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MEDIA

Joelias Silva Pinto Junior

**SmartB: AN ARTIFICIAL INTELLIGENCE ARTIFACT FOR BUSINESS
DIAGNOSIS PREDICTION**

*SmartB: UM ARTEFATO DE INTELIGÊNCIA ARTIFICIAL PARA A PREDIÇÃO DE
DIAGNÓSTICO EMPRESARIAL*

Florianópolis

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"It is in knowledge that there is a chance of liberation."
"É no conhecimento que existe uma chance de libertação."
(Leandro Karnal)

ABSTRACT

The creation of new businesses plays an important role in economic development, employment generation, and income distribution. In Brazil, however, despite a high rate of entrepreneurial activity, a significant number of enterprises fail within their first years of operation. The so-called "optimism bias" often contributes to business challenges, primarily due to entrepreneurs' lack of specific education and management knowledge. In this context, this thesis proposes a framework for business diagnostic prediction using artificial intelligence. This technological research is grounded in a pragmatic philosophical approach, adopting mixed methods and conducted in five stages: (1) characterization of the research; (2) development of a conceptual framework for business diagnosis and assessment; (3) implementation of an artificial intelligence-based prediction artifact to instantiate the framework; (4) evaluation of the artifact; and (5) application and dissemination of the results. Unlike previous approaches, the proposed BSM framework integrates five key dimensions, addressing a gap in current literature and practice: management, entrepreneurship, finance, market, and technology. This framework provides the conceptual basis to instantiate the SmartB artifact, an AI-driven system that applies questionnaires to collect diagnostic data from enterprises and compares this information with a curated database of real business cases. Based on this process, the artifact generates diagnostic assessments, including performance indicators, descriptive analyses, and targeted improvement recommendations for each business dimension. The development of the artifact was informed by expert interviews and both integrative and scoping literature reviews, which revealed that most existing diagnostic and predictive tools rely predominantly on financial data and do not offer a multidimensional assessment. The conceptual framework and diagnostic artifact were refined and validated with the support of 9 experienced business consultants, who provided expert feedback on both the framework's relevance and the clarity of diagnostic questions, giving an overall satisfaction assessment of 90,4%. The system was further evaluated through the analysis of 17 real business diagnostic interviews, with overall satisfaction of 93,2%. The feedback from these entrepreneurs who interacted with the SmartB artifact highlighted its practical usefulness and coherence with real business challenges. The results demonstrate that artificial intelligence, when combined with a structured diagnostic framework and real business diagnosis data, can support consistent, interpretable, and actionable business diagnosis prediction. The literature review showed no other tool currently combines these five diagnostic dimensions within a single AI-driven system, reinforcing the originality and practical contribution of this research to the fields of knowledge engineering and business management.

Keywords: Artificial Intelligence; Business Diagnosis; Knowledge Engineering; Small and Medium Enterprises (SMEs); Diagnostic Framework.

RESUMO

A criação de novas empresas desempenha um papel importante no desenvolvimento econômico, na geração de empregos e na distribuição de renda. No Brasil, porém, apesar da alta taxa de atividade empreendedora, um número significativo de empresas fracassaram nos primeiros anos de operação. O chamado "viés de otimismo" frequentemente contribui para os desafios empresariais, principalmente devido à falta de formação específica e falta de conhecimento em gestão por parte dos empreendedores. Nesse contexto, esta tese propõe um framework para diagnóstico e predição empresarial utilizando inteligência artificial. Esta pesquisa tecnológica se fundamenta em uma abordagem filosófica pragmática, adotando métodos mistos e sendo conduzida em cinco etapas: (1) caracterização da pesquisa; (2) desenvolvimento de um framework conceitual para diagnóstico e avaliação empresarial; (3) implementação de um artefato de predição baseado em inteligência artificial para instanciar o framework; (4) avaliação do artefato; e (5) aplicação e disseminação dos resultados. Diferentemente de abordagens anteriores, o Framework BSM proposto integra cinco dimensões-chave, abordando uma lacuna na literatura e na prática: gestão, empreendedorismo, finanças, mercado e tecnologia. Esta estrutura fornece a base conceitual para a implementação do artefato SmartB, um sistema baseado em IA que aplica questionários para coletar dados de diagnóstico de empresas e compara essas informações com um banco de dados selecionado de casos de negócios reais. Com base nesse processo, o artefato gera avaliações de diagnóstico, incluindo indicadores de desempenho, análises descritivas e recomendações de melhoria direcionadas para cada dimensão do negócio. O desenvolvimento do artefato foi baseado em entrevistas com especialistas e revisões bibliográficas integrativas e exploratórias, que revelaram que a maioria das ferramentas de diagnóstico e previsão existentes se baseiam predominantemente em dados financeiros e não oferecem uma avaliação multidimensional. A estrutura conceitual e o artefato de diagnóstico foram refinados e validados com o apoio de 9 consultores de negócios experientes, que forneceram feedback especializado sobre a relevância da estrutura e a clareza das perguntas de diagnóstico, resultando em uma avaliação de satisfação geral de 90,4%. O sistema foi ainda avaliado por meio da análise de 17 entrevistas de diagnóstico de negócios reais, com uma satisfação geral média dos usuários de 93,2%. O feedback desses empreendedores que interagiram com o artefato SmartB destacou sua utilidade prática e coerência com os desafios reais dos negócios. Os resultados demonstram que a inteligência artificial, quando combinada com uma estrutura de diagnóstico estruturada e dados reais de diagnóstico de empreendimentos, pode fornecer previsões de diagnósticos empresariais consistentes e interpretáveis. A revisão da literatura mostrou que nenhuma outra ferramenta atualmente combina essas cinco dimensões de diagnóstico em um único sistema baseado em IA, reforçando a originalidade e a contribuição prática desta pesquisa para os campos da engenharia do conhecimento e da gestão de negócios.

Palavras-chave: Inteligência Artificial; Diagnóstico Empresarial; Engenharia do Conhecimento; Pequenas e Médias Empresas (PMEs); Framework de Diagnóstico.

RESUMO EXPANDIDO

Introdução

A criação e sobrevivência de novas empresas são fatores relevantes para o desenvolvimento econômico, geração de empregos e distribuição de renda no Brasil. Apesar da expressiva taxa de atividade empreendedora no país, observa-se um elevado índice de mortalidade de micro, pequenas e médias empresas nos primeiros anos de operação. Entre as principais causas desse fenômeno estão o chamado "viés de otimismo", a ausência de formação específica dos empresários, bem como limitações em conhecimentos de gestão, finanças, mercado e tecnologia. Além disso, grande parte dos empresários não dispõe de acesso a consultoria especializada, o que dificulta a identificação precoce de vulnerabilidades e oportunidades de melhoria. Diante desse cenário, esta tese propõe o desenvolvimento de um framework conceitual para diagnóstico e predição de vulnerabilidades empresariais utilizando inteligência artificial, com foco no contexto brasileiro de pequenas e médias empresas.

Objetivos

O objetivo geral desta pesquisa é propor um framework conceitual para a predição de diagnóstico empresarial, usando inteligência artificial. Os objetivos específicos são: (1) Pesquisar o estado da arte das dimensões de diagnóstico empresarial; (2) Investigar ferramentas, técnicas e métodos que usam Inteligência Artificial para predição de diagnóstico empresarial; (3) Desenvolver e avaliar um artefato de IA para a predição de diagnóstico empresarial baseado no framework conceitual proposto.

Metodologia

Trata-se de uma pesquisa tecnológica, de natureza aplicada, fundamentada em uma abordagem filosófica pragmática e na utilização de métodos mistos. O estudo foi conduzido em cinco etapas principais: (1) caracterização da pesquisa; (2) desenvolvimento de um framework conceitual para diagnóstico e avaliação empresarial, integrando dimensões identificadas na literatura e na prática de consultoria; (3) instanciamento de um artefato de predição baseado em inteligência artificial a partir do framework; (4) avaliação do artefato por especialistas e usuários finais, por meio da aplicação do sistema em casos reais e coleta de feedback qualitativo e quantitativo; e (5) aplicação prática e disseminação dos resultados em empresas e ambientes acadêmicos.

Resultados e Discussão

O Framework BSM proposto integra cinco dimensões essenciais para o diagnóstico empresarial: gestão, mercado, finanças, empreendedorismo e tecnologia. Essa abordagem multidimensional foi construída com base em revisão sistemática e escopo da literatura, associada à análise de dados de consultorias reais. O artefato SmartB operacionaliza este framework por meio de um questionário estruturado, cujas perguntas foram refinadas com apoio de ferramentas de inteligência artificial generativa e validação por especialistas. O sistema permite a coleta de dados qualitativos e quantitativos, gerando relatórios de diagnóstico que incluem indicadores de desempenho, análises descritivas e recomendações de ações estratégicas personalizadas para cada eixo avaliado. A avaliação do artefato

envolveu a participação de nove consultores de negócios experientes, que atribuíram ao sistema uma taxa de aprovação de 90,4%, destacando a clareza, relevância e aplicabilidade das perguntas e recomendações geradas. Além disso, o sistema foi testado por meio de 17 diagnósticos reais com empresas, obtendo uma média de satisfação dos usuários de 93,2%. Os depoimentos dos empreendedores reforçaram a utilidade prática do SmartB, principalmente para empresas que não têm acesso a consultoria tradicional, ressaltando a pertinência das recomendações e a facilidade de compreensão dos relatórios produzidos. Os resultados evidenciam que a maioria das soluções existentes na literatura nacional e internacional concentra-se em indicadores financeiros, enquanto o SmartB permite uma análise mais ampla e integrada das diferentes áreas da empresa, possibilitando diagnósticos mais completos e recomendações alinhadas à realidade das PMEs brasileiras.

Considerações Finais

A pesquisa demonstra que a inteligência artificial, aliada a uma estrutura metodológica clara e ao uso de dados reais de empresas, pode apoiar de forma consistente e interpretável o processo de diagnóstico empresarial e a antecipação de vulnerabilidades. O framework BSM e o artefato SmartB apresentam contribuição original ao integrar, em um único sistema, as cinco dimensões de diagnóstico consideradas mais relevantes para a sustentabilidade dos negócios. A aplicação prática do sistema mostrou potencial não apenas para apoiar empresários e consultores, mas também para orientar políticas públicas e programas de desenvolvimento econômico voltados ao fortalecimento de pequenas e médias empresas no Brasil.

Palavras-chave: Inteligência Artificial; Diagnóstico Empresarial; Engenharia do Conhecimento; Pequenas e Médias Empresas (PMEs); Framework de Diagnóstico.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
Anprotec	Brazilian National Association of Entities Promoting Innovative Ventures (<i>Associação Nacional de Entidades Promotoras de Empreendimentos Inovadores</i>)
API	Application Programming Interface
BSM	Business Strengthening Methodology
CAPES	Brazilian Federal Agency for Support and Evaluation of Graduate Education (<i>Coordenação de Aperfeiçoamento de Pessoal de Nível Superior</i>)
DSR	Design Science Research
EGC	Engineering and Knowledge Management (<i>Engenharia e Gestão do Conhecimento</i>)
Gen AI	Generative Artificial Intelligence
IDE	Integrated Development Environment
IFMT	Federal Institute of Education, Science and Technology of Mato Grosso (<i>Instituto Federal de Educação, Ciência e Tecnologia de Mato Grosso</i>)
INPI	National Institute for the Intellectual Property (<i>Instituto Nacional da Propriedade Intelectual</i>)
IP	Intellectual Property
JWT	JSON Web Token
KE	Knowledge Engineering
KM	Knowledge Management
ML	Machine Learning
NLP	Natural Language Processing
SO	Specific Objective
PPGEGC	Graduate Program in Knowledge Engineering and Management (<i>Programa de Pós-Graduação em Engenharia, Gestão e Mídia do Conhecimento</i>)
RAG	Retrieval Augmented Generation
SME	Small and Medium Enterprises
UFSC	Federal University of Santa Catarina (<i>Universidade Federal de Santa Catarina</i>)
XGBoost	Extreme Gradient Boosting
WoS	Web of Science

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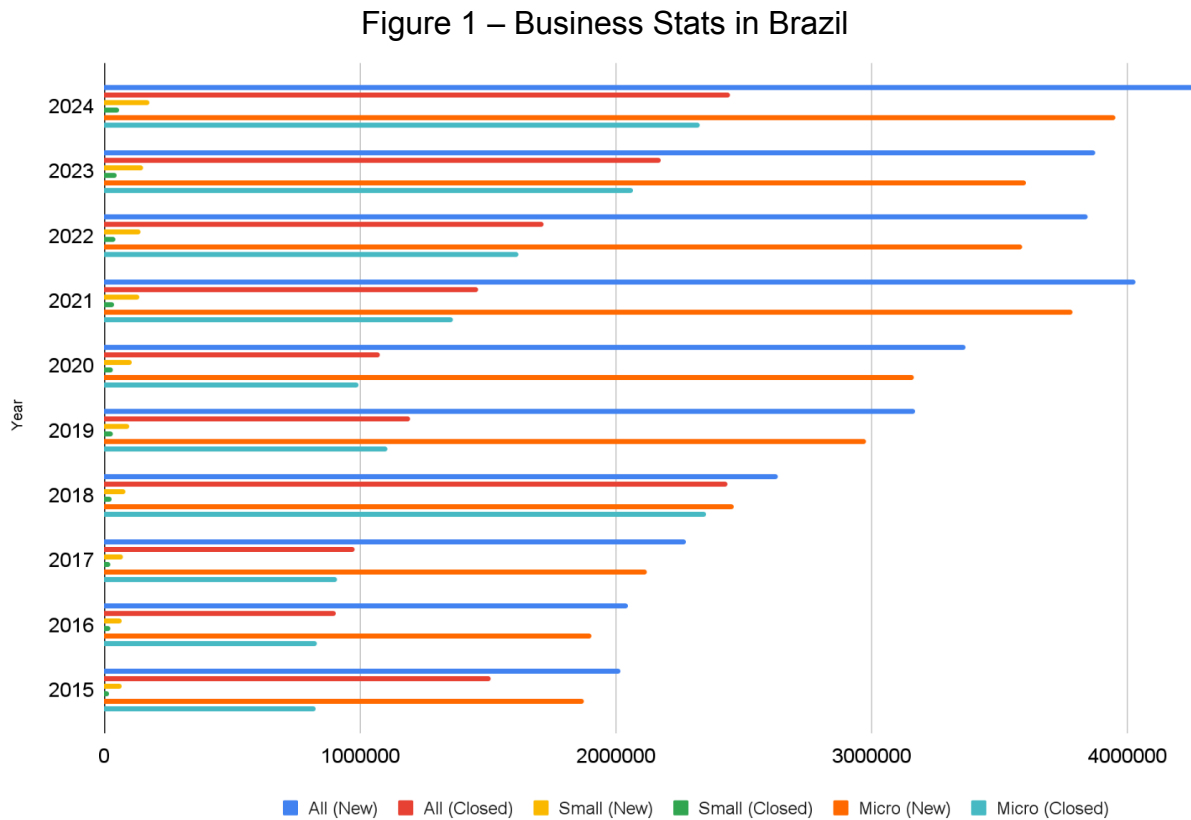
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1 INTRODUCTION

1.1 CONTEXT

In Brazil, there is a high demand for new business openings every year. In 2024, according to the Brazilian Federal Government (Brasil, 2025), over 4.2 million companies were created. However, in the same year, more than 2.4 million businesses closed, of which 97.6% were micro and small enterprises.

Figure 1 shows details of these numbers since 2015, where we can see a significant increase in both the creation and closure of enterprises in Brazil, with micro and small businesses making up the vast majority of these movements. Particularly from 2020 onwards, there is a notable rise in the number of new micro and small enterprises, which likely reflects changes in the Brazilian economic environment, such as shifts toward entrepreneurship and self-employment during and after the COVID-19 pandemic (GEM, 2025; IBGE, 2025). However, it shows the number of closures has also grown, especially with micro-enterprises, indicating that while more businesses are being created, many face challenges in remaining active.



Source: prepared by the author using Brazilian Federal Government data (Brasil, 2025).

The data reveals a dynamic but also unstable business environment, where high rates of new business formation are matched by high closure rates. This pattern suggests the need for additional support and policies aimed at improving the sustainability of micro and small businesses, so that the growth in entrepreneurship can lead to more lasting economic development (Battisti; Deakins; Perry, 2013; Helen Samujh, 2011).

The formation of an enterprise can be a solution to bring an innovative idea to the market (Autio et al., 2014; Harvard Business Review, 2013), which emerged in a research environment, or a source of income for those seeking financial independence or needing an alternative work (GEM, 2025; Stephan; Roesler, 2010). In all cases, it is common for the entrepreneur to possess reasonable technical knowledge in their field, to be motivated, and to have a workforce, but to have little administrative or entrepreneurial knowledge (Baptista; Karaöz; Mendonça, 2014; Camuffo et al., 2020; Lazear, 2004; Ucbasaran et al., 2013). This phenomenon is known in the entrepreneurship literature as "optimism bias" (Sharot, 2011a, 2011b) and can lead the entrepreneur to business problems (Åstebro et al., 2014; Lowe; Ziedonis, 2006; Zhang; Cueto, 2017).

In order to understand and address the root causes of business problems, it is necessary to analyse beyond surface-level indicators. Organizational theory, particularly the concepts established by March and Simon (1958) regarding bounded rationality, and Porter's (1980) frameworks for strategic analysis, provide a structured approach for examining the internal functioning of enterprises.

These potential problems, recurrent in the business management of SMEs (Small and Medium Enterprises), can lead the entrepreneur to seek consulting with experts (Mole; North; Baldock, 2017; Ramsden; Bennett, 2005) to diagnose the challenges faced by the company and return a report with the diagnosis. Based on this report, a work plan can be developed to address the improvement points identified (Jibril; Wishart; Roper, 2023; Robson; Bennett, 2000; Teece; Peteraf; Leih, 2016).

The motivation for this research emerged from direct involvement of the researcher in practical contexts that reflect the entrepreneurial difficulties faced by small and micro-entrepreneurs, as documented in the literature. Through involvement in various research projects, extension activities, and work in a business incubator (Morais; Pinto-Junior; Silvestro, 2021; Pinto Junior et al., 2021; Pinto-Junior;

Campos; L., 2021; Pinto-Junior, 2021, 2024; Pinto-Junior et al., 2021a, 2021b, 2021c, 2023; Pinto-Junior; Novaes, 2021; Pinto-Junior; Silvestro, 2021; Pinto-Junior; Silvestro; Moraes, 2021; Silvestro; Pinto-Junior; Duncke, 2021), we observed that, indeed, the main challenge for most ventures was management. A possible way to mitigate this problem was to seek support from consultants experienced in the subject.

Accurate consulting diagnoses contribute to the consolidation of stable enterprises in society (Mole; North; Baldock, 2017; Ramsden; Bennett, 2005) and also foster business innovation. Going deeper into the study of business diagnosis, it brings the need to investigate the knowledge involved in company processes and flows, in order to analyze the possibility of predicting business diagnoses (Narne et al., 2024; Van Der Aalst; Carmona, 2022). Along with this need, it is observed from other works found in the literature (Alaka et al., 2018; Clement, 2020; Dasilas; Rigani, 2024; Dept. of CSE, GIT, GITAM University, Visakhapatnam, Andhra Pradesh, India; Devi; Radhika, 2018; Gajdosikova; Gabrikova, 2023; Iparraguirre-Villanueva; Cabanillas-Carbonell, 2024; Kezelj; Gruenbichler, 2021; Kristóf; Virág, 2020; Rozenbaha, 2018; Rufsana.; Baiju, 2023; Shi; Li, 2019a, 2019b; Soukal et al., 2024; Veganzones; Severin, 2021; Zhao; Ouenniche; De Smedt, 2024) that artificial intelligence techniques can be created to support the diagnosis process. It is within this context that the **research question** guiding the origin of this study is situated: **How is it possible to use Artificial Intelligence in business diagnostics for identifying potentialities and opportunities for organizational growth?**

To achieve a reliable and comprehensive prediction of business health, it is first necessary to identify the critical dimensions that affect organizational performance (March; Simon, 1958; Porter, 1980). This can be done by conducting benchmark interviews with business consultants and reviewing both recent and classical academic studies in the field of business diagnostics (Bizzotto et al., 2018; Kaplan; Norton, 1996; Machado; Silva; Bizzotto, 2017).

In this context, analyzing data and indicators from different entrepreneurial areas can provide the basis for Artificial Intelligence to be a suitable tool for enabling the prediction of business diagnoses. Haefner et al (2021) point out in their research that AI (Artificial Intelligence) has made it possible to rethink the entire innovation process and improve knowledge management systems due to rapid technological advancements and improvements in AI systems. Aiming to explore this contemporary

scientific and technological exponent, which is Artificial Intelligence, a literature review is crucial to help identify how artificial intelligence (AI) can contribute to this business analysis process for small and medium-sized enterprises (SMEs).

This research integrates organizational theories (March; Simon, 1958; Porter, 1980) with artificial intelligence to predict business diagnosis. It was designed to investigate how business diagnostic processes could be supported by artificial intelligence in a more comprehensive and applicable manner for SMEs enterprises. The practical difficulties faced by entrepreneurs, combined with the predominance of diagnostic models centered mainly on financial data, motivated the development of a broader diagnostic perspective.

This context led to the definition of a Knowledge Engineering research strategy that integrates empirical knowledge from real consulting practices with structured scientific methods. By integrating organizational theory with contemporary data-driven approaches, this research advances the analysis of SMEs beyond financial indicators. The study operationalizes the concepts of bounded rationality and strategic management in the design of an AI-supported diagnostic framework, aiming to capture the complexity of organizational processes and provide actionable insights for business improvement.

1.2 OBJECTIVES

1.2.1 General Objective

Propose a conceptual framework for business diagnosis prediction using artificial intelligence.

1.2.2 Specific Objectives

- OE1: Research the state of the art of business diagnosis dimensions;
- OE2: Investigate tools, techniques, and methods that use Artificial Intelligence for business diagnosis prediction;
- OE3: Develop and evaluate an AI artifact for business diagnosis prediction based on the proposed conceptual framework.

1.3 NOVELTY AND RELEVANCE

Bicas (2008) defines novelty as the quality of something being new or unique, distinguishing it from other existing things. In this sense, this research contributes with the following novel contributions:

- We present a new conceptual framework for business diagnosis assessment, considering five different business dimensions (Management, Finance, Market, Technology, Entrepreneurship). Our literature review (mentioned in Chapter 3) show that no other paper retrieved used all these five dimensions.
- We employ a configuration for the technological prediction artifact (explained in Chapters 3 and 4), involving a data extraction tool, prompt engineering, user interface, backend for data preparation and processing, and processing via a generative AI API, which was not identified in any other work from the literature review.
- The database used consists of real business diagnostic interviews. This type of data was not found in any of the reviewed studies. These frequently presented public financial and/or market data or indirect business quantitative and qualitative data, such as those extractable from documents and systems.
- Integrating the resources mentioned above, we developed an AI artifact that is based on real data to make decisions, considers 5 business dimensions, and can be used directly by the entrepreneur. We emphasize that the works retrieved from the literature demonstrated the creation of tools that serve only a research purpose, and none of them showed the development of a tool that could be directly and appropriately used by the entrepreneur.

We consider that these points of novelty bring **academic relevance** to the work, as it advances this discussion and records such progress scientifically through the publication of this thesis and the articles derived from it.

The work is also **socially relevant** for individuals, legal entities, and the government, according to the following logic. The primary reason for the high number of business closures in Brazil today is the lack of appropriate management. Diagnosing management problems in advance can allow for addressing these issues and preventing the subsequent bankruptcy of these companies. As this research aims to assist in this early and accurate diagnosis, this anticipation of problems can positively impact the recovery and maturation of enterprises. Healthier and growing businesses generate more employment and higher revenue, consequently

contributing to increased income for society. They also pay more taxes, leading to an increase in government revenue with direct benefits for the public sector.

1.4 **RESEARCH SCOPE**

Considering that the objective of this work is to develop an artificial intelligence artifact for predicting business diagnosis, we highlight here the scope limitations of the research.

Regarding the target audience, the research is limited to Brazilian small and medium-sized enterprises (SMEs), from any sector of activity. The Brazilian context is justified by it being the country in which this research is developed and the familiarity and access of the research to the data. The focus on small and medium-sized enterprises is already recurrent in the literature, market, and government and is due to the similarity of management issues, market and challenges among these sizes of companies. We also decided to work with this audience, instead of considering large companies, because SMEs have a significant social, employment, and income impact, as they are frequently family subsistence businesses with local or regional operations.

The diagnostic assessment is related to internal business indicators in the areas of management, entrepreneurship, market, technology, and capital, and does not consider factors external to the companies, such as market, political, economic, or financial factors.

This research does not directly address the prediction or prevention of bankruptcy, since this topic constitutes a distinct field of study that predominantly considers the financial and legal factors related to business insolvency.

Regarding the application of technology to develop the business diagnostic prediction tool, we chose to work with artificial intelligence because, through literature searches, participation in conferences, and discussions with other researchers, it became clear that this is a scientific and technological leader with the potential to contribute to the research proposal of performing predictions and improving business diagnoses based on a database.

1.5 **ADHERENCE TO THE KNOWLEDGE ENGINEERING PROGRAM**

This research adheres to the PPGEKC (Postgraduate Program in Knowledge Engineering and Management) because it identifies a problem of knowledge

management in organizations that leads to situations of business failures or weaknesses. Therefore, I developed an artificial intelligence artifact, using knowledge engineering techniques, to operate in the prediction of diagnoses and mitigate problems in this context.

Business problems occur recurrently due to a lack of knowledge, a lack of knowledge systematization, and a lack of sharing of solutions. Using the cognitivist approach to knowledge, it is possible to determine criteria that are critical for an organization and can identify the strengths and weaknesses of an enterprise. Using knowledge engineering techniques, it is possible to search for patterns in previous data and predict potential business problems from a new set of data from a company.

The research is situated in the area of Knowledge Engineering, within the research line of Knowledge Engineering Applied to Organizations. It is a research project that demands the interdisciplinary nature inherent to the PPGEGC, as it involves the application of tools and techniques from Computer Science, Probability and Statistics, and Information Science to analyze and solve problems related to knowledge applied to companies, which also require knowledge from Production Engineering and Administration.

Although haven't found another work within the PPGEGC that addressed the use of knowledge engineering techniques for anticipating business diagnoses, it was possible to find works that: used AI as an integrated tool within a Knowledge Engineering model or artifact aimed at error detection (Pinto, 2023), supporting document analysis (Faraco, 2020), knowledge extraction for predicting financial crises (Coutinho, 2024), applying generative AI to support the higher education teaching environment (De Souza, 2025), and optimizing public procurement processes Forbici (2024). Others were concerned with using knowledge management to address business problems (Suzuki, 2008; Vieira, 2022); developed a knowledge engineering model to support diagnostic processes (Lopes, 2012); and sought to create processes and frameworks that support knowledge management in organizations (Alvez, 2023; Helou, 2015; Marques, 2022; Maximo, 2021).

1.6 THESIS STRUCTURE

The research is structured to show that it is possible to generate consistent and meaningful business diagnoses using artificial intelligence supported by a multidimensional framework and real-world data. From Theoretical Foundation

([Chapter 2](#)) to identify critical business dimensions and existing approaches to diagnostic anticipation, to the development of a conceptual framework to organize diagnostic knowledge across five business areas: management, entrepreneurship, finance, market, and technology. The Methods for these are detailed in [Chapter 3](#), highlighting the research characterization and its stages. [Chapter 4](#) presents the Conceptual Framework, which serves as the basis for the instantiation of an artificial intelligence–based artifact, presented in [Chapter 5](#), designed to process structured diagnostic data collected directly from entrepreneurs and compare it with a curated database of real business cases. In [Chapter 6](#) the artifact was then evaluated by specialists and applied in practical contexts, allowing the assessment of both its technical adequacy and its perceived usefulness. Finally, the [Final Remarks](#) chapter provides insights from the research, outline the main contributions and limitations, as well as expectations for future research.

2 THEORETICAL PERSPECTIVE

This chapter is organized into two sections to support a clear understanding of the theoretical background required for this research. The first section, titled "[Literature Review and Related Works](#)," presents a summary of the literature reviews that supported the research, as well as the main related studies identified. The second section, "[Theoretical Foundation](#)", introduces the fundamental concepts derived from the literature review that are essential for the development of this thesis.

2.1 LITERATURE REVIEW AND RELATED WORKS

2.1.1 Integrative Review: *"Is it possible to anticipate a diagnosis of business vulnerability?"*

To validate the initial research proposal of this doctoral thesis, an integrative literature review was first conducted, entitled "Business Vulnerability Diagnosis: An Integrative Review" (Pinto-Junior et al., 2023). The review aimed to investigate the possibility of anticipating the diagnosis of business problems based on the existing global literature. The review followed the methodological criteria established by Whittemore and Knafl (2005) and by Botelho, Cunha and Macedo (2011).

The keywords used can be verified in Table 1. All words were in English to ensure better literature coverage. The search was conducted on the Scopus and Web of Science platforms, and works from the last 10 years were considered.

Table 1 – Search Strategies for the Integrative Review

Information Sources	Search String
Web of Science	(TI=((("business" OR "company") AND ("diagnosis" OR "vulnerability diagnosis" OR "diagnosis anticipation" OR "vulnerability diagnosis anticipation")))) OR (AB=((("business" OR "company") AND ("diagnosis" OR "vulnerability diagnosis" OR "diagnosis anticipation" OR "vulnerability diagnosis anticipation")))) OR (AK=((("business" OR "company") AND ("diagnosis" OR "vulnerability diagnosis" OR "diagnosis anticipation" OR "vulnerability diagnosis anticipation"))).
SCOPUS	TITLE-ABS-KEY(("business" OR "company") AND ("diagnosis"

	OR “vulnerability diagnosis” OR “diagnosis anticipation” OR “vulnerability diagnosis anticipation”))
--	--

Source: prepared by the author.

Table 2 shows a detailed breakdown of the result flow and the search filters applied at each stage of the review. A total of 44,650 retrieved documents underwent various filters until 16 articles remained, which were read in their entirety to compose the review.

Table 2 – Fluxo de Resultados e Filtros da Busca

	SCOPUS	Web of Science
Initial result	40,210 documents	4,240 documents
Filter 1	Year of publication: 2012 to 2022	Eight categories were selected: Management, Computer Science Artificial Intelligence, Computer Science Information Systems, Computer Science Theory Methods, Business, Computer Science Interdisciplinary Applications, Multidisciplinary Sciences, Business Finance.
Results	11,800 documents	686 documents
Filter 2	Four areas were selected: Computer Science, Business Management and Accounting, Economics, Econometrics and Finance, Multidisciplinary Research.	Two research areas were selected: Computer Science, Business Economics.
Results	1044 documents	654 documents
Filter 3	Publication status: final	Year of publication: 2012 to 2022
Results	1017 documents	391 documents
Filter 4	Selected language: English	Reading titles
Results	886 documents	31 documents
Filter 5	Keyword exclusion: Human, Humans, Fault Detection, Health Care, Medical Imaging, Pattern Recognition, Diseases, Support Vector Machines, Manufacture, Patient Treatment, Constraint Theory, Forecasting.	Selected language: English
Results	546 documents	27 documents
Filter 6	Reading titles	Reading abstracts
Results	53 documents	9 documents
Filter 7	Reading abstracts	Repeated documents at SCOPUS

		were excluded
Final Results	23 documents (1 full text not found)	4 documents (1 full text not found)

Source: Pinto-Junior et al. (2023).

During the data extraction, the 16 selected articles were categorized according to the type of diagnosis they performed, the technologies used, the samples, and the business size. A summary of that can be seen in Table 3. The articles categorized in the "Technological Diagnosis" group of the diagnosis categorization showed that it is possible to diagnose technological issues in companies, although the authors did not discuss anticipating or predicting this type of diagnosis. Those in the "Organizational Diagnosis" group also demonstrated diagnostic possibilities, but with a focus on a macro-level and managerial organizational perspective. However, those in the "Failure Prediction" group presented models that allow for making predictions, which can be seen as a way to anticipate business failures. Nevertheless, most of the techniques used only financial variables.

