonic tests applied to samples subjected to accelerated corrosion methods.
(NGO et al., 2022)	Estimating the axial strength of steel tube confined concrete	1. SVR-GWO 2. ANN 3. SVR 4. RF	1) R2 = 0.99, MAPE = 7.0 , RMSE = 209.1 2) R2 = 0.98, MAPE = 17.3 , RMSE = 337.8 3) R2 = 0.88, MAPE = 19.9, RMSE = 857.1 4) R2 = 0.98, MAPE = 10.3, RMSE = 337.5	136 samples of STCC columns infilled with various strength concrete were collected to develop and evaluate the proposed model.
(HAN et al., 2021)	Monitoring and tracking of changes in the structural integrity and durability of concrete structures	1. Single and Dual Convolutional neural network	1) AUC: Only the charts are reported 2) Accuracy: Dual model trained with the SNR of −20 dB exhibited the best accuracy. Over 80% in almost all experiments.	1) Acoustic Emission (AE) signals emitted from compressive failure of concrete specimens; 2) noise signals by man-made activities; and 3) AE signals acquired during the physical model experiments
(MARINIELLO et al., 2021)	Structural Health Monitoring to build reliable automatic damage-assessment procedures.	1)Extreme ML (ELM)-stress 2)Extreme ML (ELM)-vibration	1) RMSE = 0.07; R2 = 0.94; MaxErr = 0.16 2) RMSE = 0.42; R2 = −0.33; MaxErr = 0.81	Stress and vibration dataset
(ASTERIS et al., 2021)	Durability design and service life prediction of concrete structures in civil engineering projects.	1) ANN 2) MARS-L 3) Gaussian Process Regression 4) Hybrid ensemble model	1) R2 = 0.87, MAPE= 18.4 , RMSE = 0.075 2) R2 = 0.88, MAPE = 17.1 , RMSE = 0.072 3) R2 = 0.88, MAPE = 17.1, RMSE = 0.071 4) R2 = 0.89, MAPE = 16.3, RMSE = 0.070	1030 records have been compiled from the machine-learning repository of the University of California, Irvine.
(CAI et al., 2020)	Prediction of the surface chloride the concentration of concrete, for durability design and prediction of the service life of concrete structures in the marine environment.	1) Ensemble ML 2) SVM 3) ANN 4) RF	1) R2 = 0.83, MAPE = 39.1 , RMSE = 0.16 2) R2 = 0.47, MAPE = 68.7 , RMSE = 0.27 3) R2 = 0.76, MAPE = 37.3 , RMSE = 0.16 4) R2 = 0.81, MAPE = 37.2 , RMSE = 0.16	642 records of field exposure data of surface chloride concentration in marine concrete are collected
(ATHANASIOU et al., 2020)	Quantification of digitally crack patterns on reinforced concrete cxshell elements.	1) Bagged Trees 2) Subspace KNN 3) RUSBoosted Trees	1) Accuracy: 89.3 2) Accuracy: 80.1 3) Accuracy: 71.4	A dataset with 119 images from crack patterns of reinforced concrete shells
(JIAO et al., 2019)	The debonding behavior between High-performance fiber reinforced concrete and Normal Concrete subjected to direct shear loading is analyzed.	1)Linear-GP techniques	1) R2 = 0.97, MAE = 0.24, RMSE = 0.3	HPFRC-NC data is manufactured using two bonding strategies, i.e. mechanical surface treatments with and without chemical agent.

(BEHNOOD; GOLAFSHANI, 2020)	Prediction of concrete properties applied to the programming of framework removal activities.	1) MP5	1) R2 = 0.91, MAPE = 0.09 , RMSE = 1.97 The averages of the different predicted variables are reported.	A dataset containing information on the mixture proportions and the values of the mechanical properties at different ages was collected.
(HUANG; BURTON, 2019)	A data-driven approach to classifying the in-plane failure modes of infill frames.	1) RF 2)Adaptative Boosting 3) SVM	1) Accuracy: 81.1 2) Accuracy: 78.5 3) Accuracy: 77.2	A database consisting of 114 infill frame specimens are constructed.
(NILSEN et al., 2019)	Prediction of the coefficient of thermal expansion of concrete.	1) RF 2) Linear Regression	1) R2 = 0.76, RMSE = 0.22 2) R2 = −0.04, RMSE = 0.46	Wisconsin database of concrete mixes
(BAYAR; BILIR, 2019)	Automation, safety, cost, and time savings through observation and estimation of crack propagation	1) Voronoi processes digital images	Thickness of the crack geometry.	Real cases of concrete cracks
(ZIOLKOWSKI; NIEDOSTATKIEWICZ, 2019)	Prediction of the compressive strength of concrete to improve the safety and durability of this	1) ANN	The comparison is reported through bar charts.	The database is generated, from numerous sources, including literature, companies, institutions and laboratories.
(TAFFESE; SISTONEN; PUTTONEN, 2015)	The reliable prediction of the carbonation depth of concrete structures applied to the maintenance of structures.	1)Artificial Neural Network 2) Decision Tree 3)Bagged decision Tree 4)Boosted decision Tree	1) MSE = 0.24, MAE = 0.29, RMSE = 0.49 2) MSE = 0.42, MAE = 0.32, RMSE = 0.64 3) MSE = 0.38, MAE = 0.34, RMSE = 0.61 4) MSE = 0.26, MAE = 0.31, RMSE =0.51	The data used for the development of the prediction model was prepared in the Finnish DuraInt-project.
(ZHENG et al., 2019)	Percussion-based method to identify the moisture level of concrete	1) SVM	1) Accuracy >98%	The four cubic specimens, with dimensions 150 mm x 150 mm x 150 mm and cubic compressive strength is 50 MPa.
(YOON et al., 2018)	Optimization of embodied energy and carbon dioxide emissions of a reinforced concrete column.	1) Cost 2) CO2 3) Embodied Energy	when a 10% cost increase is assumed, embodied energy and emissions are reduced by up to 22% and 63%, respectively.	A short RC column with a square section, subjected to both axial force and moment, is modeled.

Various performance metrics were used to evaluate the performance of the developed models, including the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), the coefficient of determination (R2), and the correlation coefficient (R). The results indicated that the proposed models could provide reliable predictions of the target mechanical properties.

The coefficient of thermal expansion (CTE) significantly influences the performance of the concrete. However, CTE measurements are expensive; therefore, CTE is often predicted from empirical equations based on historical data and concrete composition. In Nilsen et al. (2019), the authors were focused on applying linear and random forest (RF) regression methods to predict CTE and other properties from a Wisconsin concrete mix database. The results of this article show that the accuracy of the RF model is significantly better than the prediction methods recommended by the American Association of Highway and Transportation Officials (AASHTO) for CTE. Additionally, RF significantly outperformed the linear regression technique, where the value of R2 was much lower. The latter shows that the behavior of CTE does not have a linear dependence on the independent variables.

The compressive strength of concrete is a fundamental parameter in the design of durability and the prediction of the useful life of concrete structures in civil engineering projects. Therefore, being able to predict this resistance has a significant practical utility. In Asteris et al. (2021) the authors proposed a hybrid ensemble surrogate ML technique for predicting the compressive strength of concrete. The proposed model is robust in handling overfitting problems and is therefore suitable for predicting the compressive strength of concrete.

Predicting the carbonation depth of concrete structures is essential for optimizing their design and maintenance. In Taffese, Sistonen and Puttonen (2015), a way to improve the prediction of carbonation is proposed using a model based on ML. The model in question considers the parameters that influence the carbonation process. In the study, an example is carried out that allows us to see the model's applicability, which allows predicting the depth of carbonation with high precision. Underwater and hydraulic concrete structures require periodic inspection due to the constant water loads. Determining the humidity in the structures is very important since it guarantees the correct functioning of the structures. In Zheng et al. (2019), the authors proposed a method for determining humidity based on percussion. The method includes the Mel Frequency Cepstral Coefficients (MFCC) used as a characteristic of the sound included by impact. A microphone was also used with which the impact-induced sound signals were obtained. The use of ML techniques, particularly a support vector machine (SVM), is proposed to predict moisture in the concrete. Finally, the authors report that the proposed system has a precision greater than 98%.

Estimating the axial strength of concrete columns confined with steel tubes is essential when making structural designs. However, this estimation is challenging because it depends non-linearly on a series of parameters such as the compressive strength of the concrete, the elastic limit of the steel, the diameter of the column, the thickness of the steel tube, the length of the column. In Ngo et al. (2022), an optimized hybrid ML model was proposed with the aim of predicting the axial force in columns. To address this challenge, a hybrid method was used that integrates the support vector regression method with the Gray wolf optimization metaheuristic. To verify the quality of the results, they were compared with models that use neural networks, random forest, and linear regression. With the hybrid method, an R2 coefficient was obtained with respect to the real values of 0.992 and an average error percentage of 7%.

Concrete mixing is a complex process that contains several stages. In Ziolkowski and Niedostatkiewicz (2019), ML techniques are used to improve the design of concrete mixes. By building and analyzing an extensive database of concrete recipes and their respective laboratory validations. One of the main results of this study is the translation of the architecture of the proposed ANN to a mathematical equation that can be used in practical applications in the real world.

One of the most common uses of machine learning is to generate prediction models. In Cai et al. (2020), the use of ML models to predict chloride concentration in marine concrete surfaces is addressed. The study uses a ML ensemble model to predict the concentration of surface chloride (Cs) in concrete. In the first place, a database is established that is then used to train five ML models, which are: linear regression (LR), Gaussian process regression (GPR), support vector machine (SVM), artificial neural network multilayer perceptron (MLP-ANN) and RF. In addition, the metaheuristic combination of predictions of RF, MLP-ANN, and SVM achieves greater precision when predicting compared to each model independently.

The use of machine learning methods also applies to sustainable concrete design. Specifically, in Yoon et al. (2018) the embodied energy and carbon dioxide emissions of a reinforced concrete column are optimized. Conventionally, the design of reinforced concrete structures focuses on minimizing construction costs while satisfying the structural design code. However, the aspect of sustainability is a relevant dimension in structural design. According to the experiments, it is concluded that when a cost increase of 10% is assumed, the embodied energy and the CO2 emissions can suffer an overall reduction of up to 22% and 63%, respectively.

A second group identified in the bigram analysis corresponded to crack detection and concrete monitoring. Checking the damage status of a structure is essential when checking concrete structures. In the article Das, Suthar and Leung (2019), it is proposed to design a framework for the automated probabilistic classification of cracks in cementitious components based on acoustic emission (AE) signals. Waveform parameters, including RA and average frequency (AF) values, are grouped by an unsupervised grouping algorithm dictated by density. Using the Support Vector Machine (SVM) algorithm, clusters that intersect in the data are separated through a hyperplane. Finally, it is possible to establish that the expectations based on the compound theory are correct; this is achieved through the cracking modes that are obtained from the proposed machine learning approach.

Cracks in concrete structures are certainly an indicator that something is wrong, and over the years, the process of detecting these indicators has been carried out manually; that is, there must be a person in charge of the process that generates the precision of the measurements is not entirely correct. In Kim et al. (2019), the way to perform this inspection automatically using ML techniques is proposed. In principle, there is a training stage where images are binarized, used to extract possible regions of cracks, then classification models with a convolutional neural network. Finally, the proposed method is evaluated with other concrete images that contain and do not contain cracks. The same is raised in Yokoyama and Matsumoto (2017), where they proposed automatically detecting cracks through images using a convolutional neural network.

In Bayar and Bilir (2019), the Voronoi Diagram algorithm was used to estimate crack patterns and spread on a random concrete surface. A random photo of a concrete crack located on the surface of a fountain is taken, and the dimensions and directions of the crack are measured. After that, the crack was divided into 12 parts to assess the algorithm’s ability to estimate the crack pattern, including its direction. As a result of the study, it is identified that this method is precise, fast, economical, and useful for monitoring and estimating the propagation of cracks in concrete surfaces.

High-Performance Fiber Reinforced Concrete (HPFRC) is a standard concrete (NC) structure repair material. In Jiao et al. (2019), a prediction model based on HPFRC and ML to address repair problems in concrete structures is addressed. This is achieved in the first instance by conducting a study on the disunity behavior between HPFRC and NC subjected to a direct shear load. A finite element (FE) model is then developed to predict the direct debarking response. Finally, a ML model is developed that makes it possible to formulate the shear strength of HPFRC-NC.

In concrete crack analysis, acoustic emission monitoring has taken an important role since it allows for monitoring changes in structural integrity and durability. However, it is necessary to distinguish crack signals from ambient noise. In Han et al. (2021) a convolutional network model is explored, allowing us to distinguish environmental noise signals from the crack's own signals. In particular, a two-dimensional convolutional model was proposed, able to distinguish and separate both sets successfully.

In Chun, Izumi and Yamane (2021) the authors address the problem of automatic detection of cracks in concrete structures from images. The article indicates that a more practical and precise method is necessary, for which they propose a method based on image processing using the light gradient magnification machine (LightGBM). It is possible to obtain a precision of the proposed method of 99.7%, a sensitivity of 75.71%, a specificity of 99.9%, a precision of 68.2% and an F measure of 0.6952. With these results, it is possible to demonstrate that the proposed method manages to detect cracks with great precision in concrete structures.

