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A review and classification of technology readiness assessment techniques based on TRL scale

Una revisión y clasificación de las técnicas de medición de la madurez tecnológica basadas en la escala TRL

Abstract: The Technology Readiness Levels (TRL) emerged in the late 1970s, proposed by the National Aeronautics and Space Administration (NASA). There are nine levels that seek to measure the maturity of a technology or product. The process that aims to assess the TRL level of a technology or product is called Technology Readiness Assessment (TRA). In the early 2000s, the TRL scale began to be used by industry and governments around the world, leading to an increase in the importance of TRA. Given this scenario, this work aimed to investigate the existing approaches in the literature for the execution of TRA based on the TRL scale. For that, a systematic review of the literature was conducted on scientific article databases and thesis and dissertation repositories. As a result of the review, three groups of approaches were identified: one based on human experts, another that uses a calculator to support the expert, and, finally, a third that uses semi-automatic or automatic tools, such as bibliometric indicators and text mining algorithms. The study identified the advantages and disadvantages of each of these approaches, as well as gaps still open in the literature.

Keywords: TRL; Technology Readiness Levels; TRA; Technology Readiness Assessment.

Resumen: La Escala de Madurez Tecnológica (TRL) fue propuesta por la Agencia Espacial Estadounidense (NASA) a fines de los años 1970. Se divide en nueve niveles que buscan medir la madurez de una tecnología o producto. El proceso que determina el nivel TRL de una tecnología o producto se denomina Evaluación de Madurez Tecnológica (EMT). A principios de los años 2000, la escala TRL comenzó a ser utilizada por la industria y los gobiernos de todo el mundo, lo que hizo que la EMT ha cobrado relevancia. En este contexto, este estudio tuvo como objetivo realizar una búsqueda en la literatura acerca de los enfoques existentes para la ejecución de la EMT basada en la escala TRL. Para ello, se realizó una revisión sistemática de la literatura basada en artículos científicos y repositorios de tesis. Como resultado, se identificaron tres grupos de enfoques: el enfoque basado en expertos humanos, el que utiliza una calculadora para apoyo del experto y el enfoque que emplea herramientas semiautomáticas o automáticas, como indicadores bibliométricos y algoritmos de minería de texto. Este estudio permitió recopilar las ventajas y desventajas de cada uno de estos enfoques, además de conocer lagunas aún abiertas en la literatura.

Palabras clave: TRL; escala de madurez tecnológica; TRA; evaluación de madurez tecnológica.

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1 INTRODUCTION

In the late 1970s, Stan Sadin, an employee of the National Aeronautics and Space Administration (NASA), developed a scale of Technology Readiness Levels (TRL). With six or seven levels, it measured the maturity of a technology and facilitated communication between those involved in the project, despite not defining each level in detail (Mankins, 2009).

Over the years, the need for NASA to adopt and standardize the scale became latent, especially after the loss of the Challenger space shuttle in 1986, which led to a process of restructuring the agency's technological bases (Mankins, 2009).

In 1995, Mankins, also a NASA employee, published a document ("a white paper") (Mankins, 1995) expanding the TRL scale to nine levels and improving the definition of each of them.

Since the 2000s, the TRL scale has been adopted by numerous bodies, agencies, and companies, including the United States Department of Defense (USDOD) and the European Space Agency (ESA) (Mankins, 2009). Some adopt the scale defined by NASA, making minor modifications involving the substitution of space-related terms. This is the case with the United States Department of Homeland Security (DHS). Others, such as the European Space Agency (Straub, 2015), created variations of NASA's TRL, describing each of the levels in more detail.

In Brazil, several initiatives have led to the adoption of the TRL scale, for example, the Brazilian Space Agency (Xavier *et al*., 2020), the Department of Aerospace Science and Technology (Rocha, 2016) and the Department of Science and Technology of the Brazilian Army (Girardi; França Junior; Galdino, 2022).

Recently, the Brazilian Ministry of Science, Technology and Innovation published Ordinance MCTI No. 6,449, of October 17, 2022, dealing with the use of the Technological Readiness Level Measurement and Identification System within that ministry to contribute to the selection of projects to be financed, as well as capturing non-budgetary resources, offering agile criteria that allow the private sector to recognize investment opportunities (Brazil, 2022).

The TRL scale allows us to measure a technology's degree of reliability, that is, how much it has already been tested and verified, as it identifies which steps it already meets. For example, TRL 9 attests to an operational technology in a system demonstrated in real operations. TRL 4 guarantees that the technology has been tested in a laboratory environment. This idea of reliability is very important in the development of critical technologies, such as those used in aerospace (Mankins, 2009).

Despite being widely used, a difficulty in using the TRL scale is determining the level of maturity corresponding to a given technology. This process is called Technology Readiness Assessment (TRA) (Girardi; França Junior; Galdino, 2022).

Traditionally, TRA seeks to assess the maturity level of a product or technology. However, it is possible to identify in the literature its use in evaluating the development of a technology in a broader sense, something closer to technological prospecting[1]. This suggests the success of this tool, as new applications emerge.

1 A process by which a more complete understanding can be reached of the forces that shape the long-term future and that must be taken into account in policy-making, planning and decision-making (Coates, 1985).

The scarcity of studies addressing the state of the art on ways of carrying out TRA, particularly in the context of research and development (R&D) projects, motivated this work, whose objective is to identify and analyze different applications of TRA based on the TRL scale. To this end, a systematic review of the literature was conducted, in which 180 articles from five databases were found. After applying the inclusion criteria and expanding the search, 18 articles and one dissertation were found to be relevant to the analyzed context. They were divided into three groups, using the taxonomy proposed in this article.

It is worth highlighting that there are TRA approaches that combine the TRL scale with other scales, for example, Manufacturing Readiness Levels (MRL) (Wu *et al*., 2017) and Commercial Readiness Level (CRL) (Gerdsri; Manotungvorapun, 2021). These approaches were not considered here, as they go beyond the scope of this work, that is, they go beyond the R&D context. MRL focuses on assessing manufacturing maturity, and is especially useful for identifying risks and gaps in the transition process between technology and manufacturing (Wu *et al*., 2017). The CRL analyzes aspects related to the marketing of the product and its consumer market (Gerdsri; Manotungvorapun, 2021).