Table 3 – Matriz de Síntese da Revisão Integrativa

AUTHOR	DIAGNOSIS	TECHNOLOGIES	SAMPLE	SIZE
Acuña-Carvajal et al. (2019)	Plan, structure, and validate a strategic business unit.	BSC; MCDM; Fuzzy DEMATEL; Forms; ICP Matrix.	1 Colombian bank	Large
Ceballos et al. (2021)	Incorporating business rules	Relational Database; MBD; CSP; minLik parameter; AHP	15 BDCs - 864 instances	Any
Chuang (2013)	Predicting business failure	CBR hybrid model; RST-CBR; RST-GRA-CBR; CART-CBR	279 healthy companies and 42 with problems. All IT in Taiwan based on Taiwan Stock Exchange Corporation (TSEC) and Taiwan Economic Journal (TEJ) database.	All

Govender and Parumasur (2016)	Diagnose critical aspects for business effectiveness	Descriptive and inferential statistics.	1 Trade and Investment Agency	Not informed
Hernández-Díaz et al. (2021)	Business sustainability of SMEs	Qualtrics; 106-item questionnaire with the 5 MOPSE dimensions.	108 questionnaires (SMEs)	Micro and SMEs
Hoa and Tuyen (2021)	Aptitude for digital transformation	Linear and non-linear regression algorithms; the fuzzy method;	510 SMEs	SMEs
Le et al. (2019)	Bankruptcy prediction based on financial data.	HAOC; CBoost; Python; Scikit-learn	Korean bankruptcy database. 307 bankrupt companies and 120,048 “normal” ones.	All
Martynuk (2017)	Business failures	Fuzzy; OWA;	Modeling	Not applicable
Metz (2017)	Organizational diagnostic model	Questionnaires; Statistical analysis;	1 Multinational ICT industry in Romania; 776 employees;	Large
Ozmen and Ozcan (2022)	Diagnosis of employee turnover.	CNN; ECDT; ECDT-GRID	1186 employees	SMEs
Salazar et al. (2022)	Feasibility of e-commerce implementation	No computer technologies	29 companies and 261 clients	SMEs
Santos and Martinho (2020)	Maturity related to Industry 4.0	Questionnaires	2 automotive companies	Large
Scherger et al. (2014)	Diagnose the cause of failure in groups of SMEs.	Fuzzy model	15 companies	SMEs
Scherger et al.	Business management and	Convolutional algorithms with	6 companies	Large

(2017)	technological maturity	fuzzy logic.		
Terceño et al. (2018)	Predicting causes of business failure	Fuzzy; OWA;	Modeling of 5 companies, no case study	Not applicable
Vigier et al. (2017)	Enterprise failure diagnostics with fuzzy OWA operators	Fuzzy; OWA;	98 SMEs	SMEs

Source: Pinto-Junior et al. (2023).

With this review, it was also possible to understand that "anticipation of business diagnosis" can also be understood, without loss of meaning, by other terms, such as "Business Diagnosis Prediction," "Business Failure Prediction," "Business Failure Anticipation," and "Business Bankruptcy Prediction"; these topics are closely correlated in the literature with corporate sustainability and bankruptcy.

One fact to highlight is that, with the exception of two articles, the other 14 sought to identify failures or improvement points to avoid business problems. Some articles demonstrated that it is possible to diagnose technological issues in companies, others presented diagnostic possibilities focusing on macro organizational and managerial perspectives, and some even presented models for predicting business failures.

2.1.2 Scope Review: *"What are the AI approaches used to analyze enterprise risk in small and medium-sized companies?"*

Once the first review allowed us to comprehend the possibility of anticipating business diagnosis, it was needed to understand the state of the art about that. So, we conducted a Scope Review aiming to identify the most effective AI approaches for analyzing enterprise risk in small and medium-sized enterprises (SMEs). The research question was established as "What are the AI approaches used to analyze enterprise risk in small and medium-sized companies?"

The Scoping Review (SR), followed the methodological guidelines of De Luca Canto (2020) for protocol registration, database search, study selection, data collection and analysis, text writing, and article formatting. We also considered the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist (Page et al., 2021) in its version for Scoping Reviews (PRISMA-ScR) for the

development of the review protocol. The protocol was developed in consonance by the researchers, specialists in engineering and knowledge management, and reviewed by a librarian specializing in the elaboration of protocols for literature reviews. The protocol was registered on the OSF (Open Science Framework) platform under identifier “4E386” (Pinto-Junior et al., 2025).

Considering that this review addresses business risk analysis through AI approaches, and that the research has an interdisciplinary character that permeates the areas of computing, engineering, and applied social sciences, we executed our search strategy in databases that are a reference for these areas. The searches were conducted in May 2025 in the following 8 databases: ACM Digital Library, Compendex - Engineering Village, IEEE Xplore, SciELO, ScienceDirect (Elsevier), Scopus, Web of Science (WoS), and Google Scholar.

Moher et al. (2021) recommend in PRISMA that, to assess the completeness and accuracy of the search and to enable its replication, authors should present the complete search strategy for at least one database, and not only the keywords used. Thus, we present in Table 4 the full search strategies used for each platform. Search Strategy 1, the complete one, was used in all databases that admitted it in its entirety, namely: Compendex - Engineering Village, IEEE Xplore, SciELO, Scopus, and Web of Science (WoS). Search Strategy 2, the simplified one, was used for those platforms that offered restrictions on the number of characters or logical operators, namely: ACM Digital Library, ScienceDirect (Elsevier), and Google Scholar.

Table 4 – Search Strategies for the Integrative Review

SEARCH STRATEGY 1 - COMPLETE <i>(Compendex - Engineering Village, IEEE Xplore, SciELO, Scopus and Web of Science)</i> ("small enterprises" OR "small scale industry" OR "SME" OR "SMEs" OR "small business" OR "small businesses" OR "medium business" OR "medium businesses" OR "small industries" OR "medium industries" OR "small companies" OR "medium companies" OR "medium-sized enterprises" OR "medium enterprises") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "smart data discovery" OR "predictive analysis" OR "neural networks" OR "learning systems" OR "learning algorithms" OR "prediction methods" OR "intelligent systems" OR "natural language processing" OR "regression analysis") AND ("vulnerability diagnostic" OR "diagnostic anticipation" OR "fault anticipation" OR "fault prediction" OR "fault forecasting" OR "vulnerability prediction" OR "bankruptcy prediction" OR "bankruptcy anticipation")
--

OR "risk diagnostic" OR "risk prediction" OR "risk anticipation" OR "risk management" OR "risk assessment" OR "risk analysis" OR "risk perception")
NOT (finance OR financial OR credit OR medicine OR medical OR dental OR dentistry)

SEARCH STRATEGY 2 - SIMPLIFIED

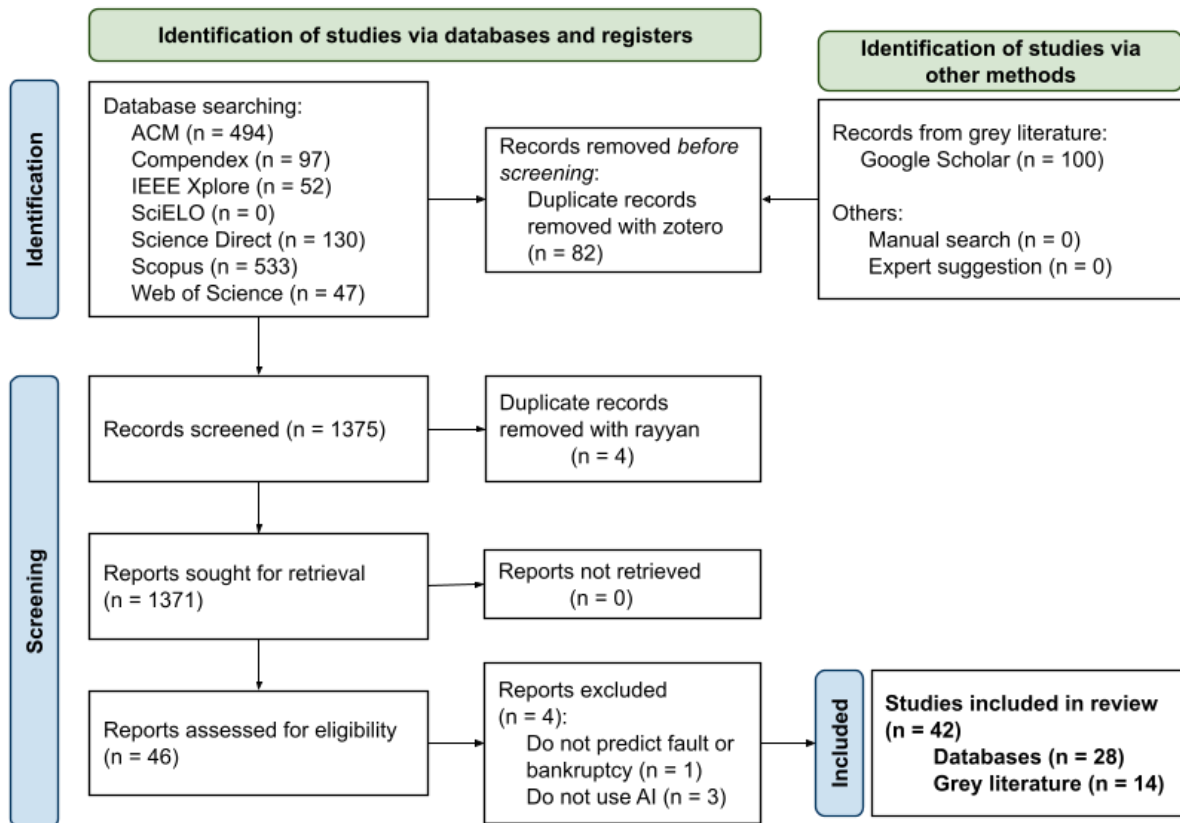
(ACM Digital Library, ScienceDirect and Google Scholar)

(enterprises OR businesses) AND ("artificial intelligence" OR "machine learning")
AND (bankruptcy OR risk) AND (prediction OR vulnerability)

Source: prepared by the author.

A total of 1453 studies were initially retrieved. After the removal of 82 duplicate studies, we read the title and abstract of the remaining 1371, of which 46 met the eligibility criteria and proceeded to full-text reading. After full-text reading, an additional 04 were excluded, leaving 42 studies to compose this review. Figure 2 represents this process of identification, screening, and selection of studies.

Figure 2 – Scoping Review Flow Diagram



Source: prepared by the author. Adapted from: (Page et al., 2021).

In accordance with the PRISMA-ScR protocol for scoping reviews, all selected articles included in the review underwent full-text reading, and data were extracted. The paper presents detailed results of the analysis, like the bibliometric characteristics of the review; characteristics of the studies and the responses to the research questions. We'll highlight here just some of the main findings and part of the discussion, that seems to be more relevant to build the theoretical perspective of this research.

Only 2 (5%) of the reviewed studies did not use financial data for their analysis: Bajo et al. (2012), which examines variables such as "process efficiency" and "auditor recommendations" without mentioning accounting indicators, and Hasbaoui & Saida (2022), which uses management data and market factors but disregards financial statements. The remaining 40 articles (95%) relied on financial data, with 6 of these using it indirectly—either by reviewing finance-based studies or citing financial aspects in their models without directly collecting such data.

Among all studies, only 7 incorporated more than one analytical dimension beyond purely financial data. Of these, Veganzones et al. (2021), Lin et al. (2009), Xie et al. (2024), and Hasbaoui & Saida (2022) considered a total of 3 dimensions, while Uthayakumar et al. (2020), Sartori et al. (2016), and Bajo et al. (2012) examined just 2 dimensions, as detailed in Table 5.

Table 5 – Papers analysing non-financial dimension

Paper	Management Analysis	Market Analysis	Technological Analysis
Veganzones et al. (2021)	Corporate governance, business efficiency.	Macroeconomic market data and competition	----
Uthayakumar et al. (2020)	Managerial competence, financial flexibility. Qualitative data (interview with experts).	----	----
Lin et al. (2009)	Directors' shareholding, value added per person.	Market data (business cycle)	----
Sartori et al. (2016)	Companies legal status	----	----
Xie et al. (2024)	----	Financial news, investor sentiment analysis.	Blockchain and AI data
Hasbaoui & Saida (2022)	Labor costs	Exchange rate, number of competitors.	----
Bajo et al. (2012)	----	----	Multi-agent systems for risk management

Source: prepared by the author.

Regarding the origin of sample data across the studies, it was observed that 29 studies (70%) utilized public databases from financial data providers (such as AIDA, CERVED, TEJ, RESSET), academic repositories (including UCI and Kaggle), and

stock exchanges. Another 15% of studies employed interview data and web scraping techniques, while the remaining 15% were literature reviews without specified primary data. A notable geographical bias emerged, with 60% (26 studies) focusing exclusively on data from Europe, China and the USA. Among the remaining studies using location-specific data, only 14% referenced emerging economies such as Brazil, India, Peru, Morocco, Vietnam, and Ghana. Concerning sectoral distribution, manufacturing/industry dominated (18 studies), followed by financial services (12 studies) and retail/commerce (8 studies). Less represented sectors included technology (6), agriculture (3), construction (3), and telecommunications (2), demonstrating a pronounced concentration on traditional industries in bankruptcy prediction research.

In respect with the AI Approaches identified, the three most frequently employed across the reviewed studies were Neural Networks (NN), appearing in 18 studies (42.9%), followed by Support Vector Machines (SVM) with 15 studies (35.7%), and Random Forest (RF) with 14 studies (33.3%). All 15 identified approaches along with their corresponding papers are presented in Table 6. Also, a pie chart graphically represents the approach's frequency in Figure 3.

Table 6 – Approaches frequency and papers

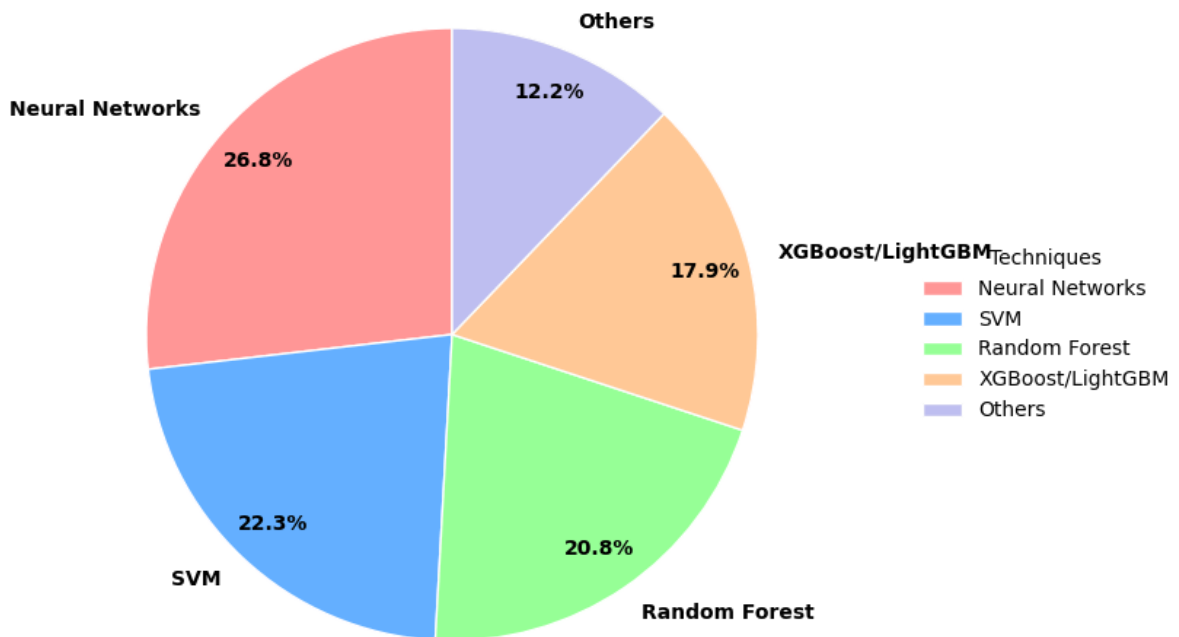
N	%	Papers
Neural Networks (NN)		
18	42.9%	(Brenes; Johannssen; Chukhrova, 2022; Clement, 2020; Dasilas; Rigani, 2024; Dept. of CSE, GIT, GITAM University, Visakhapatnam, Andhra Pradesh, India; Devi; Radhika, 2018; Gordini, 2014; Iparraguirre-Villanueva; Cabanillas-Carbonell, 2024; Kezelj; Gruenbichler, 2021; Kim et al., 2020; Kristóf; Virág, 2020; Le et al., 2019b; Perboli; Arabnezhad, 2021; Ravi Kumar; Ravi, 2007; Rozenbaha, 2018; Shi; Li, 2019b; Son et al., 2019; Wang; Li; Zhao, 2022; Xie, 2024; Yang et al., 2025)
Support Vector Machines (SVM)		
15	35.7%	(Chaudhuri; De, 2011; Dasilas; Rigani, 2024; Dept. of CSE, GIT, GITAM University, Visakhapatnam, Andhra Pradesh, India; Devi; Radhika, 2018; Gordini, 2014; Hung; Chen, 2009; Iparraguirre-Villanueva; Cabanillas-Carbonell, 2024; Kim et al., 2020; Kristóf; Virág, 2020; Le et al., 2019b; Ravi Kumar; Ravi, 2007;

		Rozenbaha, 2018; Shi; Li, 2019b; Son et al., 2019; Wang; Li; Zhao, 2022; Xie; Tan; Liu, 2024)
Random Forest (RF)		
14	33.3%	(Ansah-Narh et al., 2024; Da Silva Mattos; Shasha, 2024; Dasilas; Rigani, 2024; Dept. of CSE, GIT, GITAM University, Visakhapatnam, Andhra Pradesh, India; Devi; Radhika, 2018; Gnip; Drotar, 2019; Iparraguirre-Villanueva; Cabanillas-Carbonell, 2024; Kim et al., 2020; Ma et al., 2024; Perboli; Arabnezhad, 2021; Son et al., 2019; Veganzones; Severin, 2021; Wang; Li; Zhao, 2022; Zigiene; Rybakovas; Alzbutas, 2019)
XGBoost/LightGBM		
12	28.6%	(Ansah-Narh et al., 2024; Da Silva Mattos; Shasha, 2024; Dasilas; Rigani, 2024; Gnip; Drotar, 2019; Iparraguirre-Villanueva; Cabanillas-Carbonell, 2024; Le et al., 2019b; Ma et al., 2024; Perboli; Arabnezhad, 2021; Son et al., 2019; Veganzones; Severin, 2021; Wang; Li; Zhao, 2022; Zhao; Ouenniche; De Smedt, 2024)
Logistic Regression		
10	23.8%	(Antunes; Ribeiro; Pereira, 2017; Calabrese; Marra; Osmetti, 2016; Da Silva Mattos; Shasha, 2024; Gordini, 2014; Hung; Chen, 2009; Kim et al., 2020; Perboli; Arabnezhad, 2021; Ravi Kumar; Ravi, 2007; Son et al., 2019; Veganzones; Severin, 2021)
Decision Trees (DT)		
9	21.4%	(Bajo et al., 2012; Dasilas; Rigani, 2024; Hung; Chen, 2009; Iparraguirre-Villanueva; Cabanillas-Carbonell, 2024; Kim et al., 2020; Rozenbaha, 2018; Uthayakumar; Vengattaraman; Dhavachelvan, 2020; Veganzones; Severin, 2021; Zhao; Ouenniche; De Smedt, 2024)
Genetic Algorithms (GA)		
6	14.3%	(Ansah-Narh et al., 2024; Gordini, 2014; Lin et al., 2009; Ma et al., 2024; Nwogugu, 2006; Uthayakumar; Vengattaraman; Dhavachelvan, 2020)
Case-Based Reasoning (CBR)		
5	11.9%	(Bajo et al., 2012; Lin et al., 2009; Ravi Kumar; Ravi, 2007; Sartori; Mazzucchelli; Gregorio, 2016; Uthayakumar; Vengattaraman; Dhavachelvan, 2020)
Fuzzy Logic		
4	9.5%	(Chaudhuri; De, 2011; Nwogugu, 2006; Ravi Kumar; Ravi, 2007; Uthayakumar; Vengattaraman; Dhavachelvan, 2020)

Deep Learning (DL)		
4	9.5%	(Son et al., 2019; Wang; Li; Zhao, 2022; Xie; Tan; Liu, 2024, p. 2; Yang et al., 2025)
K-Nearest Neighbors (KNN)		
3	7.1%	(Dasilas; Rigani, 2024; Iparraguirre-Villanueva; Cabanillas-Carbonell, 2024; Kim et al., 2020)
Multi-Agent Systems (MAS)		
2	4.8%	(Bajo et al., 2012; Hasbaoui; Saida, 2022)
Ant Colony Optimization (ACO)		
1	2.4%	(Uthayakumar; Vengattaraman; Dhavachelvan, 2020)
Bayesian Networks		
1	2.4%	(Ravi Kumar; Ravi, 2007)
Gaussian Processes (GP)		
1	2.4%	(Antunes; Ribeiro; Pereira, 2017)

Source: prepared by the author.

Figure 3 – Approaches Frequency



Source: prepared by the author.

We classified the employed methods according to the periods in which they were most frequently used. The Traditional Methods group comprised 11 studies published between 2006 and 2018, predominantly employing approaches such as SVM, Bayesian Networks, and Fuzzy Logic. This was followed by the Ensemble Methods group, consisting of 14 articles published from 2016 to 2022, where Random Forest, Genetic Algorithms, and Ensemble Methods were the dominant approaches. Finally, the period spanning 2019 to 2025 was characterized as the "Hybrid Models" group, encompassing 17 studies that frequently utilized approaches like XGBoost, Deep Learning, and Transformers. The period from 2011 to 2018 marked a transition from statistical methods to ensemble learning, with Random Forest appearing in 43% of the studies during this phase. In contrast, between 2019 and 2024, XGBoost and Deep Learning dominated 58% of publications, reflecting the growing demand for models capable of handling big data in SMEs.

Due to their characteristic small teams and centralized management, SMEs typically possess limited recorded data while simultaneously facing intense market dynamics that require frequent adaptation to both macroeconomic and local trends. In this context, we recommend employing XGBoost and Random Forest approaches

for business risk prediction, as these have proven effective among the reviewed studies for handling unstructured and limited data respectively. When interpretability is a key requirement, Decision Trees seem to be effective by enabling rule-based analysis. For scenarios demanding adaptation to specific contexts, Hybrid Models emerge as the most prominent solution. The application of NLP also proves valuable in these situations, as it enables analysis of non-financial and unstructured data such as reports, news, sentiment, and interviews transcripts. A comprehensive summary of the recommended approaches for each SME context is presented in Table 7.

Table 7 – Approaches recommended

SME Context	Recommended Approach	Why	Limitations
Limited data	Random Forest	Robustness to overfitting and interpretability	Worse performance than XGBoost on large datasets
Unstructured data	XGBoost + SMOTE	High accuracy (AUC > 0.90) and explicit treatment of rare classes	Computational complexity
Interpretability requirements	Decision Tree	Clear rules for managers	Less accurate for non-linear relationships
Specific Areas	Hybrid Models	Adaptability to unique contexts	Requires detailed historical data
Qualitative Data	NLP	Unstructured data analysis capability	Implementation complexity

Source: prepared by the author.

Regarding non-financial data, this represents a significant bottleneck identified in the analyzed studies. The ANPROTEC - Brazilian Association of Entities Promoting Innovative Enterprises and the Model of Vaz, Carvalho and Teixeira, recommends that business strategic planning consider at least five distinct entrepreneurial areas: Technological, Entrepreneurial Profile, Management, Market, and Financial (Anprotec, 2018; Vaz, Carvalho & Teixeira, 2023). While all 42 reviewed studies incorporated financial data, only 7 (16.6%) included other types of management, market, or technological information. Notably, all studies treated

financial factors as the core of their analysis, with none considering more than three business areas simultaneously.

In business management practice, financial outcomes typically reflect the strategies and operations implemented across all functional areas. Consequently, restricting risk assessments and diagnostics solely to financial metrics provides only a partial view - essentially capturing just the end results of business strategies (or lack thereof). This limitation reveals a clear research gap, highlighting the need for predictive tools that adopt a comprehensive business context approach. Such tools should deliver holistic diagnostics reflecting all organizational dimensions, enabling early identification of problems and risk points across the entire enterprise.

It is pertinent to note that although this literature review drew from information sources worldwide, it does not critically represent all global scenarios, as the published researches covers only 29 different countries out of the 190+ existing nations. The represented countries include 18 European nations, 6 Asian countries, 3 American nations, and 2 African countries. Consequently, there exists a potential geographical bias heavily skewed toward European countries, which account for 27 of the selected papers, followed by Asian countries. Though fewer in country count than Europe, Asia contributes significantly to the article quantity in this sample (17 articles).

Regarding potential biases, there also appears to be a publication bias, as articles frequently use positive phrasing to describe their results, claiming their models "significantly outperform" or "improve accuracy by x%." However, some studies reported only accuracy while omitting recall - a metric that can be critical for bankruptcy identification; other studies had data imbalances that also make the presented positive results questionable. Furthermore, most studies report that their proposed approaches surpassed traditional methods and rarely pointed out limitations or counterarguments.

Another gap in studies proposing prediction approaches or tools is that only 3 of the analyzed studies explicitly stated having tested models in real SMEs. Although 11 studies used real data, they did not report testing in operational situations. Thus, while the developed proposals may have shown relevance with the samples used, they might yield different results, require adjustments, or reveal limitations when tested in real-world environments.

An additional bias to consider is that 90% of studies used historical datasets that are imbalanced and primarily represent the period between 2006 and 2018. Consequently, recent crises that have dramatically altered economic and business management dynamics - such as COVID-19, wars, global inflation, the implementation of digital currencies, and the massive emergence of AI - are realities not represented in these proposals. There is no evidence to determine whether these tools and approaches would remain relevant if applied to current data incorporating all these aforementioned changes.

2.2 THEORETICAL FOUNDATION

2.2.1 *Organizations*

The theory of organizations has its roots in foundational works that continue to shape contemporary research and practical approaches to management and business diagnosis. The seminal contribution of March and Simon in *Organizations* (1958) introduced the concept of "bounded rationality," emphasizing that decision-makers in organizations operate under constraints of information, cognitive limitations, and time. Rather than always pursuing optimal decisions, organizational actors often seek solutions that are "good enough" to meet objectives. This perspective provided a more realistic understanding of decision-making within organizations and challenged the assumptions of perfect rationality in classic economic theory.

Recent studies continue to build on the bounded rationality framework, recognizing its applicability in today's complex and uncertain business environments. On this matter, Baptista et al. (2020) discuss how digital and AI tools are reshaping organizational decision-making processes, creating new configurations of human and algorithmic work that both mitigate and expose the cognitive and informational limitations described in classic organizational theory. Their findings underscore the ongoing importance of behavioral perspectives while illustrating how technology can augment or constrain managerial judgment in modern organizations.

Similarly, Baumann, Schmidt, and Stieglitz (2019) provide a comprehensive review of how organizations conduct search and adaptation on so-called "rugged performance landscapes"—situations characterized by multiple, conflicting objectives and uncertainty. Their work highlights that, while digital tools and analytics can enhance the search for optimal strategies, the process remains fundamentally

shaped by bounded rationality and organizational learning. This aligns directly with the challenges faced by small and medium-sized enterprises (SMEs) in Brazil, as addressed in this thesis, where decision-makers must navigate complexity and resource constraints, often relying on both human judgment and technological support to identify viable paths for business improvement and innovation.

Considering the challenges faced by enterprises with strategic management, another influential author in this field is Michael E. Porter (1980, 1991). Porter's contributions shaped the way organizations understand and develop competitive strategies. His classic Five Forces Framework was first introduced in the article "How Competitive Forces Shape Strategy" (Porter, 1979), and later updated (Porter, 2008a). This framework identifies five key forces that determine the competitive intensity and attractiveness of a market: the bargaining power of buyers, the bargaining power of suppliers, the threat of new entrants, the threat of substitute products or services, and the rivalry among existing competitors. By analyzing these forces, organizations can better understand the structure of their industry, anticipate shifts in competition, and identify strategic opportunities or threats.

In addition to the Five Forces, Porter developed the concept of Value Chain Analysis, initially presented in his book *Competitive Advantage* (Porter, 1985) and further discussed in Porter (2008b). The value chain framework enables organizations to analyze their internal activities and processes to identify sources of competitive advantage. By decomposing a company's activities—from inbound logistics to operations, outbound logistics, marketing and sales, and service—managers can pinpoint areas where value is created or lost, and implement strategies to optimize efficiency, reduce costs, or differentiate offerings.

Porter's theories have evolved to address the dynamics of contemporary competition, especially in light of technological change and globalization. His updated works (Porter, 2008b, 2008a) emphasize the need for organizations to continuously adapt their strategies to new competitive realities, including digital transformation and the emergence of new business models. For small and medium-sized enterprises (SMEs), applying Porter's frameworks provides a structured approach to understanding both external industry pressures and internal processes, which is essential for developing robust strategies in an increasingly complex environment.

Contemporary research extends these concepts to examine how digital transformation and data-driven decision-making impact organizational

competitiveness (Farissi; Roudab, 2024; Maulidian et al., 2024). These studies highlight that organizations must assess both internal capabilities and external threats with greater agility, reinforcing the importance of continuous business diagnosis as part of strategic management.

Within the Brazilian context, studies focused on SMEs have identified a persistent gap in managerial knowledge and diagnostic capability (Bizzotto et al., 2018; Nowak; Grantham, 2000). Research indicates that entrepreneurs often lack the tools and frameworks necessary for effective organizational analysis, especially regarding financial management, market positioning, and technological adaptation. The application of artificial intelligence in business diagnostics, such as the approach proposed in this thesis, is seen as a promising way to bridge this gap by offering structured, evidence-based recommendations that account for both the limitations and opportunities identified in classic organizational theory (Elia; Margherita, 2016).

Recent literature also highlights the potential of combining qualitative assessments with quantitative tools, such as machine learning models and natural language processing, to enhance diagnostic accuracy and support managerial decision-making (Brenes; Johannssen; Chukhrova, 2022; Zhang, 2020). These approaches are consistent with the pragmatic orientation of March and Simon, as well as the strategic and market-oriented frameworks of Porter and Kotler, respectively. In this context, managerial decisions can benefit from both human expertise and technological support.

These theoretical perspectives provide a foundation for understanding the complexities of organizational decision-making. By integrating classic and contemporary approaches, this thesis aims to operationalize these concepts through the development of an AI-based framework and artifact for business diagnosis, applied to the realities of Brazilian SMEs. This integration ensures that both human expertise and technological tools are leveraged to address the multiple challenges faced by small and medium-sized enterprises.

The evolution of organizational theory demonstrates the importance of understanding both the behavioral and analytical aspects of organizations. Thus, these classic approaches can be integrated with artificial intelligence and data analytics in order to achieve more precise business diagnosis, offering new pathways for small and medium-sized enterprises in Brazil to enhance their competitiveness and sustainability.

2.2.2 Business Diagnosis and Diagnostic Models

Business diagnosis refers to the systematic process of assessing an organization's internal and external environments to identify strengths, weaknesses, and areas for improvement. It provides a foundation for strategic planning and informed decision-making, especially for small and medium-sized enterprises (SMEs) facing resource constraints and dynamic markets (Harrison, 2005).

Kasik (2017) described the genesis and development of business diagnosis, focusing on its evolution in the Czech and Slovak contexts and presenting new trends and approaches. Lim et al. (2012) in a review of 172 studies, revealed inconsistencies in the definition of "failure" within the business context. Sometimes, the term refers to situations of financial crisis and difficulty meeting financial obligations, while in other contexts, it denotes formal bankruptcy or legal closure.

Hernández-Díaz et al. (2021) explored the sustainability of SMEs in Puerto Rico using a comprehensive questionnaire based on the five MOPSE dimensions, emphasizing that business sustainability covers all organizational aspects, not just environmental issues. This multidimensional approach is increasingly recognized as essential for effective diagnosis.

In the context of Industry 4.0, Santos and Martinho (2020) developed a maturity model to evaluate how enterprises are integrating advanced digital technologies, validating it through case studies of large Brazilian automotive firms.

The relationship between resistance to change and organizational performance has also been studied through diagnostic models. Metz (2017) applied an organizational diagnosis covering 14 dimensions—including structure, leadership, motivation, and resistance to change—to a large multinational ICT company, using survey data from 776 employees to analyze the linkage between resistance and performance.

Recent advances have focused on predictive models for business failure, especially using financial data. Le et al. (2019b) proposed a hybrid approach combining oversampling and cost-sensitive learning, applying it to a Korean bankruptcy database. They used several machine learning techniques (HAOC, CBoost, Python, Scikit-learn) and highlighted that most predictive models do not limit their analysis to a specific company size.

Historically, business failure prediction from the 1960s to the 1990s relied on statistical models, mainly Multivariate Discriminant Analysis and Logistic Regression. Machine learning (ML) techniques emerged in the late 1980s and have since become prominent due to their adaptability and flexibility (Brenes; Johannssen; Chukhrova, 2022). ML techniques, such as logistic regression, decision trees, random forests, XGBoost, neural networks, and SVM, are now often favored over traditional statistical methods for their superior performance in many contexts (Rufsana.; Baiju, 2023).

However, most studies in this area focus primarily on financial data, largely because such data is easier to collect and analyze than qualitative or market-related information. As a result, financial distress prediction is a well-established field, dating back to the 1930s (Brenes; Johannssen; Chukhrova, 2022).