In Huang and Burton (2019), a classification of in-plane failure modes are established for concrete frames using ML. In the first instance, an experimental database is built, then six ML algorithms are implemented and evaluated for the failure mode classification. In this article, it was obtained a result that the highest precision (85.7%) was achieved with the Adaptive Boosting and Support Vector Machine algorithms.

In Athanasiou et al. (2020), a study is presented proposing an automated approach to quantifying digitally documented crack patterns in reinforced concrete shell elements subjected to reverse cyclical shear loads. A set of artificial cracks is analyzed using multifractal analysis. With the results of the parametric study, a multiclass classification model is trained and used to estimate the level of damage for cracked concrete elements. Finally, the multifractal characteristics manage to translate the shape of the crack patterns into meaningful information with an accuracy of 89.3%.

4.2. Retaining walls design

Retaining walls are rigid concrete walls used to laterally support the soil so they can be retained at different levels on the two sides. Optimizing cost and CO2 emissions in retaining walls is a relevant issue for the competitiveness of construction companies and the environmental impact of the construction of these structures. Within ML applications in the efficient design of retaining walls, hybrid models have been used to estimate safety factors. The particle swarm optimization (PSO) algorithm has been used to calculate the optimal construction cost of reinforced concrete retaining walls. Models that combine ANN with the artificial bee colony algorithm (ABC) have also been used to estimate and optimize the safety factors of retaining walls.

4.2.1. Bigram document analysis

This section details the bigram analysis performed for the concepts of machine learning and retaining walls. The results are shown in Figure 4.2. When analyzing the treemap in the upper left corner, retaining wall concepts such as geotechnical engineering, carbon emissions, bearing capacity, and loads, all of them typical of the retaining wall subject. However, ML concepts such as forecasting, classification, neural networks, mean square error, and convolutional neural networks are also mentioned. Additionally, a third group is observed that is related to optimization, with concepts such as optimization algorithms and artificial bee colonies appearing. When co-words are analyzed, and subsequent grouping occurs, the lower right figure illustrates groups associated with retaining walls, wall height, friction angles, and artificial intelligence algorithms or prediction models. Additionally, there is a subgroup for optimization, specifically of reinforced concrete walls, and metaheuristic algorithms such as harmony search or hybrid algorithms. When creating a conceptual structure map, we notice that the major groups correspond to two (lower left Figure): on the one hand, concepts related to retaining walls and ML algorithms such as neural networks appear predominantly in red. On the other hand, another group appears in blue, which is concerned with optimizing the design of walls and metaheuristic algorithms. The dendrogram illustrates the relationship between the various concepts mentioned previously (Figure top right).

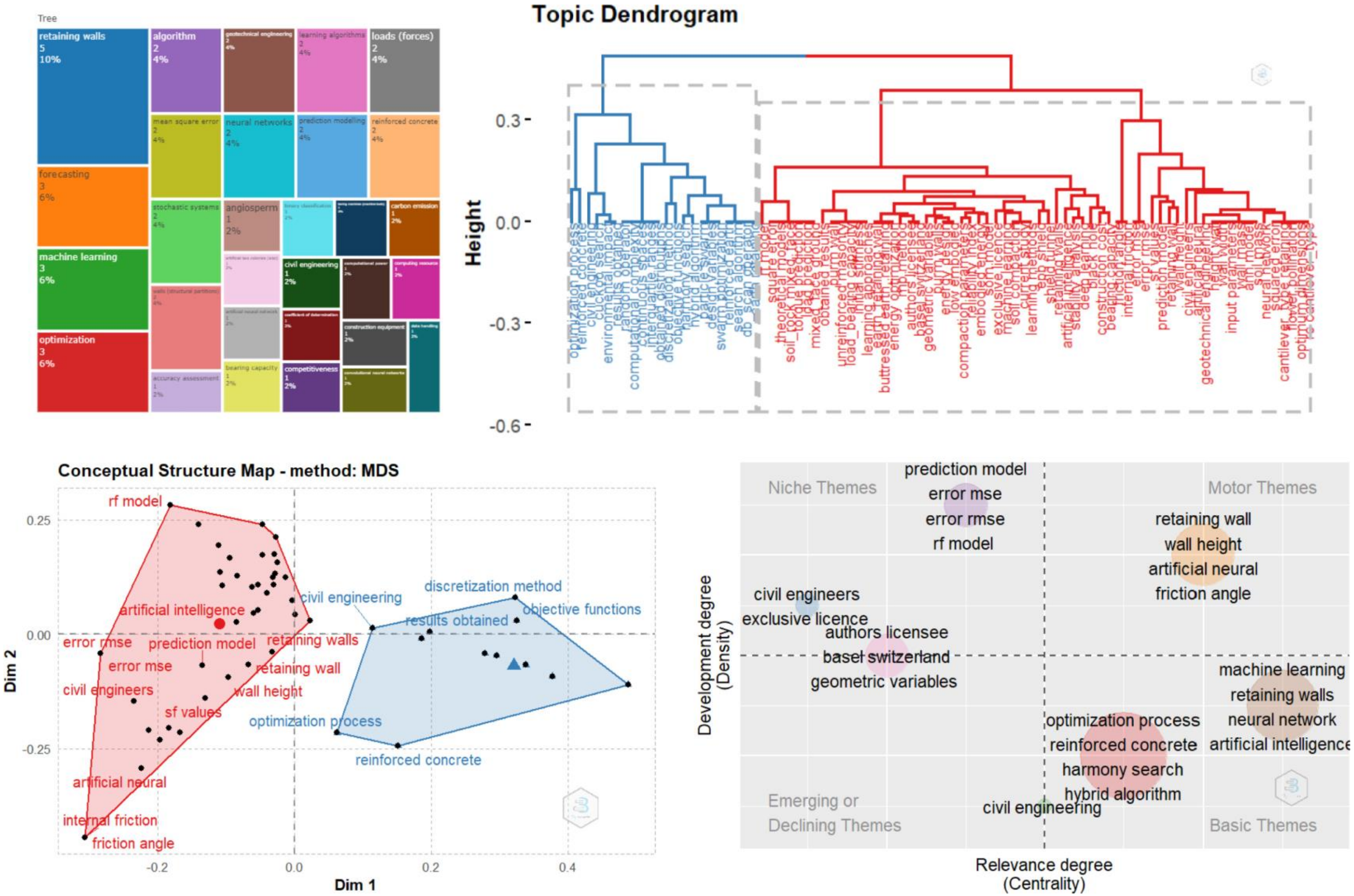

Figure 4.2. Tree, Thematic, conceptual and dendrogram maps applied a retaining wall dataset.

4.2.2. Traditional analysis

In Table 4.2, a summary of the different articles selected for retaining wall structures is shown. There is an important group of applications related to metaheuristics, machine learning, and optimization of costs, emissions, and embodied energy. On the other hand, there are also ML applications in retaining walls related to safety factors. When going into detail in the articles regarding the group related to optimization, metaheuristic or hybrid techniques are mainly explored to solve the optimization of costs, emissions, or energy consumption. It was found that optimizing cost and CO2 emissions in earth retaining walls is critical for a construction company's competitiveness and that optimizing emissions is critical for the environmental impact of construction. In Yepes, Martí and García (2020), the optimization based on the black hole algorithm was used, along with a discretization mechanism based on min–max normalization. The results obtained were compared with another algorithm that solves the problem (Harmony Search algorithm). Solutions that minimize CO2 emissions prefer the use of concrete rather than those that optimize cost. When compared to another algorithm, the results show good performance in optimization using the black hole algorithm. In García, Martí and Yepes (2020), the buttressed walls problem was determined using an application of a hybrid clustering PSO algorithm. In this study, the focus was the optimization in the design of reinforced earth retaining walls, particularly minimizing the amount of CO2 emissions generated in its construction and the economic cost. This problem has high computational complexity since it involves 32 design variables. The authors propose a hybrid algorithm in which the PSO method is integrated that solves optimization problems in continuous spaces with the db-scan clustering technique. The db-scan operator significantly improves the solutions' quality, showing good results compared to the harmony search algorithm.

Table 4.2. Summary of applications and techniques in retaining walls.

Reference	Application	Techniques	Results	Data
(YEPES; MARTÍ; GARCÍA, 2020)	Sustainable design of counterfort retaining walls	Black Hole metaheuristic optimization	Reduction in Cost and CO2 emissions	A retaining wall defined at different heights and applying restrictions of the construction regulations
(GHALEINI et al., 2019)	Predicting safety factor of retaining walls in geotechnics	1) ANN 2) ABC- ANN	1) RMSE = 0.038 , R2 = 0.916 2) RMSE = 0.018 , R2 = 0.983 Average over models.	Safety factors of 2800 retaining walls were modeled.
(GARCÍA; MARTÍ; YEPES, 2020)	The buttressed walls problem optimization	PSO	Reduction in Cost and CO2 emissions	A buttressed wall defined at different heights and applying restrictions of the construction regulations
(BENBOURAS; LEFILEF, 2023)	Estimating soil compaction parameters for seeking safe and economic of retaining walls	1) RF		Database of 147 samples collected from different studies.
(GARCÍA; YEPES; MARTÍ, 2020)	The retaining walls problem optimization	Cuckoo search algorithm	Reduction in Cost and CO2 emissions	A retaining wall defined at different heights and applying restrictions of the construction regulations
(GORDAN et al., 2019)	Design of safety factors of retaining wall under both static and dynamic conditions	1) ABC- ANN	1) RMSE = 0.005, R2 = 0.998 Average over models.	Safety factors of 2800 retaining walls were modeled.
(KIM et al., 2021)	Optimization of factors for the selection of retaining wall techniques during the decision-making stage	Self-organizing maps	1) Accuracy: 79.8%	Data from 129 excavation project cases without missing values were collected from building construction companies in large South Korean cities.
(MARTÍNEZ-MUÑOZ et al., 2021)	Automated process to obtain low embodied energy buttressed earth-retaining wall optimum designs	1) Simulated annealing with mutation operator	Reduction in Cost and embodied-energy	A retaining wall defined at different heights and applying restrictions of the construction regulations
(LIU et al., 2022)	Image-data-driven deep learning in the stability analysis of geosystems	1) Convolutional Neural Network	1) Accuracy: 97.94%	2D images for retaining walls, organized as datasets of sizes 500 to 200,000, labeled using a traditional mechanical method.
(MISHRA; SAMUI; MAHMOUDI, 2021)	Evaluation of the failure probability of retaining walls	1) MARS 2) EmNN 3) SOS-LSSVM	1) RMSE = 0.0017, R2 = 0.9999 2) RMSE = 0.0183, R2 = 0.9860 3) RMSE = 0.0002, R2 = 1.0000	Datasets were generated based on consideration of uncertainties in soil parameters
(MOAYYERI; GHAREHBAGHI; PLEVRIS, 2019)	Calculation of the load capacity through different methods of optimization of reinforced concrete retaining walls	1) PSO	Cost Optimization	A retaining wall defined at different heights and applying restrictions of the construction regulations

In García, Yepes and Martí (2020), a hybrid k-means cuckoo search algorithm was applied to the counterfort retaining walls problem. In Moayyeri, Gharehbaghi and Plevris (2019) a PSO algorithm is employed to calculate the optimum construction cost of reinforced concrete retaining walls. Geotechnical and structural limitations are considered constraints for the optimization problem. The critical role of building in natural resource use is driving structural design professionals to develop more efficient structural designs that reduce emissions and energy consumption. In Martínez-Muñoz et al. (2021), an automated approach to generating optimal buttressed earth retaining wall designs with minimal embodied energy is described. In this research, two objective functions were used to compare the cost optimization and embodied energy optimization strategies. This study employed a hybrid simulated optimization algorithm to determine the geometry, concrete resistances, and concrete and material quantities required to create the optimal buttressed earth-retaining wall with the lowest embodied energy. A relationship was discovered between the two optimization criteria, implying that cost and energy optimization are inextricably related. This permits the statement that a 1€ cost reduction results in a 4.54 kWh reduction in energy consumption.

The other interesting group obtained from the bigrams analysis was the application of ML techniques to prediction and classification. Particularly in Ghaleini et al. (2019), the authors present intelligent models to solve problems related to retaining walls. For this, the safety factors of 2800 retaining walls were modeled and recorded, considering different effective parameters of retaining walls. This includes the following parameters: wall height, wall thickness, friction angle, soil density, and rock density. A combination of the artificial bee colony (ABC) and ANN algorithm was used to approximate the safety factors of the retaining wall (compared to a previously developed ANN without ABC). The performances of the generated models were evaluated using coefficients of determination ($R2$) and performance indices of the error (RMSE). The new hybrid model (ANN + ABC) can significantly increase the performance capacity of the network (compared to ANN without ABC). $R2$ values of 0.982 and 0.985 for training and testing of the ABC + ANN model, respectively, compared to values of 0.920 and 0.924 for the ANN model (without ABC). In conclusion, the results showed that the new hybrid model could be introduced as a sufficiently capable technique in the field of this study to estimate the safety factors of RW. In Gordan et al. (2019), a combination of ANN and artificial bee colony (ABC) is employed for predicting and optimizing safety factors of retaining walls. A comprehensive database of 2880 datasets was used; the input parameters included wall height, wall width, wall mass, soil mass, and internal angle. A critical point in the study of retaining walls is the structure's failure probability. In Mishra, Samui and Mahmoudi (2021), a reliability study of the structure is conducted using ML techniques, incorporating geotechnical variables. They are predicted using Neural Networks, Multivariate Adaptive Regression Splines, and vector machine support techniques. The application of these techniques yielded results that deviated by less than two % of the real values, simplifying the process of calculating these safety factors.

