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A PROPOSAL OF A PRESCRIPTIVE MODEL TO EVALUATE THE MATURITY OF THE INTELLIGENCE PROCESS

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Abstract

Objective: This study proposes a prescriptive model for evaluating the maturity of Intelligence processes.
Methodology: A Systematic Literature Review was conducted to identify existing maturity models and key practices, which were consolidated and subjected to a Delphi Card-Sorting with Intelligence experts, leading to the proposal of a preliminary model. The model was then subjected to a survey with 374 Intelligence professionals for validation.
Originality: The validation of the model allows for the proposal of a method that, in addition to diagnosis, contributes to the evolution of organizations' Intelligence processes through the prescription of improvement actions.
Results: Development of a prescriptive maturity model for Intelligence processes. The survey indicated that most participating organizations have mature Intelligence processes, although these are not always recognized or formalized.
Theoretical and Methodological Contributions: The use of a combination of methodological procedures, including the Delphi Card-Sorting, combined with a survey with a significant number of respondents. The developed model is also expected to contribute to the development of longitudinal research that analyzes the relationship between Intelligence and its impact on organizational performance. The application of the Delphi Card-Sorting method can also be considered an important academic contribution, as the preliminary instrument resulting from this method was partially validated.
Social Contributions: The proposed model helps organizations evaluate their maturity level in Intelligence processes, diagnosing and guiding their practices.

Keywords: intelligence maturity, Delphi Card-Sorting, maturity model, model validation

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Proposta de um modelo prescritivo para a avaliação da maturidade do processo de inteligência

Resumo

Objetivo: Este estudo propõe um modelo prescritivo para avaliação da maturidade dos processos de Inteligência.
Metodologia: Revisão Sistemática de Literatura para identificar os modelos de maturidade existentes e identificação de práticas-chave, que foram consolidadas e submetidas a um Delphi Card-Sorting com especialistas de Inteligência, propondo um modelo preliminar. O modelo foi submetido a uma survey com 374 profissionais de Inteligência para validação.
Originalidade: A validação do modelo permite a proposição de um método que, além do diagnóstico, contribuiu para que as organizações evoluam seu processo de Inteligência por meio da prescrição de ações de melhoria.
Resultados: Desenvolvimento de modelo de maturidade prescritivos em processos de Inteligência. Survey apontando que a maior parte das organizações participantes possuem processos de Inteligência maduros, embora nem sempre reconhecidos ou formalizados.
Contribuições teóricas e metodológicas: O uso de uma combinação de procedimentos metodológicos incluindo o Delphi Card-Sorting, somado à survey com um número significativo de respondentes. Com o modelo desenvolvido também espera-se contribuir para o desenvolvimento de pesquisas longitudinais que analisem a relação entre a Inteligência e seus resultados para o desempenho da organização. A aplicação do método Delphi Card-sorting também pode ser considerada uma contribuição acadêmica importante, pois o instrumento preliminar originado deste método foi parcialmente validado.
Contribuições sociais: O modelo proposto serve para que organizações possam avaliar o seu nível de maturidade em processos de Inteligência, diagnosticando e orientando suas práticas.

Palavras-chave: maturidade de inteligência, Delphi Card-Sorting, modelo de maturidade, validação de modelo

Una propuesta de un modelo prescriptivo para evaluar la madurez del proceso de inteligencia

Resumén

Objetivo: Este estudio propone un modelo prescriptivo para la evaluación de la madurez de los procesos de Inteligencia.
Metodología: Se realizó una Revisión Sistemática de la Literatura para identificar los modelos de madurez existentes y las prácticas clave, que fueron consolidadas y sometidas a un Delphi Card-Sorting con expertos en Inteligencia, proponiendo un modelo preliminar. El modelo fue sometido a una encuesta con 374 profesionales de Inteligencia para su validación.
Originalidad: La validación del modelo permite la propuesta de un método que, además del diagnóstico, contribuye a que las organizaciones evolucionen su proceso de Inteligencia mediante la prescripción de acciones de mejora.
Resultados: Desarrollo de un modelo de madurez prescriptivo en procesos de Inteligencia. La encuesta señaló que la mayoría de las organizaciones participantes poseen procesos de Inteligencia maduros, aunque no siempre reconocidos o formalizados.
Contribuciones teóricas y metodológicas: El uso de una combinación de procedimientos metodológicos, incluyendo el Delphi Card-Sorting, sumado a la encuesta con un número significativo de encuestados. Con el modelo desarrollado, también se espera contribuir al desarrollo de investigaciones longitudinales que analicen la relación entre la Inteligencia y sus resultados en el desempeño de la organización. La aplicación del método Delphi Card-Sorting

también puede considerarse una importante contribución académica, ya que el instrumento preliminar originado a partir de este método fue parcialmente validado. **Contribuciones sociales**: El modelo propuesto sirve para que las organizaciones puedan evaluar su nivel de madurez en procesos de Inteligencia, diagnosticando y orientando sus prácticas.

Palabras clave: madurez de inteligencia, Delphi Card-Sorting, modelo de madurez, validación de modelo

1 Introduction

Globalization, technological evolution, and changing social expectations shape the volatile, complex, dynamic, and uncertain environment in which organizations operate (Kelly, 2015; Vecchiato, 2015; Rohrbeck & Kum, 2018). To remain competitive in the market, organizations have intensified their search for strategies that provide sustainable competitive advantage (Popadiuk & Choo, 2006), with their main challenge being the implementation of processes that assist in this development (Kaivo-Oja & Lauraeus, 2018). In this context, Strategic Intelligence is a process that acts as an organizational capability (Heinze & Janissek-Muniz, 2019) for environmental monitoring, which can be developed to detect and exploit opportunities, forming the foundation for creating competitive advantages and long-term business sustainability (Adegbile, Sarpong & Meissner, 2017; Rohrbeck, Battistella & Huizingh, 2015). According to Lesca and Caron-Fasan (2008), the Strategic Intelligence process is a complex system whose success, effectiveness, and sustainability are related to various factors, both in the design phase and during its implementation and execution.

Becker (2002) and Cainelli (2018) emphasize the need to establish structured and systematic Strategic Intelligence processes so that the organization has better support for decision-making. In this regard, Mettler (2011) suggests that the maturity of a process is determined by how well its activities are defined, managed, measured, and controlled; the more structured an Intelligence process is, the greater the chances of promoting organizational improvements and developing valuable Intelligence products for decision-makers to lead the organization toward sustainable competitive differentiation (Nelke & Hakansson, 2015). According to Rohrbeck (2010a), maturity models help promote, implement, and enhance organizational Intelligence capability, fostering knowledge about best practices and the contexts in which they can be most effective. The primary purpose of these models is to detect and eliminate deficient capabilities; their application is expected to diagnose stages and describe maturation paths so that the current status and the desired degree of evolution, as well as necessary improvement measures, can be assessed (Pöppelbuss & Röglinger, 2011). De Bruin et al. (2005) point out that descriptive, prescriptive, and comparative models can be considered evolutionary stages of a maturity model. Initially, when a model is developed, it goes through the first descriptive phase, where the current situation of the organization concerning the analyzed process is portrayed; afterward, the model moves to the prescriptive phase, where it is possible to develop a roadmap for process improvement; in the comparative phase, the model is applied to a wide range of organizations, allowing comparisons.

Considering that the models identified in the literature point to a lack of theoretical foundation (Becker et al., 2009; De Bruin et al., 2005), a lack of tests confirming validity and reliability (De Bruin et al., 2005; Lee, Gu & Jung, 2019; Röglinger et al., 2012), and a lack of tools offering support to practitioners (Röglinger et al., 2012), an important gap is identified that needs to be investigated. Thus, this study aims **to propose a prescriptive model for evaluating the maturity of the Strategic Intelligence process to diagnose and improve the activities carried out by the organization** since it is through a structured Intelligence process that the organization can potentially manage information proactively, supporting decision-making and developing long-term competitive advantage. The proposed model was born from a Systematic Literature Review and was subjected to preliminary validation using Delphi Card-Sorting (Martini & Janissek-Muniz, 2021). The results of this study present the evaluation of Intelligence process maturity, proposing a Prescriptive Maturity Model aimed at mitigating some gaps in maturity models identified in the literature. In terms of the structure of this article, starting from the theoretical framework that supports the concept of Strategic Intelligence and Intelligence process maturity, the research model is presented, followed by the methodological procedures adopted and the main results, with the proposed diagnosis and model validation being the primary contributions of this study.

2 The intelligence process

Prospective Intelligence, also known as Anticipatory Strategic Intelligence (Lesca, 2003), originated from the French School of Intelligence, where Gaston Berger, in the 1950s, addressed the need to formally consider the future in the organizational decision-making process (Durance, 2010). What Berger called "La Prospective" refers to the idea that there is not just one but multiple futures that can be constructed based on present actions (Martin, 2010). For Berger, decisions arising from intelligence activities will only be meaningful if the method used involves collaborative thinking among the actors in the process, including decision-makers (Rohrbeck et al., 2015).