Therefore, the remainder of the article is structured as follows: in section 2 we present the theoretical basis for TRA based on the TRL scale. Section 3 details the methodological aspects of the literature review carried out. Section 4 presents the existing approaches, classified using a taxonomy proposed in the study. Section 5 discusses TRA in the context of each of the approaches identified. Finally, the last section concludes the study, pointing out gaps in the literature.

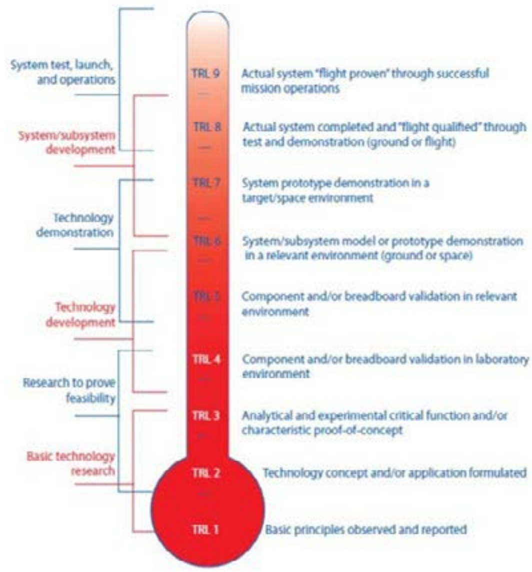
2 THEORETICAL FOUNDATION

Currently, NASA adopts nine levels of technology readiness. Level 1 represents the most basic, in which basic principles are observed, while level 9 represents an actual system that has carried out successful operations. Figure 1 illustrates these levels.

NPR 7123.1C (National Aeronautics and Space Administration, 2020), published in 2020, presents the most recent definition for readiness levels, particularizing them for software- or hardware-based applications. This document takes precedence over other NASA directives regarding TRL definitions. This is important as it contributes to promoting common understanding on the subject, given the various proposals for changes in the definition of levels, which have been made over time.

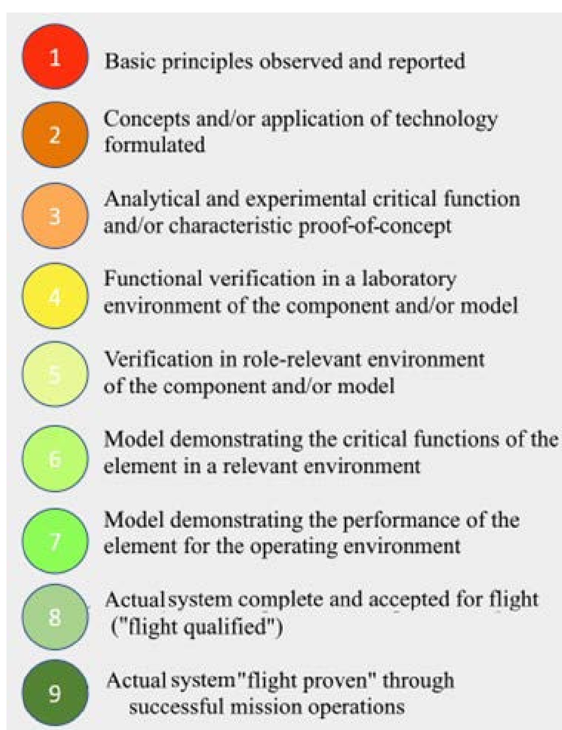
In Brazil, the ABNT NBR ISO 16290:2015 standard (Associação Brasileira de Normas Técnicas, 2015) deals with spatial systems, definitions, and evaluation criteria for TRL. Using ISO 16290:2013 as a reference, ABNT NBR ISO 16290:2015 standardizes the definition of relevant terms, thus contributing to promoting common understanding. Furthermore, it explains each level of the scale, including examples of framing in the scale levels and asserts that although these levels have been defined for spatial systems, they can be used in a broader context. Figure 2 consists of a summarized adaptation of the definitions of each level of the TRL scale (Associação Brasileira de Normas Técnicas, 2015).

Figure 1 – Technological readiness levels



Source: from Hirshorn, Voss, and Bromley (2017).

Figure 2 – Definitions of TRL scale levels



Source: Adapted from Associação Brasileira de Normas Técnicas (2015).

In fact, the TRL scale began to be applied in contexts other than space, through adaptations of the original proposal made by NASA, such as in aviation, defense, the medicines sector, wave energy, and composite recycling (White *et al*., 2022). These adaptations occur in the definitions, quantities, and terminologies used in the scale.

An interesting point to note is that the lower the TRL, the broader the spectrum of possible applications of the technology. As research develops, and new levels of maturity are reached, technologies become more specific (White *et al*., 2022).

Another point indicated in the literature is that when carrying out a TRA, as originally conceived, for the highest levels of the scale, the element inserted in a target product is considered. Thus, the same element can have a high TRL in one product and a low TRL when used in another product.

In this sense, França Junior, and Galdino (2022) discuss this characteristic of the classification of technological maturity, exploring the example of the Army's armored equipment modernization program, particularly the armored vehicle EE-9 Cascavel. Some existing automotive subsystems and technologies on the market were evaluated and could be considered in the process of modernizing the aforementioned vehicle as they are already in operation on certain platforms, therefore, with maximum TRL. However, despite being tested and certified, considering the specific requirements of these products or platforms, when evaluated in terms of meeting the specific requirements of the rattlesnake vehicle, they reached intermediate TRL of, at most, TRL 6.

3 METHODOLOGY

This work carried out a literature review to investigate existing approaches for implementing TRA based on the TRL scale. For this, five research databases relevant to the topic were selected, a search string was constructed, and inclusion criteria were applied. Additionally, the search was expanded through the snowball technique and expert suggestions.