Making design decisions is a subjective process that considers multiple dimensions such as economic, social, and environmental. In Kim et al. (2021), self-organizing maps (SOM) were used to simulate decision-making in order to determine the most appropriate retaining wall technique. N-fold cross-validation was used to validate the model. This study demonstrates that self-organized maps are beneficial for decision-making when selecting a retaining wall method. The SOM had a maximum accuracy of 81.5 percent and a mean accuracy of 79.8 percent. Through the use of classification convolutional neural networks, in Liu et al. (2022), models were built that were trained using previously classified retaining wall images. These images indicated whether the constructed wall was safe or not. In the training process of the convolutional network, image sets that had between 500 and 200,000 images were used to verify the results against 20,000 images later in the testing stage. The result of the models achieved an accuracy of 97.94% in the safety classification of a wall. In Benbouras and Lefilef (2023), an estimation of compaction parameters is performed. Estimating these parameters is an essential point in the design of retaining walls. The Proctor Test is usually used to make this estimate. However, this test is expensive and time-consuming. The study developed a new model for predicting compaction parameters based on eleven new progressive ML methods to overcome these limitations. The modeling phase was performed using a database of 147 samples collected from different studies. Model performance was evaluated across six metrics in addition to incorporating K-fold cross-validation. The comparative study demonstrated the effectiveness of the RF technique, which showed the highest performance in predicting soil compaction parameters.

4.3. Pavement Engineering

Pavement engineering is a discipline that uses engineering techniques to optimize the design and maintenance of flexible asphalt and rigid concrete pavements. Determining the shear strength of soil is an essential task in the design phase of a pavement construction project. For this purpose, models integrating the support vector machine (SVM) algorithm and cuckoo search optimization (CS) have been used. Some architectures based on convolutional neural networks (CNN) have also been used for the detection of pavement cracks on asphalt surfaces. With this same purpose, deep convolutional neural networks with transfer learning have been used to detect and classify pavement faults based on computational vision automatically.

4.3.1. Bigram document analysis

This section details the bigram analysis performed for ML and pavement concepts. The results are shown in Figure 4.3. When analyzing the treemap, concepts related to crack detection, monitoring, and conditions and the prediction of coefficients or variables related to the pavement are highlighted. This can be seen in the upper left Figure by complementing the analysis with an analysis of co-words and clustering, which is shown in the lower image on the right. We see that there is a group related to pavement maintenance policies. Another group is associated with cracks, and a third group is related to pavement condition prediction. On the other hand, techniques such as deep learning and RF stand out. Finally, when performing a conceptual map clustering, two groups stand out. The first group in blue is mainly distinguished maintenance and policies related to pavement maintenance. On the other hand, the red cluster is a little more diffuse, highlighting the application of ML techniques related to cracks in the pavement analysis of parameters such as vibration, shear strength, and pavement surface. This is complemented by the dendrogram shown in the upper right image, which indicates the closeness between the different concepts.

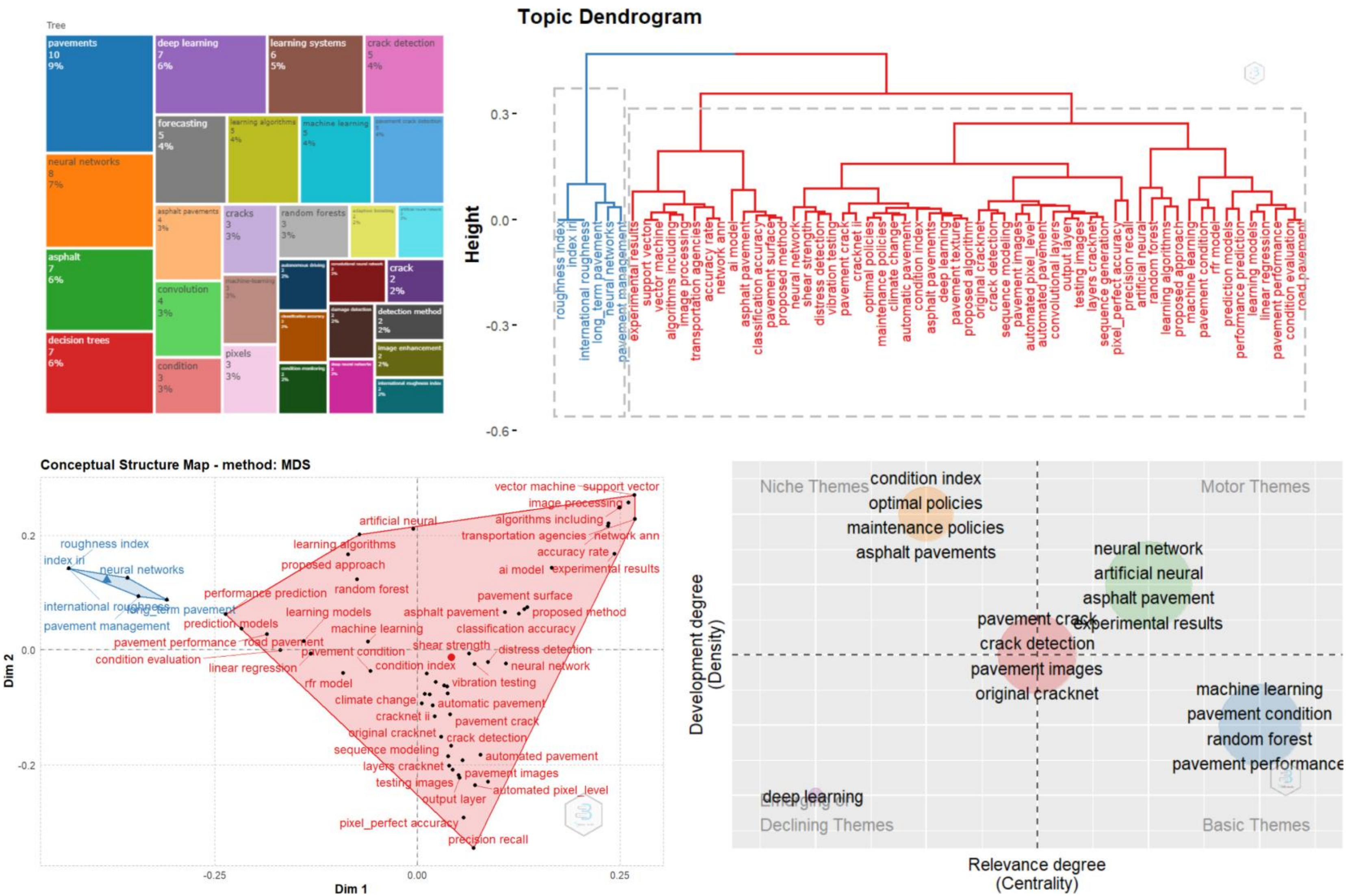

Figure 4.3. Tree, Thematic, conceptual and dendrogram maps applied a pavement dataset.

4.3.2. Traditional analysis

In Table 4.3, a summary of the different articles selected for Pavements structures is shown. Among the main techniques used, different architectures of convolutional networks stand out, in addition to ANN multilayer perceptron, RF and SVM. Regarding the applications, the detection of Crack, and prediction of indicators related to its monitoring and deterioration stand out. When performing traditional analysis driven by the topics found in bigram analysis. An interesting group that appears is related to pavement maintenance policies. The effects of climate change in particular, which are related to temperature changes, directly impact the pavement. Having a guide to guarantee the adequate maintenance of the pavements allows efficiencies to be made when maintaining them. In Mahpour and El-Diraby (2021) the authors address this problem in the case of Iran. Particularly in certain areas, climate change has changed from a cold semi-desert to a relatively hot semi-desert. In the article, ML algorithms are used to develop a methodology that allows evaluating the necessary maintenance differences and thus developing a maintenance policy. This policy allows an adequate evaluation of the costs involved in the maintenance process due to the effects of climate change. In Mahpour and El-Diraby (2022), a framework was proposed using ML to find optimal maintenance policies in a road network. The stages included grouping the network based on relevant factors, identifying criteria that impact optimal policies, and determining policies and application periods. Additionally, regression algorithms such as gradient boost regression, lasso, ridge, RF regression, and neural network, among others, were used to quantify and predict the cost of policies.

A second line found in the bigram analysis is related to the detection of cracks and distress in the pavement. In Zhang et al. (2017), an architecture based on Convolutional Neural Networks (CNN) called CrackNet, is developed and employed for pavement crack detection on three-dimensional (3D) asphalt surfaces. This same group of authors from the School of Civil and Environmental Engineering at Oklahoma State University (USA) published three new versions, in [63], of the CNN-based pavement crack detection architecture, CrackNet II, CrackNet-V, and CrackNet-R. In Zhang et al. (2019a), a CrackNet version using recurrent neural networks was developed (called CrackNet-R), four times faster and with better accuracy than the original CrackNet version. This version proposes a gated recurrent multilayer perceptron (GRMLP) to update the internal memory recursively. GRMLP is intended for deeper input and hidden state abstractions by conducting multilayer nonlinear transforms at gating units. The training of CrackNet-R is completed using 3,000 diverse 3D images.

Table 4.3. Summary of applications and techniques in pavements.

Reference	**Application**	**Techniques**	**Results**	**Data**
(BANHARNSAKUN, 2017)	Pavement surface deterioration detection and classification system	1) ANN 2) SVM	1) Accuracy = 97.5 2) Accuracy = 95.0 Averages	Images of 600 pavements of road surfaces in Thailand
(CHEN et al., 2022)	Detect and analyze road macrotexture on pavement types	1) Augm-RF 2) GAN-DenseNet	1) Accuracy = 58 2) Accuracy = 82	Small dataset of images of pavement
(FEI et al., 2020)	Automated pixel-level crack detection in 3D asphalt pavement images	1) CrackNet-V	1)Pr:84.3, Re: 90.1, F-1:87.1	500 test images
(ESCALONA et al., 2019)	Automatic pavement crack segmentation	1) U-net-A 2) U-net-B 3) U-net-C	1) Pr:96.9, Re: 93.5, F-1:95.0 2) Pr:97.3, Re: 94.3, F-1:95.8 3)Pr:95.8, Re: 82.4, F-1:87.7	CFD and AigleRN
(GONG et al., 2018)	Estimate the international roughness index of flexible pavements using deterioration, traffic, weather, maintenance, and structural data.	1) RF	1) MSE = 0.974, R2 = 0.006	Data with over 12.300 samples of distress, 28.700 of rutting data, and 19.900 of IRI data for asphalt pavement (LTPP)
(GOPALAKRISHNAN et al., 2017)	Automated pavement distress detection and classification	1) VGG-16 2) VGG-16+RF 3) VGG-16+LR	1) Pr:90.0, Re: 90.0, F-1:90.0 2) Pr:86.0, Re: 86.0, F-1:85.0 3) Pr:88.0, Re: 88.0, F-1:87.0.	1056 pavement images (HMA-surfaced and PCC-surfaced) from the FHWA/LTPP
(HOANG, 2018)	Detecting potholes on asphalt pavement surface	1) LS-SVM 2) ANN	1) CAR = 88.75, AUC = 0.96 2) CAR = 85.25, AUC = 0.92	A dataset consisting of 200 image samples has been collected
(HOANG; NGUYEN, 2019)	Detecting and classifying asphalt pavement crack.	1) SVM 2) ANN 3) RF	1) CAR = 87.5 2) CAR = 84.3 3) CAR = 70.0	The dataset consists of 200 samples
(MAHPOUR; EL-DIRABY, 2021)	Sustainability of the pavements against the increase in temperature	1) GBR 2) RF 3) ANN	1) Accuracy = 90.71 2) Accuracy = 86.92 3) Accuracy = 77.65	The data used was provided by a local company, 537 records of asphalt pavement segments.
(INKOOM et al., 2019)	Pavement crack prediction	1)ANN-Model1	1) R2 = 0.89, RMSE = 0.525 Averages	The FDOT's PMS data of about 9109 pavement segments were monitored over a period of 40 years.
(MAHPOUR; EL-DIRABY, 2022)	Find optimal maintenance policies in a road network	1) GBR 2) RF 3) ANN	1) Accuracy = 91.2 2) Accuracy = 87.9 3) Accuracy = 78.7 Averages	The data is from asset management companies in the entire network of Iran.
(MARCELINO et al., 2021)	Pavement performance prediction models in pavement management systems	1) RF	1) R2 = 0.955, MSE = 0.279 Averages for IR indicator	Different datasets were created for the 5 and 10-years predictions.
(PEI et al., 2022)	Pavement Surface Technical Condition Index Deterioration Prediction Model	1) LightGBM	1) R2 = 0.754, MSE = 2.651	Highway Pavement Data.
(SHTAYAT et al., 2022)	Pavement condition monitoring and maintenance	ANN, SVM, Neuro Fuzzy, Linear Regression	R2, MSE, MAE. It is a summary of prediction models of the asphalt pavement degradation condition	Long-term pavement performance

(TIEN BUI; HOANG; NHU, 2019)	Prediction of soil shear strength for road construction	1) LSSVM	1) RMSE = 0.082, MAPE = 14.841, R2 = 0.885	A dataset of 332 soil samples collected from the Trung Luong National Expressway Project in Viet Nam
(ZHANG et al., 2019)	Automated pixel-level crack detection on three-dimensional asphalt pavement surfaces	1) CrackNet-R	1) Pr = 88.9, Re = 95.0,F-1 = 91.8	3000 diverse 3D images for training and 500 for testing
(ZHANG et al., 2018a)	Automated pixel-level crack detection on three-dimensional asphalt pavement surfaces	1) CrackNet-II	1) Pr = 90.2, Re = 89.1, F1 = 89.6	2500 diverse 3D images for training and 200 for testing
(ZHANG et al., 2017)	Automated pixel-level crack detection on three-dimensional asphalt pavement surfaces	1) CrackNet	1) Pr = 90.1, Re = 87.6, F-1 = 88.9	1800 diverse 3D images for training and 200 for testing

The analysis using 500 testing pavement images shows a precision of 88.9%, a recall of 95.0%, and a F-measure of 91.84%. In Fei et al. (2020), CrackNet-V was developed as a more efficient version of the CNN-based architecture. This version has a deeper architecture but fewer parameters, with improved accuracy and efficient feature extraction.