Anticipation is an essential condition for Intelligence, as organizations must proactively “clarify present actions in light of possible and desirable futures” (Godet, 2006, p.2). This understanding is necessary to differentiate predictive Intelligence methods based on forecasting and trends, known as Forecast, from those based on prospecting, known as Foresight (Borges, 2021). The goal of prospective strategic monitoring is to use anticipatory signals about environmental changes to guide future business opportunities (Lesca, 2001).

According to Lesca (2011), predictive methods are based on the analysis of historical data that indicate trends, cycles, and even accidents that have interfered with a certain trajectory and may repeat in the future. The author emphasizes that although retrospective data are useful for understanding the past and generating expectations about a possible future, they do not help identify disruptions and discontinuities. The simple extrapolation of trends based on past data generates a single future to consider; however, there are not just one, but multiple potential futures, shaped by the actions and decisions made "today" (Bootz, Durance & Monti, 2019; Will, 2008). A future-oriented approach, whether prospective or anticipatory, enhances organizational survival and growth, with a company's ability to anticipate changes being associated with identifying, analyzing, and incorporating environmental information into strategy formulation (Lesca, 1989).

Thus, attention to the external environment, where changes that can impact organizational competitiveness originate, is essential for Intelligence with a prospective or anticipatory focus. Organizations are constantly immersed in information that, depending on the observer's perspective, may represent an alert for a potential evolving event. This type of information, fragmented, imprecise, uncertain, ambiguous, and camouflaged among various raw data, is called a weak signal (Lesca & Lesca, 2014). Becker (2002) and Cainelli and Janissek-Muniz (2019) stress the importance of formalized intelligence processes, as only through them can the necessary systematization be achieved to interpret signals and generate insights for decision-making. Additionally, as reported by Brito-Cabrera and Janissek-Muniz (2021), such processes can increase firms' chances of developing competitive advantages by anticipating market movements and proactively adjusting to those movements.

According to Rohrbeck (2010b), numerous studies related to Intelligence have not been sufficient for organizations to detect and adequately respond to discontinuities, thus developing competitive advantages. The author asserts that the high rate of environmental change, ignorance, and inertia are barriers to developing Intelligence processes oriented towards the organizational future. Janissek-Muniz (2016) supports this view, noting that implementing a structured Intelligence process is challenging for organizations and is often considered a complex task that presents various difficulties. Therefore, it is essential to recognize the critical factors that influence the success of the Intelligence process, thereby increasing the chances of successful implementation and sustainability (Janissek-Muniz, 2016; Lesca & Caron-Fasan, 2008).

Bullen and Rockhart (1981, p. 385) point out that there is a "limited number of areas in which satisfactory results will ensure successful competitive performance for the individual, department, or organization." They suggest that the organization should focus on improving performance in a few key factors, compatible with the key areas of maturity models based on the Capability Maturity Model structure. Both aim to synthesize key points that influence the outcome of what is being analyzed, whether it be a process, department, or the organization itself.

Cainelli and Janissek-Muniz (2019) identified five key factors determining the Intelligence process: Individual, Informational, Organizational, Technological, and the structuring of the Intelligence Process (Figure 1). According to the authors, these factors indicate barriers or guides to the Intelligence process, and when planned, configured, and managed by the organization, they can significantly drive its realization. Conversely, if neglected, they can prevent the company from achieving its goals with the activity.

Chart 1

Key Factors Determining the Intelligence Process

Factors	Description
Organizational	**Organizational factors** relate to the conditions that the organization needs to provide for the success of the Intelligence process.
Individual	**Individual factors** concern the individual profile of those involved in the Intelligence process.
Informational	**Informational factors** consider the sources and amount of information, as well as the structure available for analysis.
Technological	**Technological factors** are related to the technological infrastructure necessary to support the Intelligence process.
Processual	**Processual factors** are aligned with the formalization, continuity, and organization of the stages of the Intelligence process itself.

Source: Based on Cainelli and Janissek-Muniz (2019)

To increase strategic flexibility, organizations need systematized processes capable of identifying, interpreting, and responding to the environment; however, most organizations lack comprehensive, stable, and effective processes that help them develop a competitive advantage to ensure their survival. Thus, maturity models can assist the organization in evaluating and improving its Intelligence process.

Indeed, the use of maturity models for process evaluation is well established in the literature (Becker, Knackstedt & Pöppelbuss, 2009; Demir, Collins & Porras, 2018; Filbeck, Swinarski & Zhao, 2013; Pöppelbuss & Röglinger, 2011; Röglinger, Pöppelbuss & Becker, 2012; Van Looy, De Backer & Poels, 2010). However, most models address the analysis of organizational process maturity holistically, while a minority focus on the maturity of specific processes within the organization. In this sense, the aim was to identify which maturity models focus on analyzing a particular organizational process, in this case, the Intelligence process.

To systematize the evolutionary stage and analyze the similarities of maturity model proposals for Intelligence processes, a Systematic Literature Review (Martini & Janissek-Muniz, 2021) was conducted, following the steps indicated by Webster and Watson (2002) and Okoli and Schabram (2010). In the initial search, 98 results were found that had the search terms in their title, abstract, or keywords. After excluding duplicate results, 64 publications remained, and their abstracts were evaluated. After a preliminary analysis to verify whether the article addressed maturity models, 47 items were excluded for discussing maturity in other fields of study. Finally, 17 articles were analyzed in full, of which only six addressed, proposed, or applied maturity models. From the six selected works, three different maturity models were found to evaluate the Intelligence process of organizations. Given the limited number of maturity models related to the Intelligence process found in the academic literature, a search was also conducted for models used by professionals, leading to the inclusion of one more maturity model in the analysis, which was proposed and is used by the consulting firm Mbrain (Martini & Janissek-Muniz, 2021).

The three maturity models found in the academic literature for evaluating the Intelligence process were: the Foresight Maturity Model (FMM), developed by Terry Grim; Organization Future Orientation (OFO), developed by René Rohrbeck; and Strategic Intelligence Maturity Model (SIMM), developed by Gianita Bleoju and Alexandru Capatina. The maturity model found in the managerial literature is called the Market Intelligence Framework (MIF) and was developed by Mbrain, a consulting firm specializing in Market Intelligence that has applied this model's questionnaire since 2007. Chart 2 presents a summary of the located models, as well as the articles from the Systematic Literature Review that addressed them, based on the article by Martini and Janissek-Muniz (2021).

Chart 2

Summary of Intelligence Maturity Models Identified in the Systematic Literature Review

Model name	Model author	Key Factors Used	Maturity Levels Used	Publications Using the Model
Foresight Maturity Model (FMM)	Grim (2009)	1. Leadership 2. Framing 3. Scanning 4. Forecasting 5. Vision 6. Planning	1. Ad hoc 2. Aware 3. Capable 4. Mature 5. Best-in-class	Grim (2009) Kononiuk e Glińska (2015) Kononiuk e Sacio-Szymańska (2015)
Organizational Future Orientation (OFO)	Rohrbeck (2010a)	1. Information use 2. Method Sophistication 3. People and networks 4. Organization 5. Culture	1. Level 1 2. Level 2 3. Level 3 4. Level 4	Rohrbeck (2010) Rohrbeck e Kum (2018)
Strategic Intelligence Maturity Model (SIMM)	Bleoju e Capatina (2015)	1. Strategic Scope 2. Organizational Agility 3. Organizational Cultural Change Process 4. Competitor Approach	1. Opportunity Advocate 2. Opportunity Capturer 3. Vigilant Learner 4. Intelligence Provider	Bleoju e Capatina (2015)
Market Intelligence Framework (MIF)	Mbrain (2018)	1. Scope 2. Stakeholder Management 3. Process 4. Digitization 5. Deliverables 6. Tools 7. Organization 8. Management and Leadership 9. Culture	1. Informal 2. Basic 3. Intermediate 4. Advanced 5. First-Class	Mbrain (2018)

Source: Martini e Janissek-Muniz (2021)

The selected models were subjected to an analysis of the general design principles of maturity models using the framework proposed by Pöppelbuss and Röglinger (2011). The use of this tool allows for the verification of the basic information of each model, which characteristics of descriptive models they exhibit, and which models possess attributes of prescriptive maturity models. All the analyzed models aim to study the Intelligence process, targeting both public and private organizations, with a descriptive purpose. Regarding the prescriptive purpose of use, none of the models explicitly state this intention, but improvement measures are implied in the description of each maturity level for each practice in the FMM and OFO models. The MIF lists some improvement measures when presenting the evaluation results along with the maturity diagnosis of the assessed process. However, such measures are not available in the documentation.

The analysis of the general design principles of Intelligence process maturity models brings three main conclusions: the basic principles are well met by all the analyzed models; the principles for descriptive purposes are sufficiently addressed by the evaluated models; and the principles for prescriptive purposes are not explicitly addressed in the analyzed models. Thus, the proposition of a prescriptive maturity model that provides clear guidance for the selection and prioritization of improvement measures is relevant.