Other notable studies include Le et al. (2019a), who proposed an XGBoosting approach for bankruptcy prediction using GPU processing, and Gordini (2014), who compared genetic algorithms, logistic regression, and SVM for predicting bankruptcy based on financial data. Brenes, Johannssen e Chukhrova (2022) also examined the effectiveness of multilayer perceptrons for predicting business failure in Thai companies.

Despite the proliferation of models, there is no clear consensus on the best predictive method. After reviewing both intelligent and statistical models, Shi and Li (2019b), concluded that the literature has yet to determine a universally superior approach, as evidenced by the diversity of models implemented in 321 reviewed articles.

Classic diagnostic frameworks, such as SWOT analysis (Benzaghta et al., 2021), the Balanced Scorecard (Kaplan; Norton, 1996), and the Nadler & Tushman Congruence Model (Nadler; Tushman, 1980), remain influential, particularly for multidimensional assessments that go beyond financial indicators. The integration of these frameworks with advanced AI and machine learning holds promise for more holistic business diagnosis, especially for SMEs operating in complex and uncertain environments.

2.2.3 Knowledge Engineering and Knowledge Management

Knowledge Engineering (KE) is an interdisciplinary field positioned at the intersection of computer science, management, and cognitive science. It is fundamentally concerned with the creation of tools, methods, and techniques to

support the systematic management and application of knowledge—particularly organizational knowledge—within specific domains (Schreiber, 2000; Zhang, 2020). Knowledge Management (KM) provides the foundational context for KE, serving as an effective approach to organizing, sharing, and leveraging both explicit and tacit knowledge in organizations (Davenport, 1998).

A central concept in KE and KM is the distinction between tacit knowledge (personal, context-specific, and hard to formalize) and explicit knowledge (codified, easily communicated, and stored). The process of transforming tacit knowledge—such as the expertise of consultants or managers—into explicit knowledge that can be embedded in information systems is a key challenge and opportunity in this field (Nonaka, 2009). This transformation is especially relevant for the development of intelligent systems for business diagnosis, where the goal is to capture the practical insights of organizational actors and operationalize them in AI-based tools.

Schreiber et al. (2000), in their book "Knowledge Engineering and Management: The CommonKADS Methodology," provide one of the main bibliographic foundations for the study of Knowledge Engineering, exploring essential methodologies and techniques for this discipline. They present KE as a specialized branch of Artificial Intelligence focused on capturing human knowledge and integrating it into intelligent systems, typically to solve complex problems that require high levels of expertise.

Because it is interdisciplinary by nature, Knowledge Engineering can be applied in diverse domains, including business, healthcare, and finance. Cognitive science definitions are relevant for the design of knowledge-based systems, highlighting the involvement of fields such as neuroscience, philosophy, linguistics, and psychology (Núñez et al., 2019). However, as Haykin (2009) and Yun et al. (2021) point out, this interdisciplinarity and variability of application domains can create methodological challenges, due to the variety of techniques and the lack of standardization.

Regardless of context, the core processes in KE are knowledge acquisition (often through interviews, questionnaires, and observation) and knowledge representation (structuring data in databases, ontologies, or semantic networks for processing by computational algorithms) (Schreiber, 2000; Yun et al., 2021). The ultimate aim is to make organizational knowledge actionable—enabling the creation

of intelligent systems that can perform tasks at a level comparable to human understanding.

Knowledge Engineering and Knowledge Management provide the theoretical and methodological backbone for transforming the often tacit organizational knowledge of experts into explicit. This way, KE and KM are foundation theories that allow structured formats to be suitable for computational processing. This transformation is critical for the development of AI-based business diagnostic artifacts, as proposed in this thesis.

2.2.4 Artificial Intelligence in Business Decision-Making

Artificial intelligence (AI) is broadly defined as the field of computer science dedicated to creating systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, and problem-solving (Russell; Norvig, 2021). In the context of business, AI has become a transformative force in decision-making, enabling organizations to derive knowledge from large volumes of data and to automate complex processes.

AI research is deeply intertwined with data science, an interdisciplinary field that leverages principles, methods, techniques, and tools from statistics, computer science, and domain-specific knowledge to extract actionable insights from data. Data science relies on AI foundations, with much of its theoretical basis established in the widely recognized book *Artificial Intelligence: A Modern Approach* by Russell and Norvig (2021). They highlight that data is the essential input for AI systems, enabling them to learn, adapt, and make decisions. Through the process of generalization, AI systems build models that can apply learned patterns from specific examples to broader contexts—a capability that is central to the effectiveness of AI in business applications.

At the core of data science is machine learning (ML), a subfield of AI that focuses on developing algorithms capable of learning from data and making predictions. Russell e Norvig (2021) identify several key paradigms in ML, including supervised, unsupervised, and reinforcement learning. Briefly, supervised learning involves training models on labeled datasets to predict known outcomes (such as classification or regression tasks); unsupervised learning seeks to discover structures within unlabeled data (such as clustering or dimensionality reduction); and

reinforcement learning enables models to learn optimal actions through interactions with an environment, guided by rewards or penalties (Haykin, 2009).

In this thesis, the focus is on supervised learning (Bishop, 2006), as there is a known dataset and the goal is to predict outcomes with predefined labels. Classification techniques—where the aim is to assign new instances to established categories based on their features—are especially relevant to business diagnosis.

A recent and highly impactful development in AI is **Generative AI** (GenAI), which refers to models capable of generating new content such as text, images, or code by learning from large datasets (Bommasani, 2021). GenAI models, such as GPT-4 (OpenAI Platform, 2025a, 2025b) and similar architectures, have revolutionized human–AI interaction and opened new opportunities for business process automation, knowledge management, and decision support. In business diagnostics, GenAI can be leveraged to analyze unstructured data, generate reports, or assist in the interpretation of complex scenarios (Rane, 2023; Ravichandran; Machireddy; Rachakatla, 2024; Sourav; Asha; Reza, 2025).

Another contemporary advancement in the use of GenAI is the technique known as **Retrieval Augmented Generation (RAG)**. RAG enhances the quality and accuracy of generative models by allowing them to retrieve relevant, up-to-date information from external sources or datasets at prompt query time (OpenAI Platform, 2024). This approach shows to be especially valuable for answering questions that fall outside the model's original training data, thus improving contextualization and precision in business diagnosis applications (OpenAI Platform, 2024).

Prompt engineering has emerged as a critical skill for effectively utilizing GenAI systems. A prompt is the textual input or instruction given to a model like ChatGPT. Research by Denny et al. (2024) and Dang et al. (2022) highlights that most end-user interactions with GenAI are iterative and experimental, requiring thoughtful design to achieve optimal outcomes. Korzynski et al. (2023) propose a comprehensive prompt engineering framework that recommends clearly articulating instructions, specifying expected outputs and context, refining prompts to avoid ambiguity, providing examples and feedback, managing interaction, and limiting complexity. OpenAI's documentation also provides best practices for prompt construction and optimization (OpenAI Platform, 2025c).

AI is driving transformation in organizations, fundamentally changing how business innovation is managed. Haefner et al (2021) observe that rapid

technological advances and improvements in AI systems are prompting organizations to rethink their innovation processes, making them more agile and data-driven. The integration of knowledge engineering, GenAI, prompt engineering, and RAG techniques enables the creation of intelligent diagnostic systems, which can capture and operationalize organizational knowledge, deliver precise analysis, and support decision-makers in complex environments.

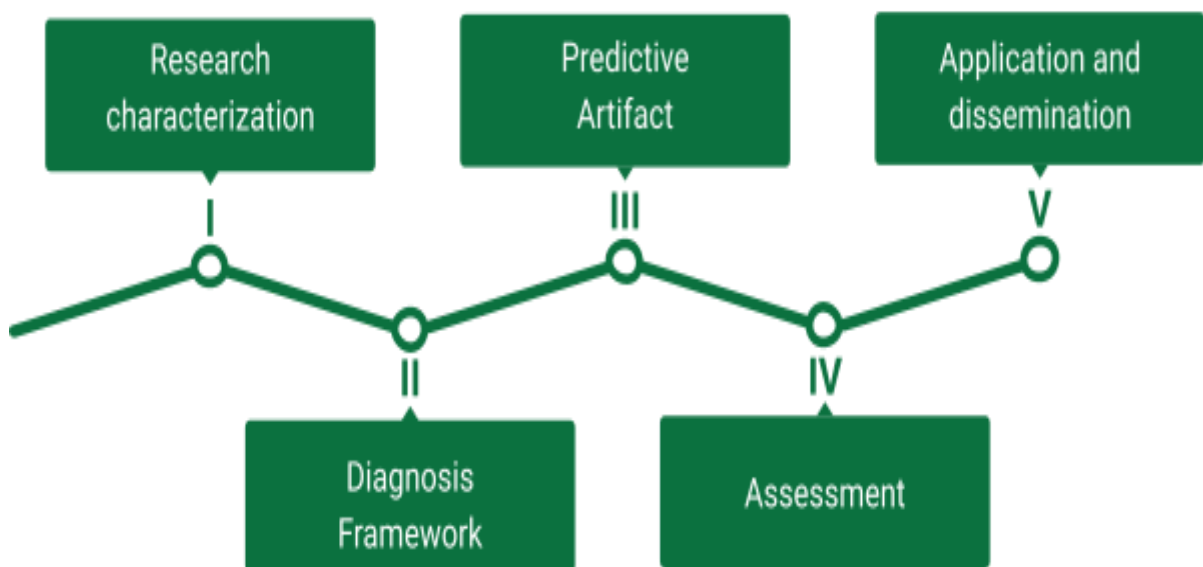
The application of AI and GenAI in business decision-making, supported by data science, prompt engineering, and retrieval-augmented generation, forms the technological backbone of the diagnostic artifact developed in this thesis. These tools empower organizations to leverage both structured and unstructured data for more informed, accurate, and timely decision-making.

3 METHODS

According to Cupani (2006), technological research—such as this work—involves applying both scientific and practical knowledge to generate feasible, reliable, and efficient solutions that offer strong cost-benefit relations.

Accordingly, the methodological workflow adopted in this thesis follows five main stages: (1) characterization of the research and its philosophical foundations; (2) design and refinement of the business diagnosis framework, including data collection and framework development; (3) development of an AI-based predictive artifact; (4) assessment and validation of both the framework and the artifact; and (5) application and dissemination of results. The Figure 4 illustrates the relationship between these stages.

Figure 4 – Steps of the Research



Source: prepared by the author.

A detailed account of the procedures and decisions taken at each stage can be found in the following subsections. Table 8 provides a summary of each step, including the respective outcomes achieved and the materials and methods employed.

Table 8 – Results, Methods and Materials of the Steps

Step	Results	Methods	Materials
1. Characterization of the Research	Definition of the philosophical conception, approach, type of research, and methodological strategies used.	Literature searches and reviews, reading, and methodological adaptations.	Methodological guidelines of Creswell and Creswell (2017), Goodman (1996), Creswell and Clark (2010), Russell (1910) and Cupani (2006).
2. Diagnosis Framework	Definition of the diagnostic and evaluation framework for companies.	Interview Analysis and Methodological Refinement with Generative AI.	Interview Database, Metodologia IncubE (Pinto-Junior; Silvestro; Morais, 2021) and Generative AI.
3. Prediction Artifact	Business Diagnostic Prediction Artifact.	Literature review; prototype development for testing; artifact development with text/speech analysis.	BSM Framework; Interview Database; Programming Languages; Artificial Intelligence; Development IDE and API.
4. Assessment	Scientific and technological validation of the prediction artifact.	Expert evaluation. Publication of articles.	Artifacts and evaluation forms. Published scientific articles.
5. Application and Dissemination	Assistance to companies and public awareness of the research.	Application to voluntary SMEs. Scientific dissemination.	Predictive artifact. Published scientific articles. Thesis.

Source: prepared by the author.

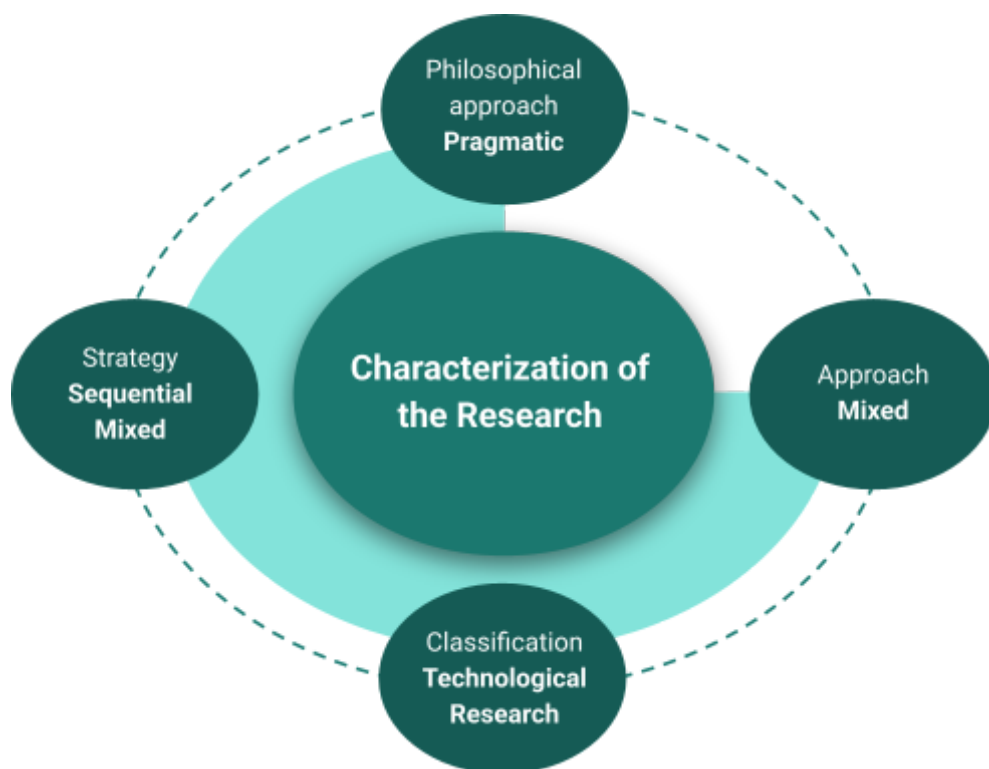
3.1 CHARACTERIZATION OF THE RESEARCH

Figure 5 presents a diagram that characterizes the research conducted in this study. The philosophical conception adopted reflects the way the researcher views the world. In this work, a pragmatic approach is employed—commonly found in interdisciplinary research—which emphasizes solving real-world problems.

Regarding the research approach, pragmatism does not adhere to any single philosophical system or specific concept of reality; therefore, we have chosen a mixed methods approach. This is typical of pragmatic researchers, as it allows for the use of both quantitative and qualitative assumptions within the same study. In our case, we employ a sequential mixed methods strategy, alternating between qualitative and quantitative approaches, and allowing for interconnections between them.

Concerning the classification of the research, it is defined as technological research due to its applied nature, with a focus on addressing a real problem: diagnosing businesses and developing an artificial intelligence technology to provide a solution. Each of these topics relevant to the characterization of the research is detailed in the subsections that follow.

Figure 5 – Characterization of the Research



Source: prepared by the author.

3.1.1 *Pragmatic Philosophical Conception*

Creswell and Creswell (2017) argue that the pragmatic philosophical conception in scientific research enables the integration of scientific and

non-scientific methods, drawing upon real-world problems as a basis for focusing on how to solve them. The central concern of this approach is finding solutions, with an emphasis on addressing a given situation by analyzing its context and potential consequences.

In developing their framework for pragmatic inquiry, Creswell e Creswell (2017) emphasizes the use of pluralistic approaches and the foundations of social sciences. These characteristics align well with interdisciplinary research, where it is often necessary to utilize knowledge, techniques, methods, and tools from more than one field of study. Consequently, this fusion also blends approaches and philosophies, but always with the underlying aim of resolving a problem that spans across different domains. Pragmatism, therefore, provides the researcher with the flexibility to choose whatever is necessary to address the research problem, making use of all relevant resources, methods, and techniques.

For pragmatists, the world is not organized as an absolute entity. Goodman (1996) explains that this philosophical conception emerged in the late nineteenth and early twentieth centuries, led by figures such as Ralph Waldo Emerson, Charles Sanders Peirce, William James, and John Dewey. Goodman notes that pragmatism fosters a connection between the past (historical experience) and the future, with a foundation rooted in the present. This concept is closely aligned with the aims of this research, as we seek to utilize contemporary data from previously conducted business consulting projects (which reflect the business's past) to predict the company's future in terms of business health. Pragmatism is also understood as an approach oriented towards practical outcomes, with its scientific validity supported by social or political results produced.

It is common for pragmatic researchers to employ mixed methods, combining various approaches for data collection and analysis rather than limiting themselves to a single, quantitative or qualitative methodology.

3.1.2 Mixed Methods Approach

Because pragmatism is not tied to any particular philosophical system or specific concept of reality, it is typical for researchers to converge on a mixed methods approach. In mixed methods research, both quantitative and qualitative assumptions are applied within the same study (Creswell; Clark, 2010).

For this research, we align with Russell's (1910) critique of pragmatism, understanding that truth consists not only in what works, but in what produces a positive impact on the reality to which it is applied. Therefore, we value the usefulness of results, but do not consider their practical consequences as representing absolute truth.

Thus, in adopting a mixed methods approach, it becomes possible to use both quantitative and qualitative tools and techniques to arrive at a more comprehensive understanding of the problem. However, such combinations are not made randomly; there is always a purpose, a logical basis, a theoretical foundation, and a careful analysis of concise data. For the mixed methods researcher, pragmatism paves the way for combining multiple methods, conceptions, and assumptions, as well as a variety of data collection and analysis strategies, in support of achieving the intended research outcomes.

3.1.3 Sequential Mixed Methods Strategy

The mixed methods approach typically involves three main research strategies: sequential, concurrent, and transformative (Creswell; Clark, 2010). All these strategies employ both qualitative and quantitative approaches. In the sequential mixed methods strategy, however, the two approaches are implemented one after the other, and can be interconnected. In the concurrent strategy, qualitative and quantitative approaches proceed in parallel but independently, only being integrated at the interpretation stage. In the transformative approach, sequential and concurrent strategies can be combined within a single study.

In this research, the mixed approach is employed as follows: qualitative data are obtained from interviews conducted during business consultancy sessions; a qualitative assessment is performed through analysis of these interviews and scores are assigned; these scores are then used for statistical processing by artificial intelligence techniques for diagnostic prediction. Furthermore, in a subsequent stage after the qualification of the research, additional qualitative data (for instance, through natural language processing) will be collected and analyzed quantitatively, together with data previously obtained, again through statistical methods.

3.1.4 Type: Technological Research

Cupani (Cupani, 2006) discusses the existence of two main types of research: scientific and technological. No Table 9 summarizes the key characteristics that Cupani attributes to each type. Within this framework, the current thesis aligns itself with technological research, since it is focused on solving a real-world problem—that of diagnosing businesses and developing an artificial intelligence technology to address this need.

The technological knowledge required originates from the predictive and diagnostic tasks that must be carried out, and data are collected from business consultancy interviews, which constitutes a non-scientific source. Additionally, the processing of the collected data yields predictions that enable the understanding, control, and modification of the strengths and weaknesses within real business contexts.

Table 9 – Scientific and Technological Research

ASPECT	SCIENTIFIC RESEARCH	TECHNOLOGICAL RESEARCH
Main Focus	Develops science	Develops technology
Primary Concern	Understanding how things work; theories, laws	Solving problems
Nature of Knowledge	“Limited by theory”	“Specified by the task”
Data Requirement	Requires data relevant to technical, economic, and cultural demands the artifact must meet	Mostly uses data from non-scientific experiments
Relation to Reality	Seeks to understand reality	Seeks to control and modify reality
Approach	More reliant on theoretical, scientific thinking	Relies more on analogical thinking than scientific thinking
Output	Formulation of theories and laws	Formulation of action rules for generating artificial phenomena

Source: prepared by the author.

3.2 DIAGNOSIS FRAMEWORK

Before discussing a model for business failure prediction, Brenes, Johannssen, and Chukhrova (2022) emphasize that, more important than the predictive model itself, is having a clear understanding of the underlying causes that lead to business failure. The direct involvement of this researcher in practical contexts through involvement in various research projects, extension activities, and work in a business incubator (Morais; Pinto-Junior; Silvestro, 2021; Pinto Junior et al., 2021; Pinto-Junior; Campos; L., 2021; Pinto-Junior, 2021, 2024; Pinto-Junior et al., 2021a, 2021b, 2021c, 2023; Pinto-Junior; Novaes, 2021; Pinto-Junior; Silvestro, 2021; Pinto-Junior; Silvestro; Morais, 2021; Silvestro; Pinto-Junior; Duncke, 2021), helped with this comprehension of what usually causes problems to SMEs.

Iturriaga and Sans (2015) support this understanding, noting that an appropriate combination of problem characteristics together with a suitable classification tool is more effective than relying solely on a standard classification tool. In this context, the support of a framework alongside a diagnostic tool can be valuable for business assessment. In this research, we present both methodological and technological-instrumental components within the scientific workflow that enabled the development of this study.

The diagnostic framework results from two foundational activities:

1. **Business Incubators Interview and Literature Review:** To identify critical dimensions for business health, major dimensions are identified through benchmark interviews with business incubators and then the findings are ascertain with a literature review of recent and classical studies in business diagnostics;
2. **Expert-Curated Question Database:** an author's database containing business diagnostics, which was used to generate diagnostic questions subsequently refined through the support of Generative AI and validated by specialists.

3.2.1 Data Collection

Data were collected through structured interviews with micro, small, and medium-sized businesses in five Brazilian states. Interviews were conducted by senior consultants with extensive management and consulting experience, sometimes accompanied by junior consultants for consensus and methodological

training. In total, 96 enterprises were interviewed by June 2024, leveraging both academic collaborations and independent application of the methodology for robustness and transferability.

3.2.2 Steps to Create the Framework

Figure 6 illustrates the eight sequential steps to summarize the process of creating the business diagnostic framework, demonstrating the systematic and integrated design of the methodology, as explained:

1. Step 1: Business Incubators Interview and Literature Review for Dimension Identification

The process begins interviewing business incubators in order to identify with them the most relevant dimensions for business diagnosis. Then conducted a review of the relevant literature to identify the main dimensions that are important for business diagnosis. Here, we have a cross-analysis of both strategies to define the dimensions and, also the validation of specialists about the selected dimensions. This step ensures that the framework is grounded in established research.

2. Step 2: Expert Consultation and Initial Question Set

Next, consultations with subject matter experts are conducted. These experts contribute to the development of an initial set of diagnostic questions, ensuring that the instrument addresses practical and context-specific issues.

3. Step 3: Diagnostic Interviews and Data Collection

In this step, diagnostic interviews are carried out with entrepreneurs from target enterprises. The data collected from these interviews provides insights into common challenges and operational realities faced by businesses.

4. Step 4: Data Processing and AI-aided Refinement

The collected data is then processed. Artificial intelligence tools, including prompt engineering and generative AI, are used to refine the set of diagnostic questions and ensure they are relevant, clear, and comprehensive.

5. Step 5: Final Diagnostic Instrument (Survey)

Based on the previous steps, the diagnostic instrument is finalized. This survey incorporates all validated and refined questions, making it ready for systematic application.

6. Step 6: SME Questionnaire Application

The final instrument is then applied to small and medium-sized enterprises (SMEs). This step involves distributing the questionnaire and collecting responses from participating businesses.

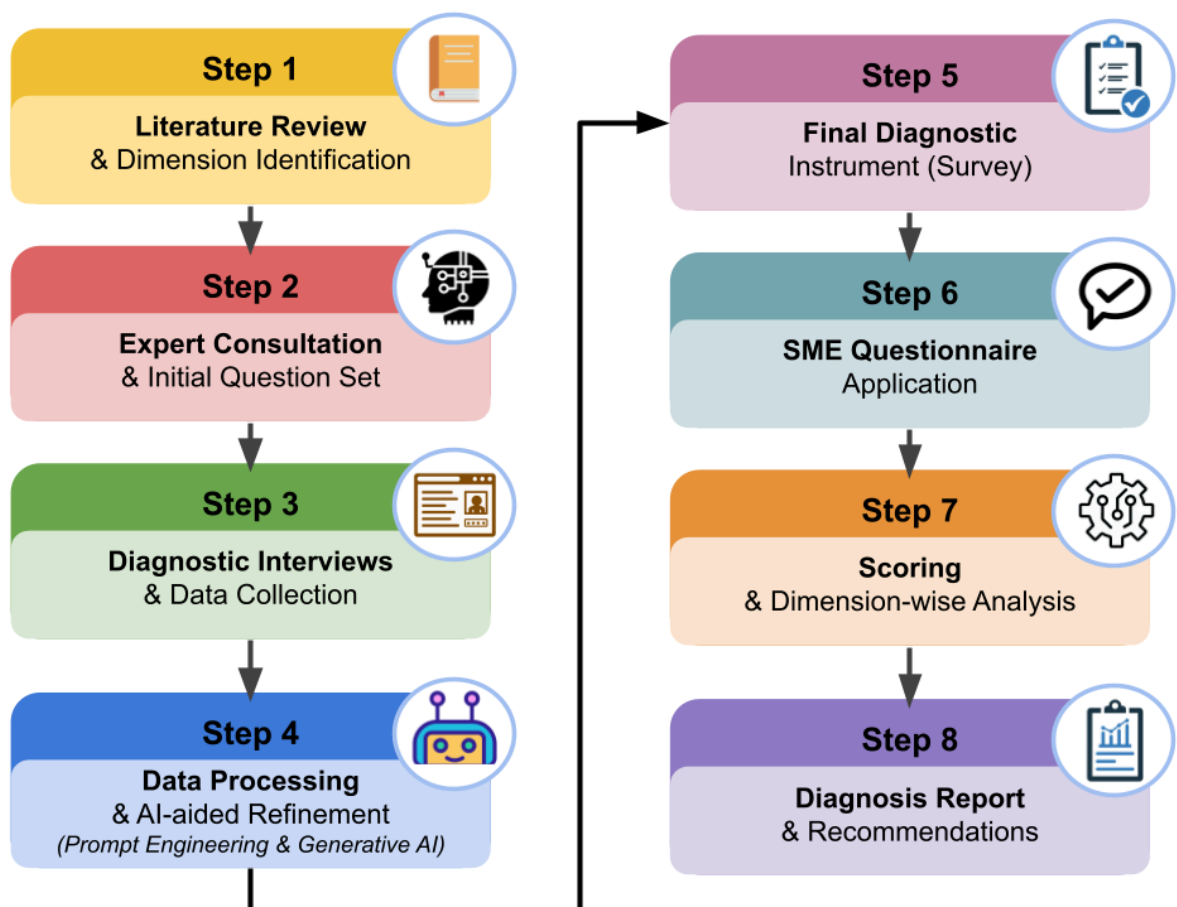
7. Step 7: Scoring and Dimension-wise Analysis

After data collection, responses are scored. Each dimension identified in the framework is analyzed to determine the relative strengths and areas for improvement within each business.

8. Step 8: Diagnosis Report and Recommendations

Finally, a diagnostic report is generated for each enterprise. This report includes an analysis of the business's strengths and weaknesses, along with tailored recommendations for improvement based on the identified dimensions.

Figure 6 – Steps to the Creation of the Framework



Source: prepared by the author.

This end-to-end visualization reinforces the systematic and integrative nature of the framework and helps to clarify the linkages among its steps, from literature and expert-driven dimension identification, through iterative design and refinement of the diagnostic instrument, to the steps of data collection, AI-aided enhancement, scoring, and the production of tailored diagnostic reports and improvement recommendations.

3.3 PREDICTION AI BASED ARTIFACT

Knowledge Engineering focuses on the integration of human knowledge into intelligent systems to address complex problems. According to Schreiber et al. (2000) it is essential to adopt a systematic approach to capture, organize, and operationalize knowledge so that artificial intelligence tools can use it to support decision-making processes.

In this research, the main challenge is to predict business diagnoses. The knowledge required for this task comes from both the enterprises being analyzed and the consultants who conduct the interviews. This knowledge has been synthesized into a structured framework, as described in the previous section. The current section describes the artifact that will instantiate this framework. The artifact is designed to capture relevant knowledge, organize it for analysis, and use it to generate predictions through artificial intelligence models.

The development of the artifact begins with an analysis of the literature reviewed in [Chapter 2](#), which provides an overview of techniques and approaches used by other researchers in the field. This review allows to understand the techniques and approaches that have been used by researchers around the world.

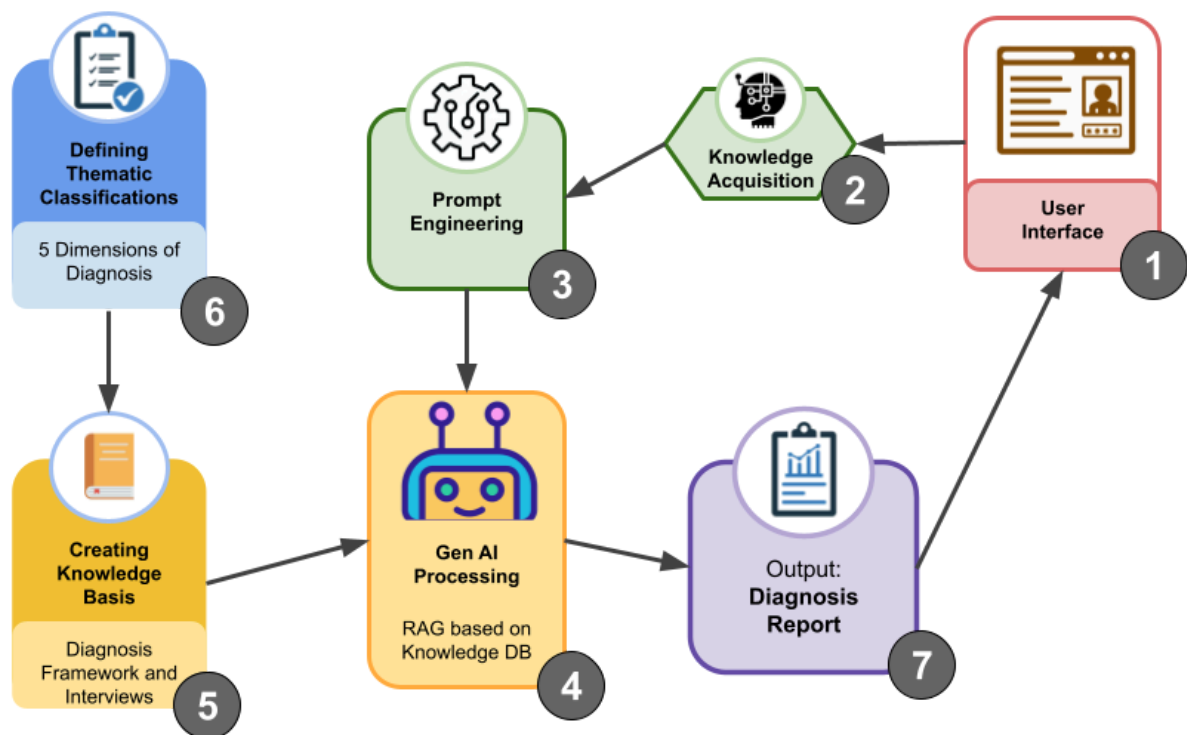
The process for developing and implementing the artifact is illustrated in Figure 7. The sequence of steps is as follows:

1. **User Interface:** The artifact provides an interface for users (entrepreneurs or consultants) to input data and receive a diagnosis report.
2. **Knowledge Acquisition:** The system collects data from users based on the structured framework.
3. **Prompt Engineering:** Tasks are defined and structured to guide the interactions between the system and the generative AI model.
4. **Generative AI with Retrieval-Augmented Generation (RAG):** The generative AI processes the prompt, using RAG to enhance the response with relevant external information.

5. **Knowledge Database:** The RAG component accesses a knowledge base built from the Diagnosis Framework, transcriptions of diagnostic interviews, business diagnosis reports, and thematic classifications developed in step 6.
6. **Thematic Classification:** Diagnostic content and supporting information are organized according to the thematic categories established in the framework.
7. **Diagnosis Report Generation:** The generative AI produces a diagnosis report, which is presented to the user through the interface.

This structure ensures that the artifact appropriately instantiates the framework, capturing and processing knowledge in order to provide consistent and explainable predictions for business diagnoses.

Figure 7 – Artifact Overview



Source: prepared by the author.

3.4 ASSESSMENT

This thesis adopts a KM methodology to develop a KE artifact. So, the methodological aspects related to KM will be evaluated through the publication of articles describing these processes.

According to Cupani (2006), a technological artifact must be evaluated, and its utility clearly demonstrated by specifying whether it meets the desired requirements

and by recording contextual factors relevant to its effective performance. Therefore, the evaluation of the framework and technological artifact will be conducted through the submission of articles and feedback collection from reviewers. Additionally, evaluation forms will be provided to KE experts to assess the artifact's applicability, usability, and functionality. Table 10 summarizes the assessments done by the research in order to evaluate the framework and the artifact.