In Gopalakrishnan et al. (2017), Deep Convolutional Neural Networks (DCNN) with transfer learning were applied for computer vision-based automated pavement distress detection and classification. The FHWA/LTPP database with multiple Pavement images datasets was used. The truncated DCNN was used to build deep features for road imaging. Various ML classifiers were trained using semantic image vectors. A neural network classifier trained in deep transfer learning vectors gave the best results.

In Banharnsakun (2017), a novel method based on a hybrid ABC-ANN model for pavement surface distress detection and classification was used. In this study, the ANN was used to classify a hazard area as a specific hazard type, including transverse cracks, longitudinal cracks, and potholes. The study results demonstrate that the hybrid ABC-ANN approach works well for pavement distress detection and can classify types of distress on pavement images with reasonable precision. The precision obtained by the proposed ABC-ANN method achieves an increase of 20% compared to the existing algorithms.

In Hoang and Nguyen (2019), the performance of different ML algorithms was analyzed for asphalt pavement crack classification, including support vector machine (SVM), ANN, and the RF. The feature set consisting of the properties derived from the projective integral and the properties of crack objects can offer the most desirable result. Experimental results show that SVM has achieved the highest classification accuracy rate (87.50%), followed by ANN (84.25%) and RF (70%). The proposed approach may be useful in assisting transportation agencies and inspectors in the task of assessing the condition of the pavements.

A relevant issue in public safety is related to cracks in the pavement, despite advances in imaging techniques and segmentation. Segmenting or recognizing pavement cracks is a non-trivial problem. This is because there is no regularity in the pavement cracks, so there is no clear pattern. At In, (ESCALONA et al., 2019), a variation of the U-net topology was developed to perform automatic pavement crack detection. To validate the proposal, benchmark data such as CFD and AigleRN were used.

The primary non-destructive pavement evaluation methods are image recognition models, ML algorithms, and visual inspections. While the previous methodologies are efficient, they include uncertainty, noise, and overfitting. By and large, the cracks do not follow a predictable pattern. The use of ANN to predict the qualification of cracks in pavements is addressed in

Inkoom et al. (2019) to strengthen the results of the learning models already used in predicting cracks in pavements. An interesting facet of the work is the data used. The model formulation incorporates variables such as average daily traffic and truck factor, road functional class, asphalt thickness, and pavement condition time series data. By and large, the work concludes that ANNs are considered suitable ML models for crack classification.

In Hoang (2018) also uses ML techniques to detect potholes on the asphalt pavement surface. In this case, Gaussian filters, steerable filters, and integral projection are used to extract features from digital images. Once the feature set was generated, the robustness of the LS-SVM and ANN methods was evaluated. The evaluation was performed using 200 images as a training and validation set. Both methods had values in the precision indicator above 85% and a ROC-AUC of 0.96. Particularly LS-SVM was the one that obtained the best results. An application thinking of autonomous cars corresponds to detecting the texture of the road since it directly affects the operation of the tires and braking. In Chen et al. (2022), deep learning is used to perform pavement texture recognition. As a first step, the captured images were pore-processed and subsequently augmented using the Generative adversarial networks (GANs). Finally, the RF technique and the Densenet network were used for the texture identification process. The latter obtained better precision than RF. Particularly when using the data augmented with GANs, a better quality database is obtained, and therefore when training with this new set of images, it is observed that the accuracy improves from 59% to 82%. To train the adversary network, 250,000 iterations were used. These methods were also found to work better than manual methods.

Regarding the third group related to using ML in order to predict pavement properties. The shear strength property of the soil is critical. Determining the shear strength of the soil is an important task in the design phase of the construction project. In Tien Bui, Hoang and Nhu (2019), the authors present a hybrid AI model that integrates the Least squares support vector machine (LSSVM) algorithm and the cuckoo search optimization (CSO). A dataset of 332 soil samples collected from the Luong National Highway Project in Vietnam was used to construct and validate the model. The input variables used in this study were: the depth of the sample, the percentage of sand, the percentage of clay, the percentage of clay, the moisture content, the wet density of the soil, the specific gravity, the liquid limit, the plastic limit, the plastic index, and the liquid index. LSSVM is used to generalize functional mapping that estimates shear strength from the information provided by the input variables. The LSSVM model requires proper configuration of the regularization and parameters of the kernel function; instead, the CSO algorithm is used to determine these parameters automatically. The experimental results show that the prediction precision of the LSSVM and CSO hybrid method (RMSE = 0.082, MAPE = 14.841, and $R2$ =

0.885) is better than that of the reference approaches that include the standard LSSVM, the ANN, and the tree regression. Therefore, the proposed method is a promising alternative to assist construction engineers in estimating the shear strength of the soil.

Another interesting indicator to consider in flexible pavements is the international roughness index (IRI). The RF technique is used in Gong et al. (2018) to perform automatic prediction on this indicator. Eleven thousand samples were used to create the dataset. Eighty percent of the data was used in the training process, with the remaining twenty percent reserved for validation. Sampling was conducted at random. The results outperformed regularized linear regression models, with indicators exceeding 95%. When the importance of variables is analyzed, it is discovered that the primary influencing variables are the initial value of IRI, as well as the average rainfall, fatigue cracking, and transverse cracking. In Marcelino et al. (2021) a general ML technique be used to construct models for pavement performance prediction in pavement management systems (PMS). The proposed models were developed using a RF algorithm and datasets that included past IRI observations as well as structural, meteorological, and traffic data. The proposed approach is compatible with a variety of machine learning algorithms and emphasizes generalization performance. A case study is presented for the prediction of the IRI over the next five and ten years utilizing the Long-Term Pavement Performance.

Pavement condition prediction is a powerful and critical tool for determining the most effective maintenance approaches and treatment processes. Similar to previous works, in Shtayat et al. (2022), use ML methods to forecast the IRI and pavement condition indices (PCI). These performance indices are frequently used in pavement monitoring to correctly determine the state of a pavement's health. Additionally, the paper discusses the most critical variables that pavement condition prediction models include. In Issa, Sammaneh and Abaza (2022), the prediction of the PCI indicator is addressed through the use of cascade models. The goal is to be able to replace visual inspections, and in order to calibrate the models, they chose the six most frequent defects: patches, alligator cracks, transverse and longitudinal cracks, shoving, and potholes. The cascade architecture uses traditional learning models integrated with a neural network. After applying the statistical cross-validation techniques, the results show that the model can predict the index with an adequate degree of precision. Finally, the pavement maintenance quality index (PQI) prediction is covered in Pei et al. (2022). The study proposes a prediction model for the deterioration of the technical condition index of the pavement surface based on the Light Gradient Boost Machine. To properly fit the model, the grid-search technique was used. The prediction result is compared with the prediction result using a RF. The comparison indicates that the boost method has a good prediction; this is observed when analyzing the *R*2 indicator, which obtained a value of 0.754 and the MAE that reaches 2.651.

4.4. Tunnels

Tunnels are underground infrastructure that seeks to connect two external points by crossing flat surfaces, mountainous accidents, and even seas. One of the main challenges in tunnel engineering is the inspection, evaluation, maintenance, and safe operation of the infrastructure. In order to study structural damage in tunnels, computer vision techniques have been used, including combinations of convolutional neural networks (CNN) and fuzzy spectral clustering (Fuzzy spectral clustering). On the other hand, predicting machinery performance is critical for accurate cost estimation in tunnel construction projects. For this purpose, deep neural network models have been used to predict the penetration rate of tunnel boring machinery. These systems offer high detection accuracy compared to existing methods.

4.4.1. Bigram document analysis

The bigram analysis is shown in Figure 4.4. In the upper left Figure, tunnel inspection and crack detection are obtained as major issues being developed in tunnels. This is confirmed in the graphs below. In the thematic map, shown in the lower right Figure, we see that three groups appear. One group is related to tunnel inspection, another group is related to crack detection, and a third group does not have a precise meaning. When analyzing the clusters generated by the conceptual map, shown in the Figure lower left. It is noted that two clusters appear; the blue one is related to the concept of monitoring and structural health with image segmentation, ML, deep learning, and convolutional networks. In a second cluster in red, the concept of crack detection appears related to penetration rates, excavations, and geotechnics and in conjunction with metaheuristic optimization techniques, deep learning, and ML. When analyzing the dendrogram in the upper right Figure, we see that tunnel inspection is very close to convolutional networks and image segmentation concepts. On the other hand, in the red group, crack detection concepts are related to metaheuristic techniques such as artificial bee colony and ML regression and classification techniques.

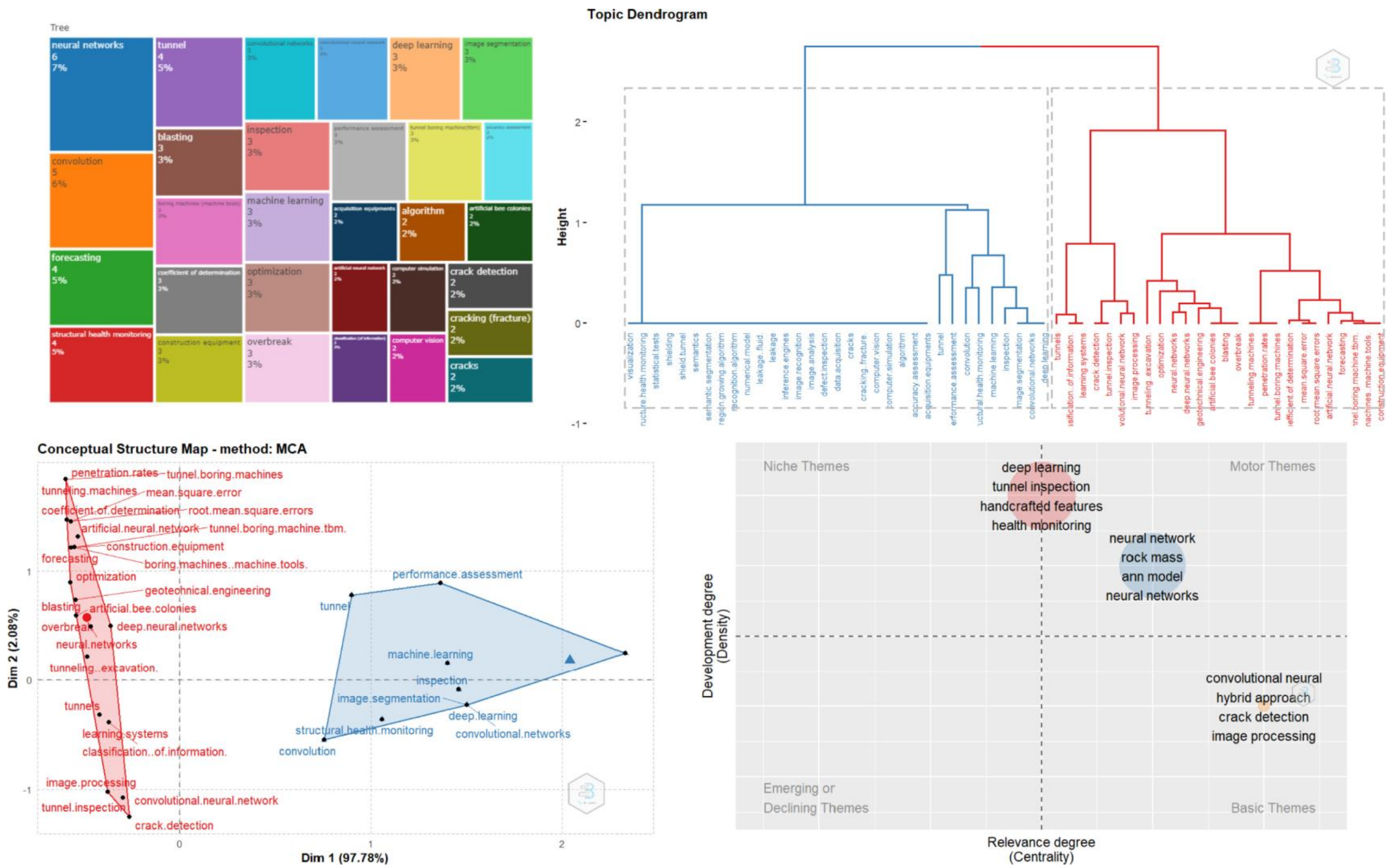

Figure 4.4. Tree, Thematic, conceptual and dendrogram maps applied a Tunnel dataset.