3 Research Model

The analyzed maturity models presented 24 distinct key factors, comprising 86 key practices. Based on this analysis, the key factors proposed by Cainelli and Janissek-Muniz (2019) were adopted as indicators of the maturity of the Intelligence process, defining areas in which the organization should focus to improve its process (Paulk, 2008). Thus, the proposed preliminary model considers that the maturity level of the Intelligence Process is composed of the key practices related to the key factors: Individual Factors, Informational Factors, Organizational Factors, Technological Factors, and the Intelligence Process itself (Cainelli, 2018). The characteristics of each factor, according to the authors, are described below.

Individual Factors (IND) are related to the individual profile of the participants in the process, who need to possess specific skills. Internal engagement is essential for the success of the process; the team needs to be convinced of its importance and relevance to the informational needs.

Informational Factors (INF) consider that the volume of available information requires the development of well-structured processes so that the organization can analyze relevant information that will contribute to decision-making.

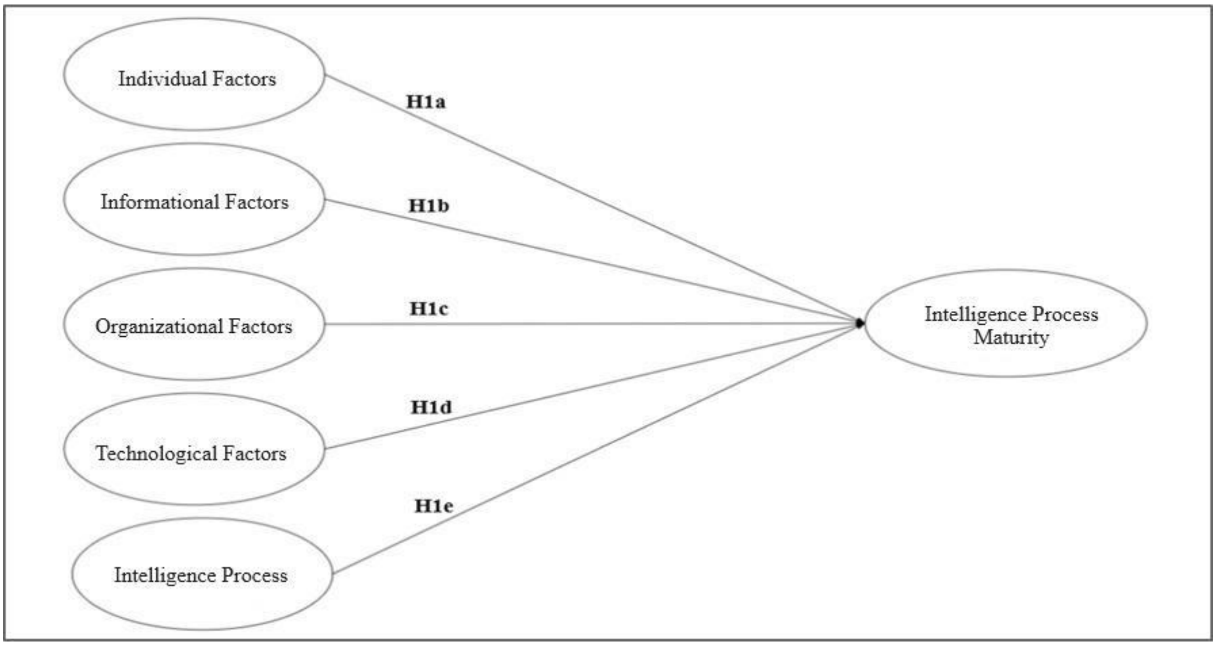
Organizational Factors (ORG) refer to creating favorable internal conditions for the success of activities, such as investment in education, training, equipment, and tools.

Technological Factors (TEC) are related to the technological infrastructure needed to support the Intelligence process. A combination of tools, software, and hardware can enhance the organization's ability to better manage the informational flow.

The factors related to the **Intelligence Process structure (PRC)** concern the formalization, continuity, and organization of the process steps themselves, meaning they address the "inherent conditions of the structured Intelligence process" (Cainelli & Janissek-Muniz, 2019, p. 14). Various procedures were conducted to relate the key practices of the Intelligence process to the proposed key factors to arrive at the preliminary model. The conduction of these procedures culminated in the research model presented in Figure 1.

Figure 1

Maturity Model - Preliminary Proposal



Source: Prepared by the authors

The goal of this exercise was to relate the key factors of the Intelligence process and incorporate these key practices into the proposed research model as indicator variables for Intelligence Process Maturity. A survey was conducted in an attempt to validate the proposed research model, assessing the strength of each key factor in the Intelligence Process Maturity construct. At the end of the method applied in the second stage, the research model was consolidated into five key process factors that determine the Intelligence Process Maturity, defining the hypotheses described in Chart 3:

Chart 3

Research Hypotheses

Hypothesis	Justification	Reference
H1: The key factors are directly related to the Maturity of the Intelligence Process (MAT).		
H1a: The Individual Factors (IND) are directly related to the MAT.	These factors are related to the individual profile of the participants in the process, who need to possess specific skills. The person responsible for the process must have the competence to motivate, lead, and execute Intelligence activities with legitimacy, fostering a culture of knowledge sharing at all levels of the organization. Internal engagement is essential for the success of the process; the team needs to be convinced of its importance and relevance in addressing informational needs.	Cainelli e Janissek-Muniz (2019)
H1b: The Informational Factors (INF) are directly related to the MAT.	These factors consider that the volume of available information requires the development of well-structured processes so that the organization can analyze relevant information that will contribute to decision-making. In this sense, it is essential that the distribution of information takes into account the needs of the recipients, personalizing the format, style, and message, as "inadequate dissemination structure and poorly identified recipients can impoverish the circulation of Intelligence products and reduce trust in the process" (Cainelli & Janissek-Muniz, 2019, p. 8).	Cainelli e Janissek-Muniz (2019)
H1c: The Organizational Factors (ORG) are directly related to the MAT.	These factors concern the creation of favorable internal conditions for the success of activities, such as investment in education, training, equipment, and tools. Providing relevant information sources, promoting a culture of information sharing, and support from top management in leading the Intelligence process are also considered essential for driving strategic planning.	Cainelli e Janissek-Muniz (2019)
H1d: The Technological Factors (TEC) are directly related to the MAT.	These factors are related to the technological infrastructure necessary to support the Intelligence process. A combination of tools, software, and hardware can enhance the organization's ability to better manage the informational flow. There is urgency in the development and dissemination of Intelligence products within the organization, and it is necessary to consider that informational overload during the stages of collection and analysis impacts the time involved in the task.	Cainelli e Janissek-Muniz (2019)

H1e: The factors related to the structure of the Intelligence Process (PRC) are directly related to the MAT.	These factors concern the formalization, continuity, and organization of the process stages themselves, i.e., they address the "inherent conditions of a structured Intelligence process." Maintaining a structured process with well-established methods, clearly defined activities, and well-organized and documented information allows the company to be ready to provide reliable information for decision-making.	Cainelli e Janissek-Muniz (2019)

Source: Prepared by the authors

The proposed method for calculating the **Intelligence Process Maturity (MAT)** is based on the average of each of the presented key factors. The arithmetic mean is calculated by "summing the observations divided by their number" (Bussab & Morettin, 2010). This measure of central tendency was chosen for calculating maturity as it balances the value of a factor by dividing it by the number of items it comprises, thus allowing comparison between two factors composed of different numbers of items. Therefore, to determine an organization's Intelligence process maturity, the average of the items for each of the factors (IND, INF, ORG, TEC, PRC) is calculated. After computing the averages for the five key factors, the overall average for the organization is calculated, and the final result is categorized according to one of the four proposed maturity levels, following the criteria presented in Chart 4.

Chart 4

Maturity Model - Initial Proposal

Overall Maturity Average	Maturity Level
average less than 2	*Adhoc*
average greater than or equal to 2 and less than 3	Basic
average greater than or equal to 3 and less than 4	Intermediate
average greater than or equal to 4	Mature

Source: Prepared by the authors

The preliminary maturity model proposed for the intelligence process aims to help executives identify the maturity level of intelligence processes in any organization engaged in intelligence activities, specifically regarding anticipation. The characterization includes a general description of each level, and after validating the model, a detailed breakdown of the key factors in the process may be proposed. Chart 5 presents the four proposed levels of evolution.

Chart 5

Summary of the Proposed Intelligence Maturity Levels

Level 1 *Adhoc* *average < 2*	Level 2 Basic *2 ≤ average < 3*	Level 3 Intermediate *3 ≤ average < 4*	Level 4 Mature *4 ≤ average ≤ 5*
Activities are performed on demand, with little or no defined process, making it difficult to predict performance or learn from experience when everything is new and unique.	Basic process management levels are established, and the most common processes are standardized and integrated.	There are well-defined and documented processes. The focus is on organizational learning through process definition and improvement.	Processes are understood and controlled by indicators. Feedback allows for continuous improvement of the process and the pursuit of innovative ideas and technologies.

Source: Prepared by the authors

After validating the maturity diagnostic instrument for the Intelligence process, a prescriptive model for evaluating the Intelligence process is proposed. The next section presents the research method used in each stage of the study.

4 Research Method

A multimethod approach was adopted to develop the research model and validate its instrument, combining qualitative data collected through a Delphi Card-Sorting method with quantitative data collected through a survey.