Table 10 – Assessments of the Research

What	How	Why
Evaluation by peers	Submitting papers to journals and conferences.	To validate with experienced peers the effectiveness and scientific relevance of the research.
Evaluate the Framework	Forms to experts	To check the relevance, accuracy, trustability, and completeness of the framework.
Evaluate the Artifact	Forms to experts	To verify the relevance, applicability, usability, trustability and functionality.

Source: prepared by the author.

To rigorously assess the diagnostic quality, credibility, and professional utility of the SmartB artifact, must be conducted a targeted validation with business diagnosis specialists and consultants. This approach is grounded in best practices from the evaluation of decision support and expert systems in both software engineering and information systems fields (Dybå; Dingsøyr, 2008; Kitchenham et al., 2002).

The literature highlights the importance of involving domain experts to verify the content accuracy, completeness, and practical relevance of automated systems (Shneiderman; Plaisant, 2010). To this end, our assessment instrument incorporates structured questions addressing the accuracy of SmartB's outputs, the relevance and actionability of its recommendations, and a direct comparison to traditional expert assessments.

The inclusion of Likert-scale items, comparative judgment, and open-ended feedback aligns with established methods for expert evaluation of intelligent systems (Brooke, 1996; DeLone; McLean, 2003). Such a strategy ensures a multidimensional

appraisal, facilitating both quantitative benchmarking and qualitative insights necessary for iterative refinement of the artifact.

Specialists (consultants) evaluated the platform following this protocol: online meeting showing them the tool and all the functionalities. Then, they were invited to answer some questions, in an interview as specified in Table 11.

Table 11 – Questions for Consultants Evaluation

Questions for Business Diagnosis Experts Evaluation
Diagnostic Accuracy and Completeness 1. To what extent does the SmartB-generated diagnosis accurately identify the main strengths and weaknesses of the enterprise? <i>[Likert scale from 1 to 7]</i> 2. How well does the SmartB report cover all five business dimensions (Management, Market, Financial, Technology, Entrepreneurship)? <i>[Likert scale from 1 to 7]</i> 3. Are the strategic recommendations provided by SmartB actionable and appropriate for the business context? <i>[Likert scale from 1 to 7]</i> Comparison to Human Diagnosis 4. How does the SmartB system's diagnosis compare to a human expert diagnosis for the same case? <i>[Likert scale from 1 to 7]</i> 5. How would you, as an expert, use the SmartB system as a tool in a business diagnosis consultancy? <i>[Likert scale from 1 to 7]</i> Trust and Reliability 6. How would you trust the SmartB system to perform a preliminary diagnosis for SMEs without human intervention? <i>[Likert scale from 1 to 7]</i> 7. To what extent do you think SmartB can be used by entrepreneurs as a self-diagnostic and self-knowledge tool for their business, without the presence of a consultant? <i>[Likert scale from 1 to 7]</i> Usability and Clarity 8. Is the SmartB interface and report layout clear and logically organized for professional interpretation? <i>[Likert scale from 1 to 7]</i>

9. Do you think the questions in the form are understandable and relevant for a business diagnosis?

[Likert scale from 1 to 7]

Perception and Trust in AI

10. How aware are you that the SmartB system uses artificial intelligence to generate diagnostic reports?

[Likert scale from 1 to 7]

11. In your professional view, how much value does the integration of AI bring to the business diagnosis process in SmartB?

[Likert scale from 1 to 7]

12. Compared to traditional human-made diagnoses, how would you rate your trust in AI-driven reports like those from SmartB?

[Likert scale from 1 to 7]

13. How much do you trust the diagnostic results when you know they are generated supported by an AI system?

[Likert scale from 1 to 7]

Overall Assessment

14. How suitable did you find the BSM Framework for business diagnostic assessment?

[Likert scale from 1 to 7]

15. How would you rate SmartB as a tool for supporting business diagnosis?

[Likert scale from 1 to 7]

16. Please share any thoughts you have about your understanding of the BMS framework and the SmartB artifact, or suggestions about how to improve this project, based on your expertise.

[Open text]

Source: prepared by the author.

3.5 APPLICATION AND DISSEMINATION

As the final stage of the methodological process, this research aims to promote the dissemination of its results, including through practical application. The genesis of this research lies in a social purpose, as the business diagnosis tool was conceived to support micro, small, and medium-sized enterprises—particularly those unable to afford professional consulting services—by providing them with a diagnostic assessment of their business situation, enabling them to work towards necessary improvements and recovery. Therefore, upon completion of this work, one method for dissemination will be the application of the tool to a selected group of such enterprises, providing them with free feedback on their business health.

It is essential to evaluate not only the technical soundness but also the real-world usability and perceived value of SmartB from the perspective of end users—namely, entrepreneurs and enterprise managers. The use of structured questionnaires and open-ended feedback to capture users’ experiences draws directly from validated methodologies in human-computer interaction and technology acceptance research (Brooke, 1996; Davis, 1989; Venkatesh et al., 2003). These frameworks emphasize the necessity of assessing perceived usefulness, ease of use, and intention to continue using the system, as articulated in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Moreover, the inclusion of questions regarding actionability and impact on decision-making follows recommendations from the DeLone and McLean Information Systems Success Model (DeLone; McLean, 2003). Open-ended items are included in accordance with mixed-methods evaluation best practices (Creswell; Plano Clark, 2017), allowing for deeper exploration of user needs and contextual factors. By centering evaluation on users’ perceptions, comprehension, and practical outcomes, this assessment makes SmartB effective, trustworthy, and accessible to its intended audience.

When completing their diagnosis users were invited to answer a structured survey, after interacting with the system. The survey focused on usability, clarity of recommendations, and perceived accuracy of the diagnosis. The questions used in the survey are specified in Table 12.

Table 12 – Questions for User Evaluation

Questions for User Evaluation
Usability and Interface Experience 1. Was it easy to register, fill out the diagnostic form, and obtain your report? [Likert scale from 1 to 7] 2. Were the questions in the form understandable and relevant to your business? [Likert scale from 1 to 7] 3. How did you find the steps technically difficult or confusing? [Likert scale from 1 to 7] Perceived Value of Diagnosis 4. Did the SmartB diagnostic report helped you understand your business’s strengths and areas for improvement?

[Likert scale from 1 to 7]

5. Did you find the recommendations useful?

[Likert scale from 1 to 7]

6. Did you find the recommendations clear and applicable to your context?

[Likert scale from 1 to 7]

Actionability and Implementation

7. Do you feel able to implement at least some of the recommended actions from the SmartB report?

[Likert scale from 1 to 7]

8. Do you think you need more additional support or information in order to implement these recommendations?

[Likert scale from 1 to 7]

Trust and Credibility

9. How credible did you find the SmartB-generated diagnosis?

[Likert scale from 1 to 7]

10. Would you use SmartB again or recommend it to another entrepreneur?

[Likert scale from 1 to 7]

Perception and Trust in AI

11. Did you realize that SmartB uses artificial intelligence to analyze your responses and create the report?

[Likert scale from 1 to 7]

12. Do you believe using artificial intelligence in business diagnostics makes the results more valuable or trustworthy?

[Likert scale from 1 to 7]

13. How comfortable do you feel receiving business advice generated by an AI system?

[Likert scale from 1 to 7]

14. Would you prefer if an experienced consultant also reviewed or confirmed the AI-generated diagnosis?

[Likert scale from 1 to 7]

Overall Satisfaction

15. How satisfied are you with your experience using SmartB?

[Likert scale from 1 to 7]

16. Please share any thoughts you have about your experience with SmartB or suggestions about how to improve the platform for users like you:

[Open text]

Source: prepared by the author.

3.5.1 Dissemination

According to Dresch, Lacerda, and Antonio Junior (2021), this stage of dissemination should clearly present the lessons learned, conclusions drawn, and the generalization of findings to a broader class of problems. Generalizations are pursued through the assessments and applications mentioned above, while insights and conclusions are presented in scientific articles submitted to conferences, academic journals, and in this thesis itself. In these dissemination opportunities, particular emphasis is placed not only on how the research is scientifically structured, but, given its technological nature, also on the relevance of the problem addressed, its practical application, and the explanation of the artifacts developed to solve it.

4BSM - CONCEPTUAL FRAMEWORK FOR BUSINESS DIAGNOSIS

This chapter presents the BSM, a Conceptual Framework for Business Diagnosis, which underpins the methodology used to develop the AI-based diagnostic artifact described in this research. Guided by both literature and expert practice, this framework structures the diagnostic process into five key business domains—Management, Market, Finances, Entrepreneurship, and Technology—selected for their demonstrated relevance to SME performance and survivability (see Table 14). Each domain is assessed through a refined set of questions, developed iteratively with subject matter experts and enhanced via Generative AI tools, ensuring both contextual appropriateness and clarity for respondents. This structured framework not only enables business diagnosis but also facilitates replicability, transparency, and actionable outputs for business improvement.

4.1 BSM VISUAL CONCEPTUAL FRAMEWORK

The BSM Framework provides a structured process for business diagnosis, guiding the assessment and identification of improvement opportunities in small and medium-sized enterprises. To support a better overview of the framework, Figure 8 presents a conceptual visual framework showing the key stages of the business diagnosis process developed in this research as follows:

1. Domain Areas

The process begins by defining the main business domains to be assessed: Management, Market, Financial, Technology, and Entrepreneurship. These areas represent the critical dimensions for evaluating an enterprise's overall health and potential weaknesses.

2. Questions for Diagnosis

For each domain area, specific diagnostic questions are developed. These questions are designed to collect relevant information from the business, ensuring that all important aspects across the domains are addressed.

3. Diagnosis Foundation

The answers to the diagnostic questions form the foundation of the diagnosis. The collected data is analyzed according to established principles and

methodologies, providing a structured basis for understanding the business context and identifying key issues.

4. Score Criteria

Clear criteria are used to score each domain area. These criteria enable the assessment of the business's maturity and performance in each dimension, allowing for objective comparison and prioritization of areas that require attention.

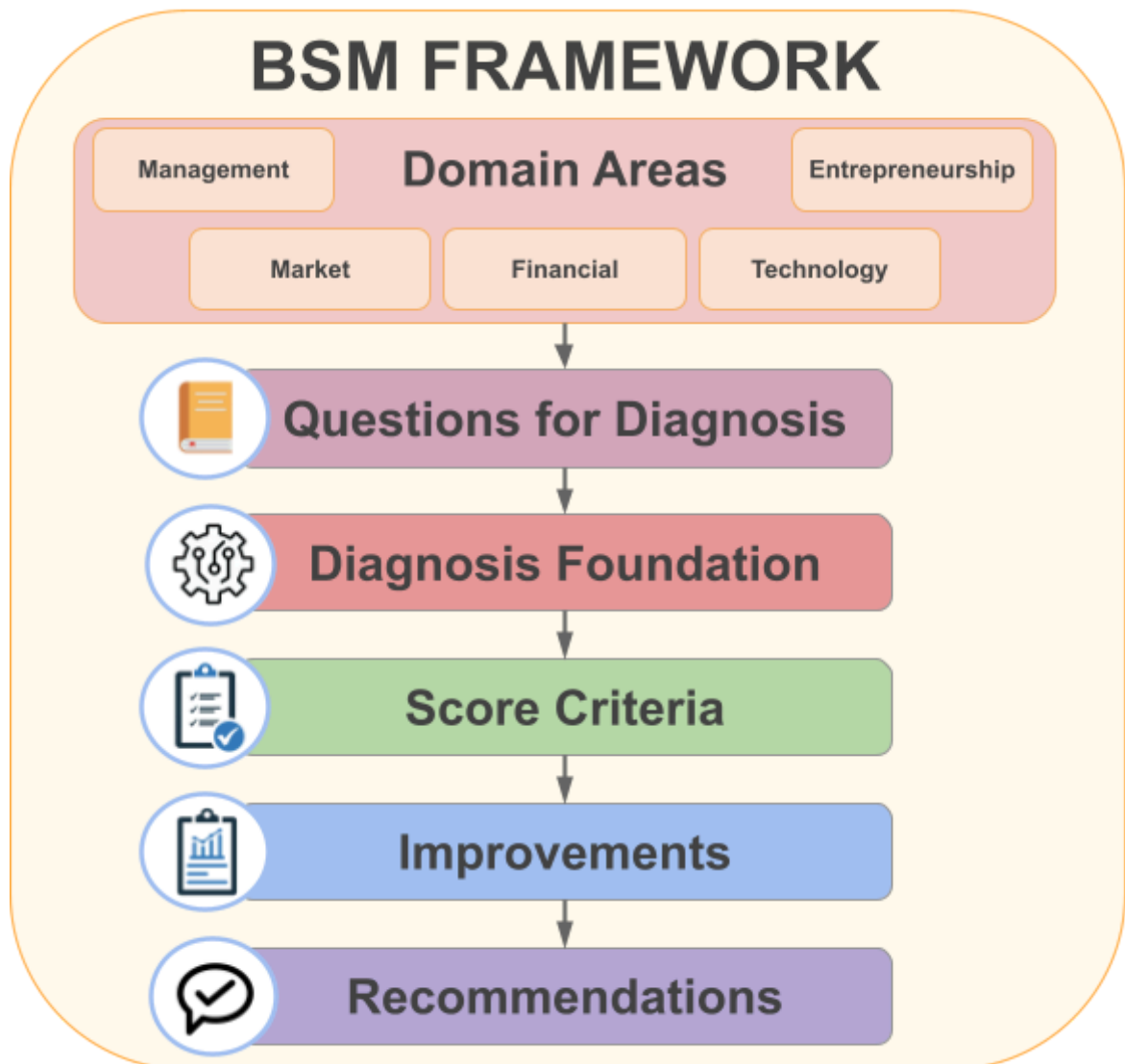
5. Improvements

Based on the scores and analysis, specific improvement opportunities are identified. These highlight the main actions the business can take to address weaknesses or enhance its strengths in each domain area.

6. Recommendations

Finally, tailored recommendations are generated. These recommendations provide practical guidance to the business, supporting informed decision-making and the implementation of effective strategies for development and sustainability.

Figure 8 – Visual Conceptual Framework for BSM



Source: prepared by the author.

This visual step-by-step helps to clarify the logical progression of the BSM Framework, beginning with the identification of relevant domains and ending with actionable recommendations for business improvement. The following sections will explain how every step of the framework is structured.

DIMENSIONS DEFINITIONS

Before discussing a model for business failure prediction tool, Brenes, Johannssen, and Chukhrova (2022) emphasize that having well-established causes leading to business failure situations is more important than the predictive model itself. Iturriaga and Sans (2015) also support this argument, stating that an

appropriate combination of problem characteristics along with a classification tool will be more effective than relying solely on a standard classification tool. In this context, using a framework in conjunction with a tool for business diagnosis can be extremely valuable. In this thesis, we present both the methodological and the technological-instrumental components within the scientific workflow that enabled the development of this research.

For the development of the framework, we were guided by: (1) business incubators interviews and a literature review that identified the most relevant dimensions for business diagnosis, and (2) an author's database of business diagnostics, which was used to create diagnostic questions that were subsequently refined with the support of Generative AI and specialists' assessment.

In order to better understand the most relevant entrepreneurial dimensions for the diagnosis, we firstly conducted a series of interviews with business incubators. We have chosen business incubators for this benchmarking because they are specialists in business diagnosis. Every cycle of business incubation begins with a diagnosis that will be the foundation for the strategic planning of the whole incubation process. Also, business incubators are an important stakeholder in the entrepreneurship and innovation ecosystem, frequently sought to perform this task of assessing enterprises.

To select the business incubators to interview, we considered the CERNE certification. CERNE (Anprotec, 2022) is a Brazilian methodology for good practices and quality patterns of business management. It certifies business incubators according to their level of maturity, in 4 different levels. Based on a mapping carried out (Table 13) with the National Association of Entities Promoting Innovative Enterprises (ANPROTEC), eight incubators with the level 4, the maximum level of certification, were identified throughout Brazil. The five first of #tab_incubator were randomly selected to participate in data collection and on-site interviews, through interviews with their respective lead managers. The collected data were stored under the custody and supervision of the researchers on their personal computers, and any future disclosure will only be made after processing and analysis, preserving the identity of the participants.

Table 13 – Dimensions and Authors

BUSINESS INCUBATOR	CITY
Santos Dumont Business Incubator - Itaipu Tech Park	Foz do Iguaçu (PR)
Habitat Senai Aceleradora	Curitiba (PR)
CEI (Centro de Empreendimentos em Informática) / UFRGS	Porto Alegre (RS)
Feevale Business Incubator - TechPark	Novo Hamburgo (RS)
Unidade de Inovação e Tecnologia - UNITEC UNISINOS	São Leopoldo (RS)
Nexus Business Incubator - Associação Parque Tec. de São José dos Campos	São José dos Campos (SP)
USP/IPENCIETEC Business Incubator	São Paulo (SP)
Incamp - Unicamp Business Incubator	Campinas (SP)

Source: Anprotec (2025)

To guarantee a conceptual alignment, first we did some questions to check about the procedure. It was confirmed that the first step for all incubators when welcoming a new business is to diagnose it. Four of them does the diagnosis supported by a consultant, focusing on the general maturity assessment. The other one firstly makes available a self-diagnosis for the entrepreneurs and after uses a consultant to give feedback.

Thus, we made an open question about “which domain areas within the entrepreneurial context are addressed in this diagnosis”. All the five incubators answered the same five dimensions—entrepreneurship, management, financial, market, technology and partner network—, with one of them adding the “impact” dimension, related to social and environmental impact. Regarding the “partner network” dimension, all incubators clarify this was assessed and taught cross-dimensionally. Considering the “impact” dimension, the incubator who has it clarified it was related to institutional policies and not exactly a diagnosis demand.

We ascertain these findings with a literature review, where it became clear that the dimensions most frequently assessed in business diagnoses are: Entrepreneurship, Technology, Partner Network, Financial Management/Capital, Management/Business Model, and Market. Table 14 presents a summary of these business dimensions and highlights several authors who emphasize the importance of each dimension for understanding how a business operates.

Table 14 – Dimensions and Authors

DIMENSION	AUTHORS
Management	(Bizzotto et al., 2018; Farissi; Roudab, 2024; Maulidian et al., 2024; Nowak; Grantham, 2000; Vaz; De Carvalho; Teixeira, 2023)
Market	(Bizzotto et al., 2018; Farissi; Roudab, 2024; Grimaldi; Grandi, 2005; Joita; Carutasu; Botezatu, 2010; Jones-Evans, 2009; Nowak; Grantham, 2000; Tzafestas, 2008; Vaz; De Carvalho; Teixeira, 2023)
Financial	(Bizzotto et al., 2018; Campbell; Kendrick; Samuelson, 1985; Farissi; Roudab, 2024; Grimaldi; Grandi, 2005; Maulidian et al., 2024; Nowak; Grantham, 2000; Tawil et al., 2016; Tzafestas, 2008; Vaz; De Carvalho; Teixeira, 2023)
Entrepreneurship	(Bizzotto et al., 2018; Ciocoiu et al., 2014; Jones-Evans, 2009; Maulidian et al., 2024; Nowak; Grantham, 2000; Smilor, 1987; Tawil et al., 2016; Vaz; De Carvalho; Teixeira, 2023)
Technology	(Bizzotto et al., 2018; Ciocoiu et al., 2014; Farissi; Roudab, 2024; Grimaldi; Grandi, 2005; Maulidian et al., 2024; Nowak; Grantham, 2000; Smilor, 1987; Vaz; De Carvalho; Teixeira, 2023)
Partner Network	(Elia; Margherita, 2016; Joita; Carutasu; Botezatu, 2010; Maulidian et al., 2024; Nowak; Grantham, 2000; Vaz; De Carvalho; Teixeira, 2023)

Source: prepared by the author.

Six distinct dimensions were initially identified as highly relevant for understanding a business and conducting a business diagnosis. However, upon further analysis, it was observed that the competencies within the "Partner Network" dimension could be addressed transversally within the "Market" and "Entrepreneurship" dimensions. This allowed for a simplification of the business dimensions, considering Partner Network competencies as transversal in other dimensions and then reducing them to five:

- **Management Dimension:** Analyzes issues related to business management and modeling, decision-making, control variables and tools, as well as basic data and the characterization of the business.
- **Market Dimension:** Assesses the effectiveness of the business model in relation to the enterprise's activities and the market it operates in. It deals with marketing issues, pricing criteria, sales strategies, and relationship policies with customers, suppliers, and partners.

- **Capital Dimension:** Covers financial management, external economic factors that influence the business, cash flow, accounting, tax issues, investment funds, and lines of credit.
- **Entrepreneurship Dimension:** Examines the alignment between the company's value proposition and its key activities. It identifies the leadership and commitment level of the manager, the presence of partners, and connections with the local ecosystem. This dimension also covers aspects related to organizational culture, human capital development, and intellectual property.
- **Technology Dimension:** Evaluates the company's ability to adapt to necessary digital transformations, the use of technologies to support business processes and operations, and the capacity to create market differentiation and intellectual property through technology. This dimension also checks whether the company utilizes digital tools for managing any of its activities or business dimensions.

QUESTIONS FOR DIAGNOSIS

Once these five dimensions were defined, the next step was to formulate the questions necessary for a comprehensive Business Diagnosis. Between 2019 and 2025, in collaboration with three other specialists, I conducted 96 business diagnostic interviews. All interviews have written records with consultants' notes, and 44 of them have full audio recordings. These diagnostics were carried out based on the IncubE methodology (Pinto-Junior; Silvestro; Morais, 2021), which holds that diagnostic consulting aims to identify business strengths and problems and to generate an action plan to overcome any issues.

However, this framework uses a limited set of guiding, non-structured questions (Lakatos, 2022), where interviewers follow a general script with a minimum number of required questions to be posed to all interviewees. The interview script can be found in Table 15.

Table 15 – Questions for the Diagnosis

QUESTIONS
1. Name, email, gender, age, phone number, and CPF (Brazilian equivalent to Individual Taxpayer Registry) of the manager.

2. Educational level of the manager.
3. Name and CNPJ (National Registry of Legal Entities) of the business.
4. What is the size of your business?
5. In which city is your business located?
6. Please describe your business. Why did you start this business? What motivated you, and why do you wish to continue?
7. Does your business have partners?
8. What is the sector of your business?
9. How many employees currently work in your business?
10. Do you have any administrative control systems in place (software, cashbooks, notes in diaries, electronic spreadsheets, etc.)?
11. Do you believe your business has vulnerabilities in any of the following areas? Please explain. Management, finance, administration, logistics, inventory, technology, personnel, among others.
12. Please describe, in detail, the problems your business faces. This description will help us assess the level of vulnerability and prioritize your case.
13. If this diagnosis identifies vulnerabilities in your business, how much time could you dedicate to following the action plan suggested by the consultants to address and overcome these vulnerabilities?
 - a. I can dedicate at least 1 hour per day.
 - b. I can dedicate at least 2 hours per day.
 - c. I will dedicate a minimum of 2 hours up to as much as possible daily until my business recovers or stabilizes.
 - d. Currently, I am unable to dedicate any time daily to these activities.

Source: prepared by the author.

With the assistance of the other specialists, a list was compiled of the additional questions that were most frequently necessary during interviews to obtain further information for the business diagnosis. These questions were classified according to the five business dimensions defined earlier, and then underwent refinement with the support of Generative AI. Tests were conducted using the three most popular Generative AI models with the largest known training datasets: ChatGPT, Gemini, and DeepSeek. ChatGPT was selected because, among the three, it exhibited the most appropriate "temperature" and adequate questions for the context. Temperature is a parameter in Artificial Intelligence and Machine Learning

that allows for adjusting the output of Large Language Models (LLMs) by controlling the randomness of text generation during the inference process (Noble, 2025). Questions were assessed for clarity, relevance, and their ability to minimize respondent confusion, in line with best practices observed in the literature.

To structure the textual prompt for ChatGPT, we relied on the Prompt Engineering Framework proposed by Korzynski et al. (2023). In the case of text-to-text AI prompts, the framework recommends, at minimum: articulating the instruction; indicating prompt elements; providing the expected output and context; refining instructions to avoid ambiguity; offering feedback and examples; interacting with the model (interaction management); and limiting the task size by length or complexity.

Thus, to utilize ChatGPT for refining the questions developed by the specialists, I first transcribed all the recorded interviews, made the necessary lexical adjustments for comprehension, and defined markers such as "<entry>" and "</entry>" in the text to indicate where each interview begins and ends. Subsequently, I sent the compiled interview files along with the following prompt:

<TASK>

Based on the context and methodology, use the attached *entries* of enterprise interviews to recommend the best questions for a clear and complete form to collect the data needed to predict a diagnosis. Each interview is delimited by these marks: **<entry>**
</entry>.

</TASK>

<OUTPUT>

Say the number of interviews that were analysed. Give a list of recommended questions useful and clear to understand; avoid the possibility of confusing the participant; facilitate the processing by AI models.

</OUTPUT>

As an output, the tool suggested a list of questions, which were then reviewed again by all the experts. After applying the experts' adjustments, the final list of diagnostic questions is expressed in Table 16.

Table 16 – Questions for diagnosis

Cross-cutting questions, covering all areas.

1. Name of the business.
 2. Name of the person responsible.
 3. Individual Taxpayer Registry (CPF).
 4. Email address.
 5. Telephone number.
 6. State.
 7. City.
 8. Company National Registry (CNPJ);
 - a. ☐ Does not have a CNPJ.
 9. Main sector of activity (e.g., agriculture, technology, services, retail, etc.).
 10. Number of employees (including partners):
 - a. ☐ 1
 - b. ☐ 2
 - c. ☐ 3 to 5
 - d. ☐ 6 to 10
 - e. ☐ 11 to 20
 - f. ☐ More than 20
 11. Please briefly describe what your business does.
 12. Does the company have any type of administrative control, management system, or tool?
 - a. ☐ No
 - b. ☐ Partial (spreadsheets or manual notes)
 - c. ☐ Structured (software, dashboards, etc.)
 13. Is there a formalized strategic plan?
 - a. ☐ Yes
 - b. ☐ No
 14. Is there a seasonality plan?
 - a. ☐ Yes
 - b. ☐ No
 15. Are there internal process controls?
 - a. ☐ No
 - b. ☐ Partial, not documented
 - c. ☐ Yes, documented
 - d. ☐ Yes, documented and regularly reviewed
 16. What are the main management challenges today?
 17. Who is your ideal customer (persona)?
 18. What customer pains/problems does your product/service solve?
 19. Have you conducted validation with potential customers?
 - a. ☐ Yes
 - b. ☐ No
 20. Describe how a customer currently discovers and hires your service.
 21. Are there active marketing and/or digital marketing strategies?
-

-
- a. ☐ Yes
 - b. ☐ No
22. Are customer satisfaction surveys conducted?
- a. ☐ No
 - b. ☐ Rarely
 - c. ☐ Yes, but improvements are not implemented
 - d. ☐ Yes, and feedback is used for improvements
 - e. ☐ Yes, with a structured process
23. Is there a portfolio of products/services?
- a. ☐ Yes
 - b. ☐ No
24. Is there a defined sales flow or pipeline?
- a. ☐ Yes, structured
 - b. ☐ Yes, automated
 - c. ☐ No
25. What is the monthly revenue?
- a. ☐ Not yet generating revenue
 - b. ☐ Yes: Less than R\$5,000
 - c. ☐ Yes: R\$5,000 - 20,000
 - d. ☐ Yes: R\$20,000 - 50,000
 - e. ☐ Yes: More than R\$50,000
26. How does the month usually close financially?
- a. ☐ Deficit
 - b. ☐ Break-even
 - c. ☐ Small surplus
 - d. ☐ Stable surplus
27. What are the main sources of income (which products/services and how are they paid)?
28. How are prices defined?
29. What are the main costs?
30. Are there any debts, financing, or active lines of credit?
- a. ☐ No
 - b. ☐ Yes
31. Is there cash flow control?
- a. ☐ No
 - b. ☐ Partial
 - c. ☐ Structured
32. Does the business use digital tools for management, production, or sales?
- a. ☐ No
 - b. ☐ Yes
33. Has the business undergone any process of digital transformation?
34. Are there automated or technology-based processes (systems, platforms, specialized equipment)?
- a. ☐ No
-

-
- b. ☐ Yes
35. Is there interest in developing additional technological tools?
- a. ☐ No
- b. ☐ Yes
36. At what stage is the business currently?
- a. ☐ Idea
- b. ☐ Prototype
- c. ☐ MVP
- d. ☐ In validation
- e. ☐ In operation with clients
- f. ☐ Established
37. Please indicate the main educational backgrounds of the manager(s).
38. Has the manager taken courses on entrepreneurship/management/innovation?
39. Does the business have formal or informal partnerships?
40. Are there actions for people management or development?
41. What are the business's main strengths?
42. What are the main weaknesses?
43. How much time per week does the main manager dedicate to business management? (*Report in hours, considering only administrative and management activities, not operational or production activities.*)
44. Does the manager perform operational/executive activities in the business? (*If yes, indicate the main activities.*)
- a. ☐ No
- b. ☐ Yes
45. If you receive a diagnosis with a work plan, how much time could you dedicate to developing the suggested improvements?
46. What are the greatest risks threatening your business today?
- a. ☐ Financial
- b. ☐ Operational
- c. ☐ Commercial
- d. ☐ Technological
- e. ☐ Regulatory
- f. ☐ Other
47. How do you rate the current maturity of the business?
- a. ☐ Initial
- b. ☐ Under development
- c. ☐ Intermediate
- d. ☐ Advanced
- e. ☐ Scalable
48. What are currently your company's top three priorities?
49. What are your main doubts or questions regarding management, finance, market, or technology?
50. If you could have an external consultant supporting your company in only
-

4.2 **DIAGNOSIS FOUNDATION**

Using the questions shown above, the diagnosis process intends to identify business strengths and areas for improvement, as it allows for a detailed diagnosis of the venture's current situation. Once one enterprise answers to the questions presented in Table 16, the consultants performs analyses and assigns a score for the enterprise's situation, indicating its strength or areas for development. For each of these domain areas, what was considered for evaluation and score assignment are explained below.

4.2.1 *Management*

Analyzes the presence of management and decision-making strategies; Verifies whether the venture understands and controls management variables; Seeks to determine the level of management maturity; Checks for the use of management control tools, such as strategic planning, action plans, SWOT analysis, management dashboards, etc; Verifies the basic data and characterization of the venture; Allows for a macro-level evaluation of the company, based on the analysis of all other dimensions and how challenges in other dimensions may or may not pose a risk to the venture's operation.

4.2.2 *Market*

Verifies the enterprise's business model and its effectiveness for the market it operates in; Analyzes whether there is a mature pricing strategy; Understands how market insertion occurs and the policies for market retention and expansion; Considers sales and prospecting strategies; Observes customer and supplier relationship policies; Analyzes business opportunities and how the venture positions itself regarding external opportunities; Performs a cross-evaluation between the opportunities for growth identified in the consultancy and those reported by the interviewee as the main areas for attention of the company.

4.2.3 Financial

Ascertains whether the venture has debts, financing, or lines of credit, and how much they affect monthly closings; Verifies if the venture is in surplus; Considers the existence of emergency reserves, cash flows, and/or funds for investments.

4.2.4 Technology

Assesses the venture's capacity to have undergone and adapted to digital transformation; Verifies the extent to which the company leverages technologies to enhance and/or automate its production workflows; Ascertains whether the venture utilizes digital tools and platforms for management, marketing, customer relationship management, etc.

4.2.5 Entrepreneurship

Analyzes the alignment between the venture's value proposition and the interviewee's account of the activities executed in the company; Verifies the entrepreneurial profile of the interviewed top manager and the suitability of this profile for the role performed; Analyzes the manager's availability to increase efforts to enhance the enterprise's current standing; Consider the existence of partnerships; Addresses organizational culture issues and how much it contributes to business success; Checks if there are policies, strategies, or actions for human resource appreciation.

4.3 DOMAIN AREA'S SCORE CRITERIA

Once the statements above are considered to evaluate the enterprise, then it is possible to assign scores across the five strategic business domain areas explained earlier as foundational in an organization. For each domain area, a score between 1 and 5 is assigned, based on the assessment of maturity of the business in that area. These scores, as well as their criteria, are not discretionary; they stem from an ongoing improvement project, having been curated by experts and refined based on feedback from consultants and entrepreneurs. Table 17 shows the scores in detail.