4.4.2. Traditional analysis

In Table 4.4, a summary of the techniques, applications, and results obtained in the different works analyzed is shown. Regarding the applications, the inspections and monitoring of tunnels stand out, in addition to the prediction of penetration rates and performances. Among the techniques, the use of SVM, convolutional networks and Multilayer perceptron stands out. On the other hand, the first line identified in the bigram analysis is related to tunnel crack detection. In Doulamis et al. (2018), convolutional neural networks and fuzzy spectral clustering were used for real-time crack detection in tunnels. This article proposes a computational vision model for tunnel crack detection, a challenging process due to low visibility, curvature, and crack structures that, although very narrow, are very deep. The proposed system integrates a robot that examines tunnels in real-time as it moves through the infrastructure. Initially, a convolutional neural network is used to detect cracks. Then, a combined fuzzy spectral clustering is introduced to refine the detected crack regions. The model was tested in tunnels on the Egnatia Highway. Due to the low visibility and geometry of the system, the accuracy and F1-score values are not that high; however, the system offers a considerable improvement in detection compared to existing methods. Additionally, the ability of the robot to touch the crack allows for on-site measurements with accuracy.

In Gong et al. (2021), an image acquisition system is designed, which uses multi-line scanning cameras. The objective is to capture images of the tunnel surface to generate a model for automatic crack detection. For the training of the model, three stages were developed. The first is an improvement of the dataset through a frequency-domain improvement algorithm. A filter is then generated to remove noise generated by water stains and existing devices on the tunnel’s surface. Finally, a segmentation algorithm is used to segment the cracks. The algorithm was tested on Line 1 of the Beijing subway, surpassing state-of-the-art algorithms.

Predicting cracks or overflows in the face of critical conditions is vital in monitoring and maintaining essential infrastructure. In Koopialipoor et al. (2019a, 2019b), a neural network was built, which was used to predict the overbreak induced by the blasting operations of the Gardaneh Rock tunnel. R2 values of 0.923 were obtained in the validation set. With this model and considering that overbreak is one of the main difficulties in tunnel excavations, the excavation operation is improved. Specifically, extra drilling of 47% was achieved.

Table 4.4. Summary of applications and techniques in Tunnels.

Reference	Application	Techniques	Results	Data
(DOULAMIS et al., 2018)	Tunnel inspection for structural monitoring	1) CNN-FuzzySpectral 2) SVM (Rbf) 3) SVM (Linear)	1) Acc = 0.64, F1 = 0.49 2) Acc = 0.58, F1 = 0.33 3) Acc = 0.54, F1 = 0.31	Images are from the Metsovo motorway tunnel in Greece.
(GONG et al., 2021)	Automatic visual inspection of cracks in tunnels	A proprietary framework that includes Crack enhancement, threshold segmentation, and filtering.	1) Acc = 0.85, Re = 0.93	100 cracks as experimental data. In the experiment, a positive detection is considered if more than 50% of the crack is identified
(KOOPIALIPOOR et al., 2019a)	Predict overtopping induced by blasting operations in tunnels.	1) ABC-ANN	1) R2 = 0.923, RMSE = 0.428	Dataset of Gardaneh Rokh tunnel, Iran.
(KOOPIALIPOOR et al., 2019b)	Predict overtopping induced by blasting operations in tunnels.	1) ABC-ANN 2) ANN	1) R2 = 0.904, RMSE = 0.090 2) R2 = 0.947, RMSE = 0.065 Best values	330 datasets
(LI; LI; SU, 2016)	Reliability for the evaluation of the stability of tunnel structures	1) UD-SVM	1) R2 = 0.997, MSE = 0.023	20 training samples and 10 testing samples
(SÁNCHEZ-RODRÍGUEZ et al., 2018)	Periodic inspections of electrical energy, railway, structural and signaling infrastructures.	1) SVM (Linear)	1) Pr = 0.98, Re = 0.91, F1 = 0.94 Averages without consider others	The datasets used come from LYNX Mobile Mapper from Optech Inc.
(MAKANTASIS et al., 2015)	Inspection, evaluation, maintenance and safety of tunnels	1) CNN 2) AnchorGraph 3) SVM (Rbf)	1) Acc = 0.886, F1 = 0.886 2) Acc = 0.757, F1 = 0.822 3) Acc = 0.719, F1 = 0.795	Over 100,000 samples acquired with a single monocular camera
(KOOPIALIPOOR et al., 2019c)	Prediction of the penetration rate of tunnel boring machines.	1) ANN 3 Layers (DNN)	1) R2 = 0.934, RMSE = 0.032	A database comprising 1286 datasets of five parameters was considered.
(XU et al., 2019)	Performance prediction in mechanized tunnel projects	1) KNN 2) ANN 3) SVM	1) R2 = 0.907, RMSE = 0.204 2) R2 = 0.924, RMSE = 0.180 3) R2 = 0.914, RMSE = 0.183	Data 209 records generated in 13 km of the PSRWT tunnel.
(TORABI-KAVEH; SARSHARI, 2020)	The convergence rates of two tunnels from the Namaklan Twin Tunnel were predicted	1) ANN-MLP 2) ANN-RBF	1) R2 = 0.93, RMSE = 0.17, MAE = 0.12 2) R2 = 0.81, RMSE = 0.27, MAE = 0.22	The dataset was collected through field investigations and laboratory experiments.
(ZHANG et al., 2022b)	Prediction of lining response for twin tunnels	1) MARS 2) Decision Tree	1) R2 = 0.968 2) R2 = 0.994	A total of 682 cases were modeled considering five key parameters on twin-tunnel structural forces
(PROTOPAPADAKIS; DOULAMIS, 2015)	Detection of concrete defects in tunnels	1) CNN 2) SVM (Poly) 3) SVM (Rbf)	1) Acc = 0.886, F1 = 0.886 2) Acc = 0.877, F1 = 0.719 3) Acc = 0.864, F1 = 0.795	Detections are captured and validated by an expert
(REN et al., 2020)	Automatic detection and segmentation of concrete cracks in tunnels	1) U-Net 2) CrackSegNet-Dilated 3) CrackSegNet-FocalLoss	1) Pr = 63.85,Re = 47.46,F1 = 54.45 2) Pr = 74.84,Re = 70.46,F1 = 72.58 1) Pr = 66.07, Re = 85.54,F1 = 74.55	A total of 409 images, 4032 x 3016, were obtained in a tunnel in Huzhou

In Li, Li and Su (2016) stability evaluation using reliability was applied; the main difficulty of the above is the nature of the limit state function. The article developed a hybrid approach, integrating the uniform design with a regression model using the support vector machine technique, was developed. The hybrid proposal was evaluated in three tunnels with different characteristics—a first simplified case and later two real cases. The results concluded that the hybrid method could train adequately with less data than traditional methods, maintaining the quality of the predictions.

The second line of research obtained from bigram analysis is related to tunnel inspection and analysis of operational conditions. One way to detect the health status of structures in tunnels is by laser scanning. This form is proposed in the article by Sánchez-Rodríguez et al. (2018), where they focus directly on railway tunnels because they represent one of the tunnels whose accidents can be more catastrophic. However, it is mentioned that the human component in these types of constructions continues to be predominant, which is why it is worrying and generates a need to advance through automation. The study determined that laser scanning in conjunction with custom processing tools can provide data for additional structural operations. A methodology is used divided into the preprocessing of the point cloud, then the division of the cloud into terrestrial and non-terrestrial points, and finally, the detection of the elements present and each of the clouds.

In Makantasis et al. (2015), Deep convolutional neural networks were used for efficient vision-based tunnel inspection. One of the main challenges facing engineers today is the safe inspection, evaluation, maintenance, and operation of civil infrastructure. For this process, manual processes are used, which are slow and produce subjective results, or automated approaches, which depend on complex handmade characteristics, where it is seldom known in advance which characteristics are important for the problem in question. This article proposes a fully automated tunnel evaluation approach. Complex features were hierarchically constructed with a monocular camera using a deep learning model. The obtained features were used to train a defect detector using a convolutional neural network to build high-level features and, as a detector, a multilayer perceptron was used due to its global function approximation properties. Very rapid predictions were obtained with the proposed system due to the advancing nature of convolutional neural networks and multilayer perceptrons.

In Koopialipoor et al. (2019c), an application of deep neural networks was employed to predict the penetration rate of tunnel boring machines(TBM). Performance prediction is critical to accurate and reliable cost estimation using a TBM in mechanized tunnel construction projects. A wide variety of artificial intelligence methods have been used in predicting the penetration rate of TBM. This focuses on developing a deep neural network (DNN) based model, an advanced version of an ANN, for predicting the penetration rate of TBM based on data obtained from the transfer tunnel of raw water Pahang–Selangor in Malaysia. Based on the results obtained from the coefficient of determination and the root mean square error (RMSE), a significant increase in the prediction of the performance of the penetration rate is achieved through developing a predictive DNN model. The DNN model demonstrated better performance for estimating the penetration rate than the ANN model.

In Xu et al. (2019), a supervised machine learning technique was used to predict tunnel boring machine penetration rate. Prediction of the penetration rate is a complex and challenging task due to the interaction between the tunnel boring machine (TBM) and the rock mass. This article discusses the use of supervised ML techniques, including k-nearest neighbor (KNN), chi-squared automatic interaction detection (CHAID), SVM, classification and regression trees (CART), and ANN to predict the penetration rate (PR) of a TBM. To achieve this goal, an experimental database based on field observations and laboratory tests was created for a tunnel project in Malaysia. In the database, uniaxial compressive strength, Brazilian tensile strength, rock quality designation, weathering zone, push force, and revolution per minute was used as inputs to predict the TBM PR. Then KNN, CHAID, SVM, CART, and NN predictive models were developed to select the best. In this article, the KNN model has the best performance to predict the PR of TBM. The KNN model identified uniaxial compressive strength (0.2) as the most important and revolution per minute (0.14) as the least important factor in predicting the TBM penetration rate.

In Torabi-Kaveh and Sarshari (2020), the topic of tunnel convergence prediction using ML methods is addressed. The study focuses on the construction of a tunnel in Namaklan where ANN, multivariate linear regression (MLR), multivariate nonlinear regression (MNR), support vector regression (SVR), Gaussian process regression (GPR), regression trees (RT), to predict the convergence rate (CR). Six predictive parameters were selected, which are: cohesion, internal friction angle, uniaxial compressive strength of the rock mass, rock mass classification, overburden height, and the number of rock bolts installed. Using the coefficient of determination ($R2$) it was possible to determine that the MLP-ANN model is the most optimal, with $R2 = 0.93$. In contrast, the MLR model has a prediction with the lowest $R2 = 0.61$, and the RT and GPR models are the least indicated for predicting these indicators.

In Zhang et al. (2022b), it is mentioned how to predict the linear response for tunnels built in anisotropic clay. This is important when building a tunnel because it considerably impacts the duration and safety it will have over time. Five parameters were taken into account to measure:

Burial depth, the center-to-center distance of the tunnel, soil resistance, stiffness ratio, and degree of anisotropy. These are known as finite elements (FE). Then, through the application of multivariate adaptive regression splines and decision tree regression methods, the prediction of the bending moment within the linings of the first tunnel is evaluated based on the cases of FE constructed. This allows engineers to estimate the structural response of tunnels with greater reliability.

In Protopapadakis and Doulamis (2015), the use of an automated robotic inspector that can assess the condition of a tunnel is proposed. This inspector has mobile autonomy, has a crane arm, and is directed by the crack detector based on computer vision. In addition, the robotic inspector has ultrasound sensors, stereo cameras, and a laser scanner. The inspector's method is initially crack detection through a deep learning approach, using a visual inspection based on convolutional neural networks. Then this generates a detailed 3D model of the cracked area using photogrammetric methods. In Ren et al. (2020), the idea of detecting cracks in tunnels and their segmentation is raised. They do this using a convolutional deep neural network technique called ''CrackSegNet,'' and a dense segmentation of cracks is carried out in the form of pixels. The network consists of a backbone, dilated convolution, spatial pyramid cluster, and jump connection modules. The proposed network achieves significantly higher precision and generalizability than the compared methods, thus achieving greater efficiency at a low cost.

The manual inspection procedure for cracks and leaks in metro shield tunnels is slow. One of the main causes of the slowness is the difficulty, which is an interference defect that occurs in the tunnels. In Huang, Li and Zhang (2018), the manual procedure was replaced with an automatic procedure based on deep learning. In particular, a semantic segmentation algorithm is proposed to identify cracks and leaks. The proposed method was compared against state-of-the-art methods, finding that the semantic segmentation algorithm is superior to the other methods analyzed. This superiority was not only in the quality of the recognition but also in the processing times to obtain the result. Robotics is a fundamental actor in the automation of tunnel inspection. In Protopapadakis et al. (2016), a robotic inspector is used for tunnel evaluation. Among the important features, the robotic inspector is able to navigate autonomously in the structure. In addition, it captures images and finally analyzes them to identify defects in the structure. The cracks are detected through deep learning techniques, and later the robot can create a 3D model with the detail of the cracked area. The autonomous system was evaluated in railway and road tunnels.