4.1 Data Collection Instrument

The survey was conducted using an instrument developed based on the consolidation of key practices in the Intelligence process identified in the maturity models outlined by RSL (Martini & Janissek-Muniz, 2021). The initial questionnaire was validated for face and content with Intelligence experts through individual interviews, and then a Delphi Card-Sorting was conducted, resulting in a preliminary instrument that was applied to companies involved in Intelligence activities in Brazil. This allowed for the identification of these professionals' perceptions regarding the Intelligence practices in their organizations. The questionnaire was administered from August 2020 to October 2020, using the Survey Monkey software, which facilitated access to professionals. Mechanisms were put in place to increase the response rate, such as sending reminders and follow-up invitations. The preliminary data collection instrument consisted of 53 items distributed across five factors: Individual Factors (8 items), Informational Factors (4 items), Organizational Factors (17 items), Technological Factors (3 items), and Intelligence Process (21 items), and was subjected to a pre-test as described below.

4.2 Population and Sample

The target population of this study comprises organizations that perform Intelligence activities to some extent and are operating in Brazil, both national and multinational. The sample of the study is non-probabilistic and convenience-based. Invitations were sent to professionals listed on the social network LinkedIn, whose current job titles were director, supervisor, manager, analyst, executive, or specialist in Intelligence, Market Intelligence, Competitive Intelligence, and Strategic Intelligence. Screening questions were included at the beginning of the instrument to ensure that respondents had the necessary knowledge to answer the survey. Due to the limited quantitative population parameter references for analyzing Intelligence process maturity models, the G*Power software version 3.1.9.6 was used, based on the number of predictors for the dependent variable to estimate the minimum sample size. Hair et al. (2009) recommend 0.80 as a reference for test power and 0.15 as the effect size (f^2). In this study, five predictors were considered for the dependent variable, resulting in a minimum sample size of 92 observations with a significance level of 5%. Sarstedt, Ringle, and Hair (2017) indicate that the risk of underestimating or overestimating results can be reduced by increasing the number of indicators per construct and the sample size. Thus, this study aimed to maximize data collection to enhance the consistency of the results.

4.3 Pre-Test Survey

After finalizing the structure of the instrument based on the results of the Delphi Card-sorting, data collection was carried out with 51 professionals from the target population of the study. Invitations to participate in the survey were sent via email and LinkedIn messages to individuals whose current job titles on their profiles were Specialist, Executive, Analyst, Supervisor, Manager, or Director of Intelligence.

Two analyses were conducted to detect outliers: (1) checking for monotone responses and (2) measuring Mahalanobis' Distance D^2. From a multivariate perspective, Hair et al. (2009) suggest using Mahalanobis' Distance D^2 for this purpose. The authors recommend using conservative significance levels for the D^2 analysis, suggesting the removal of observations with significance below 0.001. No outliers were detected in the pre-test sample in either of the tests.

To analyze the reliability of the preliminary instrument and its factors, Cronbach's Alpha coefficient and CITC (Corrected Item-Total Correlation) were used to verify internal consistency. According to Hair et al. (2009), the value of Cronbach's Alpha should exceed a reference of 0.70, and this value should be even higher when the instrument exceeds 10 items, which is the case for this research. CITC analysis is useful for checking the correlation of each item with the factor to which it was assigned. CITC classification can be considered minimally acceptable when it is between 0.3 and 0.4, practically significant from 0.5, and indicative of a well-defined structure when it exceeds 0.7 (Hair et al., 2009). This study adopted a cutoff line of 0.5; thus, items with CITC below 0.5 were excluded from the final instrument, as suggested by the authors. The Individual, Organizational, Technological Factors, and the Intelligence Process Factors showed good reliability according to Cronbach's Alpha analysis, with coefficients ranging from 0.848 to 0.933. The CITC values for the Individual and Technological Factors were considered adequate, and no changes were needed in their composition.

However, the items comprising the Informational Factor did not reach a CITC of 0.5, and the factor also did not achieve a satisfactory Cronbach's Alpha, falling below 0.7. Thus, the entire factor, composed of items INF01, INF02, INF03, and INF04, was eliminated from the full study due to both their CITC values ranging from 0.230 to 0.473 and their Cronbach's Alpha, which only reached 0.583. In the Organizational Factor, items ORG04, ORG11, and ORG14 were removed from the full study due to their CITC values being 0.478, 0.444, and 0.426, respectively, all below the cutoff parameter of 0.5, even though the Cronbach's Alpha for this factor was considered satisfactory. In the Intelligence Process Factor, items PRC03 and PRC18 were also removed from the final instrument because their CITC values did not reach the cutoff line of 0.5, being 0.498 and 0.468, respectively. Cronbach's Alpha, CITC, and the number of items per factor in the final instrument, after the changes made in the pre-test, are available in Table 1.

Table 1

Reliability Analysis - Cronbach's Alpha Coefficient and CITC of the Instrument After Pre-Test Sample Analysis

Variable	Cronbach's Alpha Final Instrument	CITC Final Instrument	Items Final Instrument
Individual Factors	0,868	0,517 - 0,747	8
Informational Factors	removed	removed	removed
Organizational Factors	0,917	0,502 - 0,749	14
Technological Factors	0,848	0,673 - 0,748	3
Intelligence Process	0,931	0,517 - 0,717	19
Total Instrument	**0,963**		**44**

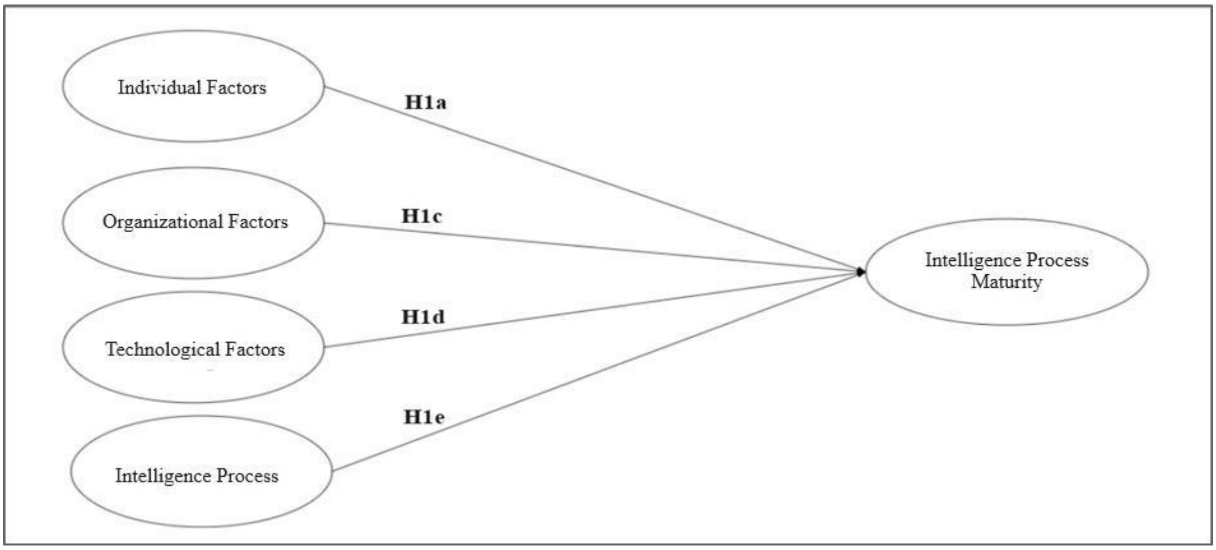
Source: Prepared by the authors

After the changes made during the Reliability Analysis, the final instrument consisted of 44 items distributed across four key factors: Individual Factors, Organizational Factors, Technological Factors, and Intelligence Process, all with satisfactory Cronbach's Alpha and CITC.

Following the Reliability Analysis, an Exploratory Factor Analysis was conducted to verify the unidimensionality of the factors using the Principal Component Analysis method. The factor loadings for each item were considered satisfactory as they exceeded the minimum of 0.5 recommended by Hair et al. (2009). After conducting the Exploratory Factor Analysis, a descriptive analysis of the pre-test results was performed, taking into account the changes made to the preliminary instrument. In the pre-test, most organizations were classified at an Intermediate and Mature level for the Intelligence process, each with 43.14% of observations. Only 9.80% were at a Basic level of maturity for the Intelligence process, and 3.92% were considered Adhoc. The pre-test resulted in a more objective maturity assessment model with four key factors and 44 items. The final research model is presented in Figure 2.

Figure 2

Final Maturity Model



Source: Prepared by the authors

5 Results Analysis

After completing the pre-test, data collection for the final survey was carried out. A total of 415 complete responses were collected from professionals who belong to the target population of the study. Invitations to participate in the survey were sent via LinkedIn messages and email, similar to the pre-test process. The LinkedIn Sales Navigator online platform was used to filter and send personalized messages to professionals whose current positions were Specialist, Executive, Analyst, Supervisor, Manager, or Director of Intelligence. Two analyses were conducted to detect outliers: (1) the checking of monotone responses and (2) Mahalanobis' D^2 Distance measure. Although 415 complete observations were collected, three monotone responses and 38 observations were identified as outliers from a multivariate perspective using the Mahalanobis' D^2 measure. Therefore, the final sample consisted of 374 observations.