Table 17 – Domain areas' score

Score	Management
1	Has no management control.
2	Understands that management variables exist but does not control them.
3	Understands and controls some few management variables.
4	Reasonably controls management variables known within the venture.
5	Fully controls management variables known within the venture with a standard knowledge management for all of them.
Score	Market
1	Has a ready prototype and/or business model but does not commercialize it.
2	Is initiating commercialization and needs to create/adjust pricing and sales strategies.
3	Has market insertion but needs to expand. Pricing policies may require adjustments and may need improved customer and/or supplier relationship strategies.
4	Has reasonable market insertion, a mature pricing policy, and needs improvements in customer and/or supplier relationship strategies.
5	Has good market insertion, a mature pricing policy, and strong customer and supplier relationship strategies.
Score	Finance
1	Has overdue debts, and monthly closings are in deficit.
2	Has current debts, but monthly closings are in deficit.
3	Has current lines of credit, and monthly closings are in surplus.
4	Has no debts, and monthly closings are in surplus.
5	Has no debts, has cash and/or investment reserves, and monthly closings are in surplus.
Score	Technology
1	Has not undergone digital transformation and/or uses no digital/technological resources for management or production flow.
2	Uses some resources to digitally structure the business OR uses some digital/technological resources for management or production flow.
3	Uses some resources to digitally structure the business AND uses some digital/technological resources for management or production flow.
4	The business is based on a digital platform, and uses digital/technological resources for management or production flow.
5	Has already undergone digital transformation and uses digital/technological resources for management or production flow.

Score	Entrepreneurship
1	Lacks an entrepreneurial culture/ecosystem.
2	Has limited entrepreneurial culture, low engagement with the ecosystem, and no policy for entrepreneurship training.
3	Possesses some entrepreneurial culture OR some engagement with the ecosystem, and limited or no policy for entrepreneurship training.
4	Has some entrepreneurial culture AND some engagement with the ecosystem, and has policies for entrepreneurship training.
5	Possesses an entrepreneurial culture, engages with the ecosystem, and has policies for entrepreneurship training.

Source: prepared by the author.

At the end of the evaluation, based on the company's performance in each of the dimensions, the consultant should provide a general assessment of the company. This should not be just an average score of the evaluation of the 5 domain areas, but regard their expertise, guided by one of the following 5 options presented in Table 18.

Table 18 – General Score

Score	General Diagnosis Score
1	The macro analysis of the enterprise's challenges indicates a HIGH risk of closure if there is no immediate intervention.
2	The macro analysis of the enterprise's challenges indicates a MEDIUM risk of closure if there is no immediate intervention.
3	The macro analysis of the enterprise's challenges indicates a LOW risk of closure if there is no immediate intervention.
4	The macro analysis of the enterprise's challenges indicates the possibility of entering a growth opportunity zone.
5	The macro analysis of the enterprise's challenges indicates business stability (sustainability).

Source: prepared by the author.

4.4 USUAL IMPROVEMENTS IDENTIFIED

Based on the answers to the interview, some points of improvements are usually identified and are pointed out here in order to help consultants with their diagnosis decision.

4.4.1 Management

- The enterprise needs to implement or to have proper control of tools or software to control the management, like process and workflow mapping, Business modeling frameworks, Seasonality planning;
- Enterprise needs to be formally registered;
- Implement or improve short-term and/or medium and/or long-term planning strategies;
- The manager needs to map or remap all management variables/topics of the enterprise;
- Need to create a planning for low and/or high seasonality periods;
- To map organizational processes and workflows.

4.4.2 Market

- To build or update the business model;
- Update market share analyses;
- To revise or prospect new suppliers opportunities;
- Conduct a bench market study;
- Significant effort in attracting new leads, low conversion of these into clients, and low client retention;
- Inefficient customer acquisition processes, characterized by: Significant effort in lead generation, Low conversion rates, Poor client retention.

4.4.3 Financial

- Analyze the existence of better financing opportunities;
- Make a plan to pay off delayed debts;
- Build a strategy to improve the venture's surplus;
- Create funds for emergencies and investments.

4.4.4 Technology

- To map production process;
- Adapt the business model to work and sell digitally;
- Use technology to help or automate production or management activities;
- Implement digital tools to manage marketing strategies, customer relationships, etc.

4.4.5 Entrepreneurship

- Align the business model and value proposition with the main activities of the enterprise;
- Create or improve a program or strategy for human resources development and appreciation, especially concerning entrepreneurial culture;
- Look for strategic partnerships in either production processes or client acquisition;
- The need to study entrepreneurship and connect with this ecosystem.

4.5 DIAGNOSIS RECOMMENDATION

Once the diagnosis identifies growth opportunities within the assessed enterprises, based on the domain area where the improvements were identified (score 3 or lower), the consultant recommends some general strategic actions that could help surpass the improvements identified. Table 19 presents a list with some of these strategic actions, but the consultants can recommend additional ones based on the need their judgment points out. These strategic actions are used as a reference by the consultants to make a report for the enterprise recommending what they could do in order to surpass the problems identified or to consolidate the strengths they demonstrated.

Table 19 – Strategic Actions to Strengthen the Enterprise

Strategic Actions Database
Development and implementation of a Visual Management Board (attached template) as a short- and medium-term management tool.
Organizational strengths and weaknesses analysis through SWOT matrix completion.
Business model development (Business Model Canvas template attached) for macro-level organizational visualization.
Seasonal planning framework creation.
New product launch plan development.
Establish a strategic partnership plan.
Product portfolio development including catalog creation.
Service prototyping and launch planning for new offerings.
Customer acquisition strategies development and process flow mapping.
Customer database maintenance and utilization for sales/follow-up.
Customer satisfaction surveys implementation with feedback integration.

Customer relationship and loyalty program deployment.
Web presence enhancement and digital marketing strategies.
Human resources valorization policy implementation.
Revamp client relationship management across the entire customer lifecycle (prospecting to retention).
Enhance digital marketing strategies and online presence.
Develop targeted customer acquisition and loyalty programs.
Enhance client portfolio management using data-driven strategies.
Establish strategic partnerships for both production and customer acquisition.
Standardize and document production workflows.
Implement process automation solutions.
Evaluate and adopt specialized software tools to support key business functions.
Establish technology integration roadmaps.
Emphasize organizational culture.
Implement comprehensive entrepreneurship training programs.
Facilitate networking opportunities within the innovation ecosystem.
Develop clear career pathways and incentive structures.

Source: prepared by the author.

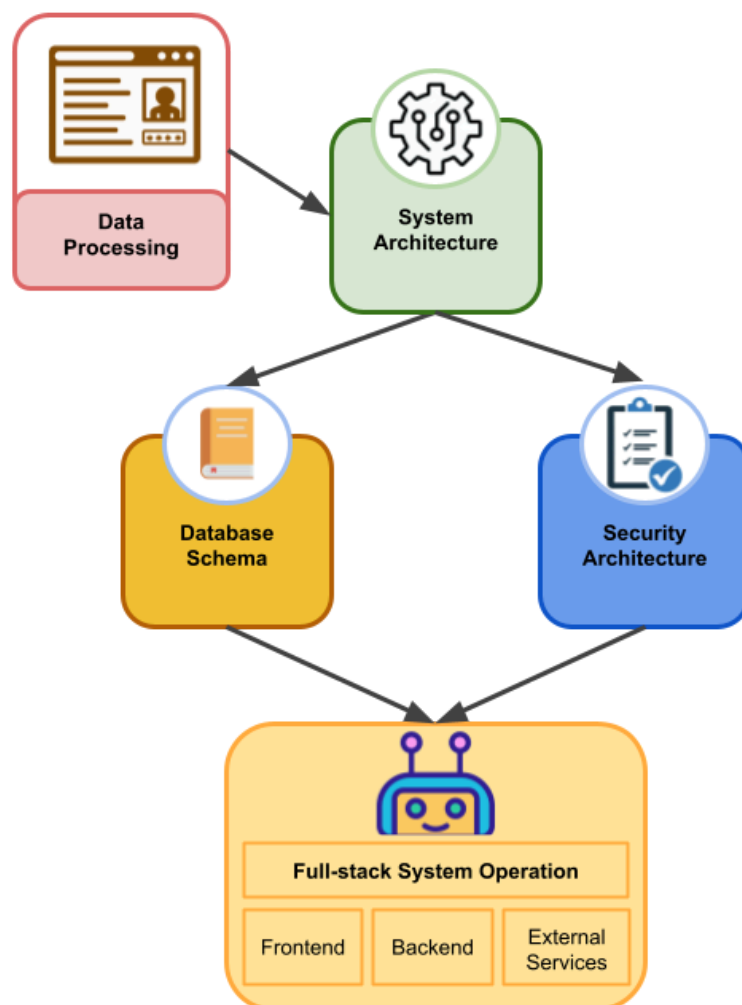
These recommendations are the last step for the conceptual framework established in this chapter. This way, the framework provides a systematic approach for diagnosing business performance across the five strategic domains critical to the success of Brazilian SMEs. By combining theoretical insights, practitioner expertise, and artificial intelligence techniques, this framework ensures a thorough and actionable assessment of each enterprise's internal landscape. The integration of Generative AI for refining diagnostic instruments demonstrates a methodological advancement, enabling greater clarity, consistency, and efficiency in data collection and analysis.

Building on this foundation, the next chapter details the development and implementation of SmartB—an AI-powered artifact designed to operationalize this framework and automate the process of business diagnosis prediction. The forthcoming discussion will address the technical architecture, data preparation, system implementation, and validation procedures that instantiate the diagnostic framework outlined here into a practical, scalable, and intelligent tool. In doing so, it will illustrate how the conceptual advances presented in this chapter are transformed into an innovative solution capable of generating impactful recommendations for business improvement.

5 SMARTB: AN AI ARTIFACT FOR BUSINESS DIAGNOSIS PREDICTION

This chapter provides a comprehensive report on the technical development, and implementation of SmartB, an AI-powered artifact for business diagnosis, created within the approach of Knowledge Engineering. The chapter is structured, as shown in Figure 9 to present, in logical sequence: the treatment and preparation of real-world business diagnostic data; explaining the architecture and technological choices underpinning the artifact; showing the structure of the database and the security architecture; and giving operational details about the backend and frontend systems.

Figure 9 – Artifact Chapter Overview



Source: prepared by the author.

5.1 DATA PROCESSING

The foundation of the SmartB system rests on a dataset of 96 real-world business diagnostic interviews conducted between 2019 and 2025, supplemented by 44 full-length audio recordings (decoding from video recordings). These interviews were structured according to the questions presented in [Chapter 4](#), Table 15 and covered five critical business dimensions: Management, Market, Financial, Technology, and Entrepreneurship.

To make these data usable by SmartB, a multi-stage preparation was required. The original material included both structured data (such as quantitative indicators and categorical responses) and unstructured data (open-ended textual responses and interview transcripts). The initial task was to digitize and transcribe all relevant audio data, resulting in a lexically standardized text corpus where each interview was marked with "<entry>" and "</entry>" delimiters. This careful transcription was necessary to ensure that downstream processes, especially those involving AI, could accurately parse and interpret the information.

Given the personal and potentially sensitive nature of the interviews, all transcripts underwent an anonymization protocol. Personal identifiers (names, CPFs, phone numbers) were decoupled from business responses and replaced with pseudonymous codes. The data were then cleaned to remove duplicate entries, correct typographic errors, and normalize categorical fields. For open-text responses, basic natural language preprocessing was applied to ensure consistency (e.g., removing stopwords, correcting spelling errors).

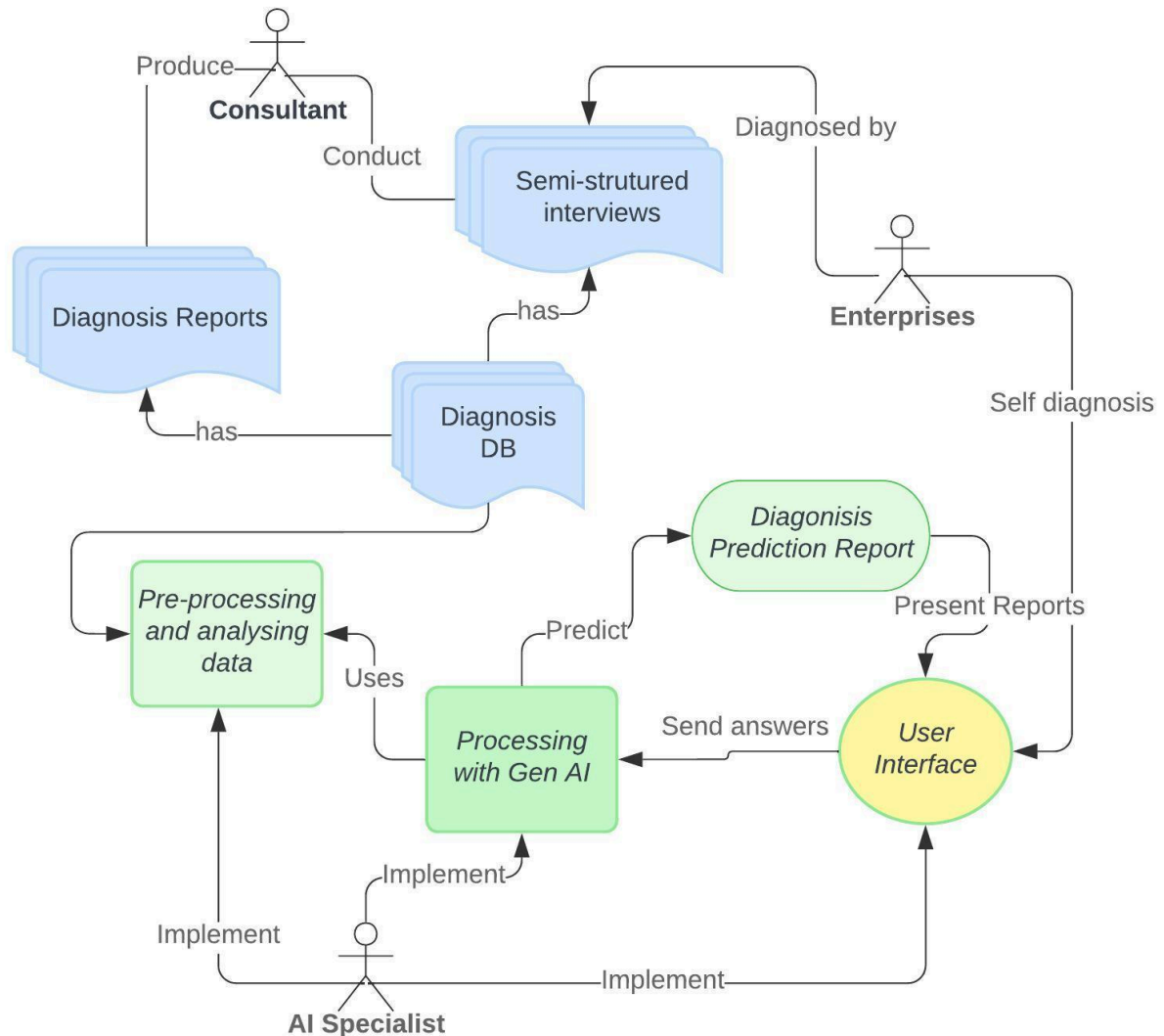
These steps ensured compliance with the Brazilian General Data Protection Law (LGPD) and prepared the data for reliable AI processing by mitigating noise and bias associated with raw textual input.

5.2 SYSTEM ARCHITECTURE

In order to illustrate the modelling of the system, we created Figure 10, that presents the UML context diagram for SmartB with the workflow of an AI-assisted enterprise diagnostic and risk prediction system. The process integrates human expertise, enterprise self-assessment, and artificial intelligence to generate actionable diagnostic reports.

Some technical topics of the system are highlighted in this section, but it is possible to access the full technical documentation of the SmartB artifact by accessing the public link <<https://smartbdiagnostico.com.br/docs>>.

Figure 10 – Context Diagram



Source: prepared by the author.

Analysing the UML Context Diagram of Figure 10 we can see two parallel data collection streams, departing from the “User Interface” box. The first one we will call “**Expert-Led Diagnosis**”, where a consultant conducts semi-structured interviews with the enterprise. The second one we can name “**Self-Assessment**”, because it allows the enterprise to conduct a self-diagnosis. Both streams produce Diagnosis

Reports, which are stored in a centralized Diagnosis Database (DB). This database serves as the foundational knowledge base for the system.

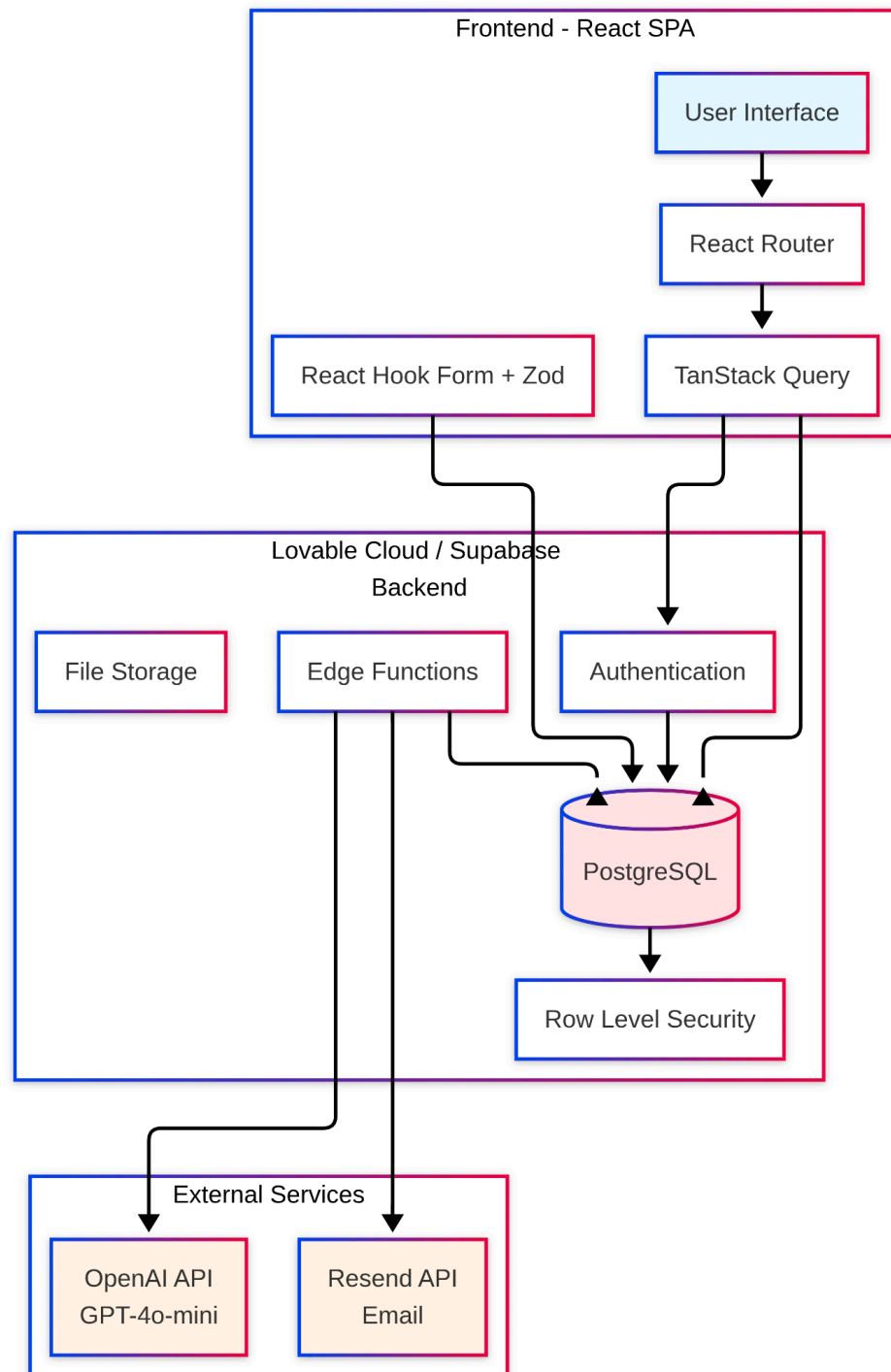
The core analytical process involves pre-processing and analysing data from the Diagnosis DB; processing with Generative AI (Gen AI) to identify patterns, generate insights, and predict risks; and predicting future states or issues based on the analyzed data. The output of this AI processing is a Diagnosis Prediction Report. This report is then presented to the end-user through a User Interface, which facilitates interaction, visualization, and decision-making.

The SmartB artifact was designed as a modular, fullstack web application, deploying a single-page application frontend and a cloud-native backend that integrates AI services, data storage, authentication, and business logic. The high-level system structure comprises:

- **Frontend:** Built as a React SPA with TypeScript for strong typing, employing TanStack Query for efficient data synchronization, and React Hook Form with Zod for robust form validation.
- **Backend:** Deployed on Lovable Cloud, leveraging Supabase for database, authentication, and edge function execution. PostgreSQL serves as the main persistent store, supporting row-level security.
- **External Services:** OpenAI GPT-4.1-mini for AI-powered diagnostic generation, and Resend API for automated email notifications.

Figure 11 provides an overview diagram for the general architecture of the system, allowing to visualize the components of the frontend, the backend (Supabase) and the connection with external services.

Figure 11 – General Architecture Diagram



Source: prepared by the author.

Due to the rapid pace at which computing technologies currently evolve, it is difficult to find recent evidence in the literature discussing the best technologies for developing full-stack applications. Therefore, we chose to adopt a more common

market approach: consulting experts and benchmarking systems that are considered references to decide which technologies could be applied in this project. Consequently, after performing these activities, each component of the stack was selected for specific reasons, which are justified below.

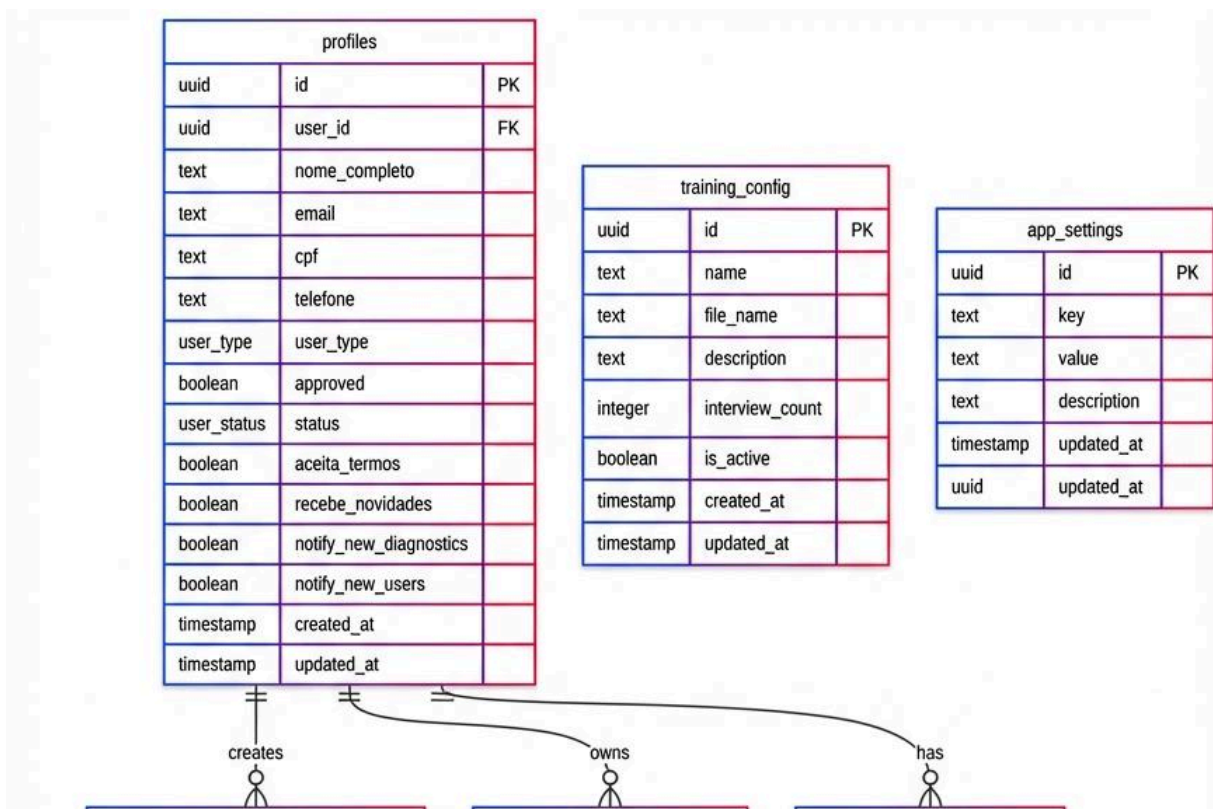
- **React 18 + TypeScript:** Ensures maintainability and scalability for complex dynamic forms and user interaction, with Vite enabling rapid development and hot-reloading.
- **TanStack Query and Zod:** Streamlines state management and enforces strong runtime and compile-time validation, preventing data inconsistencies and facilitating error handling.
- **Tailwind CSS and shadcn/ui:** Guarantees visual consistency and accessibility, allowing for rapid UI prototyping while maintaining a professional design language.
- **Supabase (PostgreSQL, Auth, Edge Functions):** Offers a managed, BaaS approach that handles authentication, authorization, and database interactions securely. Row-level security and JWT-based user management ensure fine-grained access control.
- **Deno for Edge Functions:** Provides an efficient, modern runtime for serverless business logic, reducing latency for the AI integration flow.
- **OpenAI GPT-4.1-mini:** Business diagnostics requires predictability, not creativity. The GPT-4.1 model was chosen because it has proven superior in this aspect. Even when compared to models from other companies, such as Gemini and DeepSeek, the GPT-4.1-mini demonstrated semantic consistency, the ability to follow extensive methodological instructions, and stability in ordinal classification. After comparative tests, it showed greater adherence to the business diagnostic framework, less variability between runs, greater accuracy in assigning scores, and recommendations more faithful to the trained Knowledge Base, when compared to alternative models.
- **Resend:** Enables programmable, reliable email notifications to keep users and administrators informed.

By relying on these technologies, SmartB assures a project with appropriate security, scalability, performance, and maintainability while minimizing the operational overhead of infrastructure management.

5.3 DATABASE AND SECURITY ARCHITECTURE

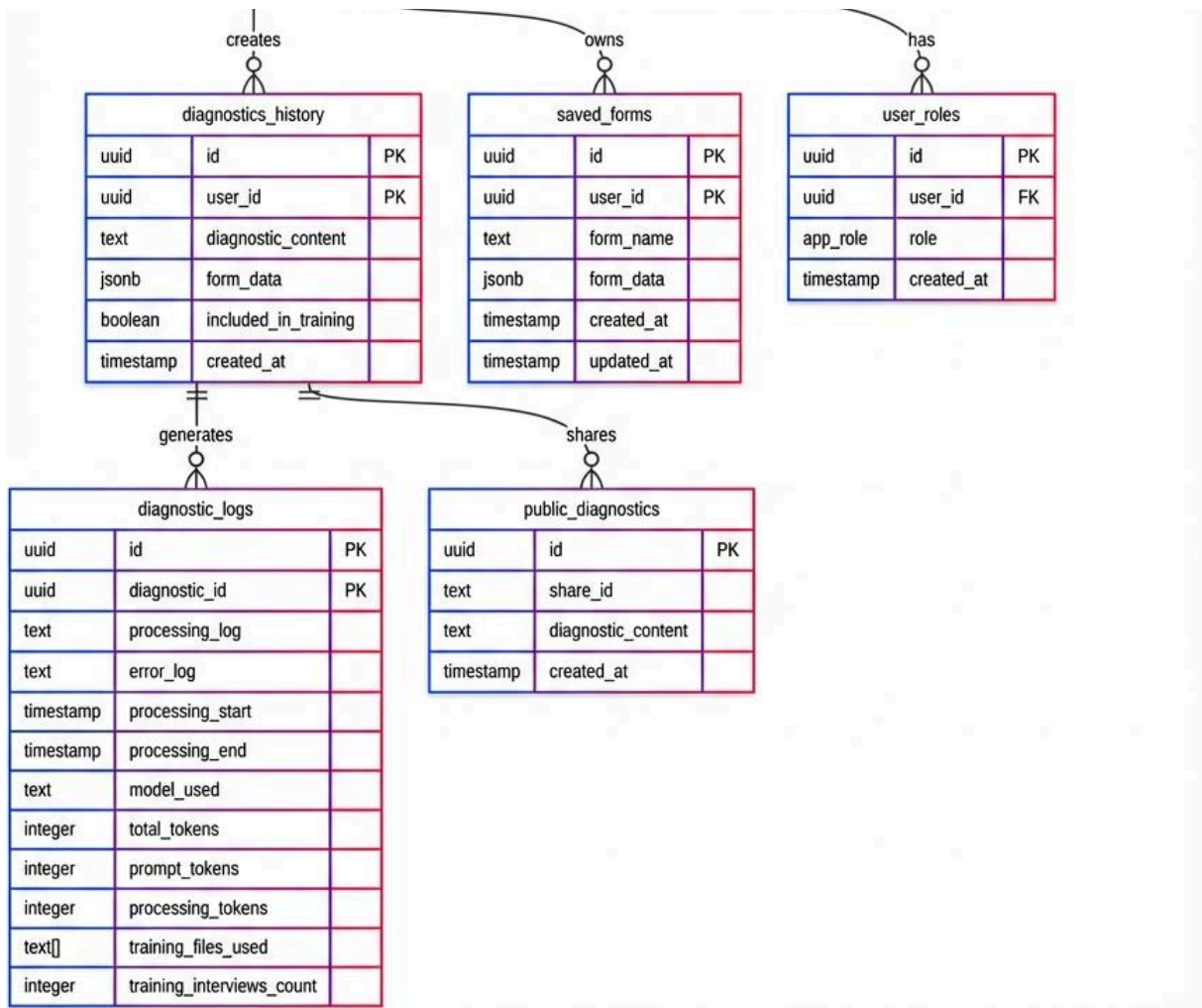
The relational database schema is shown in Figure 12 and Figure 13 with the Entity-Relationship Datagram where users, diagnostics, forms, logs, and roles are modeled. Relationships are established to tightly link user actions to their data, supporting traceability and auditability. Security is enforced with row-level security (RLS) policies, separating access for regular users, consultants, and administrators, and ensuring that only authorized individuals can access sensitive or administrative features. Rate limiting, error logging, and rigorous permission checks are performed at the edge function level.

Figure 12 – Entity-Relationship Datagram for SmartB



Source: prepared by the author.

Figure 13 – Entity-Relationship Datagram for SmartB



Source: prepared by the author.

5.4 BACKEND AND FRONTEND

This is a full-stack system, so we have fully implemented backend and frontend with distinctive operational functions. The details for both of the systems are presented as follows.

5.4.1 Backend Operation

Authentication and Authorization Flow

Upon registration, users are automatically provisioned in the system with a “pending” status. Approval is required from an administrator before access to diagnostic features is granted. JWT tokens manage session state and are validated for every protected endpoint request.

Diagnostic Generation Process

When an approved user submits a completed diagnostic form, the backend initiates the following sequence:

1. Verifies the user's JWT and checks daily rate limits using diagnostic history.
2. Loads contextual training data from storage, if required for prompt enhancement.
3. Formats the form data into a prompt according to pre-defined templates, embedding both user-specific and system-level context.
4. Sends a request to the OpenAI API via the generate-diagnostic edge function.
5. Receives, parses, and stores the AI-generated diagnostic in the database, together with detailed processing logs, including token usage and response times.
6. Logs errors or OpenAI API failures, triggers notification edge functions for consultants/admins as appropriate, and returns structured feedback to the frontend.

OpenAI API Settings

This setup of using the OpenAI API integrated with the architecture allows the system to dynamically generate business diagnostics using AI, without the need for managing dedicated servers. The calls to the OpenAI API are implemented as Edge Functions on Supabase, on the edge of the network, providing low-latency responses and automatic scalability.

Edge Functions are invoked from the frontend using the `supabase.functions.invoke()` method. Proper authentication is enforced via JWT tokens, which are validated on every request. The relevant access token is passed in the HTTP Authorization header to ensure secure and authenticated API calls. Within this Edge Function, a POST request is made to the OpenAI API endpoint.

The model to be used and the prompts (system and user) are included in the request body. The OpenAI API key is securely accessed from the environment using Supabase Secrets, and it is sent in the Authorization header of the request.

To ensure responsible and secure usage, the system enforces a limit of up to five diagnostic generations per user within a 24-hour period. All Edge Functions require a valid JWT token for execution, and CORS headers are configured to allow cross-origin requests as appropriate. Additionally, Row Level Security (RLS) policies are implemented in the PostgreSQL database to control data access.

The default OpenAI model used is the “gpt-4.1-mini” but it can be dynamically changed by a function in the front-end admin, allowing to choose one of the models presented in Table 20.

Table 20 – System OpenAI Models Available

Model	Category
gpt-5-2025-08-07	GPT-5 (Flagship)
gpt-5-mini-2025-08-07	GPT-5 Mini
gpt-5-nano-2025-08-07	GPT-5 Nano
gpt-4.1-2025-04-14	GPT-4.1 (Flagship)
gpt-4.1-mini-2025-04-14	GPT-4.1 Mini
o3-2025-04-16	O3 (Advanced Reasoning)
o4-mini-2025-04-16	O4 Mini (Quick Thinking)
gpt-4o-mini	GPT-4o Mini (Legacy)
gpt-4o	GPT-4o (Legacy)

Source: prepared by the author.