4.5. Construction Management

Due to the complex and dynamic nature of many construction and infrastructure projects, the ability to detect and classify key onsite activities by various teams and human personnel can improve the quality and management of construction projects. One of the approaches in this matter is using sensors integrated with smartphones as data collection and transmission nodes to detect activities in construction equipment. These systems of recognition and classification of the activity of construction workers are combined with data collected from sensors and ML models. In this way, it is possible to assess the condition, behavior, and surrounding context of construction workers to effectively manage and control projects. Another example is related to safety in construction management. Safety Leading Indicators are a way of flagging sites that are most at risk. Some works propose using machine learning to develop safety indicators that classify sites according to their safety risk in construction projects.

4.5.1. Bigram analysis

Figure 4.5 shows the bigram analysis performed for the management concept. In the upper left figure, the treemap indicates that Construction projects, Contract delivery, price index, and activity recognition correspond to the most frequent bigram. Regarding ML techniques, we see that the support vector machine is the only technique that appears in the treemap. When analyzing the thematic map, lower right figure, we see an important group related to project management and delivery and other groups related to the activity recognition. In the conceptual structure map, two groups are distinguished in light blue a group related to management and delivery and a more diffuse red group. In the red group, the concepts of productivity monitoring and construction productivity appear again, but there are also the concepts of activity recognition and construction safety.

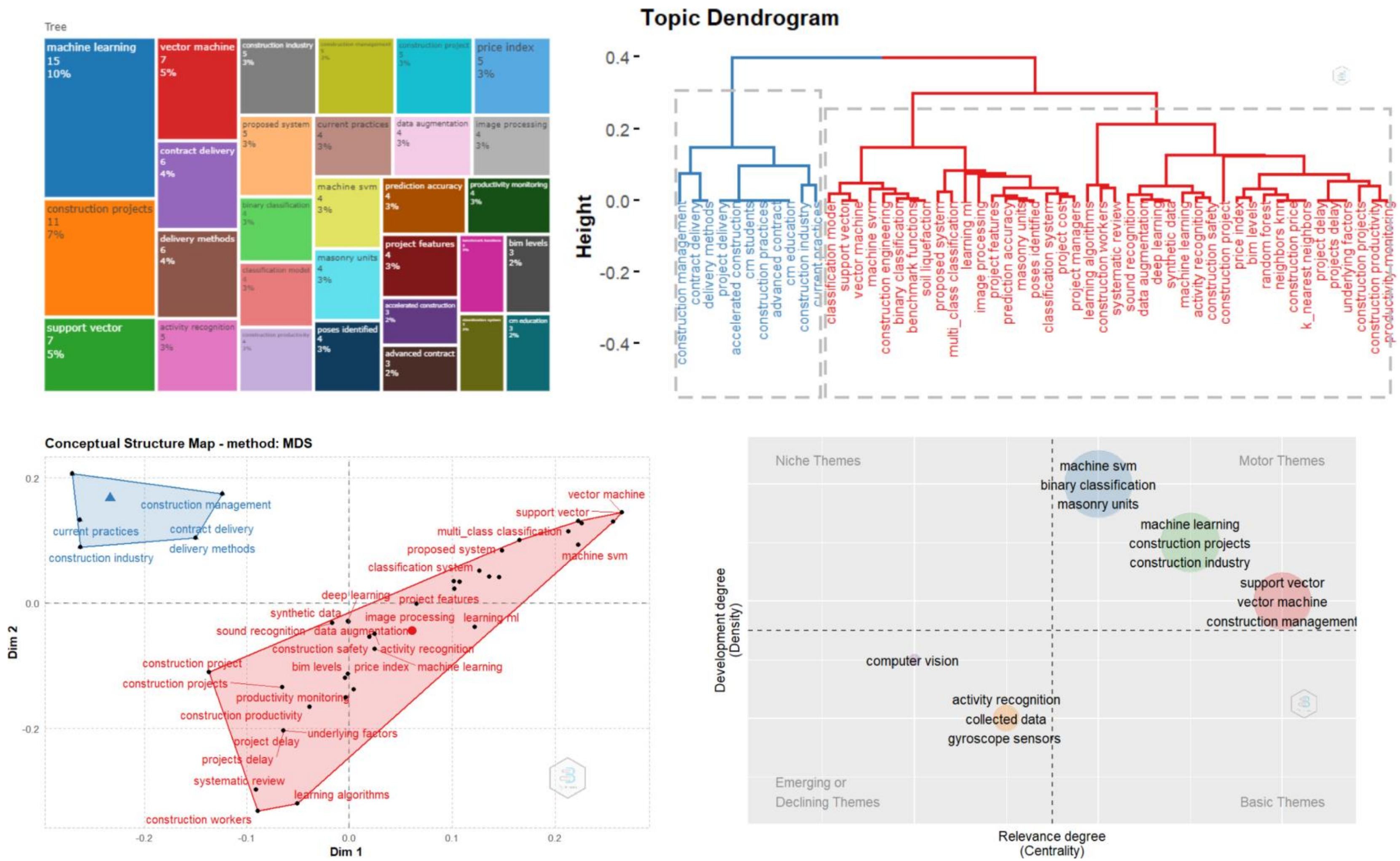

Figure 4.5. Tree, Thematic, conceptual and dendrogram maps applied a Management dataset.

4.5.2. Traditional analysis

In Table 4.5, a summary of the articles analyzed in the management area is shown. Among the applications that stand out is the detection of critical activities in relation to safety on the construction site. On the other hand, there are also works related to the prediction of cost indicators or the progress of the project. From the point of view of techniques, KNN and ANN are the main techniques used. By complementing this information with the bigram analysis, we observe a first group related to security and recognition of activities. Activity recognition is an emerging general area with great potential in the Construction Engineering Management (CEM) domain. Due to the complex and dynamic nature of many construction and infrastructure projects, the ability to detect and classify key activities carried out in the field by diverse teams and human personnel can improve project decision-making and control quality and reliability.

In Akhavian and Behzadan (2015), embedded smartphone sensors are proposed as ubiquitous multimodal data collection and transmission nodes to detect detailed activities of construction teams. Accelerometer and gyroscope sensors are used to train supervised learning classifiers. To evaluate the models, the selection of discriminatory characteristics was used to extract, the sensitivity analysis of the size of the data segmentation window, and the choice of the classifier to train. Choosing the level of detail (LoD) in describing team actions (classes) is an important factor with a major impact on ranking performance. Computational efficiency and end-use of the classification process may well influence the decision for selecting an optimal LoD to describe team activities (classes).

In Akhavian and Behzadan (2016), a smartphone-based construction workers' activity recognition and classification system is proposed. Assessing the condition, behavior, and surrounding context of construction workers is essential for effective project management and control. The embedded sensors of ubiquitous mobile phones offer a great opportunity to automate the recognition of worker activity. This study proposes the use of smartphones to capture body movements by collecting data using integrated gyro and accelerometer sensors. The collected data is used to train five different types of ML algorithms. Activity recognition precision analysis has been performed for all different ML activity categories and classifiers in user-dependent and independent ways. The results indicate that neural networks outperform other classifiers by offering accuracy ranging from 87% to 97% for user-dependent categories and from 62% to 96% for user-independent categories.

Table 4.5. Summary of applications and techniques in Construction Management.

Reference	Application	Techniques	Results	Data
(AKHAVIAN; BEHZADAN, 2015)	Detect and classify key activities carried out in the field by various teams and human personnel	1) ANN 2) Decision Tree 3) KNN	1) Acc = 88.7 2) Acc = 84.1 3) Acc = 87.5; Averages	Embedded smartphone sensors as data collection and transmission nodes
(AKHAVIAN; BEHZADAN, 2016)	Detect and classify key activities carried out in the field by various teams and human personnel	1) ANN 2) Logistic regression 3) KNN	1) Acc = 90.7 2) Acc = 88.2 3) Acc = 90.5; Averages	Embedded smartphone sensors as data collection and transmission nodes
(TIXIER et al., 2016)	Base decisions related to construction safety under the uncertainty of knowledge extracted from objective empirical data	1) Random Forest 2) SGTB	Rank Probability Skill Score 1) RPSS = 0.1148 2) RPSS = 0.0865; Averages	Using NLP, a dataset of 4400 attributes and safety outcomes was built.
(POH; UBEYNARAYANA; GOH, 2018)	Development of indicators that classify sites according to their safety risk in construction projects.	1) Decision Tree 2) RF 3) KNN	1) Acc = 0.71 2) Acc = 0.78 3) Acc = 0.73	Data were obtained from a large contractor in Singapore and the data were accumulated from the year 2010 to 2016.
(NATH; BEHZADAN, 2017)	Monitoring workers' activities	1) SVM	Confusion matrices are reported for activity recognition. Productivity analysis, the time in seconds are reported	Smartphone Sensors
(RASHIDI et al., 2016)	Automatically detect various types of building materials in building images	1) ANN 2) RBF 3) SVM	1) Pr = 65.3, Re = 60.0 2) Pr = 91.1, Re = 70.4 3) Pr = 88.1, Re = 68.0 Averages were considered	The dataset contains 750 images taken of various constructions, the job site was collected
(POUR RAHIMIAN et al., 2020)	Monitor the implementation of each individual part of the buildings and reflect them in the BIM models	A framework that includes different machine learning techniques such as CNN and SVM	No metric defined	Data from the original BIM models and the as-built images
(ZHANG et al., 2018b)	Analysis of construction sound data to monitor project procedures.	1) Hidden Markov Model	1) Acc = 94.3	Mel-frequency cepstral coefficients are extracted as the features of the six types of sound data.
(WANG; ASHURI, 2017)	Enhance Construction Cost Index forecasting	1) PERT 2) KNN 3) ARIMA	1) MAPE = 0.83, MSE = 7415, MAE = 77 2) MAPE = 0.78, MSE = 9138, MAE = 70 3) MAPE = 3.97, MSE = 161996, MAE = 368 Log term prediction	Short-, mid-, and long-term. Data from January 1985 to December 2014 is collected from ENR and the bureau of labor statistics

Construction safety is one of this industry's most relevant and concerning issues. Although ML has been considered by construction research for more than two decades, it has not yet been applied to safety concerns. In Tixier et al. (2016), RF and Stochastic Gradient Tree Boosting (SGTB) models are proposed to a set of categorical safety attributes data extracted from a large set of textual reports of construction injuries. The integration of a natural language processing tool (NLP) developed by the same researchers in previous works is proposed. Both models can predict the type of injury, the type of energy, and the part of the body with great performance (0.236 <RPSS <0.436), surpassing the parametric models found in the literature. This work opens the door to a new field of research, where construction safety is considered an empirically founded quantitative science.

The construction industry is one of the most dangerous in many countries. Safety leading indicators are a way to mark sites that are most at risk. ML is not widely used in the construction industry, especially in the development of safety-leading indicators. In Poh, Ubeynarayana and Goh (2018), an ML approach to developing safety leading indicators that rank sites according to their safety risk on construction projects is proposed. In this study, five ML algorithms were compared for predicting the occurrence and severity of accidents. The data includes safety inspection records, accident cases, and project-related data. These data were obtained from a large contractor in Singapore, and the data was accumulated from 2010 to 2016. From thirty-three input variables, 13 input variables were selected using a combination of Boruta technical feature selection and decision tree. Of the 13 input variables selected, six of them are related to the project, and seven of them are elements in the Contractor safety inspection checklists. During validation, the RF model provided the best prediction performance with an accuracy of 0.78 and has achieved substantial strength according to the Weighted-Kappa statistics of 0.70.

Constant monitoring of work progress and identifying deviations from plans are critical to designing a more efficient and safe workplace. Sustained physical work will result in work-related musculoskeletal disorders (WMSD) that can adversely affect the health of workers and the project's budget, schedule, and productivity. To prevent WMSD, health and safety organizations have established rules and regulations limiting labor-intensive activities' duration and frequency. In Nath and Behzadan (2017), a wearable sensor data and ML system was used for activity recognition, productivity analysis, and ergonomic risk assessment. The model implements embedded smartphone sensors and a multi-class Support vector machine (SVM) to recognize worker activities in the field and extract duration and frequency information, which will ultimately be used to assess productivity and ergonomic risks associated with each activity.

Project management, control, and delivery were other important groups identified in the bigram analysis. In Rashidi et al. (2016), Digital images and video clips collected at construction job sites are commonly used for extracting useful information. Exploring new applications for image processing techniques within construction engineering and management is a steadily growing field of research. One of the initial steps for various image processing applications is automatically detecting various construction materials on construction images. In this paper, the authors conducted a comparison study to evaluate the performance of different ML techniques for detecting three common building materials: Concrete, red brick, and OSB boards. The employed classifiers in this research are: Multilayer Perceptron (MLP), Radial Basis Function (RBF), and Support Vector Machine (SVM). To achieve this goal, the feature vectors extracted from image blocks are classified to compare the efficiency of these methods for building material detection. The results indicate that for all three types of materials, SVM outperformed the other two techniques in accurately detecting the material textures in images. The results also reveal that the common material detection algorithms perform very well in cases of detecting materials with distinct colors and appearance (e.g., red brick). In contrast, their performance for detecting materials with color and texture variance (e.g., concrete) and materials containing similar color and appearance properties with other elements of the scene (e.g., ORB boards) might be less accurate. For example, OSB surfaces and flooring can have similar color and texture values, making the detection process more challenging. In these cases, an interesting line to explore is strengthening the database with more images. These images can be real or artificially generated through GANs, for example.