The majority of respondents are between 25 and 44 years old, with the age group of 25 to 34 years having the highest frequency, accounting for 60.96% of the participants. Regarding education, over 90% of participants completed higher education, and 54.81% completed a postgraduate course. The respondents' relationship with the topic of Intelligence was very similar to that observed in the pre-test sample, with almost 90% of participants reporting roles as "Intelligence Analyst / Specialist" (75.40%) and "Director, Manager, or Coordinator of the Intelligence area" (14.44%). Most participants reported having between one and three years of experience in the field (39.30%), which may indicate increased interest in the topic in recent years. About 78% of participants stated that their company has a formal Intelligence process.

Most organizations are from the Services sector (46.52%), followed by Industry (33.16%) and Commerce (20.32%). Respondents from large companies were in the majority (78.61%).

To check for Common Method Bias (CMB) in the collected sample, a Harman's single-factor test was conducted, as suggested by Podsakoff et al. (2003). The test result indicated that the highest explained variance was 34.69%, which is below the 50% threshold, indicating that CMB is not a problem for the study. To avoid non-response bias, several measures were taken. First, a T-test was performed for early and late responses as suggested by Armstrong and Overton (1977). Early respondents were those who completed the survey in the first few days after the initial invitation was sent, while late respondents were those who participated after the final reminder was sent. No significant differences were found between early and late responses.

5.1 Reliability Analysis

The reliability analysis of each factor and the overall instrument was conducted by calculating Cronbach's Alpha coefficient, which measures the internal consistency of the instrument. Table 2 presents the Cronbach's Alpha values for the proposed maturity model, with values reaching a minimum of 0.832, above the 0.7 threshold indicated by Hair et al. (2009), demonstrating the internal consistency of the factors and the instrument. To assess the overall consistency of the data, Kaiser-Meyer-Olkin (KMO) sampling adequacy and Bartlett's test of sphericity were performed to determine if the data are suitable for factor analysis. The KMO measure of sampling adequacy is considered excellent when above 0.90; good when between 0.80 and 0.90; acceptable when between 0.70 and 0.80; mediocre when between 0.60 and 0.70; and inadequate when below 0.60 (Dini et al., 2014). The KMO measure obtained for this sample was 0.941, and Bartlett's test of sphericity was significant, indicating the suitability of factor analysis for the sample.

Table 2

Reliability Analysis - Cronbach's Alpha Coefficient

Variable	Cronbach's Alpha	Items	KMO
Individual factors	0,832	8	0,843
Organizational Factors	0,899	14	0,910
Technological Factors	0,808	3	0,660
Intelligence Process	0,930	19	0,941
Total instrument	**0,957**	**44**	**0,941**

Source: Prepared by the authors

After the purification process, the applied instrument consisted of 44 items and the data collection included 374 observations. Thus, the respondent-to-item ratio was 8.5, exceeding the minimum limit of five observations per item (Hair et al., 2009).

5.2 Measurement Model

The Measurement Model was validated using Confirmatory Factor Analysis (CFA) based on Structural Equation Modeling with Partial Least Squares (PLS) estimation. The evaluation was conducted using criteria such as the individual outer loadings of the survey items, composite reliability (CR), Average Variance Extracted (AVE), and Discriminant Validity (Heterotrait-Monotrait Ratio - HTMT) (Table 3).

Table 3

Evaluation of Outer Loadings, Composite Reliability, and Convergent Validity

Factors / Items	Outer Loadings	Composite Reliability (CR)	Average Variance Extracted (AVE)
Individual Factors (IND)		0,871	0,462
IND01	0,610		
IND02	0,546		
IND03	0,586		
IND04	0,614		
IND05	0,654		
IND06	0,815		
IND07	0,777		
IND08	0,780		
Organizational Factors (ORG)		0,915	0,437
ORG01	0,701		
ORG02	0,605		
ORG03	0,604		
ORG05	0,567		
ORG06	0,660		
ORG07	0,710		
ORG08	0,697		
ORG09	0,679		
ORG10	0,617		
ORG12	0,673		
ORG13	0,619		
ORG15	0,661		
ORG16	0,692		
ORG17	0,748		
Technological Factors (TEC)		0,889	0,729
TEC01	0,825		
TEC02	0,906		
TEC03	0,828		

Factors / Items	Outer Loadings	Composite Reliability (CR)	Average Variance Extracted (AVE)
Intelligence Process (PRC)		0,941	0,457
PRC01	0,559		
PRC02	0,602		
PRC04	0,733		
PRC05	0,670		
PRC06	0,710		
PRC07	0,602		
PRC08	0,504		
PRC09	0,657		
PRC10	0,773		
PRC11	0,705		
PRC12	0,618		
PRC13	0,657		
PRC14	0,716		
PRC15	0,653		
PRC16	0,717		
PRC17	0,691		
PRC19	0,707		
PRC20	0,775		
PRC21	0,731		

Source: Prepared by the authors

The Analysis of Outer Loadings indicates the correlation between the factors and their items. According to Hair et al. (2014), indicators with outer loadings below 0.40 should be removed from the scale, and indicators with outer loadings between 0.40 and 0.70 need to be carefully analyzed before removal. The authors suggest that indicators with loadings between 0.40 and 0.70 should only be removed if their exclusion improves the composite reliability or the average variance extracted beyond the suggested threshold. In this study, no loadings below 0.40 were found, and indicators with loadings above 0.50 were not removed, as they contribute to the content validity of the instrument, and their exclusion did not result in a significant improvement in composite reliability (CR) or average variance extracted (AVE).

Composite Reliability (CR) considers item loadings to determine the reliability of each factor. Hair et al. (2014) suggest that CR values can range from 0 to 1 and should be above 0.70 to indicate good internal consistency. The model showed values above 0.871, demonstrating its adequacy.

Average Variance Extracted (AVE) indicates the variance of items related to a factor. It is used to indicate the convergent validity of the instrument, with values ranging from 0 to 1. The recommendation is for this indicator to be above 0.50 (Hair et al., 2014; Koufteros, 1999), but this threshold was not exceeded in three factors of this study. It is important to note that this cutoff is not rigid, and often it is more appropriate to retain a larger number of indicators even if the AVE is slightly below 0.50 (Bido & Da Silva, 2019; Little, Lindenberger & Nesselroade, 1999). Due to the exploratory nature of this study, the decision was made to retain the indicators, as their removal would not substantially alter the CR and AVE indicators.

Discriminant Validity indicates the extent to which a factor differs from other factors in the model. In this study, the approach used to test the Discriminant Validity of the instrument was the Heterotrait-Monotrait (HTMT) ratio, which reflects the correlation between constructs. The interpretation is straightforward: if the factor indicators present an HTMT value less than 0.85, they exhibit discriminant validity (Henseler, Ringle & Sarstedt, 2014). As shown in Table 4, the values obtained in the HTMT analysis of factor relationships do not exceed the 0.85 threshold, indicating that the instrument exhibits Discriminant Validity.

Table 4

Discriminant Validity Assessment using the HTMT Approach

Variável	IND	MAT	ORG	PRC	TEC
Individual Factors (IND)					
Maturity of the Intelligence Process (MAT)	0,732				
Organizational Factors (ORG)	0,664	0,823			
Intelligence Process (PRC)	0,754	0,841	0,810		
Technological Factors (TEC)	0,547	0,843	0,687	0,696	