In addition to the model, another important parameter to define is temperature. In SmartB, the temperature is permanently set to 0.7 for models that support this feature. For newer models that do not support this feature, such as "gpt-5", "o3", and "o4", an instruction is passed to simulate behavior analogous to that temperature.

We have chosen this temperature, to ensure predictability and consistent performance in generative AI processing. The temperature can be set between 0 and 2. Values between 0.0 to 0.6 are considered as low temperature and indicated for low creativity-factual tasks or coding. From 0.7 to 1.0 we have medium temperature, which is good for creative tasks, like writing, with limited creativity in order to maintain consistency. Otherwise, high temperature, from above 1.0, increases randomness and makes more unpredictable processing, which risks some incoherence (Coursera,

2025; GPT Workspace, 2025; Noble, 2025). This way, we have made a lot of tests with different temperatures, specially from 0.7 to 1.0, with all the available models and this combination of the model “gpt-4.1-mini” and temperature “0.7” presented the best balance between consistency and creativity, allowing predictable but innovative outputs.

Additional Backend Functions

All backend logic is written in TypeScript, with error handling and extensive logging to support troubleshooting and system monitoring. Furthermore, some additional backend functions were implemented, like edge functions for cleaning up user data and testing external service connectivity; automated notifications for new users and diagnostics via Resend; and database migration and versioning managed automatically by the deployment system.

5.4.2 Frontend Operation

The design of the system emphasizes accessibility, responsiveness, and ease of use, with all components using semantic tokens for styling consistency and adherence to WCAG accessibility standards. The public homepage <<https://smartbdiagnostico.com.br/>> of the frontend is shown in Figure 14 and operations are highlighted in sequence.

Figure 14 – SmartB Homepage

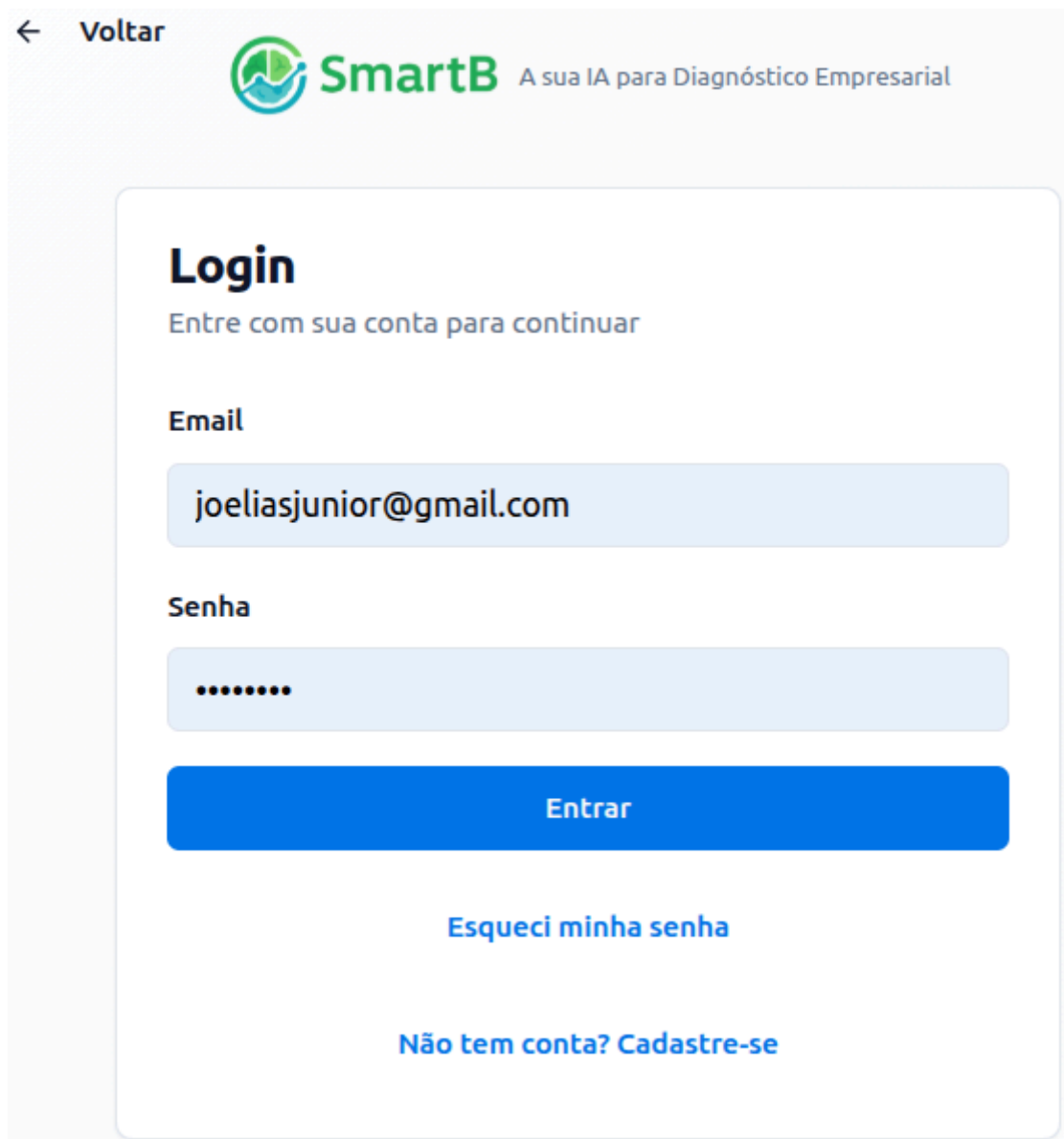


Source: screenshot of the SmartB system.

User Journey and Interface

The frontend provides a clear path from registration to diagnosis. Users must first register (Figure 15) and await approval.

Figure 15 – Registration Screen



The image shows a login screen for the SmartB system. At the top left, there is a back arrow and the text "Voltar". To the right is the SmartB logo, which consists of a green circular icon with a white line graph, followed by the text "SmartB" in green and "A sua IA para Diagnóstico Empresarial" in a smaller, grey font. Below the header, the word "Login" is displayed in a large, bold, black font. Underneath it, the text "Entre com sua conta para continuar" is shown in a smaller, grey font. There are two input fields: the first is labeled "Email" and contains the text "joeliasjunior@gmail.com"; the second is labeled "Senha" and contains a series of dots representing a password. Below these fields is a large blue button with the text "Entrar" in white. At the bottom of the form, there are two links: "Esqueci minha senha" and "Não tem conta? Cadastre-se", both in blue text.

Source: screenshot of the SmartB system.

Once approved, they can fill out the diagnostic form (Figure 16), which dynamically adapts based on schema definitions from the backend. Toast notifications and clear error messages improve user experience and guide corrective action.

Figure 16 – Form Home

SmartB

A sua IA para Diagnóstico Empresarial

Etapa 1 de 7 14% completo

Carregar Limpar Salvar

1. Nome do empreendimento *

2. Nome do responsável *

3. CPF *

XXX.XXX.XXX-XX

4. E-mail *

5. Telefone *

(XX) XXXXX-XXXX

6. Estado *

Selecione...

7. Cidade *

Source: screenshot of the SmartB system.

Form Handling and Validation

All 50 diagnostic questions are presented using React Hook Form, which, coupled with Zod schemas, validates responses for completeness and correctness before submission. Input masks and dropdowns further constrain input types,

preventing data entry errors. Figure 17 shows some examples of validations made by the system.

Figure 17 – Validation Examples

The screenshot shows a form with several fields, each with a validation error message displayed below it in red text:

- 3. CPF ***: The input field contains "001.954.611-47". Below it, the error message "CPF inválido" is displayed.
- 4. E-mail ***: The input field contains "joelias@smartb". Below it, the error message "E-mail inválido" is displayed.
- 5. Telefone ***: The input field contains "(62) 99887-766". Below it, the error message "Telefone deve ter 11 dígitos: (XX) XXXXX-XXXX" is displayed.
- 6. Estado ***: The input field is a dropdown menu showing "SC".
- 7. Cidade ***: The input field is empty.
- 8. CNPJ da Empresa ***: The input field contains "01.370.000/1377-78". Below it, the error message "CNPJ inválido" is displayed.

At the bottom of the form, there is a checkbox labeled "Não possui CNPJ" which is currently unchecked.

Source: screenshot of the SmartB system.

Diagnostic Submission and Feedback

On form submission (Figure 18), the frontend sends the payload to the backend edge function. Progress indicators and skeleton loaders keep users informed during processing. Upon receiving a response, the application displays the AI-generated diagnostic with structured highlights, recommendations, and actionable insights.

Figure 18 – Submission Screen

47. Como avalia a maturidade atual da empresa? *

☐ Inicial

☒ Em desenvolvimento

☐ Intermediária

☐ Avançada

☐ Escalável

48. Quais são hoje as 3 prioridades da sua empresa? *

Vender mais, ficar mais conhecida e ter plataformas de marketing digital.

49. Quais são suas maiores dúvidas sobre gestão, finanças, mercado ou tecnologia? *

Quero aprender a gerenciar melhor a parte financeira, melhorar a divulgação e entender melhor dos processos de gestão.

50. Se pudesse ter um experiente consultor externo auxiliando sua empresa em apenas um tópico neste momento, qual seria? *

Na parte de melhorar mercado, conseguir mais clientes.

< Anterior

Gerar Diagnóstico ➤

Source: screenshot of the SmartB system.

Figure 19 shows the first screen after submitting the responses for diagnosis. Some data of the enterprise is printed, as well as the General Evaluation. The evaluation gives first a benchmark score within a scale from 1 (worst) to 5 (best), and then a textual feedback. Then, continues highlighting the main strengths and opportunities identified in the company. If it is a consultant, in this screen it is possible to edit the diagnosis in order to do some adjustments. If both consultant or regular user, they can download a PDF version of the diagnosis or click share, so it will generate a public permanent link for the diagnosis. Here we have some parts of the

diagnosis, but Appendix 1 introduces a real case SmartB questions and answers with the full diagnosis shown in [Appendix 2](#).

Figure 19 – Diagnosis Screen

Avaliação Geral

Decisão Final de Diagnóstico | Nota: 2/5

A análise geral indica um risco médio de encerramento caso não haja intervenções imediatas. A empresa apresenta um modelo de negócio inovador e um forte potencial criativo para o mercado corporativo, porém enfrenta desafios significativos em gestão estratégica, mercado e finanças, principalmente na captação e fidelização de clientes e no equilíbrio financeiro. O uso limitado de tecnologia e o engajamento empreendedor ainda são pontos a desenvolver para garantir maior sustentabilidade e crescimento.

Análise de Forças e Oportunidades

Principais Pontos Fortes e Diferenciais do seu Empreendimento

- Modelo de negócio inovador focado em treinamentos e espetáculos teatrais para corporações, atendendo a uma demanda de criatividade com diferenciação.
- Estruturação administrativa com uso de softwares e dashboards, o que indica alguma organização interna.
- Formação em artes cênicas da gestora, garantindo expertise técnica para o ramo artístico.
- Presença ativa em operação e relacionamento inicial com clientes.
- Disponibilidade e consciência da necessidade de captar clientes e expandir no segmento corporativo.

Principais Pontos de Melhoria e Oportunidades do seu Empreendimento

- Ausência de planejamento estratégico formal, plano de sazonalidade e controle de indicadores de mercado.
- Marketing digital restrito a Instagram e sem estratégias definidas de relacionamento ou fidelização.
- Baixa diversidade no portfólio comercial e ausência de pipeline de vendas ou pesquisas de satisfação.
- Situação financeira atual deficitária, com receita anual menor que R\$5 mil e controle sem reservas ou planos financeiros.
- Falta de digitalização e automação nos processos de gestão e produção.
- Engajamento empreendedor limitado, sem formação em empreendedorismo, parcerias estratégicas claras ou políticas de valorização de recursos humanos.
- Tempo reduzido dedicado a estratégias de crescimento, fazendo com que a empresa dependa muito da atuação da gestora em atividades operacionais.

Source: screenshot of the SmartB system.

Next screens will show similar structures for every domain area, composed by a benchmark score within a scale from 1 (worst) to 5 (best), and then a textual feedback. Figure 20 presents the feedback for the sample diagnosis within the Management domain, followed by Figure 21 with the Market domain. Then, Figure 22

and Figure 23 shows the diagnosis for Finances and Technology, respectively. The last domain area would be Entrepreneurship, seen in Figure 24.

Figure 20 – Management Diagnosis

Diagnóstico Detalhado por Área

Confira uma análise detalhada por áreas de sua empresa de quais são os pontos fortes e os tópicos que deve ter atenção.

Gestão | Nota: 2/5

- A gestão possui controle com softwares e dashboards, porém não conta com planos estratégicos definidos nem planejamento sazonal.
- A falta de formalização em processos de controle e planejamento estratégico limita o desenvolvimento e a organização das variáveis gerenciais da empresa.
- Necessidade de mapeamento e controle mais robusto das atividades e seus indicadores para aprimorar a tomada de decisão.

Source: screenshot of the SmartB system.

Figure 21 – Market Diagnosis

Mercado | Nota: 2/5

- A empresa está em fase inicial de inserção no mercado corporativo, com atividades em operação, porém não possui estratégias estruturadas para captação e retenção de clientes.
- Marketing e comunicação limitados à plataforma Instagram, sem implementação de processos para fidelizar ou conquistar clientes de forma escalável.
- O mercado é promissor, dado o caráter inovador, porém falta análise regular da concorrência, fornecedores e ampliação do portfólio de produtos/serviços.

Source: screenshot of the SmartB system.

Figure 22 – Finances Diagnosis

Finanças | Nota: 2/5

- A empresa apresenta receita anual abaixo de R\$ 5 mil e encontra-se em situação deficitária nos últimos períodos.
- Controle financeiro inicial e simples, com ausência de fundos emergenciais, planos para quitação de dívidas ou estratégias para equilíbrio e geração de excedentes.
- Custos relacionados a deslocamentos, preparação e elenco impactam diretamente no resultado financeiro.

Source: screenshot of the SmartB system.

Figure 23 – Technology Diagnosis

Tecnologia | Nota: 2/5

- Apesar do uso de softwares para gestão e controle, não há utilização de tecnologia para automação ou digitalização dos processos operacionais.
- Ausência de estratégias para presença digital robusta além do Instagram, assim como falta de ferramentas digitais para ampliar vendas ou relacionamento.
- Necessidade de implementação de tecnologias que ajudem a organizar processos e ampliar o alcance comercial.

Source: screenshot of the SmartB system.

Figure 24 – Entrepreneurship Diagnosis

Empreendedorismo | Nota: 2/5

- Empresária com formação técnica específica, porém sem capacitação formal em empreendedorismo ou inovação.
- Presença de ação e engajamento, mas falta de formalização de parcerias estratégicas, políticas de valorização e plano para desenvolvimento de cultura empreendedora.
- O tempo disponível para dedicar às ações estratégicas está começando a aumentar, o que permite traçar planos de crescimento, mas ainda é limitado.

Source: screenshot of the SmartB system.

Then, the last screen (Figure 25) will present the strategic actions recommended by SmartB to be implemented by the diagnosed enterprise in order to achieve their entrepreneurial stability and maturity.

Figure 25 – Recommended Strategic Actions

Recomendações de Ações Estratégicas

Para fortalecer as áreas de gestão, mercado, finanças, tecnologia e empreendedorismo, recomendamos:

1. Desenvolvimento e implementação de um Plano Estratégico alinhado com o Business Model Canvas para estabelecer metas claras e caminhos para captação de clientes e crescimento. 🚀
2. Criação de um Plano de Sazonalidade para melhor gerenciamento do fluxo de trabalho e recursos conforme as demandas do mercado. 📅
3. Implementação de um Sistema de Gestão Financeira detalhado, com controle de custos, criação de reservas e desenvolvimento de plano para equilíbrio orçamentário e pagamentos de dívidas. 💰
4. Fortalecimento da presença digital e marketing, ampliando canais além do Instagram, adotando ferramentas para CRM, gestão de leads e análise de satisfação de clientes. 📊
5. Automação de processos de gestão e produção, buscando softwares especializados que facilitem o fluxo operacional e potencializem produtividade. 💻
6. Formação em empreendedorismo e inovação, e desenvolvimento de políticas para valorização de recursos humanos e parcerias estratégicas. 🤝
7. Realização de mapeamento e documentação dos processos operacionais para dar sustentação ao crescimento estruturado. 📋
8. Estabelecimento de um programa de fidelização e relacionamento ativo com clientes para aumentar retenção e vendas recorrentes. 📦
9. Incentivos para aumentar o tempo dedicado a ações de fortalecimento e planejamento do negócio.

Source: screenshot of the SmartB system.

Additionally, every user, when logged in, has a “users” area, where they can view previous diagnostics, download results as PDF, or share via secure links.

Administrative Features

The SmartB system includes a dedicated administrative module designed to support platform management, monitoring, user control, and AI training data supervision. Here we outline the main features of the administrative interface.

Administrative access is protected by a role-based access control system. Roles are stored in a dedicated user_roles table, and it queries the user_roles table to confirm that the user possesses the admin role.

The administrative interface adopts a unified layout that optimizes usability across devices and is divided into some modules that will be presented in the figures below, followed by an explanation.

The Dashboard, shown in Figure 26 provides consolidated metrics on platform use and resource consumption, including:

- Total Diagnostics: Number of diagnostics generated;
- Tokens Used: Total OpenAI tokens consumed;
- Estimated Cost: Calculated in USD, based on current OpenAI pricing, automatically calculated based on token consumption;
- Average Processing Time: Time taken per diagnostic;
- Graphical visualizations with line charts for all the above functions.

Figure 26 – Admin Dashboard Overview



Source: screenshot of the SmartB system.

The User Management module centralized all user-related operations. Figure 27 presents the “Automatic Approval” flag, in which new registrations are flagged for manual or automatic approval, depending on application settings. If automatic approval is disabled, then the user must register and it lays on the administrators to approve or reject users, edit their data or remove their profile permanently.

Another functionality is the “Orphan Account Cleanup”, where the system can identify and batch-delete authentication accounts without associated profiles, with reporting on successful and failed deletions.

Figure 27 – User Management Interface

 **SmartB** A sua IA para Diagnóstico Empresarial

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Gestão de Usuários

Gerencie solicitações de acesso, aprove usuários e atribua permissões.

Aprovação Automática
Novos usuários são aprovados automaticamente ☐

 Limpar Contas Órfãs

1

Solicitações Pendentes

Nome	Email	CPF	Tipo	Data da Solicitação	Ações
Test User	testuser@smartb.com.br	149.610.670-91	Empreendedor	17/11/2025	Aprovar Reprovar Editar Remover

Source: screenshot of the SmartB system.

Figure 28 is also about User Management, showing that for an approved user it is possible to assign or revoke admin privileges, edit data, remove it or see the diagnosis ruled by this user.

Figure 28 – User Data Management

The screenshot shows a user profile card for 'Test User'. The card contains the following information:

- Nome:** Test User
- Email:** testuser@smartb.com.br
- CPF:** 048.334.550-48
- Tipo:** Empreendedor (indicated by a green badge)

Below the user information, there are four buttons arranged in a grid:

- Ver Diagnósticos:** A button with an eye icon.
- Editar:** A button with a pencil icon.
- Admin:** A blue button with a shield icon.
- Remover:** A button with a trash can icon.

Source: screenshot of the SmartB system.

Another module is shown in Figure 29, is the Diagnostic History and allows administrators to view and manage all diagnostics generated on the platform, including these features:

- **Data Table:** Displays creation date/time (in Brasília time zone), company name, user name, email, and available actions.
- **Export Options:** Diagnostics can be exported in Excel, PDF, or Word formats. Question-and-answer sets and blank form templates can also be exported.
- **Processing Logs:** Detailed logs for each diagnostic include start/end timestamps, AI model used, token counts, training files referenced, and any error details.
- **Batch Operations:** Multiple diagnostics can be selected for batch deletion, including related logs.

Figure 29 – Module Diagnostic History

 **SmartB** A sua IA para Diagnóstico Empresarial

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Histórico de Diagnósticos

Visualize e exporte todos os diagnósticos gerados.

[Exportar Formulário](#) [Exportar Excel](#)

Diagnósticos Gerados

☐	Data	Empresa	Nome	Email	Ações
☐	26/12/2025 16:10:17	J[redacted]s ...	M[redacted]	ma[redacted]dvo...	🕒 Ver 📄 PDF 📄 DOCX 📄 P&R 🗑️
☐	23/12/2025 17:01:52	L[redacted]a...	SL[redacted]	sue[redacted]com	🕒 Ver 📄 PDF 📄 DOCX 📄 P&R 🗑️

Source: screenshot of the SmartB system.

The last module on the administrative panel is the “Training Data Management”. This module allows to oversee the data used for AI model training, as shown in Figure 30, with statistics of total diagnostics, new diagnostics not yet included in training, and total interview count.

There is also the function to “Export for Training”, where diagnostics not included in training can be formatted and exported as structured .txt files, and included in the RAG (Retrieval-Augmented Generation) training dataset.

Figure 30 – Training Data Module

Dados de Treinamento

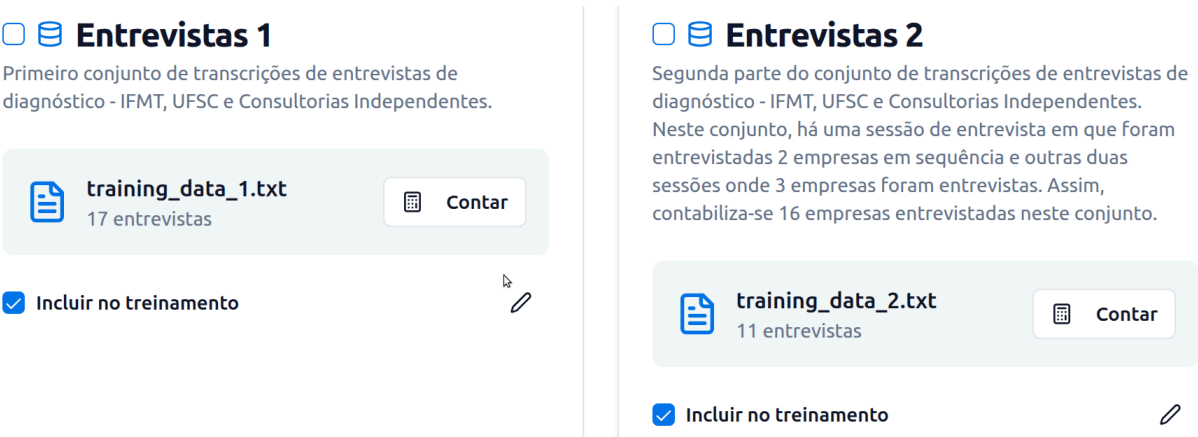
Gerenciamento dos dados de treinamento para geração de diagnósticos



Source: screenshot of the SmartB system.

Figure 31 shows the functionality of training set management, where administrators can activate or deactivate training sets, edit set details, count interviews per file, and delete selected sets to exclude it from the RAG training.

Figure 31 – Training Datasets



Source: screenshot of the SmartB system.

The last function present in this module is related to the OpenAI API setting, reported in Figure 32. It allows the selection of the AI model (e.g., GPT-4.1, GPT-5),

includes a connection test for the OpenAI API and some explanation about the models.

Figure 32 – OpenAI API Settings Interface



Source: screenshot of the SmartB system.

6 ASSESSMENT, APPLICATION AND DISSEMINATION OF THE RESEARCH

6.1 ASSESSMENT OF THE SMARTB ARTIFACT

To ensure the scientific and practical value of the SmartB artifact, a multi-layered assessment strategy was adopted. The evaluation involved both peer review and direct feedback from domain specialists, consultants, and end-users.

The methodology included submitting scientific articles describing the framework and artifact to journals and conferences, allowing for validation by experienced peers in the field. Additionally, structured evaluation forms were distributed to knowledge engineering (KE) experts. These forms assessed the relevance, accuracy, applicability, usability, and overall functionality of both the BSM framework and the SmartB artifact.

For a more targeted validation, business diagnosis specialists and consultants participated in guided sessions where SmartB was demonstrated. Following these sessions, 11 experts were invited to respond to a questionnaire using Likert scales and open-ended questions. The assessment, answered by 9 of the invited experts, covered diagnostic accuracy, completeness, the actionability of recommendations, usability, reliability, and overall trust in the AI-generated reports. Comparative judgments were also collected, evaluating SmartB's results against traditional expert diagnoses.

Table 11 in the Methods chapter lists the 16 questions addressed to business diagnosis consultants during the evaluation. The questions covered 6 domains, which the responses of the specialists are shown below. All experts were informed of and agreed to the Informed Consent Form (ICF)—available in the [Appendix 3](#)—before participating in the research.

The experts who accepted the invitation have their profile listed in Table 21. They were firstly invited to participate in a 25 minutes session, where I showed them the methodology of the research, how the framework and the artifact was created and how both of them works. After that, each of them were invited to freely answer the assessment form.

Table 21 – Experts Profile

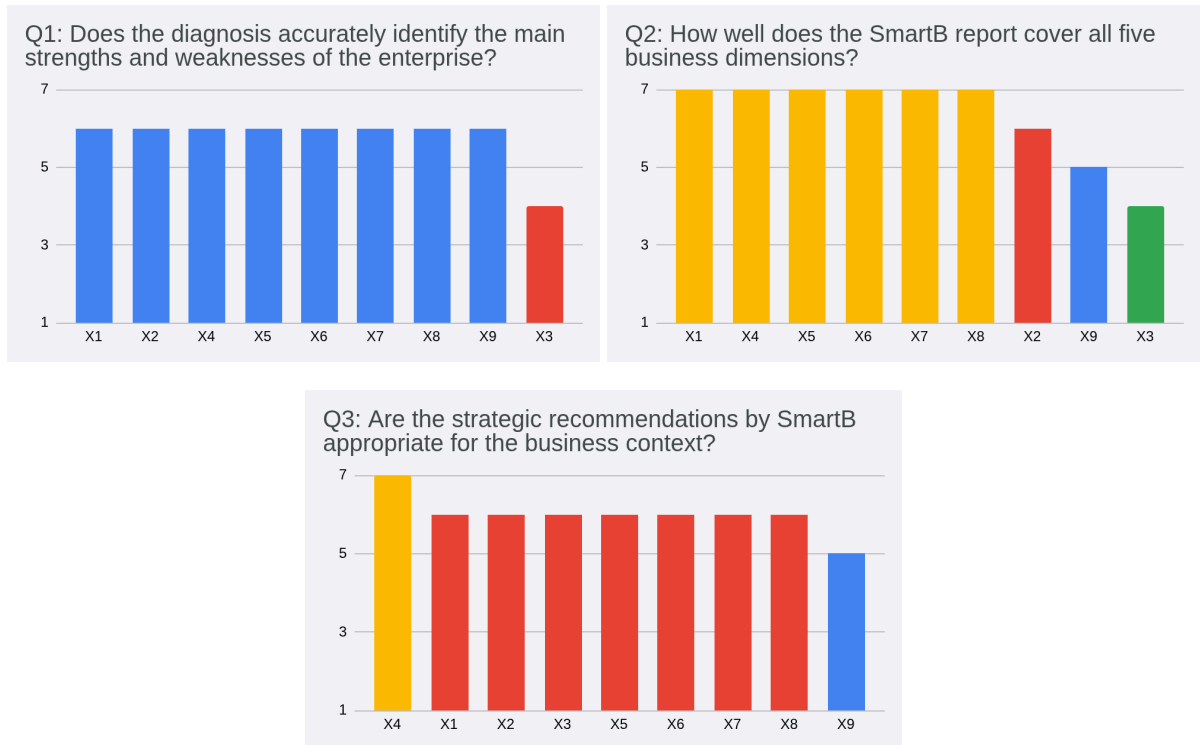
ID	Gender	Occupation/Expertise	Years Active
X1	M	Professor of Business and Entrepreneurship. Business consultant. Business Incubator Manager. Ph.D. in Knowledge Management.	13 y
X2	M	Professor of Business and Innovation. Entrepreneurship and innovation research group leader. Ph.D. in Business Management.	11 y
X3	M	Researcher in Entrepreneurship and Innovation. Business consultant. Ph.D. candidate in Knowledge Management.	14 y
X4	F	Professor of AI and Data Base. Business consultant. Full-stack developer. Master in Computer Science.	12 y
X5	M	Professor of Business Management. Business consultant. Business Incubator Manager. Ph.D. in Production Engineering	17 y
X6	F	Researcher in Entrepreneurship and Innovation. Businesswoman. Business consultant. Business Incubator Manager. Ph.D. candidate in Knowledge Management.	7 y
X7	F	Professor of Business Management. Business consultant. Business Incubator Manager. Ph.D. in Knowledge Management.	25 y
X8	M	Professor of Business Management and Economy. Business consultant. Business Incubator Manager. Ph.D. in Sustainable Development.	15 y
X9	F	Business consultant. Business Incubator Manager. Business Analyst in a Technological Park. Master in Business Management.	6 y

Source: prepared by the author.

Figure 33 present the result for the first section of question, aiming to understand the diagnostic accuracy and completeness. The first question, Q1, about the diagnosis accurately identifying the strengths and weaknesses, received one

neutral opinion and another eight with score 6, reaching a mean of 5.78 (see Table 22) out of 7, demonstrating high satisfaction with the diagnosis accuracy.

Figure 33 – Q1 to Q3: Diagnostic Accuracy and Completeness



Source: prepared by the author.

Table 22 - Statistics for Questions Q1 to Q5

	Q1	Q2	Q3	Q4	Q5
Mean	5,78	6,33	6,00	5,89	6,44
Median	6,00	7,00	6,00	6,00	6,00
Std. Deviation	0,67	1,12	0,50	1,05	0,53

Source: prepared by the author.

The second question, Q2, inquired about how well the SmartB report covers all the business dimensions. Again, we see one neutral answer by Expert X3, but a high agreement of the others, with an average score of 6.33 (Table 22), giving legitimacy to the business dimensions identified by this study, as well as to the questions curated for that matter.

Considering the cross-sectional questions through the dimensions of a business management, expert X6 supported this characteristics in her comment in the last open question:

The use of cross-sectional analyses in the area of business management, is very relevant, as it can suggest in the future which operational skills and development opportunities entrepreneurs can utilize, guiding them towards more efficient tools and practices. (X6)

Regarding the framework's dimensions and its ability to adequately cover business areas, expert X2 offered the following comment as a suggestion for future work:

The model is robust. However, the classic view of management points to four areas of the business: (1) People, (2) Finance, (3) Operations and Logistics, (4) Marketing. It would be interesting to see these areas named in the model. (X2)

Expert X8 made some specific contributions, recommending to investigate about competition and perceived differentiators in the business, within the market dimension and with the management dimension, she suggested to adopt KPIs (Key Performance Indicators) for decision making:

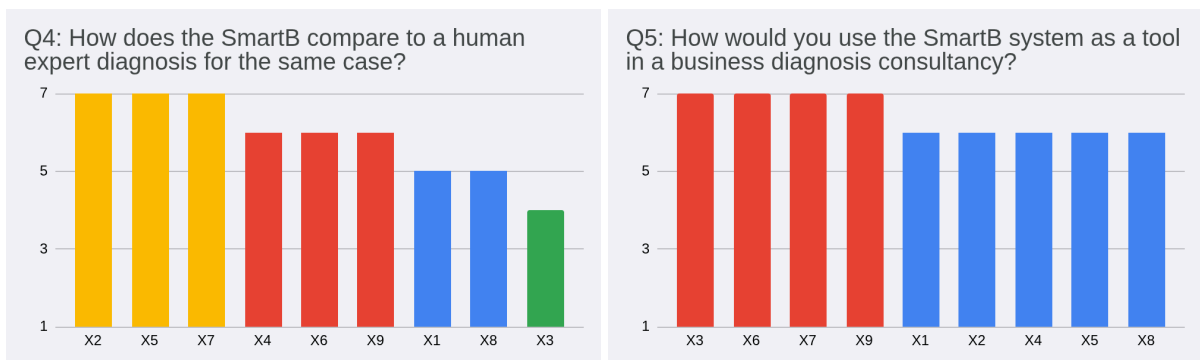
In the market axis, I felt the lack of a question about knowledge of the competition and perceived differentiators in the business [...] In management, I suggest including a question about the adoption of KPIs for decision-making, relating the main types (revenue, operating costs, average ticket, sales conversion rate, etc.). Although it is not the focus of the Framework, considering sustainable development, perhaps it would be interesting to include this topic in future updates. (X8)

In respect to Question Q3, the aim was to verify how appropriate are the strategic recommendations of SmartB for the business context. An average score of 6 (Table 22) deriving from eight score 6 and one score 7 evaluations, indicating high appropriateness perceived by experts of the recommendations offered by SmartB.