To search for articles analyzed in this survey, the following databases were consulted: ACM Digital Library, IEEE, ScienceDirect, Scopus, and SpringerLink. In order to limit the scope of the research to works that use textual analysis of documents in TRA based on the TRL scale, the search string consisted of the combination of the terms "Technology Readiness Levels" (TRL), "text mining," and synonymous terms for the latter. Thus, the search string consisted of: "text mining" OR "text-mining" OR "data mining" OR "data-mining" OR "tech mining" OR "tech-mining") AND ("technology readiness level" OR "trl"). Small adaptations for each of the databases were made.

Notably, we chose to use the acronym TRL, in the search string, instead of TRA, as some authors, despite carrying out a technological readiness assessment, did not use the acronym TRA nor the phrase Technology Readiness Assessment in the title, abstract and keywords. Even in these cases, the acronym TRL was used, as this is the main use of the scale.

As inclusion criteria, writing in Portuguese or English and the full availability of the article were adopted. Furthermore, the publication should address TRA or TRL. The results of the latter were used in the theoretical foundation of this work. Table 1 shows the number of publications found by database and the final number after applying the above-mentioned inclusion criteria. In the "Total" line, the removal of duplicates is considered, so that identical articles indexed simultaneously by two or more databases are counted only once.

After this initial survey, the snowball technique was used to identify articles of interest that cite or are cited by the selected articles. We also searched for other articles written by the authors of the selected articles. Eight articles were found using this technique, not included in Table 1, in addition to relevant manuals, ordinances and standards.

Table 1 – Result of queries by database

Database	Articles found	Articles kept
ACM Digital Library	1	0
IEEE	5	1
ScienceDirect	2	0
Scopus	15	2
SpringerLink	150	3
Total (*no duplicates*)	168	6

Source: Prepared by the authors (2023).

It should be noted that the SpringerLink database, in particular, presented many false positives, as the acronym TRL takes on different meanings in different areas. For example, in medicine, it can be used to refer to the term Triglyceride-Rich Lipoproteins, and in the computing area, it refers to Traditional Reinforcement Learning, or even Transfer Rule Learner. Thus, despite the large number of articles found in this database, few were maintained after applying the inclusion criteria.

In addition to the search in the aforementioned databases, interviews were carried out with experts in the field, seeking to collect relevant articles, theses and/or dissertations in the national context, from which the following works were identified: Rocha (2016); França Junior and Galdino (2019, 2022); Xavier *et al*. (2020); and Girardi, França Junior and Galdino (2022).

Thus, 18 articles and a dissertation were selected, some with strong theoretical foundations on TRL and others related to TRA. During the research, no survey-type studies similar to this study were found.

In relation to studies related to TRA and/or identifying the TRL level of a technology or product, three sets of approaches were found: (1) use of a team of experts; (2) use of auxiliary tools to support the expert, for example, calculators; and (3) use of automated tools.

The taxonomy proposed here allows solutions to be grouped by the level of TRA automation. The solution, based on experts, refers to a purely human assessment. The use of auxiliary tools (calculators) combines expert skills with software. Finally, automated tools are part of a partially automated process, that is, the process includes an identification and document collection phase, usually manual, followed by an automated quantitative or qualitative analysis.

In relation to TRA, it was also possible to observe that, while some authors analyze the TRL of a specific technology or product (strict sense), others made this assessment in a broader way, seeking to identify the general scenario of that technology (broad sense). This subject is covered in section 5.

4 PRESENTATION OF RESULTS

In this section, the results will be presented and discussed following the categorization of solutions described in section 3, namely: team of experts, auxiliary tools, and automation.

4.1 Team of experts

One of the most basic ways to carry out an TRA is with a team of experts, which includes not only professionals with a high technical level in the application area, but also personnel qualified in the TRL scale evaluation methodology (Britt *et al*., 2008).

The expert can, for example, establish the functions that are critical for performance, the laboratory and relevant testing environments, and assess whether the tests and procedures adopted to achieve framing into the scale are successful. There are several subjective points in the assessment that depend on the expert's interpretation.

This approach goes back to the origins of TRL, and several studies have used it to evaluate technologies. In Hrica *et al* . (2022), for example, a review of collision avoidance and warning technologies is presented, based on a TRL maturity scale adapted for the mining domain by Carr (2019). Figure 3 shows the comparison between the definitions adopted by NASA, USDOD, and Carr (2019).

In this analysis of technological maturity, the authors pointed out that the TRL scale provides a clear language about the status of the technology, facilitating communication. Furthermore, the scale allows the identification of risks associated with technological transition[2].

In this study, initially, the authors selected the documents[3] that served as support for the classification of technologies, using three databases (Compendex, Scopus, and OneMine). With the removal of duplicates, 432 articles were obtained. After the inclusion and exclusion criteria were applied, this number was reduced to 64 articles. Some articles dealt with more than one technology. Thus, 97 cases were analyzed (Hrica *et al*., 2022).

To assign the TRL of each technology covered in each article, the team met via teleconference, discussed important information about each publication and, with a consensus of at least three team members, a final classification was reached (Hrica *et al*., 2022). It is important to note that experts accessing the same information, in some cases, ascribed different maturity levels to the same technology.

2 It refers to the process in which an older, more mature technology is replaced by a newer one that offers a competitive advantage. As an example, the transition from the transistor to the integrated circuit is cited (Weck, 2022).

3 Publicly available scientific publications, such as peer-reviewed journal articles, conference proceedings, and government reports.