In Pour Rahimian et al. (2020), while unavoidable, inspections, progress monitoring, and comparing as-planned with as-built conditions in construction projects do not readily add tangible intrinsic value to the end-users. In large-scale construction projects, the process of monitoring the implementation of every single part of buildings and reflecting them on the BIM models can become highly labor-intensive and error-prone due to the vast amount of data produced in the form of schedules, reports and photo logs. In order to address the mentioned methodological and technical gap, this paper presents a framework and a proof of concept prototype for on-demand automated simulation of construction projects, integrating some cutting-edge IT solutions, namely image processing, ML, BIM, and Virtual Reality. This study utilized the Unity game engine to integrate data from the original BIM models and the as-built images, which were processed via various computer vision techniques. These methods include object recognition and semantic segmentation for identifying different structural elements through supervised training in order to superimpose the real-world images on the as-planned model. The proposed framework leads to an automated update of the 3D virtual environment with the states of the construction site. This framework empowers project managers and stockholders with an advanced decision-making tool, highlighting the inconsistencies in an effective manner. This paper contributes to body knowledge by providing a technical exemplar for the integration of ML and image processing approaches with immersive and interactive BIM interfaces, the algorithms and program codes which can help replicability of these approaches by other scholars.

In Zhang et al. (2018b), the sound recognition technology, which has been adopted in diverse disciplines, has not received much attention in the construction industry. Since each working and operation activity on a construction site generates its distinct sound, its identification provides imperative information regarding work processes, task performance, and safety-relevant issues. Thus, accurate sound data analysis is vital for project participants to monitor project procedures, make data-driven decisions, and evaluate task productivities. To accomplish this objective, this paper investigates the sound recognition technology for construction activity identification and task performance analyses. Mel-frequency cepstral coefficients are extracted for sound identification as the features of the six types of sound data. In addition, a supervised ML algorithm called Hidden Markov Model is used to perform sound classification. The research findings show that the maximum classification accuracy is 94.3% achieved by a 3-state HMM. This accuracy of the adopted technique is expected to reliably execute the construction sound recognition, which significantly leverages construction monitoring, performance evaluation, and safety surveillance approaches.

In Wang and Ashuri (2017), the Construction Cost Index (CCI) is calculated monthly and published by Engineering News-Record (ENR). CCI is utilized for capital project budgeting and construction cost estimation, especially when mid-and long-term forecasts are needed. Accurate prediction of CCI helps avoid underestimating and overestimating project costs. However, the current prevailing time series prediction models do not show promising results, especially in mid- and long-term forecasting. The capability of two machine-learning algorithms, k nearest neighbor (KNN) and perfect random tree ensembles (PERT), are utilized to enhance CCI forecasting, especially in the mid-and long-term. The proposed machine-learning algorithms can significantly enhance forecasting CCI’s predictability in all the short-, mid-, and long-term scenarios. Data from January 1985 to December 2014 is collected from ENR and the bureau of labor statistics to conduct empirical studies and quantitatively measure the performance of the proposed methods. As the outcomes show, the prediction accuracies of both proposed methods are better than those of current prevailing time series models under all the tested scenarios. It is anticipated that cost estimators can benefit from CCI forecasting by incorporating predicted price variations in their estimates, preparing more-precise bids for contractors, and developing more accurate budgets for owners.

5. Future directions

Figure 5.1 shows a summary diagram of the five main topics obtained along with the lines that are being developed in each of the topics. In addition, Table 5.1 has been introduced, which proposes four groups related to challenges and future lines. The first group in the Table, is related to the prediction of variables. The second group is concerned with safety applications, the third group with images and convolutional networks, and the fourth group with the optimization of structural designs. For the first group, which corresponds to the prediction or classification of variables, in the topic of concrete, we find the prediction of its mechanical properties or, in the case of retaining walls, the prediction of geotechnical variables. When analyzing the metrics of the ML models, it is observed that, in general, the ML models are capable of predicting the variables with outstanding results. So the challenge is to move to the second level of ML application. With this, we mean: that the previous studies have been carried out with historical datasets compiled by the authors. How can the model now be put into a production environment? The first stage is to be able to generate a data lake with information holistic and related to the production processes. The creation of the data lake implies the capture of the variables of interest to subsequently carry out all the engineering and data governance for the proper development of this. On the other hand, how does the result of this prediction fit into decision-making? A model that has good predictions but that is not useful for making decisions does not generate value within an industrial process. These same challenges related to the prediction of variables appear in tunnels, for example, for certain variables such as penetration or overtopping rates or the prediction of costs related to project management.

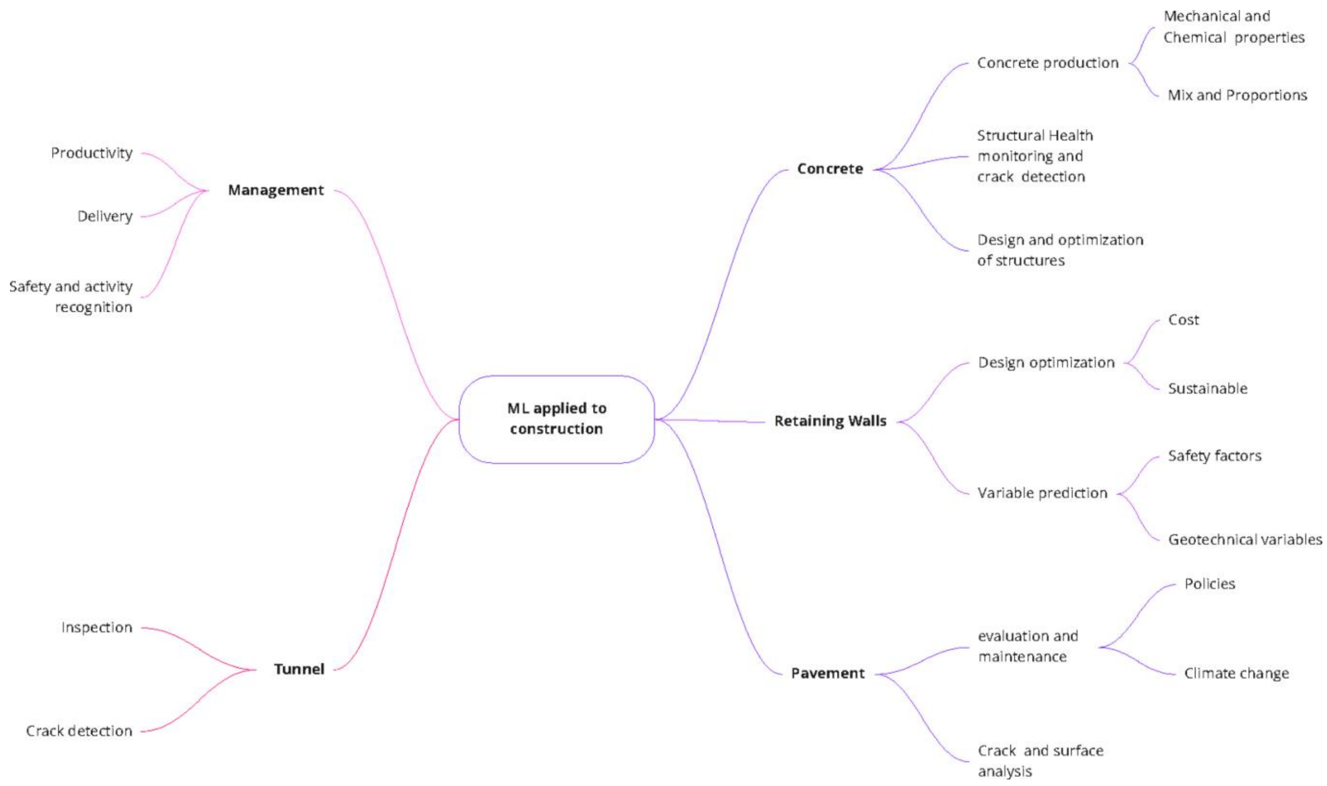

Figure 5.1. Summary of the main topics identified and lines developed in each of them.

Table 5.1. Summary of machine learning challenges.

Group	Area	Reference	Actual state	ML-Challenges
Prediction or classification Variables	Concrete	BEHNOOD; GOLAFSHANI (2020); CAI et al. (2020); HUANG; BURTON (2019); JIAO et al. (2019); NGO et al. (2022); NILSEN et al. (2019); ZHANG et al. (2022a); ZHENG et al. (2019); ZIOLKOWSKI; NIEDOSTATKIEWICZ (2019)	Traditional Machine Learning Models	1) Automatic data acquisition and structuring of the data lake. 2) Models in productive environments, integrated into the decision making 3) Evaluation of the impact of the model on the production process and feedback of the models for future recalibrations
	Retaining wall	BENBOURAS; LEFILEF (2023)		
	Pavement	INKOOM et al. (2019); MAHPOUR; EL-DIRABY (2021, 2022); MARCELINO et al. (2021); PEI et al. (2022); SHTAYAT et al. (2022); TIEN BUI; HOANG; NHU (2019)		
	Tunnel	KOOPIALIPOOR et al. (2019c); MAKANTASIS et al. (2015); SÁNCHEZ-RODRÍGUEZ et al. (2018); TORABI-KAVEH; SARSHARI (2020); ZHANG et al. (2022b)		
	Management	WANG; ASHURI (2017); ZHANG et al. (2018b)		
Safety applications	Concrete	ASTERIS et al. (2021); BAYAR; BILIR (2019); MARINIELLO et al. (2021)	Traditional Machine Learning Models	The same challenges as the previous group. Additionally, the incorporation of analytics and big data techniques for real-time
	Retaining wall	GORDAN et al. (2019); MISHRA; SAMUI; MAHMOUDI (2021)		
	Pavement	ESCALONA et al. (2019)		
	Tunnel	KOOPIALIPOOR et al. (2019a, 2019b)		
	Management	AKHAVIAN; BEHZADAN (2015, 2016); NATH; BEHZADAN, (2017); POH; UBEYNARAYANA; GOH (2018); TIXIER et al. (2016)		
Crack and failure detection	Concrete	ATHANASIOU et al. (2020); HAN et al. (2021)		1) More efficient network models 2) Use of cloud components to perform more efficient training, process more images, and with better metrics
	Retaining wall	LIU et al. (2022)		

	Pavement	BANHARNSAKUN (2017); CHEN et al. (2022); ESCALONA et al. (2019); FEI et al. (2020); GOPALAKRISHNAN et al. (2017); HOANG (2018); HOANG; NGUYEN (2019); ZHANG et al. (2017, 2018a, 2019)	Usually, models that incorporate deep learning techniques such as deep convolutional networks	
	Tunnel	DOULAMIS et al. (2018); GONG et al. (2021); PROTOPAPADAKIS; DOULAMIS (2015); REN et al. (2020)		
	Management	POUR RAHIMIAN et al. (2020); RASHIDI et al. (2016)		
Structure optimization	Concrete	YOON et al. (2018)	Optimization models that integrate machine learning techniques and metaheuristics algorithms. CO2, costs and energy optimization criteria are considered	Incorporate cradle-to-grave analysis, robust multi-objective optimization that incorporates multi-criteria decisions in environmental, social, economic, and constructability dimensions
	Retaining wall	GARCÍA; MARTÍ; YEPES (2020); GARCÍA; YEPES; MARTÍ (2020); KIM et al. (2021); MARTÍNEZ-MUÑOZ et al. (2021); MOAYYERI; GHAREHBAGHI; PLEVRIS (2019); YEPES; MARTÍ; GARCÍA (2020)		

Considering the overtopping case and safety factor prediction applications such as in the management topic, related to safety and activity recognition or in the case of safety factor prediction in retaining walls. In addition to the two previous challenges, there is a challenge that these predictions must be carried out in times close to real. This generates challenges of having to integrate these safety models with big-data techniques in order to execute decision-making in real-time. The above can also be complemented with all the technologies developed by cloud providers. Another group of interesting applications is related to detecting cracks in concrete, pavements, retaining walls, tunnels, or the case of activity recognition. Usually, the techniques used are related to convolutional neural networks. Convolutional networks, in general, are quite intensive in computation, especially in the training part and if they have a significant number of layers, also when making predictions. Again thinking about the productive case, it is interesting for networks with many layers to be able to generate simpler architectures, with fewer layers, capable of operating on simple hardware, for example, cell phones. This allows, for example, in the case of security applications to be able to carry out close detection in real-time directly in the hardware. On the other hand, in the case of having to train neural networks, it is interesting to explore the capabilities of cloud providers to generate better training in less time. Here we also emphasize the importance of generating a data lake for future experiments and development.