Regarding the comparison of the SmartB with human diagnosis, Figure 34 presents two questions. The first one, Q4, verifies how the SmartB system's diagnosis compares to a human expert diagnosis for the same case. The Expert X3 felt neutral about that matter, while all the others agreed with the equivalency with a mean of 5.89 as shown in Table 22.

The Question Q5 asked how would they, as experts, use the SmartB system as a tool in a business diagnosis consultancy. Everyone highly agreed on the possibility of using it, reaching a mean of 6.44 (Table 22) for this question. On that matter, Expert X6 praised the platform's legitimacy and added: "I found the platform very interesting and would certainly use it in my mentoring and consulting work."

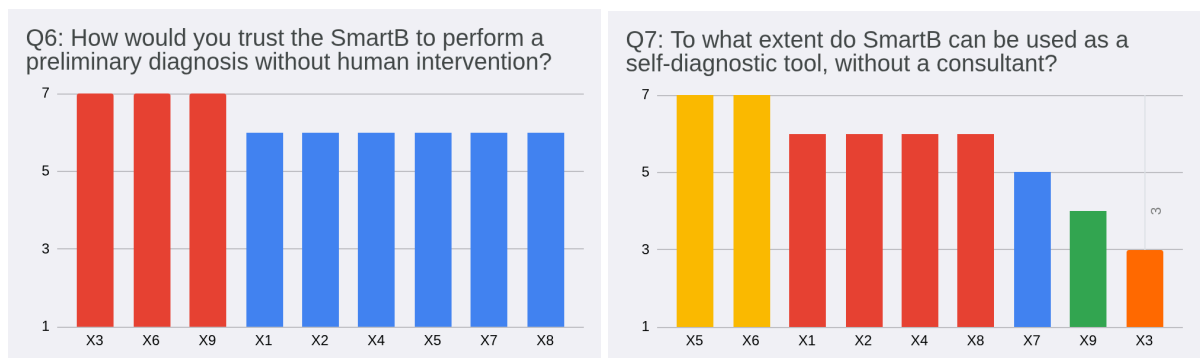
Figure 34 – Q4 and Q5: Comparison to Human Diagnosis



Source: prepared by the author.

The trust and reliability of the artifact was evaluated with questions Q6 and Q7. The results for both of them are shown in Figure 35. Every expert demonstrated trust with SmartB as a tool for business diagnosis consultancy, assigning scores 6 or 7 to it, which led to a 6.33 average score (see Table 23). Expert X2 indicated in his comment that the artifact "has already proven to be robust and is following procedures that must be observed to ensure the reliability of the measurements".

Figure 35 – Q6 and Q7: Trust and Reliability



Source: prepared by the author.

Table 23 - Statistics for Questions Q6 to Q9

	Q6	Q7	Q8	Q9
Mean	6,33	5,56	6,78	6,22
Median	6,00	6,00	7,00	7,00
Std. Deviation	0,50	1,33	0,44	1,09

Source: prepared by the author.

Question Q7, inquired to what extent do the experts think SmartB can be used by entrepreneurs as a self-diagnostic and self-knowledge tool for their business, without the presence of a consultant. Expert X9 felt neutral about that and X3 showed to disagree, assigning score 3, because he thinks the diagnosis “may have limitations compared to a broader range of companies present in Brazilian society”.

On the other hand, all other experts agreed that it could be used as a self-diagnostic tool by entrepreneurs. Expert X8 contributed with this point saying that SmartB “it's an educational tool that leads to self-analysis and reflection on essential aspects of management”. She also recommended some adjustments on the terminology for better understanding considering the use of the platform by entrepreneurs: “For independent use by entrepreneurs, I suggest adapting the terminology to facilitate technical understanding and obtain reliable answers”.

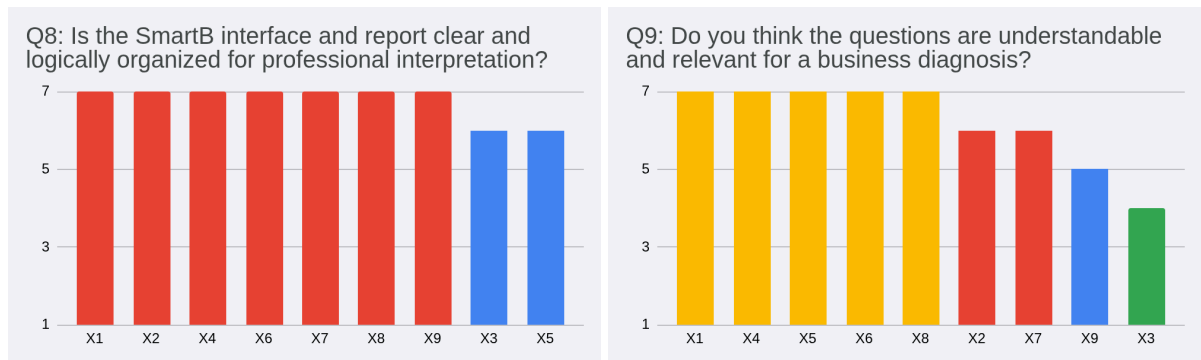
So, in cases, where the diagnosis could not have really accurate feedback, a consultant could help to better perceive that. Expert X6 contributed to the same point stating:

I believe that its use [of the SmartB] is very relevant in supporting decision-making. It doesn't exclude the importance of human analysis, but it generates support for decision-making and guidance in a more assertive and clear way. (X6)

Figure 36 shows responses for questions Q8 and Q9, regarding the usability and clarity of SmartB. Question Q8 asked if the SmartB interface and report layout are clear and logically organized for professional interpretation and Q9 inquired if the experts think the questions in the form are understandable and relevant for a business diagnosis. While Expert X3 declared neutral within Q9, he reported score 6 for Q8 and all others experts highly agreed with both questions, demonstrating

appropriate satisfaction with the usability and clarity. Table 23 shows the mean for these questions were 6.78 for question Q8 and 6.22 for Q9.

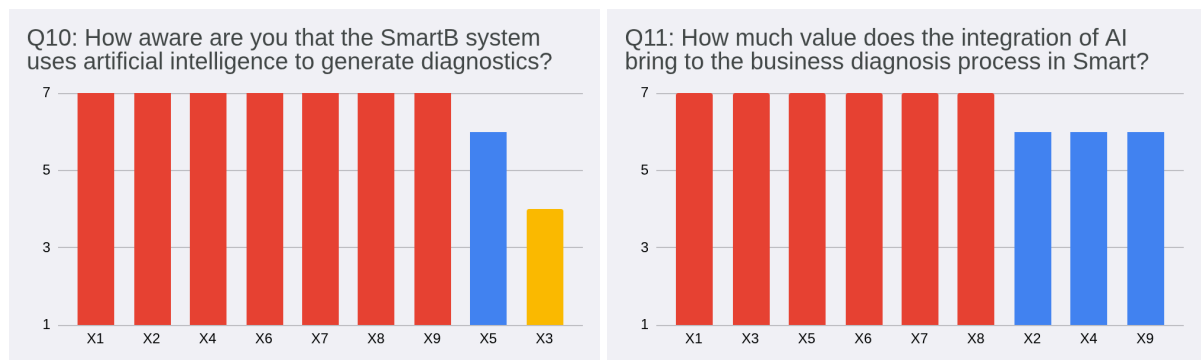
Figure 36 – Q8 and Q9: Usability and Clarity



Source: prepared by the author.

The following group of questions—from Q10 to Q13—have their responses represented in Figure 37 about the perception and trust of the experts in AI. Question Q10 asked how aware the experts were that the SmartB system uses artificial intelligence to generate diagnostic reports; Q11 considered the professional point of view of the experts, to verify how much value does the integration of AI bring to the business diagnosis process in SmartB; Q12 inquired how would them rate the trust in AI-driven reports like those from SmartB, compared to traditional human-made diagnoses; and Q13 demanded how much do they trust the diagnostic results when they know they are generated supported by an AI system.

Figure 37 – Q10 to Q13: Perception and Trust in AI





Source: prepared by the author.

Except for the neutral opinion of X3 within questions Q10, Q12 and Q13, all other answers for this group of questions were positive. Table 24 highlights the mean scores, median and standard deviation achieved by the four questions in the group. Expert X6 contributed to this topic arguing about transparency with the users by saying she thinks “it’s important, as a user, to understand what and how AI will play a part. The reliability of AI is uncertain, and despite its high valuation and speed, it still generates insecurity.”

Expert X8 also made a comment about the use of AI, stating “I think the use of AI in business diagnostics is the way of the future”, and showing trust in this technology and in the artifact by adding “I liked the tool and I would definitely use it”.

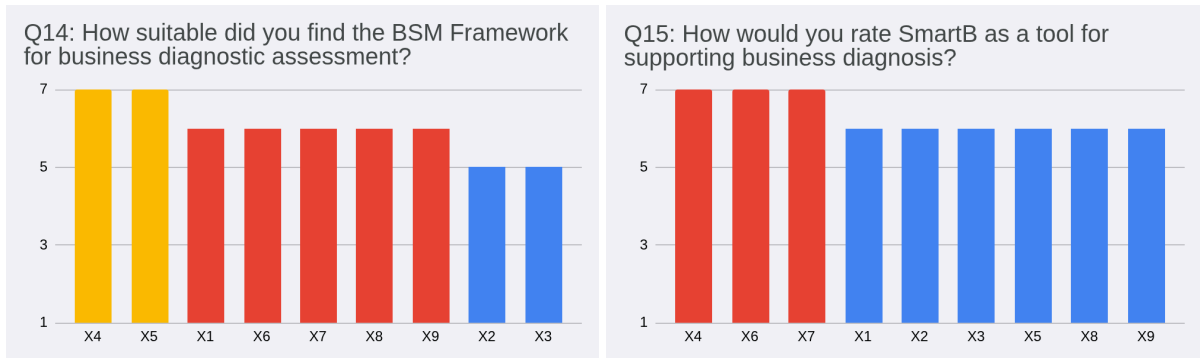
Table 24 – Statistics for Questions Q10 to Q13

	Q10	Q11	Q12	Q13
Mean	6,56	6,67	5,78	5,78
Median	7,00	7,00	6,00	6,00
Std. Deviation	1,01	0,50	0,97	0,97

Source: prepared by the author.

Figure 38 shows positive results for questions Q14 and Q15, related to the overall satisfaction of the experts with the framework and the artifact. Q14 asked how the experts found suitable the BSM Framework for business diagnostic assessment and Q15 inquired about a rate for SmartB as a tool for supporting business diagnosis. The average score for Q14 was 6 (85,7%) and it was 6.33 (90,4%) for Q15, as seen in Table 25.

Figure 38 – Q14 and Q15: Overall Assessment



Source: prepared by the author.

Table 25 – Statistics for Questions Q14 and Q15

	Q14	Q15
Mean	6,00	6,33
Median	6,00	6,00
Std. Deviation	0,71	0,50

Source: prepared by the author.

Some experts made comments related to their overall assessment. Expert X2 just gave “congratulations on the quality of the product”, while X4 stated about how the artifact could be useful to help experts save time:

I found this to be an excellent piece of work, as I've already spent days evaluating data on project diagnostics. This tool will greatly streamline our work, saving us many hours and finding information that might not have been available before. (X4)

The careful construction of the tool and its potential applications was noted by Expert X5 as quoted: “I think the tool is very well structured, built on appropriate and robust conceptual/theoretical foundations. It could be extremely useful for managers and consultants”.

Expert X6 also agreed on the applications of the saying she believes “it is a valuable tool that adapts to different realities, making it highly relevant for various areas”. She also emphasized that “the use of SmartB is also very relevant for knowledge management and understanding [the business] processes evolution”.

Regarding the use and application of the SmartB, Expert X8 recommended it as a tool for business incubators and specialists, as well as for self-diagnosis for entrepreneurs as an education tool:

This framework is extremely important for the management of micro and small businesses, for incubators and specialists. [...] Congratulations on the work; more than a diagnosis, it's an educational tool that leads to self-analysis and reflection on essential aspects of management. (X8)

The experts' feedback confirmed that SmartB instantiation of the BSM Framework effectively diagnoses main strengths and points of improvement across all wide business dimensions. They reported that the recommendations were actionable and relevant, and the interface was considered clear and accessible. Some specialists highlighted the value of using SmartB for preliminary assessments or as a complementary tool in consultancy, particularly for small and medium-sized enterprises.

6.2 APPLICATION AND FEEDBACK WITH ENTREPRENEURS

To assess SmartB's real-world utility and user acceptance, the artifact was made available to a group of entrepreneurs and business managers. After completing their own business diagnosis using SmartB, participants were invited to respond to a structured survey and provide open-ended feedback.

The survey followed the questions established on Table 12 in the Methods and focused on usability, clarity of the diagnostic process, perceived accuracy, and the practical relevance of the recommendations. Key evaluation areas included ease of registration and navigation, understandability of the questions, perceived value and clarity of the diagnosis, actionability of the recommended steps, and trust in the AI-generated report. Questions also probed users' comfort with AI-generated advice and their willingness to use or recommend SmartB in the future.

In the application phase 27 entrepreneurs—lead managers of an enterprise—were invited to try the SmartB artifact of whom 17 attended. All users were informed of and agreed to the Informed Consent Form (ICF)—available in the [Appendix 3](#)—before participating in the research.

They did all the flow of the user experience, starting registering themselves, going through the questions and the diagnosis and reaching the evaluation form at the end.

The businesses belonged to 4 different Brazilian states—Mato Grosso, Goiás, São Paulo e Santa Catarina—situated in 3 different regions of the country: middle-east, south and southeast. The most common business sector is retail and services, as shown in Table 26, but every business has a single business model.

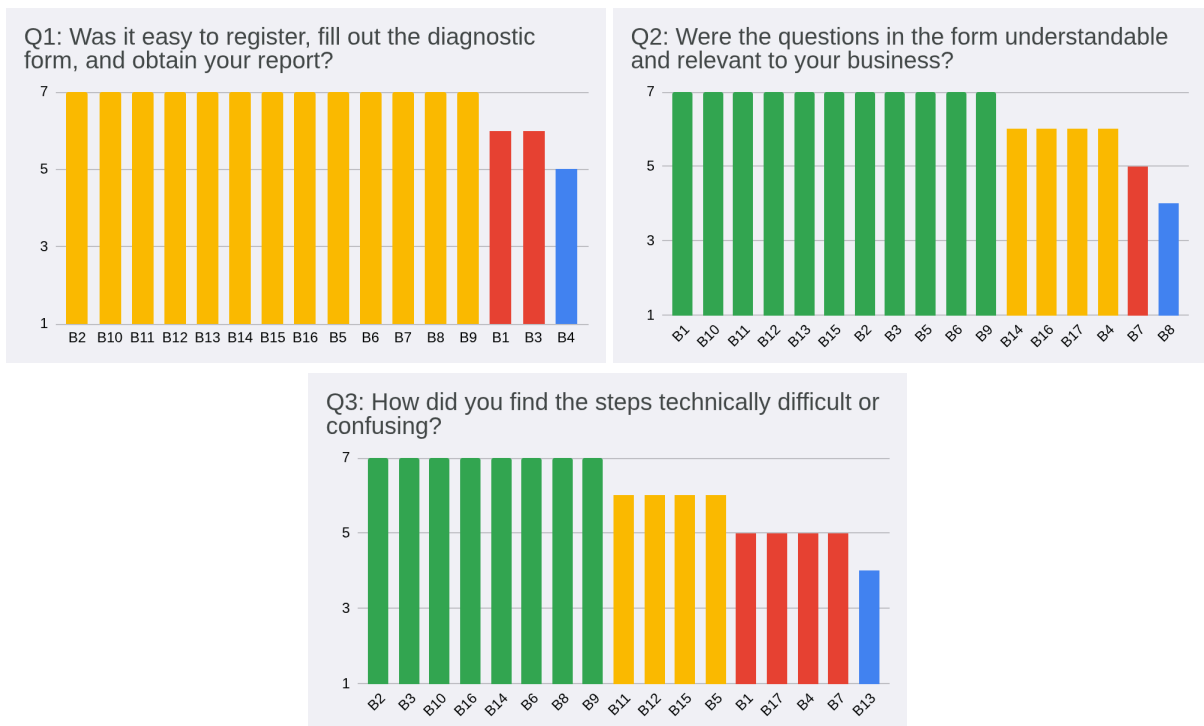
Table 26 – Businesses States and Activities

ID	State	Primary Activities
B1	MT	Party Decorations
B2	SC	Services - Tourism Agency
B3	SP	Services - Tourist Advice
B4	SC	Artistic Services
B5	SC	Service and Retail - Decorations and Costumes
B6	GO	Retail of Religious Articles of African Origin
B7	MT	Legal Consulting - Agribusiness
B8	SC	Typical Indian food restaurant
B9	GO	Lawyer Services
B10	GO	Education and Therapy
B11	MT	Creative Economy
B12	SC	Automotive Services - Mechanics
B13	MT	Retail Clothing and Cosmetics
B14	SC	Artistic Services
B15	SC	Services - Solutions for the Creative Economy
B16	SC	School of Arts
B17	SC	Health - Pilates and Functional Training

Source: prepared by the author.

Figure 39 shows the results for questions 1 to 3. The analysis indicated an average evaluation (Table 27) of 6.59, 6.47 and 6.12, respectively. Considering the maximum score of 7, these averages means high user satisfaction with the system's ease of use, understandability and technical appropriateness.

Figure 39 – Q1 to Q3: Usability and Interface Experience



Source: prepared by the author.

Table 27 – Statistics for Questions 1 to 6

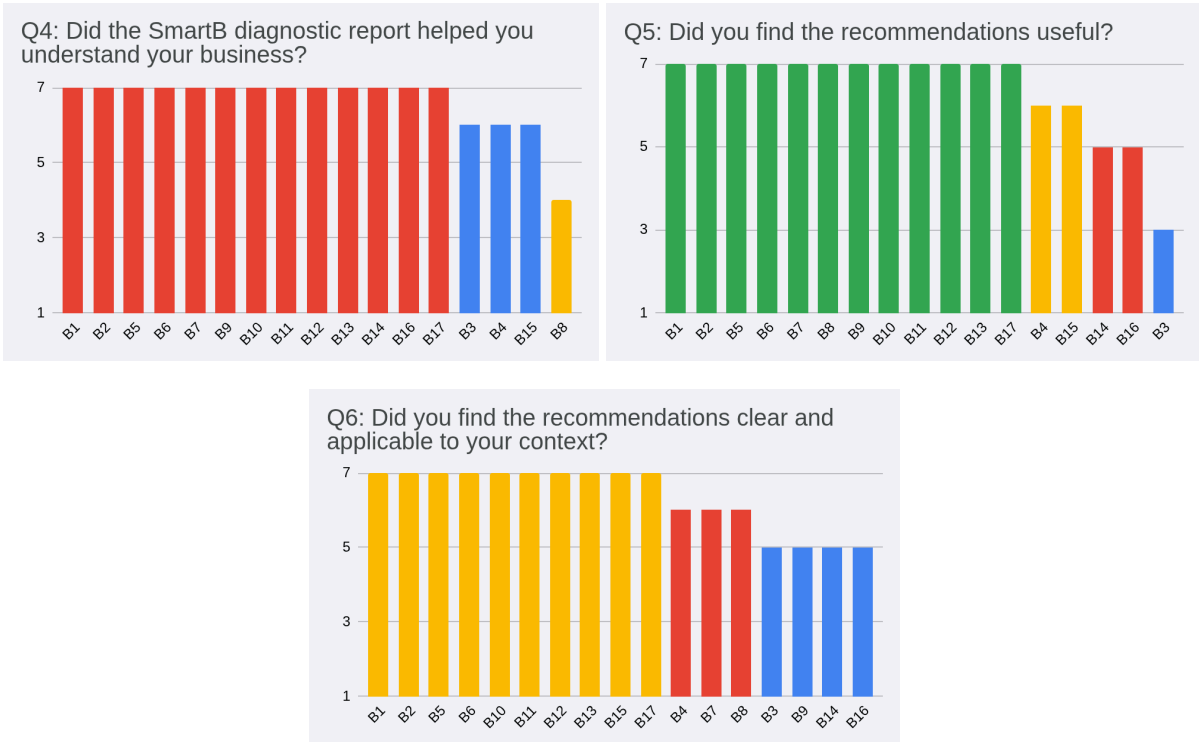
	Q1	Q2	Q3	Q4	Q5	Q6
Mean	6.59	6.47	6.12	6.65	6.41	6.35
Median	7.00	7.00	6.00	7.00	7.00	7.00
Std. Deviation	0.87	0.87	0.99	0.79	1.12	0.86

Source: prepared by the author.

The responses for questions Q4 to Q6 are shown in Figure 40. This block of questions inquired about the perceived value of the diagnosis by the users. Again, as seen in Table 27, they resulted high averages. Question 4 had one answer indicating

neutral opinion. This one was B8, the Typical Indian food restaurant, that in the last–open–question, reported it found the diagnosis helpful in identifying the pain points of the business, but the recommendations seemed to be too wide and not specific enough for his area of operation and the location of the business. In Question 5, the Tourist Advice Service (B3), gave a score 3 and reported something similar in the open question: “I found the UX-UI super appealing and easy to use. I loved the diagnostics [...] the recommendations are a bit too general and don't really help create an action plan”.

Figure 40 – Q4 to Q6: Perceived Value of Diagnosis



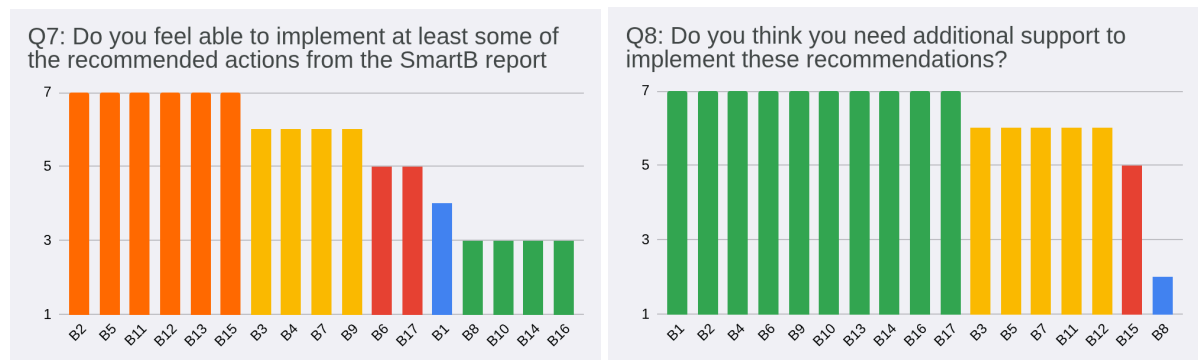
Source: prepared by the author.

Figure 41 presents the questions Q7 and Q8 that aimed at understanding how entrepreneurs felt about their ability to implement the recommendations suggested by SmartB. Analysing Q7, where we ask “Do you feel able to implement at least some of the recommended actions from the SmartB report?”, we can see a good mean of 5.41 (see Table 28), denoting the majority of the businesses (12 out of 17) felt able to implement the recommended actions, although one company symbolized neutrality within this matter and other 4 indicated inability. Analysing the feedback of

enterprises B14 and B16, both commented that it would be interesting to have a consultant monitoring the evaluation process, while B14 added: “Especially with small businesses, this [having a consultant monitoring] would lead to better understanding and allow for a discussion of each question”.

Relating to the Q8, just one business flagged no need to support to implement the recommendations, but representing an average score of 6.29, all other companies agreed on needing help to put the diagnosis into action. Contributed to this matter, the comments of B5 saying “I would appreciate it if, at the end of the analysis, you would receive suggestions on which tools/applications could be used to implement the improvements needed in the company” and the specific statement of B12 about the Q8: “I think it would be great to add spreadsheets and templates here... In my case, even though I know and understand the suggestions, I think manuals, spreadsheets, or more readily available materials would be a great help”.

Figure 41 – Q7 and Q8: Actionability and Implementation



Source: prepared by the author.

Questions Q9 and Q10 sought to evaluate how the users trusted the diagnosis of SmartB. Both questions demonstrate a high approval rate in Table 28. In Figure 42 it is possible to note that 13 of the 17 businesses felt the diagnosis totally credible, with the maximum score, while the other 4 enterprises pointed three score 6 and one score 5, reaching the mean of 6.71. Regarding Q10, except for the neutrality of B14 all other companies highly agreed on recommending SmartB for other entrepreneurs.

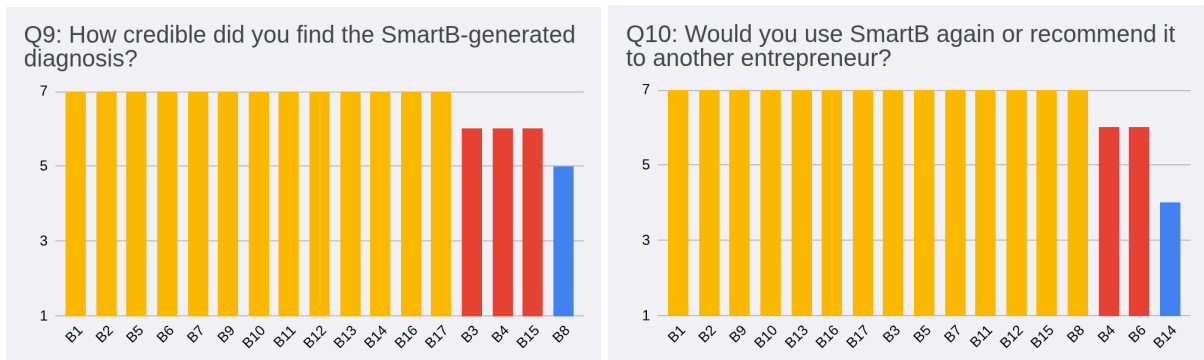
Table 28 – Statistics for Questions 7 to 10

	Q7	Q8	Q9	Q10
Mean	5.41	6.29	6.71	6.71
Median	6.00	7.00	7.00	7.00
Std. Deviation	1.62	1.26	0.59	0.77

Source: prepared by the author.

None of the comments left in the last open question was directly connected with these questions. There was nothing related with the credibility or not of the platform, and there was no reflection, as well, about recommending or not the platform to others.

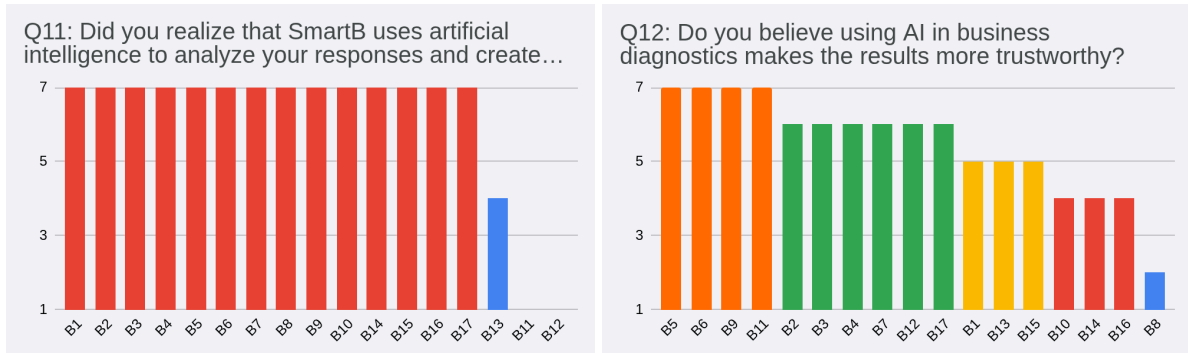
Figure 42 – Q9 and Q10: Trust and Credibility



Source: prepared by the author.

Questions Q11 to Q14 are related to the perception and trust in AI and their results are presented in Figure 43 (Q11 and Q12) and Figure 44 (Q13 and Q14). Question Q11 asked about the perception of SmartB being powered by AI. While 2 people stated no perception and one showed neutrality about that, the other 14 agreed with the maximum score, indicating being aware of that.

Figure 43 – Q11 and Q12: Perception and Trust in AI



Source: prepared by the author.

Regarding Q12, when users were asked if they believe using AI in business diagnosis makes the results more trustworthy, most of them agreed with that being four responses score 7, six with score 6 and three scored 5. Just one enterprise disagreed with that (score 2) and other 3 companies evaluated this matter with neutrality. Table 29 shows yet a high mean for this questions, but paying attention for the standard deviation.

Table 29 – Statistics for Questions 11 to 15

	Q11	Q12	Q13	Q14	Q15
Mean	6.12	5.47	5.41	6.35	6.53
Median	7.00	6.00	6.00	7.00	7.00
Std. Deviation	2.06	1.37	1.33	1.22	0.72

Source: prepared by the author.

Figure 44 presents results for the question Q13, about how comfortable the entrepreneur felt receiving business advice generated by an AI system. The average score for this response is 5.41 (shown in the Table 29), and although it includes 3 neutral responses and 1 disagreeing response, it demonstrates the entrepreneurs' good comfort level with having a diagnosis supported by AI. About the diagnosis being generated by AI, enterprise B12 said the diagnosis recommendations interface could be somehow related to Generative AI and suggested "Perhaps changing the

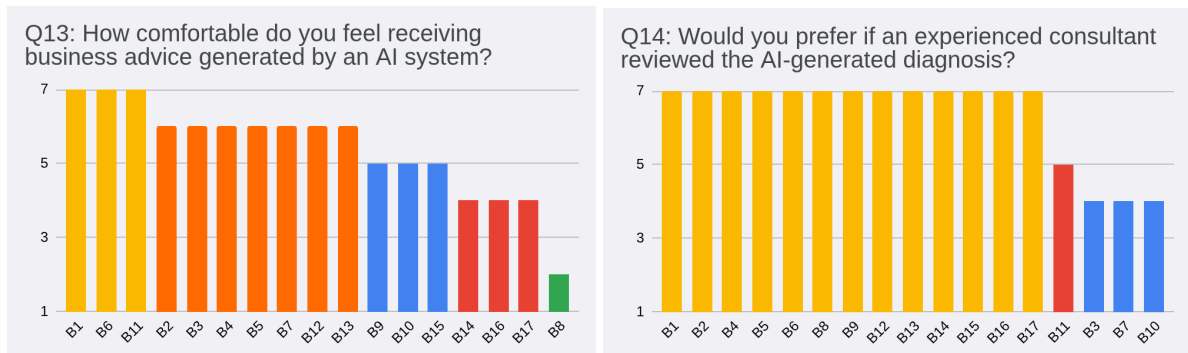
formatting and icons could generate a front end with a design that conveys more authority to the result”.

The last question about the trust in AI is Q14, where we asked if the entrepreneur preferred that an experienced consultant reviewed the AI-generated diagnosis. No opposite opinion on that matter. The average score for the question was 6.35 (Table 29) and just entrepreneurs saw that in a neutral way, while the others agreed. That was the question that more comments could be directly related to. Here are some statements of the entrepreneurs that contribute to this position:

- “The experience was good. There were a few questions I had doubts about due to a lack of knowledge.” (B4)
- “I think it can help companies, and especially consultants, in this process of identifying and clustering information for guidance and the consulting process.” (B12)
- “I think it would be very interesting for the consultant to be present during the evaluation process, especially with small businesses, so that there would be a better understanding and they could discuss each question”. (B14)
- “There were some things I didn't quite understand because I don't apply them much to my work environment; a consultant could help me understand, but I loved the tool”. (B17)

Other comments were not directly related to it, but when we analysed questions Q7 and Q8 we also showed that the entrepreneurs were missing having more specific support to implement the recommendations or to have more specific advice to create the action plan.

Figure 44 – Q13 and Q14: Perception and Trust in AI



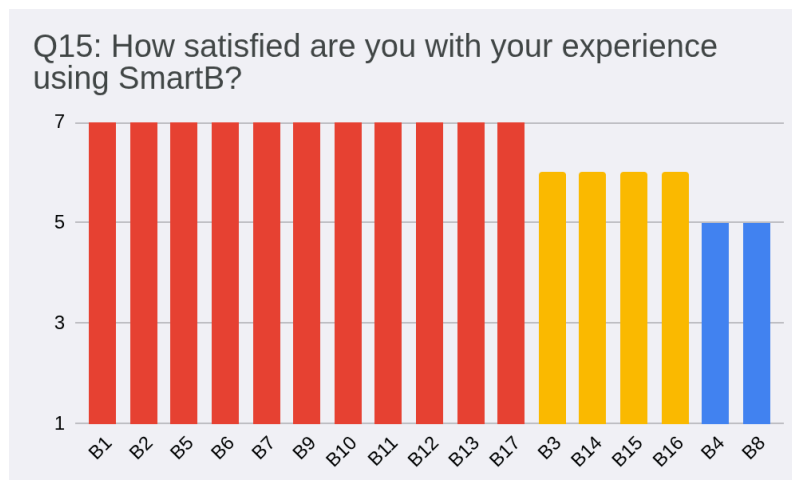
Source: prepared by the author.