Figure 3 – Comparison between NASA, USDOD and mining TRL definitions

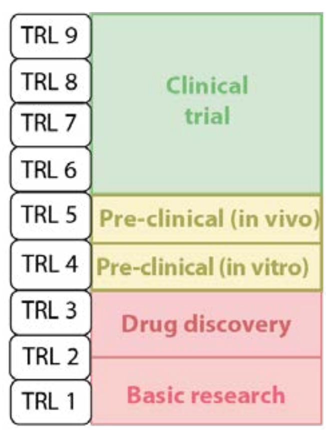
	NASA	USDOD	Mining
1	Basic principles observed and reported	Basic principles observed and reported	Basic principles observed and reported
2	Concepts and/or application of technology formulated	Concepts and/or application of technology formulated	Concepts and/or application of technology formulated
3	Analytical and Experimental critical function and/or characteristic proof-of-concept	Analytical and Experimental critical function and/or characteristic proof-of-concept	Proof-of-concept established through experimental analytical environment
4	Component and/or breadboard validation in laboratory environment	Component and/or breadboard validation in laboratory environment	Component and/or breadboard validation in laboratory environment
5	Component and/or breadboard validation in relevant environment	Component and/or breadboard validation in relevant environment	Component and/or breadboard validation in relevant environment
6	Demonstration of system/subsystem model in a relevant environment (ground or flight)	Demonstration of system/subsystem model in a relevant environment	Demonstration of system/subsystem model in a relevant environment
7	System prototype demonstration in spatial environment	System prototype demonstration in an operational environment	System prototype demonstration in a representative operational mining environment
8	Actual system completed and "flight qualified" with test and demonstration (ground or flight)	Actual system completed and accepted with test and demonstration	Actual system completed and demonstrated with field tests
9	Actual system "flight proven" with successful mission operations	Actual system proven with successful mission operations	Actual system proven with successful mining operations under a range of expected conditions

Source: Adapted from Carr (2019) *apud* Hrica *et al*. (2022).

At the end of the study, the authors found few publications that presented technologies at high levels (TRL > 6). This may have occurred due to the fact that only peer-reviewed scientific publications were considered in the study, which usually deal with results that adhere to low and intermediate levels of TRL, and commercial publications and white papers were not considered (Hrica *et al*., 2022), which may present input from initiatives with high TRL.

Another work that adopted the expert's methodology was Hardiyati *et al*. (2018). The authors used journals indexed by Scopus and Google Scholar, published until March 2017. One of the objectives of the study was to analyze the level of technological maturity of publications on biomedicine in Indonesia. A total of 1,258 publications were analyzed, of which only 546 included R&D for new medicines. The authors used experts to classify the articles on a new scale adapted for biomedicine[4], as shown in Figure 4, and created a dictionary with the typical keywords for each level. This could be used in new approaches, including for the automation of the TRA process.

Figure 4 – Relationship between TRL and the proposed scale



Source: Adapted from Hardiyati *et al*. (2018).

The authors concluded that few studies reached the last stage of maturity, generating a product for the industry. They also point out that the process of producing new medicines is long and costly (Hardiyati *et al*., 2018).

In general, this approach has the advantage of having professionals with the ability to interpret the documentation, infer information (which is not explicit) and, finally, reach a conclusion based on their knowledge. However, it has the disadvantage of excessive dependence on the experience and technical qualifications of the expert team, introducing subjectivity into the process, inducing communication problems, in addition to making the process expensive and slow (Britt *et al*., 2008) (Lezama -Nicolás *et al*., 2018).

4 Conceptual model for classifying biomedicine research developed by the authors. They present the description of each level and the equivalence with the TRL (Hardiyati *et al*., 2018).

4.2 Auxiliary tools

Aiming to reduce the possible expert bias, several studies have developed TRL calculators. In this approach, the expert does not need to have any knowledge of the scale, simply answer a series of questions. At the end, the calculator displays the TRL level that best represents the technology analyzed.

The calculator can have a variable degree of specificity, as its questions can be very precise and defined or more generic, allowing for use restricted to one application, or broader.

Of the studies that use this approach, White et al. (2022) studied the use of the TRL scale as a way of measuring the maturity of technologies aimed at the early detection of pests and pathogens in trees. During the research, they conducted interviews with experts and were able to observe the difficulty in positioning certain technologies on the TRL scale. Thus, to assist the TRA of technologies linked to the environment, aiming to bring greater objectivity, they developed a calculator. Institutions such as NASA and the Air Force Research Laboratory have also developed calculators to support the process of evaluating the TRL level of a technology or product (White et al., 2022).

TRL calculators consist of a set of questions, generally implemented through generic software, such as spreadsheet editors, and which provide the maturity of the analyzed technology at the end of the process (White et al., 2022), such as that made available by New York State Energy Research and Development Authority (NYSERDA)[5], originally developed for the clean technology industry. This calculator consists of a series of closed questions (yes or no answer), distributed in seven sections: general summary of technological readiness; market and customer needs; design and development; integration; testing and validation; environment and safety; and finally, manufacturing and scaling (White et al., 2022).

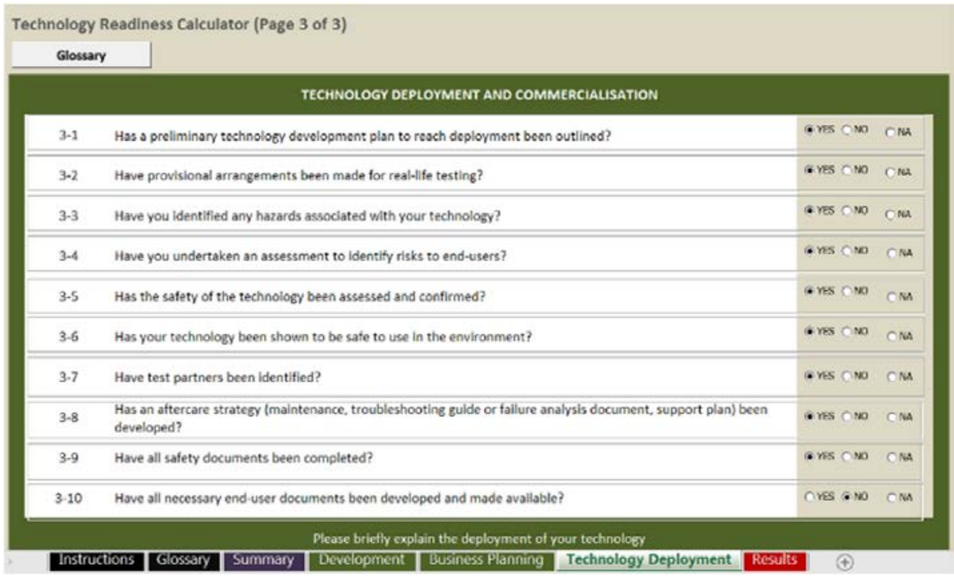
Inspired by this calculator, White et al. (2022) developed a new one, illustrated in Figure 5, focused on the area of biosafety. However, unlike that calculator, whose questions were directed to the engineering context and addressed manufacturing issues, for the new area there was a need to adopt a multi-actor approach , with the inclusion of stakeholders and end users, as interested parties could present different interpretations on the maturity of the technology, requiring a broader assessment (White *et al*., 2022).