Finally, there is a group of applications related to the optimization of structures. Usually, what is found here are cost optimizations, CO2, or embodied energy. We believe that a fundamental point that would make it easier to integrate into decision-making is to consider different sustainability criteria: economic, environmental, social, and constructability, which naturally implies multi-objective optimization with multi-criteria decisions. When defining the objective function that guides this optimization, the complete life cycle analysis must be considered: Manufacturing, Construction, Use, Maintenance, and End of Life. Furthermore, all structural designs involve variability and uncertainty. The initial parameters, the structure's dimensions, the materials' mechanical characteristics, and the loads may differ from the design values. Therefore, the optimization should naturally consider this uncertainty to obtain a robust design.

6. Conclusions

In this work, we propose a hybrid methodology. As a first instance, we used the bidirectional encoder representation for the transforms technique to find topics in the abstracts of articles obtained from Scopus. Later we used the expert knowledge to select the relevant topics.

This methodology found five topics of ML applications to construction: concrete structures, retaining walls, pavement, tunnels, and management. The leading journals in this area of research are Automation in Construction, Construction and Building Materials, and Computer Engineering.

On the topic of concrete, we distinguish two main research lines; the first is strongly related to automatic crack detection and monitoring of structures, and the second cluster is associated with the prediction or automatic identification of parameters for an efficient and sustainable design of concrete. Regarding retaining walls, the main lines of research have to do with optimizing the design of walls where hybrid techniques between ML and metaheuristics have obtained good performance. On the other hand, the prediction of design parameters of the structure through ML techniques has been studied. Regarding the pavement topic, an essential line of research is related to pavement maintenance policies and how events such as climate change affect them. A second line is related to monitoring and detecting cracks and distress in the pavement. In the case of tunnels, structure monitoring appears again as a main line of research in addition to identifying, predicting, and optimizing operational variables such as penetration rates, excavations, and geotechnical variables. Finally, in the case of construction management, incorporating ML in the control, management, costs, and delivery of projects is a line of interest. Still considering project management and administration, another line is related to the safety of workers and the identification of activities within the work.

There is an opportunity to strengthen the proposed hybrid review technique regarding the next steps. We would particularly like to carry out the analysis of other construction themes and consider other areas. Considering the research lines found, we observe that most investigations focus on obtaining the model. However, the model must be inserted into the decision-making process to generate value. At this point, we see an opportunity to extend much of the research. In the case of lines that incorporate optimizations, a large number of fixed parameters are usually considered; an extension would be to consider a robust and multi-objective optimization, considering not only the cost of the optimization but also variables such as environmental or social.

The study is particularly useful for supporting decision-making processes and optimizing the effectiveness and sustainability of construction processes. The results have their roots in the BERT methodology, which leverages ML to investigate prominent and relevant topics. Thus, identifying critical research lines that have the most significant influence in practice provides clear guidance for management to identify, select, and analyze which ML method makes sense to improve their companies’ performance and sustainability.

This is particularly relevant since the practical application of ML demands a high-skilled workforce and capabilities, which companies do not easily reach. First, information technology resources are highly disputed and often scarce. Second, construction demands compliance because of strict rules and norms, which adds further resources. Hence, having a study setting out the base and the state-of-the-art regarding ML for construction is vital for accelerating and reducing costs for achieving a more pervasive effect on the market.

Another significant implication is the results of the herein applied methodology. We uncovered critical areas in the construction sector by combining BERT methodology with experts' knowledge. Expanding such technic to include patents and other scientific and technological knowledge sources may be valuable for recognizing innovation opportunities. Considering that the construction sector is not broadly recognized for high innovativeness and given its relevance for the world's economy and sustainability, this might have a path for attracting entrepreneurs and companies to pursue innovations, primarily business model innovations combined with product innovations.

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Discussion

With the growing need for continuous BMI, imposed by the growing competitive environment turbulence, managing BMI is a vital albeit challenging activity. The main issue seems to lie in the fact that BMI is rather paradoxical. While building complementarities and improving core BMs effectiveness is crucial to compete, it often means making BMI harder because of rigidity and inertia. Hence, there is a tendency to focus on routine activities that underlies a BM. Humans are, after all, not fond of drastic changes and BMI is frequently painful. It involves changes in people's roles, layoffs and new hirings, shifting mindsets and paradigms and can involve negative impacts on existing stakeholders. Nevertheless, it is unavoidable: not conducting BMI is also life-threatening with similar (if not worse) negative effects.

Is there a way out of the paradox? This reflection motivated this doctoral thesis, whose main purpose was to address open issues on BMI management. Our findings advance in mapping and measuring DC for BMI, investigating integrated BMI structures functionality, adding to strategizing and structuring BMI efforts, and dive into BMI analytics by connecting management and engineering sciences. Although we do not provide a complete solution, we did not have such ambition, we provide advancements that assist in alleviating the pain.

In the first part, composed by Chapters 1 and 2, we contested the literature by suggesting and evidencing that DC and BMI share a bidirectional and non-recursive relationship, and that integrated BMI units may be functional for achieving sustained exploratory and radical BMI. The major deliverables of this part were a set of constructive measurements (Chapter 1) and a strategic roadmap to create functioning integrated BMI units (Chapter 2). The results of both chapters point to the same direction: making BMI part of the routine, like R&D for product and process innovations. Figure 2 summarizes the core contributions of Chapters 1 and 2. In dark red is the state of knowledge before and in dark green highlight our findings' contributions.

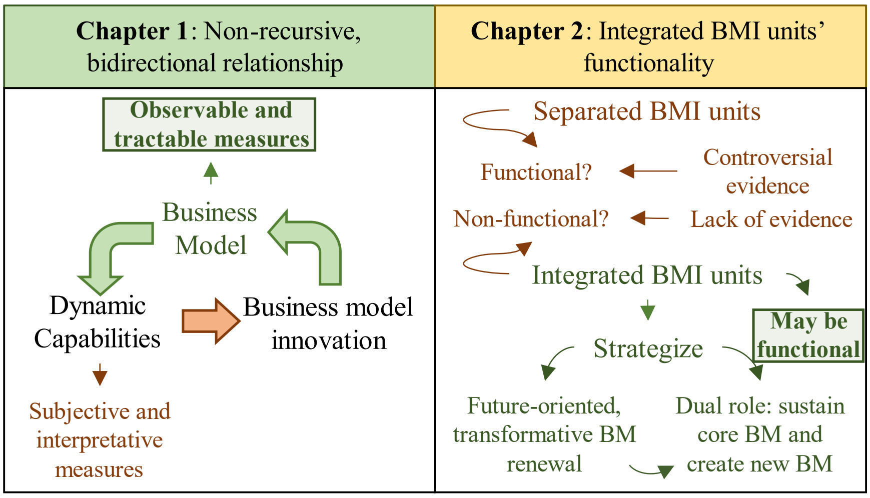

Figure 2. Summary of Chapters 1 and 2 core contributions.

Making BMI as one of the underlying mechanisms of creating, delivering, and capturing value poses a promising avenue to the paradox. Still, a relevant question regards the intensity and pace of BMI efforts through time. How sustainable are capabilities for BMI? Although environmental dynamics during this study was high because of digitalization, it will probably vary in the future, and so does the need for BMI. A path seems to lie in the balance between incrementing core BM and creating novel BMs, with wise resources' mobilization. In this regard, companies may need to create and dissolve DC for BMI on demand. The deployment of integrated BMI units, along with tractable measurements seem to be aligned with this notion.

In the second part (Chapters 3 and 4) we brought together engineering and management to propose the BMI analytics concept. Central to these chapters, is the idea of leveraging the interaction between human and machine, collaborative intelligence, to reach superior innovation performance. We also tested the application of Machine Learning technique (BERT-Topics) to improve opportunity recognition for BMI. Our findings suggest that the combination between artificial intelligence and human cognition is a promising avenue to cope with uncertainties, as the machine can augment human performance, who, in turn, can orchestrate the machine. Thus, combining a data-driven BMI process with the dominant experimentational and trial-and-error approach. While it seems impossible to change the need for experimentation, considering the existence of uncertainty, it can still be significantly improved with data science and applying more rigorous scientific methodology to BMI experiments. Figure 3 summarizes Chapters 3 and 4 core contributions.

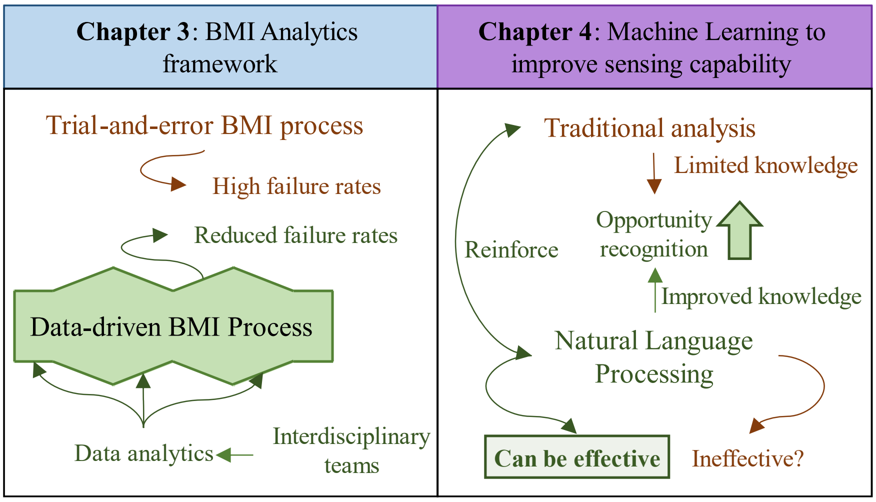

Figure 3. Summary of Chapters 3 and 4 core contributions.

Data-driven BMI opens several research avenues. Knowledge, a key resource to the BMI process, is a limited asset, with a limited scope that depends on experience, educational background and learned knowledge. Despite the possibilities to reduce such limitations through interdisciplinary teams and diversity, it will still be limited and imperfect across different companies. This knowledge configuration influences creativity, idea generation, and BM designs, in which data analytics can help to broaden knowledge bases. This combination can lead to significant changes and improvements in the BMI process, and as our chapters suggest, it may be a feasible approach. The remaining question is, however, to which extent can BMI failures be reduced and what is the boundary between real uncertainty and imperfect knowledge?

Conclusion

In all, we consider that the overall objectives of the thesis were achieved. The road forward is wide and long, and we still need much to learn. Dealing with BMI is an ongoing, never-ending endeavor. It seems, however, that the forces in play will act against BMI, regardless of our actions. The question is: will ever exist a way back to calm times and business-as-usual? Or changes will become more and more a constant to business realities and BMI a necessary part of business as usual? These questions and the BMI’s paradoxical nature are what makes it intriguing and inspiring to research.

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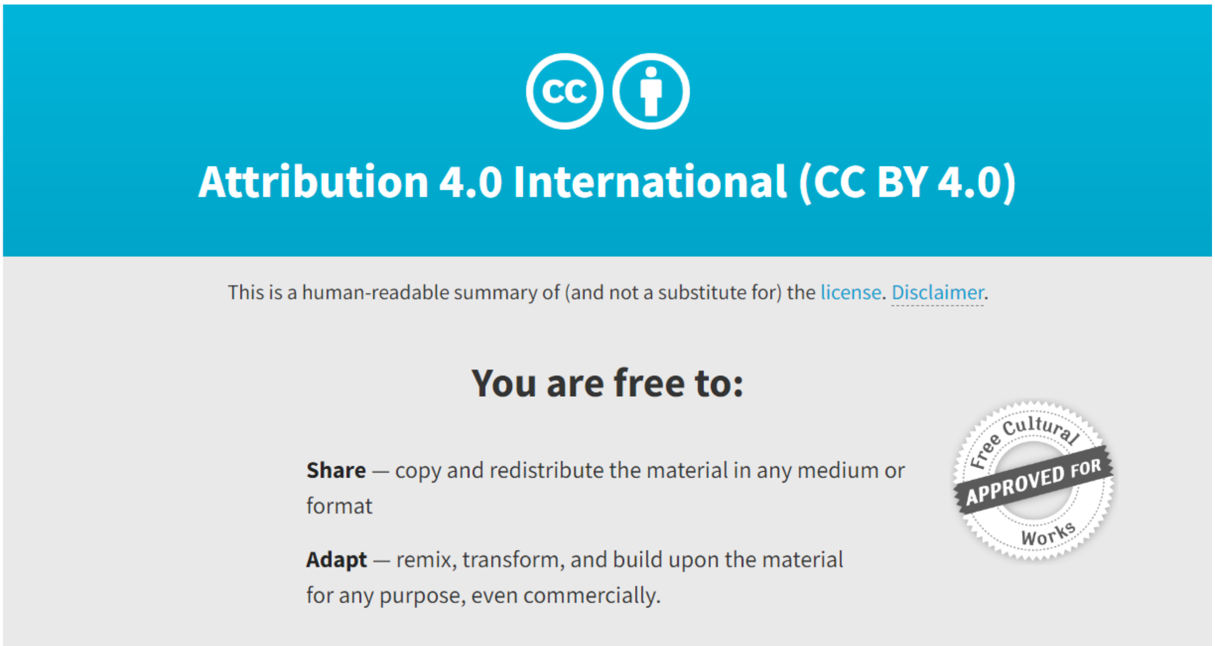
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