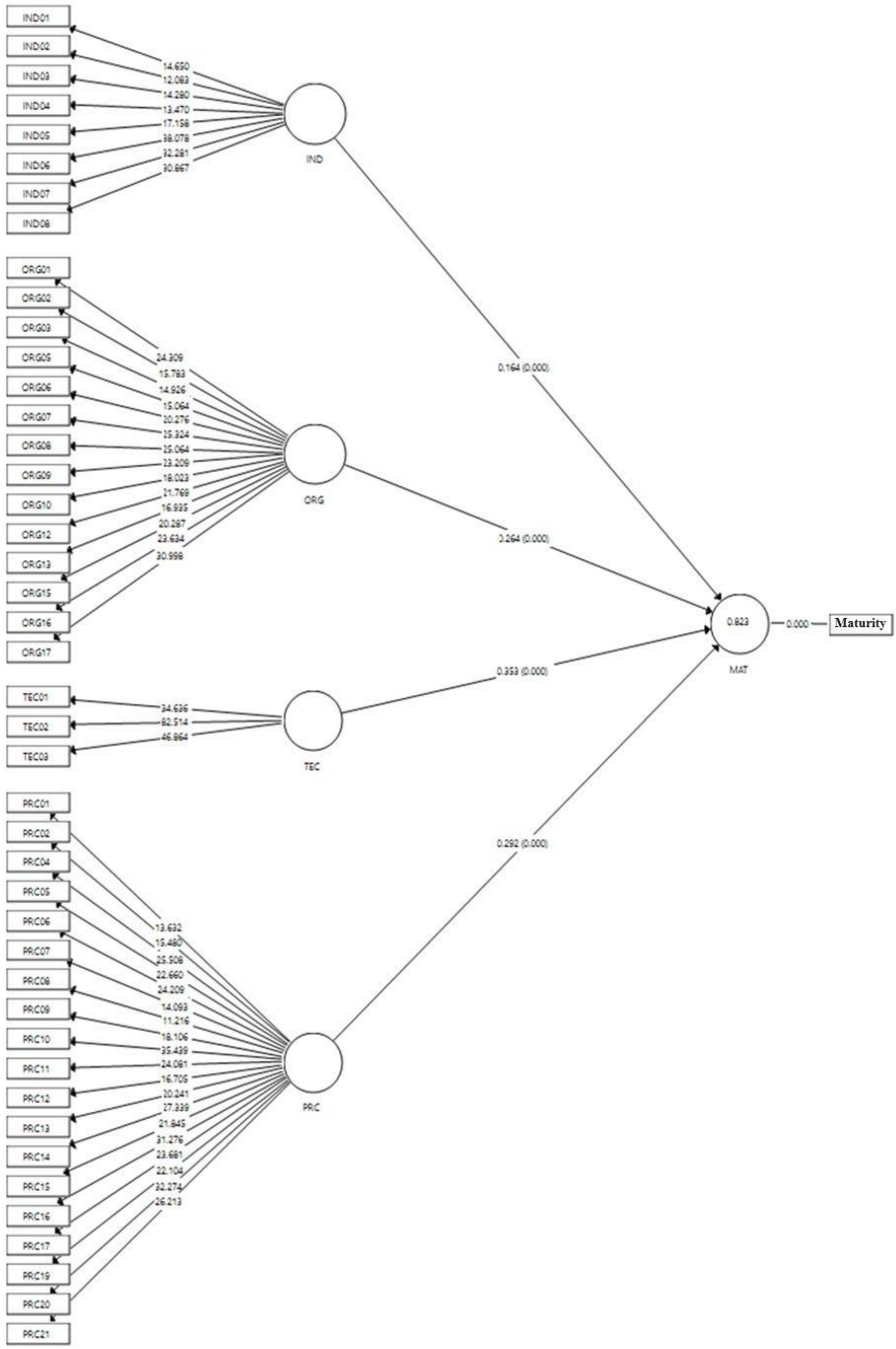
Source: Prepared by the authors

5.3 Structural Model

After verifying the validity and reliability of the Measurement Model, it is necessary to test the Structural Model. Sarstedt et al. (2017) recommend analyzing collinearity, the significance of path coefficients, the coefficient of determination R^2, the effect size f^2, the predictive relevance Q^2, and the effect size q^2. For the collinearity analysis, the Variance Inflation Factor (VIF) was used to identify whether two factors have a high degree of similarity. Sarstedt et al. (2017) recommend that VIF values should be between 0.20 and 5. In this study, the VIF indicator results for the independent variables were adequate, ranging from 1.319 to 3.439, demonstrating that the adjustments made during the pilot phase were sufficient and the model was not impaired by collinearity. The Structural Model evaluation was conducted using the SmartPLS software, employing the Bootstrap resampling technique with 5,000 samples. Figure 3 presents the significance estimates among the relationships of the factors under analysis.

Figure 3

Structural Model



Source: Prepared by the authors

A regression analysis was conducted to calculate the significance of the model's relationships. To support the hypotheses of the model, the "t" values should be above 1.64 ($p<0.10$) (Hair et al., 2014). Table 5 presents the values obtained in the hypothesis test.

Table 5

Structural Model - Obtained Results

Hypothesis	Path	Coefficient	t-Statistic	p-Values	Avaliação
H1a	IND -> MAT	0,164	5,947***	0,000	Suportted
H1c	ORG -> MAT	0,264	7,552***	0,000	Suportted
H1d	PRC -> MAT	0,292	7,567***	0,000	Suportted
H1e	TEC -> MAT	0,353	11,588***	0,000	Suportted

Note: *p<0,10 (t=1.64); **p<0,05(t=1,96); ***p<0,01 (t=2,58).

Source: Prepared by the authors

Next, the analysis of the Coefficient of Determination R^2 was performed to determine how much the dependent variable is explained by the independent variables. The R^2 value ranges from 0 to 1, with higher values indicating greater explanatory power of the regression equation, and thus better prediction of the dependent variable, as indicated by Sarstedt et al. (2017). The proposed model is able to explain 82.3% of the Maturity of the Intelligence Process in the organization. In addition to the Coefficient of Determination R^2, the authors suggest evaluating the effect size f^2, which indicates how the removal of a specific predictor construct affects the R^2 value of a construct. Generally, f^2 values greater than 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively (Hair et al., 2019). Table 6 presents the results for the analysis of the f^2 effect size obtained.

Table 6

Effect Size f^2 Analysis

	Effect f^2	Effect Size
IND -> MAT	0,081	Small
ORG -> MAT	0,157	Medium
TEC -> MAT	0,412	Large
PRC -> MAT	0,161	Medium

Source: Prepared by the authors

In this study, the effect of the relationship between Individual Factors (IND) and Maturity of the Intelligence Process (MAT) was considered small. The effects of the relationship between Organizational Factors (ORG) and Intelligence Process (PRC) with Maturity (MAT) were considered medium, while the effect of the relationship between Technological Factors (TEC) and Maturity (MAT) was considered large.

The analysis of predictive relevance Q^2 examines the predictive capability of the model for each structural relationship. To calculate this indicator, the Blindfolding procedure was used in the SmartPLS software. The resulting Q^2 of 0.809, which is greater than zero, indicates that the model has satisfactory relevance and predictive capability (Sarstedt, Ringle & Hair, 2017). The effect size q^2 indicates how much the q^2 coefficient changes when an exogenous construct is omitted from the model. In this research, the q^2 calculation was performed as outlined by Sarstedt et al. (2017). According to the authors, q^2 values up to 0.02 indicate no predictive relevance, q^2 values up to 0.15 indicate small predictive relevance, q^2 values up to 0.35 indicate medium predictive relevance, and values above 0.35 are considered to have large predictive relevance. Table 7 presents the results for the analysis of predictive relevance q^2 obtained.

Table 7

Analysis of Predictive Relevance Size q^2

	q^2 Effect Included (i)	*q^2 Effect Excluded (ii)*	**Predictive Relevance q^2=(i-ii)/(1-i)**	**Size of Predictive Relevance**
IND -> MAT	0,809	0,796	0,068	Small
ORG -> MAT	0,809	0,783	0,136	Small
PRC -> MAT	0,809	0,735	0,387	Large
TEC -> MAT	0,809	0,784	0,131	Small

Source: Prepared by the authors

All factors showed predictive relevance; however, the Individual (IND), Organizational (ORG), and Technological (TEC) factors demonstrated small predictive relevance, while the Intelligence Process (PRC) exhibited high predictive relevance.

5.4 Descriptive Statistical Analysis

Following the validation of the model through the analysis of Reliability, Measurement Model, and Structural Model, a descriptive statistical analysis of the research results was conducted. The description of the scores for the key factors used in the instrument and the average used to construct the maturity levels are presented in Table 8.

Table 8

Description of the Numeric Scores for Factors and the Average Score of Intelligence Process Maturity

	N	Minimum	Maximum	Mean	Median	Standard Deviation
Individual Factors	374	2,25	5,00	4,22	4,38	0,582928
Organizational Factors	374	1,21	5,00	3,43	3,43	0,756614
Technological Factors	374	1,00	5,00	3,87	4,00	0,978141
Intelligence Process	374	1,32	5,00	3,88	3,95	0,673232
	N	**Minimum**	**Maximum**	**Mean**	**Median**	**Standard Deviation**
Maturity	374	1,92	4,97	3,85	3,93	0,627619

Source: Prepared by the authors

Among the factors used to evaluate the maturity of the intelligence process, the Individual factors had the highest average value of 4.22. The lowest average was for Organizational factors, with a score of 3.43. All factors reached the maximum score of 5 points on the Likert scale, and the Technological factors had the lowest minimum value, reaching the minimum point of the Likert scale. The overall average calculated for the maturity of the intelligence process was 3.85, indicating an Intermediate level of maturity. The maturity levels presented by the participating companies in the study are detailed in Table 9.

Table 9

Maturity Levels Presented by the Participating Companies

Maturity Level	Frequency (n)	Percentage (%)	Cumulative Percentage (%)
Adhoc	2	0,53%	0,53%
Basic	37	9,89%	10,43%
Intermediate	161	43,05%	53,48%
Mature	174	46,52%	100,00%
Total Observations	**374**	**100,00%**	

Source: Prepared by the authors

Most of the organizations participating in the study were considered Mature (46.52%); 43.05% were classified at an Intermediate level of maturity for the intelligence process. Only 9.89% of the companies achieved a Basic level, and 0.53% were categorized as *Adhoc*.

Some tests were conducted to determine whether the presence of a formal intelligence process and certain company characteristics in association could lead to statistically significant differences. However, no statistically significant results were found in associations showing differences related to the sector of operation or the company's size regarding the implementation of formal intelligence processes.