Furthermore, they changed the number of sections, from seven to three, which became: technology development; technology and implementation; and business development. In another modification, questions that were previously closed now allow answers such as “not known” or “not applicable” (White et al., 2022). The work of White et al. (2022) does not provide an example of using the calculator, does not delve into the methodology (how to reach the level of maturity based on the answers) and also does not make it clear how it deals with new types of “not known” or “not applicable” answers.

Another initiative to build a TRL calculator is presented in Girardi, França Junior, and Galdino (2022). The authors address the issue of customizing the TRA process considering an organizational perspective of the Brazilian Army (Girardi; França Junior; Galdino, 2022).

5 Available from: files.masscec.com/innovate-clean-energy/NYSERDA-TRLCalculator.xlsm. Access on: Nov. 23, 2023.

Figure 5 – Calculator screen



Source: White *et al.* (2022).

Because of this, two TRLs were added in relation to the traditional scale. Up to level 9, the proposed scale is very similar to the traditional one. Level 10 comprises production repeatability, while 11 includes feedback from the user of the product in operation (Girardi; França Junior; Galdino, 2022). The need to build this customized scale for the Brazilian Army is presented in França Junior and Galdino (2019).

The process of building the calculator is detailed in the study and included 9 stages: initial diagnosis, bibliographical review, first draft of the calculator, workshop with 22 experts from four focus groups, version 1 of the calculator, experimental use in real cases[6], internal consultation at institutional scope of the Brazilian Army, version 2 of the calculator, and, finally, the availability of the calculator (Girardi; França Junior; Galdino, 2022).

The calculator was implemented in a web interface by the Technological Management and Innovation Agency (Agência de Gestão e Inovação Tecnológica – AGITEC)[7] and can be accessed via the Brazilian Army's corporate network. The expert answers a maximum of 11 questions to obtain the TRL classification of the object under analysis. To obtain a classification with few questions, an approach was adopted to solve the TRL classification problem in two steps. In the first, an estimate is made in one of the TRL ranges, as illustrated in Figure 6 (Girardi; França Junior; Galdino, 2022). In the second, indicators are assigned to each TRL. Thus, after answering the initial question, refinement and confirmation are made with other questions,

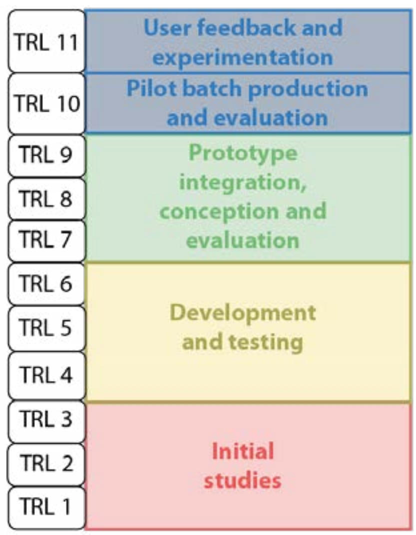
6 The programs were: Strategic Guideline for the Conceptual Formulation of the Brazilian Army's Armored Means, Software Defined Radio, and Solo Missile – Solo 1.2.

7 Military Organization of the Brazilian Army.

considering the highest level at which the indicators have been met (Girardi; França Junior; Galdino, 2022). Figure 7 displays the calculator's home screen.

Xavier *et al*. (2020) address the relationship between the TRL scale and risk management, especially the intuitive notion of technological risk, and point out the importance of developing a calculator. According to the authors, there are several calculators (XLS files) distributed free of charge on the world wide web, but they require MS Excel or a similar program. The authors point out several disadvantages of these calculators distributed in XLS or similar files, such as security problems and susceptibility to human errors (Wirth 1976; Jackson, 2001 *apud* Xavier *et al*. 2020). Another negative point is the lack of a data structure focused on storage.

Figura 6 – Faixas da primeira etapa



Source: Prepared by the authors (2023), based on Girard and Galdino (2022).

Figure 7 – Calculator screen

Source: Screenshot of the calculator, available from the AGITEC intranet page.

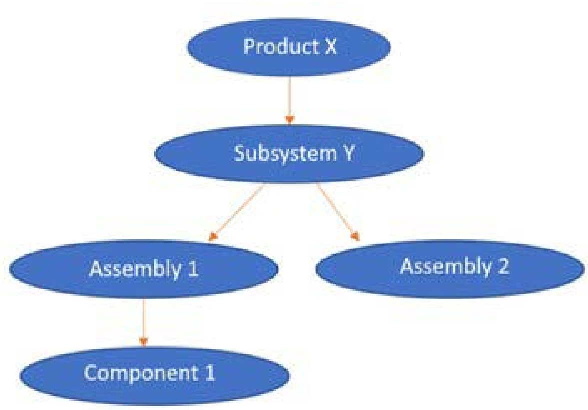
The authors of the aforementioned work propose a calculator focused on the spatial environment. They present a methodology in which, when evaluating the maturity of a product, its analytical description is used through a product division structure, the Product Breakdown Structure (PBS), in which product elements are broken down and detailed, hierarchically, into subsystems, assemblies and components (Xavier *et al*., 2020).

Figure 8 exemplifies how this concept was applied to the calculator. Figure 9 shows the structure of the example in Figure 8 presented in a tree structure. In it, Product X has subsystem Y, which in turn has Assembly 1 and Assembly 2. Finally, Assembly 1 has Component 1.

Figure 8 – PBS applied to the calculator

Source: Screenshot obtained from: https://imatec.aeb.gov.br/#/createProduct2.

Figure 9 – Presentation of PBS in tree structure



Source: Prepared by the authors (2023).

According to the authors, the maturity of a product is equal to or less than the maturity of the elements that constitute it (Xavier *et al*., 2020). In the example in Figure 8, it is observed that if Component 1 received level 3, then Assembly 1 could have received a level less than or equal to 3. If Assembly 1 received level 2 and Assembly 2 received level 6, the Subsystem Y could have received a level less than or equal to 2.