The last objective question of the form, Q15, assesses the overall satisfaction of the users, asking how satisfied they were with their experience using Smart. We have the results shown in Figure 45, with a high satisfaction of 93,2%, sustained by a mean of 6.53 (Table 29) and no neutral or negative opinion about it.

Some respondent comments attest to their overall satisfaction with the tools, as highlighted below:

- “I was impressed with the evaluation! You managed to give a good overview of the project”. (B1)
- “I loved the diagnoses [...] everything I mentioned as my next step, what I want to focus on and need to do, was what he brought me”. (B3)
- “The questions about the business were very to the point. Easy to read and understand”. (B5)
- “I found it clear and practical, which allows people with varying levels of understanding of the subject to successfully complete the questionnaire. Very good”. (B6)
- “Overall, I thought it was very good!”. (B12)

Figure 45 – Q15: Overall Satisfaction



Source: prepared by the author.

In an overview of the artifact's application to entrepreneurial end users we could see that most users found the recommendations understandable and felt empowered to implement at least some of the suggested actions. Their feedback also indicated that they valued the opportunity to receive a structured assessment and actionable advice, even in the absence of in-person consultancy.

Open-ended responses highlighted the importance of clear language and the benefit of personalized recommendations. Some users expressed interest in further support or follow-up features, while others suggested consultancy help, improvements in report customization and additional examples of best practices.

6.3 DISSEMINATION OF THE RESEARCH

Dissemination of the research findings and practical outputs was accomplished through multiple channels, targeting both the academic community and broader professional and entrepreneurial audiences. Table 30 summarizes the main dissemination actions, showing that scientific articles were submitted and presented at conferences and in peer-reviewed journals. This documented methodological advances, reviewed the state of the art, results of the prototype artifact, and the development of the BSM framework. Intellectual property registrations were completed for both the software and the framework to protect and formalize the research outputs.

Table 30 – Action to the Dissemination of the Research

What	Where	Why
Paper: A Framework for Business Diagnosis: A case study with Brazilian startups	International Conference on Knowledge and Innovation (ciKi)	Presents the methodological improvements that led us to achieve the BSM framework.
Paper: <u>Business Vulnerability Diagnosis: An Integrative Review</u>	Revista e-Tech: Tecnologias para a Competitividade Industrial	To validate the beginning of the research, understanding whether "it is possible to anticipate the diagnosis of business problems?".
Paper: <u>Predicting Business Vulnerability Using Neural Networks: Evidence From Brazilian SMEs</u>	European Conference on Knowledge Management (ECKM)	Reports the results of the prototype version of the predicting artifact.
Paper: <u>Metodología Basada en Inteligencia Artificial para la Innovación en la Toma de Decisiones Legales</u>	Accounting and Innovation Journal (RCI)	Strengthening the expertise of creating a methodology and working with AI.
Paper: Análise dos Métodos de Gestão do Conhecimento para Incubadoras de Empresas: uma Revisão de Escopo	Revista Perspectivas em Gestão & Conhecimento	<u>Under evaluation process.</u> With this review we were able to find the relevant enterprise domain areas.
Paper: AI Approaches to Predict Business Risk: a Scope Review	Journal of Contemporary Administration	<u>Under evaluation process.</u> This review retrieved the AI approaches used world-wide to analyze enterprise risk in small and medium-sized companies.
Software Intellectual Property Register: Business Vulnerability Prediction Tool	Brazilian National Institute for the Industrial Property (INPI)	First version of the thesis, as prototype, registered under the Nr. BR512025002301-4.
Software Intellectual Property	Brazilian National	Beta version of the SmartB,

Register: SmartB	Institute for the Industrial Property (INPI)	released with the thesis. Registered under the Nr. BR512025007134-5.
Framework Intellectual Property Register: BSM - Business Strengthening Methodology	Câmara Brasileira do Livro (CBL)	BSM framework formalized and registered under the ID DA-2025-107728 .

Source: prepared by the author.

These efforts ensure the visibility, credibility, and accessibility of the research outcomes, supporting their adoption by practitioners, policy-makers, and the academic community. The continued dissemination and application of SmartB and the BSM framework are expected to contribute to improved business diagnosis practices and support the development of stronger, more resilient enterprises.

7 FINAL REMARKS

In this study, we presented SmartB, a diagnostic tool based on the BSM methodology, which considers five dimensions—management, market, capital, technology, and finance—for its diagnosis. The results of the research demonstrate that it is possible to generate consistent and meaningful business diagnoses using artificial intelligence when supported by a multidimensional framework and real-world data. The proposed artifact was able to identify strengths, weaknesses, and improvement opportunities across different business areas, providing structured feedback that can support managerial decision-making. These outcomes reinforce the relevance of combining knowledge engineering principles with artificial intelligence techniques to support business diagnosis in small and medium-sized enterprises, which is the central contribution explored throughout this thesis.

Government agencies, financial institutions, and development and support organizations can also use this diagnosis to provide consulting and expert support in areas where weaknesses have been detected. They may promote resources targeted at actions that help organizations address these weaknesses. Additionally, this tool can serve as an instrument for government agencies, market analysts, and business development agencies to assess business health.

7.1 ACHIEVEMENT OF THE RESEARCH'S PURPOSE

Research Question

The research question, "How is it possible to use Artificial Intelligence in business diagnostics for identifying potentialities and opportunities for organizational growth?" was addressed through a structured methodological approach that combined literature review, data collection from real business consultancy interviews, and the application of artificial intelligence techniques.

First, literature reviews were conducted to understand current practices and limitations in business diagnostics, with particular attention to the use of AI for predicting business problems and growth opportunities. This review identified that most existing approaches focus primarily on financial indicators and that there is a lack of holistic tools considering management, market, technology, and entrepreneurship dimensions.

To address this gap, a comprehensive framework was developed that integrates these multiple dimensions. The research collected data from diagnostic interviews with small and medium-sized enterprises (SMEs) in Brazil, using a set of structured questions refined through expert input and supported by generative AI tools. This process ensured that the data captured would reflect not only risks but also the strengths and growth potential within organizations.

The collected data and the framework was then used to process with Gen AI, using RAG to compare AI-generated predictions with evaluations made by experienced consultants. The study demonstrated that AI can process structured organizational data to identify both strengths and opportunities for growth. The results showed that AI, when informed by a comprehensive diagnostic framework, can support the identification of areas for development and provide actionable recommendations for organizational improvement.

Objectives

A framework was proposed, achieving the general objective to "Propose a framework for business diagnosis prediction using artificial intelligence". This went through several stages:

- **Literature Review and Framework Definition:** The study began by reviewing existing literature to identify the main dimensions relevant to business diagnosis. These included management, market, capital, technology, and entrepreneurship. The review also guided the selection of AI methods appropriate for the SME context.
- **Data Collection:** Diagnostic data was collected from real consultancy interviews with SMEs, using a question set designed to cover all relevant organizational dimensions. This ensured that the dataset for AI learning was comprehensive and contextually relevant.
- **Framework Structuring:** Based on the literature and data collected, a conceptual framework was developed to organize the diagnosis process. This framework defined how to assess each domain within an organization and how to assign maturity scores.
- **Gen AI Processing:** Using the knowledge of structured data and the framework, we used Gen AI RAG processing to develop the ability to predict

business diagnoses, classify enterprise maturity and identify key areas for improvement or growth across the five defined domains.

- **Validation and Assessment:** The AI-based predictions were validated against expert consultant evaluations, ensuring the framework's practical applicability. Also, users made diagnoses with it and gave their positive evaluation about the artifact. This step confirmed that the proposed framework, supported by AI, could reliably predict diagnoses and highlight opportunities for business development.

This way, the main objective of the research was achieved. The specific objectives were also accomplished, as Table 31 explicitly shows how.

Table 31 – Achievement of the Specifics Objectives

Ref.	Objective	How was achieved
OE1	Research the state of the art of business diagnosis dimensions.	Literature reviews.
OE2	Investigate tools, techniques, and methods that use Artificial Intelligence for business diagnosis prediction.	Literature reviews.
OE3	Develop and evaluate an AI artifact for business diagnosis prediction based on the framework.	Structured methodology. BSM Framework. SmartB Artifact.

Source: prepared by the author.

Beyond the pragmatic achievement of its objectives, this thesis also offers other relevant contributions and impacts, which are discussed in the following sections.

7.2 TECHNICAL INSIGHTS

The development of the SmartB artifact provided several technical insights related to the application of artificial intelligence in business diagnosis, particularly in contexts characterized by limited, heterogeneous, and predominantly qualitative data, as is common among small and medium-sized enterprises. One of the main lessons learned is that the **effectiveness of AI-based diagnostic tools depends**

not only on the choice of algorithms, but also on the **structuring of diagnostic knowledge and the quality of the data** representation process.

A central technical insight concerns the decision to combine a conceptual diagnostic framework with a generative artificial intelligence model. Rather than relying exclusively on traditional machine learning classifiers trained on numerical indicators, this research demonstrated that generative AI can be effectively employed to interpret structured questionnaire data when it is grounded in a well-defined diagnostic framework and supported by curated real-world cases. This approach allowed the system to generate descriptive and context-aware diagnostic outputs that resemble expert reasoning, which would be difficult to achieve through purely statistical models.

The use of prompt engineering emerged as a critical technical component of the solution. The results showed that small variations in prompt structure, contextual instructions, and output constraints significantly affected the consistency and clarity of the generated diagnoses. This reinforces the understanding that, in generative AI-based systems, part of the system's "logic" is embedded in prompt design rather than exclusively in code or model parameters. Consequently, prompt engineering should be treated as an explicit design activity within AI artifacts, especially in decision-support applications.

Another relevant insight relates to data limitations. The SmartB artifact was intentionally designed to operate with a relatively small but high-quality dataset composed of real diagnostic interviews. This choice reduced dependency on large public financial datasets, which are often unavailable or unreliable for SMEs. However, it also revealed a trade-off between contextual richness and statistical generalization. While the system produced meaningful diagnoses within its intended scope, its performance and adaptability remain dependent on continuous data expansion and periodic review of diagnostic rules and examples.

From a technical perspective, explainability represents both a strength and a limitation of the adopted approach. The framework-based structure improves transparency by explicitly linking diagnostic outcomes to business dimensions and criteria. At the same time, the internal reasoning of the generative model cannot be fully inspected or reproduced, which may limit its use in contexts that require strict

auditability or formal validation. This reinforces the importance of positioning SmartB as a decision-support tool rather than an autonomous decision-making system.

The system architecture demonstrated that it is feasible to integrate generative AI APIs into a full-stack web application while maintaining modularity, security, and scalability. Nevertheless, the reliance on third-party AI services introduces external dependencies, such as cost variability, model updates, and service availability, which must be considered in long-term deployments. These factors highlight the need for continuous monitoring and technical governance when applying generative AI in organizational contexts.

Overall, the technical insights obtained from this research indicate that artificial intelligence can support business diagnosis in SMEs when combined with knowledge engineering principles, structured diagnostic frameworks, and careful system design. At the same time, they reveal important constraints related to data, explainability, and dependency on external AI infrastructures, which should guide future developments in this area.

7.3 USER EXPERIENCE

The evaluation of user experience provided evidence regarding the practical applicability of the SmartB artifact in real business contexts. Feedback collected from entrepreneurs who interacted with the system indicates that the tool was generally perceived as easy to use and helpful for understanding the current situation of their enterprises. The structured questionnaire, combined with the clear presentation of diagnostic results, supported user engagement throughout the diagnostic process.

A relevant insight from the user evaluations is the distinction between perceived usefulness and diagnostic accuracy. While users frequently reported satisfaction with the clarity and organization of the results, this perception should be interpreted as an indicator of usability and relevance rather than as a direct measure of technical correctness. In this sense, positive user feedback complements the technical and expert-based evaluations presented earlier in this thesis.

The results also suggest that the SmartB artifact can contribute to increasing entrepreneurs' awareness of management-related issues that are often overlooked in daily operations. For many users, the diagnostic output functioned as a structured

reflection tool, helping them articulate problems that were previously perceived only in an informal or intuitive manner.

It is also important to acknowledge that the diagnostic process relies on self-reported data provided by users, which introduces subjectivity into the results. Factors such as misunderstanding of questions, overestimation of capabilities, or lack of accurate records may influence the quality of their input data. This limitation highlights the role of user guidance and question design in improving the reliability of the diagnostic outcomes.

User experience varied according to the profile and prior knowledge of the entrepreneurs. This variation reinforces the importance of positioning the artifact as a support mechanism adaptable to different maturity levels, rather than as a prescriptive solution. When combined with expert assessment and continuous refinement, the system shows potential to support managerial learning and decision-making.

7.4 MAIN CONTRIBUTIONS

This research presents contributions that can be articulated across theoretical, technical, and practical levels, reflecting the interdisciplinary nature of the work and its alignment with the field of Knowledge Engineering applied to organizations.

From a **theoretical perspective**, the main contribution lies in the proposal of a multidimensional conceptual framework for business diagnosis that integrates five organizational domains: management, entrepreneurship, finance, market, and technology. While previous studies have typically emphasized financial indicators or a limited subset of business dimensions, this framework formalizes a broader view of business health grounded in both literature and empirical consulting practice. By structuring diagnostic knowledge in an explicit and reusable form, the framework contributes to advancing discussions on holistic business diagnosis and diagnostic anticipation within the context of small and medium-sized enterprises.

At the **technical** level, this thesis contributes through the design and implementation of the SmartB artifact, an artificial intelligence–based system that operationalizes the proposed framework. The artifact demonstrates how generative artificial intelligence can be combined with structured questionnaires, curated real-world diagnostic data, and prompt engineering techniques to generate consistent

and interpretable diagnostic outputs. This work extends existing approaches by moving beyond purely numerical or financial datasets and by showing how qualitative and mixed data can be incorporated into AI-supported diagnostic processes. The architectural solution, integrating backend processing, data management, and a web-based user interface, also serves as a reference for similar applications in organizational contexts.

Another **technical contribution** relates to the **integration of knowledge engineering principles with generative AI** in a real-world organizational problem. By transforming expert diagnostic knowledge into a structured framework and embedding it into an AI-driven artifact, this research illustrates a concrete pathway for converting tacit knowledge into actionable digital systems. This integration reinforces the relevance of knowledge engineering as a methodological bridge between human expertise and artificial intelligence in organizational analysis.

From a **practical** point of view, the research contributes by delivering a tool that can be directly used by entrepreneurs as a self-diagnostic support mechanism. Unlike many academic proposals that remain limited to experimental or simulated environments, SmartB was applied in real business contexts and evaluated by both specialists and end users. This practical application demonstrates that AI-based diagnostic tools can support managerial reflection, highlight improvement opportunities, and assist decision-making without requiring advanced technical knowledge from users. The approach also suggests new possibilities for consultants, incubators, and support institutions to scale diagnostic activities with limited resources.

7.5 RESEARCH LIMITATIONS

Nuanced Judgments: The diagnosis may present nuances in judgment if applied to companies with business models that are particularly different from those that make up the SmartB platform's knowledge base. This demonstrates the need for continuous improvement in the diversity of training data and the specificity of responses.

Human-in-the-Loop Potential: Findings suggest that SmartB is most effective as a complement to, rather than a replacement for, human consultancy in complex cases.

Dependency on data quality: An accurate and relevant diagnosis for companies depends on quality information. It is necessary to assess the impact of self-diagnosis for entrepreneurs who may have difficulty understanding their own business model and, therefore, provide information with the minimum necessary quality.

7.6 FUTURE RESEARCH

- **Continuous Learning:** With all diagnostics and logs stored securely, future versions can incorporate user feedback and new interviews to continually retrain and improve the AI's predictive abilities.
- **Integrate experts reviews:** Future iterations could deepen the integration between AI and expert review for scenarios of complex cases.

The technical development and validation of SmartB demonstrated that it is feasible and effective to deploy an AI-powered diagnostic system for Brazilian PMEs, leveraging real-world data, robust engineering practices, and iterative prompt refinement. The artifact's architecture assures privacy, scalability, and maintainability, while validation shows both high technical reliability and practical utility. These findings support SmartB's role as an innovative advancement in AI-assisted business diagnosis and a significant contribution to the field of Knowledge and Engineering Management.

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APPENDIX 1 - REAL CASE ENTERPRISE XYZ QUESTIONS AND ANSWERS

SmartB

Sua IA para Diagnóstico Empresarial

FORMULÁRIO DE DIAGNÓSTICO

Escola de Artes

Data de exportação: 27/12/2025 22:44:21

Q1. Nome do empreendimento

Resposta: Escola de Artes

Q2. Nome do responsável

Resposta:

Q3. CPF

Resposta:

Q4. E-mail

Resposta: @outlook.com

Q5. Telefone

Resposta: (48) -1064

Q6. Estado

Resposta: SC

Q7. Cidade

Resposta: Florianópolis

Q8. CNPJ da Empresa

Resposta: /0001-99

Q9. Setor de atuação principal (ex: agricultura, tecnologia, serviços, varejo, etc.)

Resposta: Artes

Q10. Número de colaboradores (incluindo sócios)

Resposta: 6 a 10

Q11. Descreva brevemente o que o empreendimento faz

Resposta: Somos uma escola de artes com cursos regulares de Teatro, Canto, Jazz Dance e Ballet para crianças, adolescentes e adultos.

Q12. A empresa possui algum tipo de controle administrativo, sistema ou ferramenta de gestão?

Resposta: Estruturado (softwares, dashboards etc.)

Especificação: Financeiro: Omie.

Q13. Possui planejamento estratégico formalizado?

Resposta: Não

Q14. Possui plano de sazonalidade?

Resposta: Não

Q15. Existe controle de processos internos?

Resposta: Parcial, não documentado

Q16. Quais são os principais desafios de gestão hoje?

Resposta: Formalizar os processos. Muitas vezes acaba o trabalho voltando sempre para as mesmas pessoas, os sócios.

Q17. Quem é o cliente ideal (persona)?

Resposta: Mãe, a partir dos 35 anos, buscando uma formação e educação melhor para seu filho (a).

Q18. Quais dores / problemas do cliente seu produto/serviço resolve?

Resposta: Comunicação, timidez, falta de confiança, falta de autoestima, isolamento social.

Q19. Já realizou validação com potenciais clientes?

Resposta: Não

Q20. Descreva como um cliente descobre e contrata seu serviço hoje

Resposta: Através de plataformas como Instagram ou indicação de outra pessoa.

Q21. Há estratégias de marketing e/ou marketing digital ativas?

Resposta: Não

Q22. São realizadas pesquisas de satisfação com clientes?

Resposta: Raramente

Q23. Existe portfólio de produtos/serviços?

Resposta: Sim

Q24. Existe fluxo de vendas ou pipeline definido?

Resposta: Não

Q25. Qual o faturamento mensal?

Resposta: Sim: R\$ 20–50 mil

Q26. Geralmente o mês fecha com:

Resposta: Pequeno superávit

Q27. Quais são as principais fontes de entrada (quais produtos/serviços e como eles são recebidos)?

Resposta: Cursos Regulares.

Q28. Como é feita a definição de preço?

Resposta: Análise dos concorrentes e análise do custo geral visando um lucro.

Q29. Quais são os principais custos?

Resposta: Aluguel, time de professores e materiais.

Q30. Existe dívida, financiamento ou linha de crédito ativa?

Resposta: Não

Q31. Existe controle de fluxo de caixa?

Resposta: Estruturado

Q32. O negócio utiliza ferramentas digitais para gestão, produção ou vendas?

Resposta: Não

Q33. Já passou por algum processo de transformação digital?

Resposta: Não.

Q34. Existem processos automatizados/baseados em tecnologia (sistema, plataforma, equipamento especializado)?

Resposta: Não

Q35. Há interesse em desenvolver ferramentas tecnológicas adicionais?

Resposta: Sim

Q36. Em qual estágio o empreendimento se encontra?

Resposta: Em operação com clientes

Q37. Indique as principais formações dos(as) gestores(as)

Resposta: Ambos são formados em Artes Cênicas na Universidade Federal de Santa Catarina. Uma das gestoras fez um ano de marketing.

Q38. O responsável já realizou cursos de empreendedorismo/gestão/ inovação?

Resposta: Não.

Q39. A empresa possui parcerias formais ou informais?

Resposta: Não.

Q40. Há ações para valorização/gestão de pessoas?

Resposta: Poucas.

Q41. Quais são os principais pontos fortes do empreendimento?

Resposta: Localização, qualidade nos serviços executados, time preparado e qualificado, cuidado com todos os clientes.

Q42. Quais são os principais pontos fracos?

Resposta: Falta de estrutura de processos, a quantidade de clientes ser muito próximo ao necessário para pagar as contas, os serviços sempre sobram para os mesmos.

Q43. Quanto tempo semanal o gestor principal dedica à gestão do empreendimento?

Resposta: 40

Q44. O gestor realiza atividades operacionais/executivas no empreendimento?

Resposta: Sim

Especificação: Professora, produtora, atriz.

Q45. Se receber um diagnóstico com um plano de trabalho, quanto tempo conseguiria dedicar ao desenvolvimento das melhorias sugeridas?

Resposta: 20

Q46. Quais são os maiores riscos que podem afetar sua empresa hoje?

Resposta: Financeiros

Q47. Como avalia a maturidade atual da empresa?

Resposta: Em desenvolvimento

Q48. Quais são hoje as 3 prioridades da sua empresa?

Resposta: Ganhar mais clientes. Definir os processos. Como evoluir?

Q49. Quais são suas maiores dúvidas sobre gestão, finanças, mercado ou tecnologia?

Resposta: Como definir os processos? Como ganhar clientes? Como utilizar a tecnologia a nosso favor?

Q50. Se pudesse ter um experiente consultor externo auxiliando sua empresa em apenas um tópico neste momento, qual seria?

Resposta: Como ganhar mais clientes?

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APPENDIX 2 - REAL CASE ENTERPRISE XYZ DIAGNOSIS

SmartB

Sua IA para Diagnóstico Empresarial

Diagnóstico Empresarial: [REDACTED] Escola de Artes

SmartB - Diagnóstico Empresarial com IA

[REDACTED] Escola de Artes

Responsável: [REDACTED] [REDACTED] [REDACTED]

Data: 27/04/2024 14:22

CNPJ: [REDACTED]/0001-99

Avaliação Geral

Decisão Final de Diagnóstico | Nota: 3/5

A [REDACTED] Escola de Artes apresenta um cenário de negócios em operação estável, com pequenos superávits e clientes em carteira, porém existem importantes oportunidades de melhoria em processos internos e formalização do funcionamento da empresa. O risco de fechamento é baixo no curto prazo, mas para impulsionar o crescimento e garantir sustentabilidade futura, é necessário estruturar melhor a gestão e o mercado, especialmente na definição de processos e estratégias comerciais. A digitalização e o fortalecimento do empreendedorismo também estão em fase inicial e carecem de atenção.

Análise de Forças e Oportunidades

Principais Pontos Fortes e Diferenciais do seu Empreendimento

- Equipe qualificada com formação acadêmica em Artes Cênicas e especialização em marketing.
- Uso estruturado de sistema financeiro (Omie) para controle das finanças.
- Porta de entrada para clientes consolidada via indicação e redes sociais (Instagram).
- Oferece cursos regulares diversificados atendendo públicos variados (crianças a adultos).
- Boa localização em Florianópolis - SC.
- Cuidado e atenção personalizados com os clientes, proporcionando qualidade nos serviços.

Principais Pontos de Melhoria e Oportunidades do seu Empreendimento

- Ausência de planejamento estratégico formal, inclusive sem documentação dos processos e divisão clara de responsabilidades.
- Falta implantação de ferramentas de gestão mais amplas e planejamento de comunicação e captação de clientes.
- Clientes atuais muito próximo do ponto de equilíbrio financeiro, sem margem confortável para investimentos ou imprevistos.
- Baixa utilização de tecnologia para operações além do financeiro e carência de automação e presença digital avançada.
- Cultura empreendedora ainda incipiente, sem formalização de estratégias de formação e parceria.
- Necessidade de desenvolver ações estruturadas para aquisição e fidelização de clientes.

Diagnóstico Detalhado por Área

Confira uma análise detalhada por áreas de sua empresa de quais são os pontos fortes e os tópicos que deve ter atenção.

Gestão | Nota: 3/5

A gestão está operacional com utilização de sistema financeiro estruturado, porém carece de formalização dos processos internos documentados, existindo sobrecarga sobre poucos sócios. Não há planejamento estratégico consolidado nem ações documentadas como Planejamento estratégico, Seasonality Plan ou planos de crescimento formais. A empresa compreende as variáveis básicas da gestão, mas falta controle e organização para planejamento e divisão de responsabilidades, o que prejudica a escalabilidade e a eficiência operacional.

Mercado | Nota: 3/5

O negócio já está inserido no mercado com uma clientela inicial, porém as estratégias de marketing e captação são ainda informais e baseadas em indicações e canais orgânicos como Instagram. Não há uma carteira organizada nem uma política ativa de fidelização, pesquisas de satisfação, ou políticas definidas de aquisição e retenção. O mercado tem potencial para expansão, mas isso exige uma presença digital robusta e campanhas direcionadas visando maior volume e qualidade na captação de alunos.

Finanças | Nota: 4/5

Com um pequeno superávit e receita na faixa de R\$ 20–50 mil, a gestão financeira usa ferramentas estruturadas e o fluxo de caixa é controlado. Não há dívidas reportadas, o que é positivo para a saúde financeira do negócio. Contudo, o faturamento e o lucro são ainda próximos do ponto de equilíbrio, restringindo investimentos em expansão e inovação. É importante criar reservas e captar oportunidades de financiamento para fortalecer o caixa e possibilitar crescimento.

Tecnologia | Nota: 2/5

Atualmente, a empresa utiliza tecnologias para o controle financeiro, mas não apresenta automação ou transformação digital em outras áreas. Não há uso consistente de ferramentas para marketing digital, CRM, ou automação de processos operacionais. A transformação digital é um ponto crítico a ser desenvolvido, uma vez que há dúvidas expressas sobre como utilizar a tecnologia para favorecer o negócio, o que torna necessária a implantação de sistemas integrados para gestão de clientes, processos e marketing.

Empreendedorismo | Nota: 3/5

Há formação acadêmica adequada dos gestores e dedicação relevante à operação da empresa. No entanto, ainda não existe uma cultura consolidada de empreendedorismo ou políticas claras para desenvolvimento de capital humano e parcerias estratégicas. A falta de formalização e políticas para valorização dos recursos humanos limita a expansão e o engajamento da equipe. A pouca participação em ecossistemas empreendedores e a falta de formação continuada representam oportunidades para fortalecer este aspecto.

Recomendações de Ações Estratégicas

1. Documentar e formalizar os processos internos para distribuir responsabilidades e evitar sobrecarga dos sócios.
2. Desenvolver um Planejamento Estratégico e Planejamento de Temporadas (Seasonality Plan) para antecipar e gerir picos e baixas na demanda.
3. Implementar um Business Model Canvas para visualizar de forma macro as atividades e relações da empresa e identificar melhorias.
4. Estruturar estratégias de marketing digital, utilizando ferramentas e campanhas orientadas para atrair novos clientes (ex.: gestão de redes sociais, Google Meu Negócio).
5. Criar e gerenciar uma carteira organizada de clientes para melhorar fidelização e comunicação personalizada.
6. Implantar pesquisas regulares de satisfação para ajustar oferta e serviços com base no feedback dos clientes.
7. Avaliar e implementar ferramentas tecnológicas de CRM e automação para processos de vendas e atendimento.

8. Desenvolver políticas de valorização dos professores e colaboradores, fortalecendo a cultura empreendedora e engajamento.
9. Buscar parcerias estratégicas para expandir oferta e alcance, seja no setor educacional ou cultural.
10. Planejar e criar um fundo de reserva financeira para investir em projetos de melhoria e contingências.
11. Participar de programas de capacitação em empreendedorismo e gestão para fortalecer habilidades e networking.

Diagnóstico gerado pela plataforma SmartB - Inteligência Artificial para Fortalecimento Empresarial

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APPENDIX 3 - INFORMED CONSENT FORM (ICF)

Título do Estudo: **SmartB: UM ARTEFATO DE INTELIGÊNCIA ARTIFICIAL PARA A PREDIÇÃO DE DIAGNÓSTICO EMPRESARIAL** (SmartB: An Artificial Intelligence Artifact to Predict Business Diagnosis)

Pesquisador Responsável: **JOELIAS SILVA PINTO JUNIOR**

Instituições Vinculadas: Programa de Pós-Graduação em Engenharia e Gestão do Conhecimento (PPGEGC) da Universidade Federal de Santa Catarina (UFSC) e Instituto Federal de Educação, Ciência e Tecnologia de Mato Grosso (IFMT).

TERMO DE CONSENTIMENTO LIVRE E ESCLARECIDO (TCLE)

O (A) Senhor (a) está sendo convidado (a) a participar de uma pesquisa. Por favor, leia este documento com bastante atenção antes de assiná-lo. Caso haja alguma palavra ou frase que o (a) senhor (a) não consiga entender, converse com o pesquisador responsável pelo estudo ou com um membro da equipe desta pesquisa para esclarecê-los.

A proposta deste termo de consentimento livre e esclarecido (TCLE) é explicar tudo sobre o estudo e solicitar a sua permissão para participar do mesmo.

Este formulário visa avaliar parte de minha pesquisa de doutorado, que tem o objetivo de "Propor um framework para a predição de diagnóstico empresarial, usando inteligência artificial" e tem como justificativa apoiar micro, pequenos e médios empreendedores na sustentabilidade empresarial.

Se o(a) Sr.(a) aceitar participar da pesquisa, os procedimentos envolvidos em sua participação são os seguintes: responder/verificar o formulário de diagnóstico SmartB com a Metodologia BSM; após, responder ao questionário de avaliação de sua experiência.

Toda pesquisa com seres humanos envolve algum tipo de risco. No nosso estudo, os possíveis riscos ou desconfortos decorrentes da participação na pesquisa são de você não gostar ou não concordar com o diagnóstico empresarial da plataforma e/ou os critérios da metodologia. Esse eventual desconforto poderá ser esclarecido/minimizado por meio de atendimento deste pesquisador e/ou de consultores que possam melhor lhe explicar o método de diagnóstico e o impacto do mesmo de acordo com seu empreendimento.

Contudo, esta pesquisa também pode trazer benefícios. Os possíveis benefícios resultantes da participação na pesquisa são: melhor compreensão de processos de diagnóstico empresarial; melhor compreensão de como IAs podem apoiar diagnósticos; melhor entendimento dos pontos fortes e de melhorias de um empreendimento; compreensão de ações estratégicas que podem apoiar o fortalecimento empresarial.

Sua participação na pesquisa é totalmente voluntária, ou seja, não é obrigatória. Caso o(a) Sr.(a) decida não participar, ou ainda, desistir de participar e retirar seu consentimento durante a pesquisa, não haverá nenhum prejuízo ao atendimento que você recebe ou possa vir a receber em quaisquer das instituições vinculadas. Você não precisa se identificar, mas pode deixar nome e e-mail, se quiser ser notificado(a) dos resultados da pesquisa, quando de sua finalização.

Não está previsto nenhum tipo de pagamento pela sua participação na pesquisa e o(a) Sr.(a) não terá nenhum custo com respeito aos procedimentos envolvidos.

Caso ocorra algum problema ou dano com o(a) Sr.(a), resultante de sua participação na pesquisa, o(a) Sr.(a) receberá todo o atendimento necessário, sem nenhum custo pessoal e garantimos indenização diante de eventuais fatos comprovados, com nexo causal com a pesquisa.

Solicitamos também sua autorização para apresentar os resultados deste estudo em eventos e publicar em revista científica nacional e/ou internacional. Por ocasião da publicação dos resultados, seu nome e o de seu empreendimento será mantido em sigilo absoluto, bem como em todas as fases da pesquisa. Serão analisados apenas os dados das respostas que forneceu, sem nenhuma divulgação ou identificação sua ou de seu empreendimento.

É assegurada a assistência durante toda pesquisa, bem como é garantido ao Sr.(a), o livre acesso a todas as informações e esclarecimentos adicionais sobre o estudo e suas consequências, enfim, tudo o que o(a) Sr.(a) queira saber antes, durante e depois da sua participação.

Caso o(a) Sr.(a) tenha dúvidas, poderá entrar em contato com o pesquisador responsável Joelias Silva Pinto Junior, pelo telefone +55 62 99280-0330, endereço (PPGEGC - Centro Tecnológico (CTC) – Universidade Federal de Santa Catarina (UFSC). Campus Universitário Reitor João David Ferreira Lima. CEP: 88040-900 –

Trindade – Florianópolis – Santa Catarina – Brasil) e/ou pelo e-mail joelias.junior@ifmt.edu.br.

Eu, Joelias Silva Pinto Junior, declaro cumprir as exigências contidas nos itens IV.3 e IV.4, da Resolução nº 466/2012 MS.

Assinatura e carimbo do Pesquisador	Data: 17/12/2025