When comparing the key factors that make up the instrument with the existence of a formal intelligence process, it was found that there are statistically significant differences between companies with formalized processes and those without. Organizations with a formal intelligence process achieve higher scores in all factors, consequently reaching higher maturity levels compared to organizations without a formalized intelligence process.

5.5 Discussion

To propose a prescriptive maturity model, it was first necessary to seek empirical validation of the proposed maturity model. In this study, a quantitative approach was chosen to validate the foundational instrument for prescribing actions. This is an important gap to address, as many maturity models available in the academic and managerial literature lack validation.

Indeed, a Systematic Literature Review on maturity models conducted by Lee et al. (2019) identified 194 different maturity models, but only 26 of them were empirically tested based on hypotheses and associated types of validity, such as predictive validity and unidimensionality. This study aimed to rigorously test the proposed instrument by analyzing validity, reliability, and through structural equation modeling to determine the predictive power of the key factors on the Maturity of the Intelligence Process.

The main result is that the research hypotheses (H1a, H1c, H1d, and H1e) were supported; that is, the Individual, Organizational, Technological, and Intelligence Process factors are directly related to the Maturity of the Intelligence Process. Hypothesis H1b was tested during the pre-test but did not demonstrate reliability and was thus removed from the full study as suggested by the literature.

An important measure to be reported and worth highlighting is the effect size, which helps in understanding the significance of the results obtained in the study:

> When a research proposes a new approach to a certain issue, it is often important to consider how much this new approach is better than those commonly used. This "improvement" is measured using a scale known as effect size. (Lindenau & Guimarães, 2012, p. 363)

In this study, the effect size measure f^2, was chosen, which is used to indicate the contribution size of a factor to the determination of the R^2 coefficient of a construct. The main result of this study shows that the f^2 effect was considered large between the key factor TEC and the Maturity of the Intelligence Process. The key factors ORG and PRC were considered to have a medium effect size, while the factor IND had a small effect. Thus, it was found that the key factor TEC has the greatest contribution to explaining the level of Maturity of the Intelligence Process; if the TEC factor were removed, the model's explanatory power would decrease more than if any of the other factors were removed.

Regarding the predictive relevance of the model, the key factor Intelligence Process showed a q^2 effect indicating high predictive relevance, while the key factors IND, ORG, and TEC showed small predictive effects. Therefore, if the key factor PRC were excluded, the predictive relevance of the model would decrease substantially, demonstrating the importance of practices related to the structuring of the Intelligence Process for calculating the level of Maturity of the Intelligence Process.

In this study, the majority of organizations were classified as Mature (46.52%) concerning the Intelligence Process. This result is surprising because previous studies indicate that the number of companies classified at the highest maturity stage is quite low (Mbrain, 2018; Rohrbeck & Kum, 2018).

In the study conducted by Rohrbeck and Kum (2018), only 2% of organizations were classified at the highest maturity level, and in the latest Mbrain report (2018), only 17% of companies were among the highest maturity levels for the Intelligence Process. This report highlights that between 2016 and 2017, Intelligence was gaining importance and many organizations started formalizing this area. The average score of the companies participating in Mbrain's study (2018) fell between the Basic and Intermediate levels, while the results of the present research show an average between the Intermediate and Mature levels. It is possible that the rising importance of the Intelligence area is being recognized.

Another possibility is that the cutoff questions of the research may have stratified the sample for companies with higher maturity since only organizations that reported conducting some Intelligence activity were eligible to complete the survey. Additionally, most organizations that responded to the survey indicated that they have a formal Intelligence process (78.10%), which might explain the high level of maturity observed in the study's sample.

Through descriptive statistical analysis, it was found that there is an association between the existence of a formal Intelligence process and the scores obtained for each key factor. Analysis of the mean and median indicates that companies with a formalized Intelligence process achieve higher maturity levels. However, the test of association between company characteristics (size and sector) and the existence of a formal Intelligence process was not significant. The following describes the proposed prescriptive model for assessing the maturity of the Intelligence process in organizations.

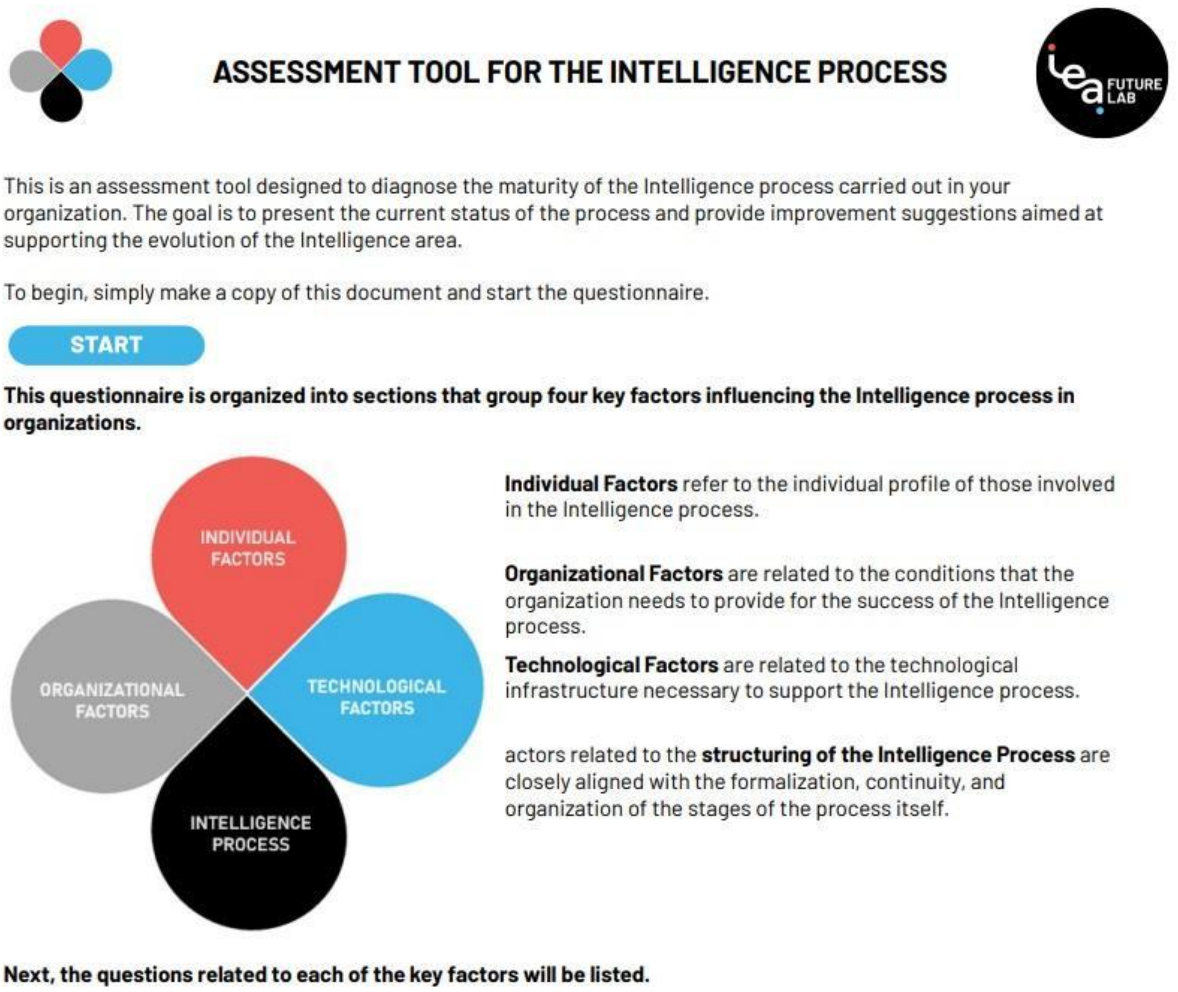
6 Proposal for a Prescriptive Maturity Model

The validation of the instrument conducted in this study allowed for the delineation of the key factors of the Intelligence process, as well as the key practices that compose them. From this, tactical actions can be defined for the organization to advance its Intelligence process. The model consists of two stages: (1) application of the maturity assessment instrument for the Intelligence process; (2) presentation of a report with the maturity diagnosis and improvement recommendations.

The interface for applying the instrument was developed using Google Sheets. The model consists of three spreadsheets: the first presents the questionnaire with the 53 key practices; the second displays the results based on the responses given in the first spreadsheet, along with a list of improvements for each key practice according to the responses; the last spreadsheet, which is hidden, includes the maturity levels and the diagnosis and prescription matrix for each key practice. Martini (2020) provides a more detailed description of the model. Figure 4 shows an example of the questionnaire presentation.

Figure 4

Proposed Maturity Assessment Tool



Source: Prepared by the authors

After presenting the tool, the key practices distributed by key factor are displayed (Figure 5). At the end, the respondent's results are calculated.