The calculator developed by these authors was called IMATEC Lite, in which the letter I is associated with the word index and MATEC with technological maturity. The word *lite* indicates the authors' intention to expand it, encompassing a broader set of tools involving programmatic and manufacturing aspects. Regarding the use of the calculator, the users initially assemble the product structure (PBS), which is stored in a data framework that can be exported. Then, they answer a series of questions, created from the National Aeronautics and Space Administration (2014)[8] , with "yes" or "no" for answers.

The calculator uses "if-else" logic to guide questions based on the answers to the previous ones. That is, when all answers to questions at a given level are yes, then questions at the next higher level are displayed. The level reached corresponds to the highest level that had all "yes" answers (Xavier *et al*., 2020).

The calculator does not require installation and uses a web interface available on the world wide web[9]. After answering the questions, the user receives a detailed report that lists not only the final product's level, but also the elements that make it up. As for the technologies used, the authors report that the login credentials are stored in a MongoDB Database, the application runs on nodeJS, the modules on AngularJS, while the visual part used the framework Bootstrap CSS (Xavier *et al*., 2020).

The authors carried out a case study involving the Serpens system, an acronym for Space System for Conducting Research and Experiments with Nanosatellites, which was broken down through PBS using 3 levels. The team then answered the questions and the system reached level 6 on the TRL scale (IMATEC 6). With this result, the authors considered that the Serpens system had the critical functions of its elements verified and its performance proven in a relevant environment (Xavier *et al*., 2020).

Another work that developed a TRL calculator was Rocha's (2016). In it, the author addresses the need for an assessment that considers not only technological aspects, but also others such as economic, documentary, and political-legal aspects. This inclusion aims to consider the Brazilian reality.

Rocha (2016) establishes five stages in his TRL methodology, namely: application decision, definition of the team, identification of technologies, collection of materials, and finally evaluation. The latter can be subdivided into demonstration of the TRL evaluation methodology, data on the technology to be evaluated, and the TRL assessment.

The assessment uses a calculator built using Microsoft Excel software, comprising 89 questions. There are questions based on a checklist from NBR ISO 16290:2015, and others with

8 Available from: https://nodis3.gsfc.nasa.gov/displayDir.cfm?t=NPR&c=7123&s=1B. Access on: Dec. 6, 2022.

9 See: https://imatec.aeb.gov.br/#/home.

technical, economic, documentary, and political-legal requirements that admit a percentage of achievement. Another distinctive feature of the calculator is that it works with a tolerance index. Thus, unlike NBR ISO 16290:2015, a TRL can be considered met, even without all requirements having been observed (Rocha, 2016).

At the end of the work, the proposed methodology was applied to three aerospace technologies: carbon thermostructural composites reinforced with carbon fibers, the L75 engine, and the VSB 30 rocket; and to a military technology: mixed armor for military aircraft. The evaluation included technicians, managers of the technologies analyzed, and a facilitator responsible for filling out the calculator. Finally, Rocha (2016) made a comparative analysis between the levels achieved through the proposed methodology and what would be obtained through an analysis purely based on NBR ISO 16290:2015, noting that in 75% of cases, the TRL with help of NBR ISO 16290:2015 was greater than that of the TRL IAE/ITA-2016-1 calculator. This observation, in the author's view, demonstrates the subjectivity of the aforementioned standard.

Therefore, regarding the approach with auxiliary tools, it can be concluded that the use of calculators simplifies the process by employing a series of standardized questions. The technology expert does not need to know the TRL scale. Furthermore, it is worth highlighting that questions can be formulated to reflect the needs of the organization. However, it should be noted that the superficiality of the questions can lead to inaccuracies in the classification.

The construction of the calculator can be carried out through an elaborate process, such as the one presented in Girardi, França Junior, and Galdino (2022). After this, carrying out the TRA, using it, becomes simplified by not requiring experts on the scale and by reducing subjectivity. In this regard, the TRL-EB calculator developed for the Brazilian Army is cited as a success, it has already been applied to around 694[10] technologies and products of interest to National Defense. Support for its use is provided only by AGITEC analysts to resolve any specific doubts of the teams in charge of maturity classification.

4.3 Automation

There are several methods that seek to automate obtaining the level of technological maturity of a technology or product based on scientific publications, news, and patent documentation. Some are quantitative, explore bibliometrics, and are based on the volume of documents, the methods of this group are more related to technological prospecting.

Others analyze documents with text mining and natural language techniques. This second group can come close to the traditional use of scale, when documents refer to a well-defined target technology or product, or technological prospecting, when the collection focuses on a technology in a broad sense.

Lezama-Nicolás *et al*. (2018), iinspired by Watts and Porter (1997), built a quantitative method that uses bibliometric estimators in a semi-automatic approach called Bibliometric

10 Number of accesses to date (April 2023) since the tool was made available within the scope of the Brazilian Army (EB).

Method for Assessing Technological Maturity (BIMATEM). They establish a relationship between the stages of the life cycle (Introduction, Growth, and Maturity), Technology Life Cycle (TLC)[11] , the types of bibliometric sources and the levels of the TRL scale, as shown in Table 1.

Table 1 – TLC relationship, bibliometric sources and TRL

TLC	Bibliometric sources	TRL
Introduction	-	1
	-	2
	Scientific papers	3
	Engineering papers	4
		5
Growth	Patents	6
		7
Maturity	News records	8
		9

Source: Watts e Porter (1997) adapted by Lezama-Nicolás *et al*. (2018).

The method consists of defining the technology to be analyzed, selecting the query bases, formulating the search string, and executing the query on the bases. In the next step, the records are tabulated. Finally, the mathematical evaluation of the retrieved results is carried out and the corresponding TRL (range) is assigned (Lezama-Nicolás et al., 2018). To illustrate the usefulness of BIMATEM, the authors employed it in a case study involving additive manufacturing technologies.

It is worth highlighting that BIMATEM considers that technologies present a linear innovation path (Lezama-Nicolás *et al*., 2018), in which initiatives advance, progressing in maturity level over time, as R&D activities are performed. However, as commented by White *et al*. (2022), this is not always how technological development occurs. A technology that has reached a certain TRL may regress to a lower TRL when unexpected results are obtained in a test. This situation can also occur, even more frequently, when the target object to which the technology of interest must be integrated is modified. This case was illustrated in section 2, through the case study of an armored vehicle brought by França Junior and Galdino (2022), in which a mature technology, when used in another product, regresses to lower TRLs.

Faidi and Olechowski (2020) highlight the importance of TRL for evaluation and planning during the development of a product or technology, highlight the role of this scale for the design of prototypes and consider automation as the way to overcome the main problems of using this scale: subjectivity and the high cost of employing teams of experts. The authors

11 The TLC stages are emerging, growing, and mature technology. The decline stage is not considered as it does not relate to the TRL scale (Lezama -Nicolás *et al*., 2018)..

analyze the coherence of the relationship between the type of document (e.g., news, patents, and scientific articles) and TRL (Faidi; Olechowski, 2020).

Faidi and Olechowski (2020) point out that works such as that of Lezama-Nicolás *et al*. (2018) associate scientific and engineering articles with the lowest TRL levels, patents with intermediate levels, and news with more mature levels. To refute this hypothesis, the authors chose 15 technologies from the nanotechnology sector with low TRL, based on the classification made in the document NASA Technology Roadmaps TA 10: Nanotechnology (2015)[12]. Five technologies from each of TRL 2, 3 and 4 were chosen and analyzed (Faidi; Olechowski, 2020).

The authors used three types of documents (patents, scientific publications, and industry news), restricted the collection to the period from 2009 to 2015 and, after analysis, found that the mapping of publication types into TRL levels was not verified (Faidi; Olechowski, 2020).

They observed, for example, that TRL 3 technologies obtained an increasing number of patents throughout the analyzed period, such as graphene sheets that obtained more than 50 patents in 2015 alone. The occurrence of patents at this low TRL level is something that contradicts considerations from part of the literature, which associates patents with intermediate levels. A similar situation occurred when identifying news records for technologies of this same TRL, which would only be expected at higher TRL (Faidi; Olechowski, 2020).

The authors assume that the specificity of the technology name and the natural use of more generic names at more embryonic levels of development make it difficult to search for documents related to the technologies analyzed (Faidi; Olechowski, 2020).

Thus, although the methods of this group, which employ bibliometric indicators, have the advantage of automating part of the process, they are still very dependent on the search string formulated in the queries and the databases used. Another criticism is that the development of different technologies may not have uniform behavior, making the search for a standard difficult. Furthermore, this group of methods is much more related to technological prospecting than to the evaluation of specific products or technologies, which have disparate characteristics in terms of critical performance functions and technical specifications. The TRL is not an absolute number, it depends on the context (França Junior; Galdino, 2022), and is not always explicit or identifiable in documents. This can also become a problem with this approach, given the need to make some concepts more flexible, such as critical performance functions, subjectively inducing the process.

Another group of methods that aim to automate the process consists of applying text mining techniques. In this approach, among other types of models, those originating from Artificial Intelligence (AI) aimed at the classification task can be applied.

Continuing studies on the classification of scientific publications in Indonesia on biomedicine, Hardiyati et al. (2018) found that computerized predictive models based on text mining provide effective and efficient classification, especially when dealing with a large volume

12 Available from: https://www.nasa.gov/sites/default/files/atoms/files/2015_nasa_technology_roadmaps_ta_10_nanotechnology_final.pdf.

of documents. In this sense, the authors published a work employing the text mining approach (Silalahi *et al*., 2018).

The study aimed to build an automated model to classify publications into one of the 4 maturity levels proposed by the scale focused on biomedicine (Figure 4), that is, basic research, drug discovery, pre-clinical and clinical trials. It is worth noting that the preclinical in vivo and in vitro levels were transformed into a single level (Silalahi *et al*., 2018).

For this, the work analyzed the algorithms KNN, Naive Bayes, and SVM. The set of publications included 539 articles, with an unbalanced distribution across classes. The class basic research had the largest number of articles (291), and clinical trials the smallest (9) (Silalahi *et al*., 2018). Typically, AI models that use supervised learning separate the data set, in this case, publications, into a training and testing set. The former aims to adjust model parameters. The second, to evaluate it.

The analysis carried out in this work was restricted to the abstracts of the articles. Initially, pre-processing was carried out by removing stopwords[13] and applying stemming[14]. Afterwards, a filter was applied to the words, based on Term Frequency- Inverse Document Frequency (TF-IDF)[15] (Silalahi *et al*., 2018).

After training the models, their evaluations were carried out. At this stage, there are several metrics that seek to convey the idea of the model's assertiveness, including accuracy and the F1-score. Accuracy represents the total number of hits divided by the total number of predictions, that is, how many publications were correctly classified in relation to the total number of publications in the test set. The F1-score is an aggregation metric based on other metrics (precision and recall) and is commonly used to indicate the overall quality of the model.

In the end, the authors concluded that the Naive model Bayes performs best, with an accuracy of 80.46% and an average F1-score of 82.61% (Silalahi *et al*., 2018).

One of the possible applications of TRL highlighted in the literature is to evaluate research in universities. For this purpose, the government of the Republic of Indonesia uses the TRL with a variation called Tingkat Kesiapterapan Teknologi (TKT). The result is used in research funding programs. In the methodology adopted by the Government, employees manually apply a questionnaire known as Teknometer with the purpose of obtaining the TRL of research (Rintyarna; Sarno; Yuananda, 2018).

Three works propose to extend this use to the construction of a university ranking, based on the assessment of academic reputation through the automated estimation of the TRL of academic publications made by people linked to universities (Aliyanto; Sarno; Rintyarna, 2017; Rintyarna; Sarno; Yuananda, 2018; Rintyarna *et al*., 2021). This association is illustrated in Figure 10.

13 *Stopwords* are words with no or little meaning, such as prepositions and conjunction.

14 This consists of removing prefixes and suffixes from words, leaving only their radical.

15 It is a Natural Language Processing technique that considers the number of occurrences of a word in a document (Term Frequency – TF) and the inverse of the number of documents that have that word (Inverse Document Frequency – IDF) (Jurafsky; Martin, 2023).