Figure 5

Presentation of the Interface Developed for Applying the Proposed Maturity Assessment Questionnaire

To perform the diagnosis of your organization, indicate, on a scale of 1 to 5, the option that most accurately reflects your degree of agreement with the statements, as follows:

1 - Strongly disagree;
2 - Partially disagree;
3 - Neither agree nor disagree;
4 - Partially agree;
5 - Strongly agree;

INDIVIDUAL FACTORS		
IND01	The Intelligence team members possess broad knowledge that goes beyond their area of expertise, blending different skills.	4
IND02	The Intelligence team members maintain internal and external contact networks.	2
IND03	Employees are proactive in monitoring the organizational environment.	3
IND04	The Intelligence team members develop good relationships with the clients of the Intelligence process.	4
IND05	The clients of the Intelligence process trust that the Intelligence team can anticipate and provide valuable recommendations.	5
IND06	The leader of the Intelligence process is recognized by colleagues as capable of creating a future vision, engaging others in a collective vision.	4
IND07	The leader of the Intelligence process recognizes the cultural elements and mental models operating within the organization and how they influence organizational decisions.	3
IND08	The leader of the Intelligence process has a clear long-term vision, making the Intelligence process increasingly relevant within the organization.	1

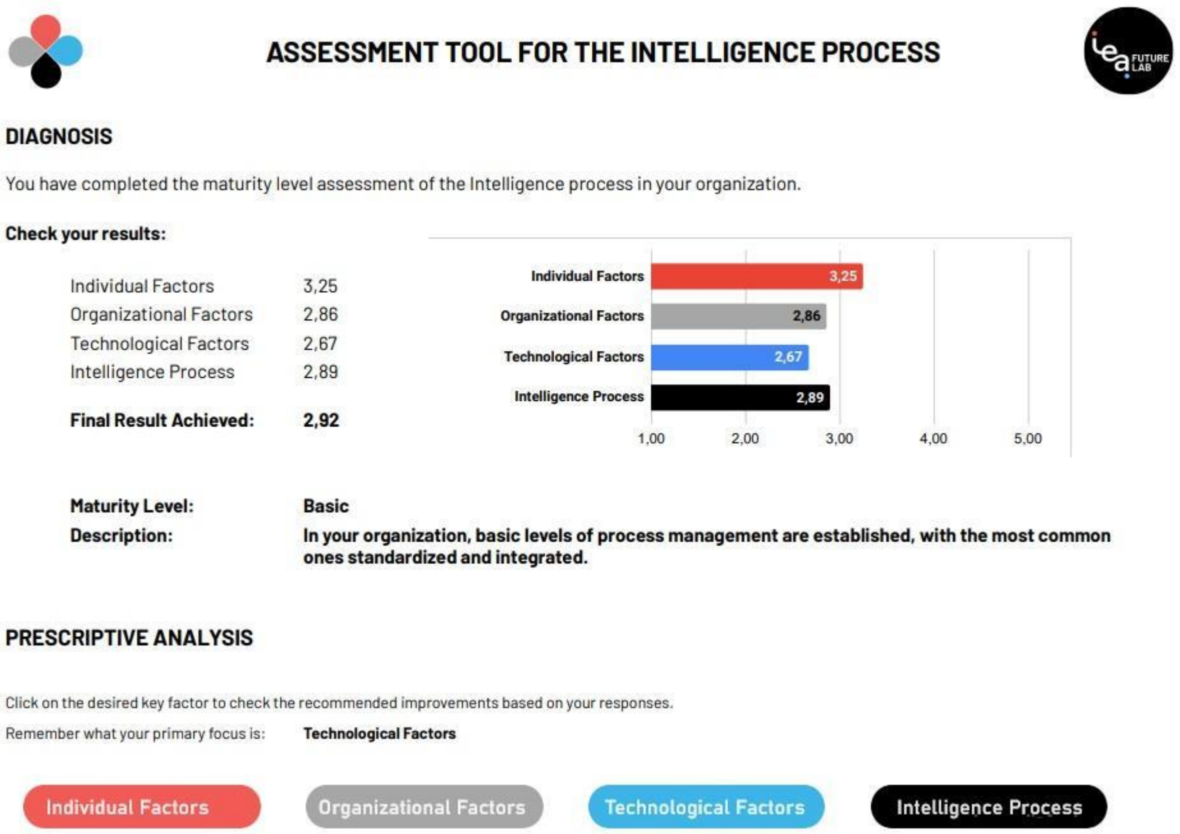
ORGANIZATIONAL FACTORS		
ORG01	The organization encourages sharing across different functions and hierarchical levels.	1
ORG02	The organization encourages its employees to develop an external network of contacts.	2

Source: Prepared by the authors

After calculating the results, a report is displayed that includes the maturity **diagnosis**, where the company's maturity level is classified and described. Following this, the average scores for each key factor are presented, as shown in Figure 6.

Figure 6

Proposed Report Model for the Intelligence Process Maturity Assessment Tool



Source: Prepared by the authors

In the **prescriptive** part, the key factor with the lowest score indicates the priority area of action, that is, where the organization should focus and prioritize its **improvement actions**. Following this, the proposed actions for evolution are listed according to the score obtained for each key practice. Figure 7 presents an example of the proposed improvement actions for the Technological Factors, based on the respondent's score.

Figure 7

Prescriptive Report Model with Proposed Improvement Actions

TECHNOLOGICAL FACTORS				
Item	**Classification**	**Score**	**Diagnosis**	**Recommendation**
TEC01	AdHoc	1	Most of the information sources and final products of the Intelligence process are not digitized, making it difficult for the flow of information collection, storage, and sharing to be seamless.	Promote the digitization of basic information sources and key final products of the Intelligence process to facilitate the flow of information.
TEC02	Basic	2	The storage and dissemination of results from the Intelligence process are standardized, but their dissemination is done manually, compromising the necessary agility.	Standardize the storage and dissemination of results from the Intelligence process using appropriate tools.
TEC03	Intermediate	3	Some more sophisticated analysis tools are used.	Provide the appropriate tools for sophisticated applications, such as statistical analysis, modeling, and data visualization, as well as train your analysts to make the best use of the available tools.

Source: Prepared by the authors

7 Conclusions

This study aimed to develop a proposal for a prescriptive model for assessing the maturity of the Intelligence process, seeking to address some of the main criticisms related to existing maturity models, such as the lack of theoretical foundation (Becker et al., 2009; De Bruin et al., 2005), lack of validation and reliability testing (De Bruin et al., 2005; Lee, Gu & Jung, 2019; Röglinger et al., 2012), and lack of ready-to-use tools that provide better support to practitioners (Röglinger et al., 2012).

The Delphi Card-sorting used for the construction of the maturity model proved to be an effective method for face and content validity (Martini & Janissek-Muniz, 2021). Although one factor (INF) did not achieve the expected reliability in the pre-test, the other factors (IND, ORG, TEC, PRC) were validated satisfactorily. The goal of the Delphi Card-sorting is to improve the quality of the proposed model, allowing each round to influence the expert based on the preceding round, even without knowing who performed the classification or in which round. This approach enables the expert to focus on more complex issues without being burdened by the evaluation of simpler questions, thus providing greater robustness to the model.

The results of the Delphi Card-sorting highlighted some important issues for discussion. First, there was a significant concentration of key practices related to Organizational Factors and the structure of the Intelligence Process, raising structural and systemic questions about how these elements impact the maturity of the Intelligence activity. Technological Factors and Informational Factors had a limited number of related practices, with three and four respectively. Regarding Informational Factors, the reliability index was not achieved for testing in the full study analysis.

It is important to note that the Delphi Card-sorting technique does not assume consensus but indicates the need to stabilize the number of classification changes across rounds. Instances of conflicting classifications, such as for key practices INF01, INF02, INF04, ORG04, and PRC18, highlight weak points in the data set that should be analyzed with particular attention (Paul, 2008). Thus, a future research possibility is to compare the consistency of the model developed through Delphi Card-sorting with a model developed through classification agreement among participants, reintroducing conflicting practices.

Survey results indicate that most participating organizations have mature and formalized Intelligence processes. However, the majority of organizations at the Intermediate maturity level reported not having a formal Intelligence process. Future studies should explore this relationship: how can organizations present a high maturity level without a formalized process?

As a contribution to academia, advancements in the study of the Intelligence process and the development of prescriptive maturity models can be highlighted. The developed model is also expected to contribute to longitudinal research analyzing the relationship between Intelligence and its outcomes for organizational performance. The application of the Delphi Card-sorting method can also be considered an important academic contribution, as the preliminary instrument originating from this method was partially validated. A future study should consider conducting a traditional Card-sorting to develop the preliminary instrument and compare it with results obtained through Delphi Card-sorting.

Some aspects were not addressed in this study due to inherent limitations in scientific research. The cross-sectional nature of the data collection is a limitation to be noted. In this type of study, the collected data reflect the respondents' perceptions at the time of collection, without considering their context or external factors that may influence their choices. Additionally, the results cannot be generalized due to the data being collected exclusively from professionals working in organizations operating in Brazil and the non-probabilistic nature of the sample. To broaden contexts and associated results, it is suggested that the proposed model be applied to probabilistic samples in different sectors and regions. Finally, despite the aforementioned limitations, it is suggested that the proposed prescriptive maturity model be used both by practitioners who wish to diagnose the maturity level of the Intelligence process in their organization and identify prioritized areas for improvement, and by academics seeking to map the maturity level of the Intelligence process in specific organizations within a region, segment, sector, or size.

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