Figure 10 – Proposed association

Source: Based on Aliyanto, Sarno and Rintyarna (2017); Rintyarna, Sarno and Yuananda (2018); Rintyarna *et al*. (2021).

The proposed automation consists of combining an expansion of Bloom's taxonomy with text mining techniques, as an alternative to the process of manual expert interviews, considered costly and time-consuming (Aliyanto; Sarno; Rintyarna, 2017).

Several text mining and Artificial Intelligence algorithms were used in the abstracts of the collected publications to support the TRL level classification, such as: Supervised Probabilistic Latent Semantics Analysis (sPLSA) (Aliyanto; Sarno; Rintyarna, 2017); LDA-Adaboost.MH (Rintyarna; Sarno; Yuananda, 2018) and Labelled Latent Dirichlet allocation (LLDA) (Rintyarna *et al*., 2021).

The works presented varying degrees of success and used different metrics when comparing the university ranking obtained with the reference (QS World University Rankings).

Both in Aliyanto, Sarno, and Rintyarna (2017) and in Rintyarna, Sarno, and Yuananda (2018) and Rintyarna *et al*. (2021), some intermediate steps of the process were not detailed, such as, for example, the training process of the classification models and the accuracy of the models regarding TRL. This can be explained by the fact that obtaining the TRL is a middle process, and not the end process of the works.

In summary, the approach that uses text mining has the benefit of making the TRA process scalable, carrying out several classifications in significantly less time than the manual process. In it, the model can classify the TRL level corresponding to a specific technology or publication.

As a negative aspect, natural language has peculiarities, such as ambiguity and vagueness, which can be difficult for building an assertive model. Furthermore, few studies were found using this approach, and even fewer were those that detailed the procedures performed.

Although it is possible to use AI and text mining algorithms to analyze a set of documents for a well-defined target product, no works were found in the literature that actually used them.

5 DISCUSSION OF RESULTS

After providing an overview of the TRA techniques identified in the R&D literature that use the TRL scale, it is necessary to discuss some important points identified throughout the study.

5.1 Framing of TRA techniques within *stricto* and *lato* approaches

From the analysis of the works found, it was possible to notice some variations regarding the use of the TRL scale. The scale emerged with the purpose of measuring the technological maturity of a technology associated with a target product, based on a well-defined set of indicators for each level, this approach being referred to here as strict analysis (*stricto*). With the popularization of the scale, other possibilities have emerged, such as its use in support of technology prospecting and management tasks, relaxing some of the concepts essential to strict analysis. This category of work has been classified here as broad (*lato*).

In the strict analysis (*stricto*) of using the more traditional scale, we can mention the case study of the Serpens system, proposed by Xavier *et al*. (2020). In fact, the calculator proposed by the authors allows the user to break down the system into smaller parts for evaluation purposes, arriving at an objective measurement of its maturity level. The system has well-defined requirements, which allows it to evaluate whether a test in a given environment was successful or not.

Similar considerations are also valid for the work of White *et al*. (2022), with the calculator focused on early detection technologies for pests and pathogens in trees; for Girardi, França Junior, and Galdino (2022), with the calculator focused on defense products; and also for Rocha (2016) with the TRL IAE/ITA-2016-1 calculator. Thus, it appears that TRA based on the use of calculators is more affected by the *stricto* approach, bearing in mind that there is a clear definition of the indicators that a technology needs to achieve to enable its integration into a specific target product.

To use the TRL scale in a broad sense, some concepts needed to be made more flexible, such as the critical function of an element. In the original definition, the critical function is specific to a technology in relation to a target product. When applied in a *lato* sense, this concept becomes more generic.

As an application of the tool in a broad sense, the use of the TRL scale to support technological prospecting activities stands out. In this sense, we can mention the works of Lezama-Nicolás *et al*. (2018) and Faidi and Olechowski (2020), who addressed the use of bibliometric indicators in defining scale levels.

Another area in which the broad approach has been used is in innovation management or technological management. In this context, Faidi and Olechowski (2020) showed that large technological organizations, such as NASA, have been using the TRL scale to support the construction of their technological roadmaps, while Aliyanto, Sarno, and Rintyarna (2017), Rintyarna, Sarno, and Yuananda (2018), and Rintyarna *et al*. (2021) presented the customization of the maturity scale for the construction of university rankings. These examples indicate that initiatives related to TRA automation, whether quantitative (bibliometrics) or qualitative (text mining), are still more closely related to the broad approach, given the complexity of TRA and the scarcity of datasets with a set of labeled documents.

In summary, these variations in the use of the TRL scale are related to the granularity of the analysis. In the first (*stricto* approach), a greater "*zoom*" is used, allowing the identification of a specific technology associated with a target product, with several particular characteristics, such as requirements and critical performance functions. This was the original purpose conceived by NASA and plays a fundamental role in the R&D monitoring of high-technology products and systems. In the second variation (*lato* approach), the "zoom" is reduced, bringing a more general view, working with a grouping of products and technologies. This aspect has disseminated the use of the TRL scale to support technology prospecting and management activities.

It appears that the approaches have different purposes, despite using the maturity scale as a reference.

5.2 Use of patents in TRA

As introduced in section 4.3, the use of patents in maturity analysis is a complex topic and subject to contestation, such as the criticisms directed by Faidi and Olechowski (2020) against the BIMATEM methodology proposed by Lezama-Nicolás *et al*. (2018).

This complexity is due to invention patents that are used for several distinct purposes, such as those listed below:

- Companies seek to increase their market presence by assembling a portfolio with patent deposits, even if they do not represent a major technological advance and have low commercialization potential.
- Individual inventors can use patent filing as a way of enriching their CVs. An emblematic example of how it is possible to file a patent for something clearly unpatentable is the case of researcher Henry Jun Susuki. Seeking to prove this hypothesis, he successfully carried out all the necessary bureaucratic procedures to start filing a patent for an emoji (BR 102018004918-6 A2), showing that it would be possible for an inventor to include spurious filings in their portfolio (Suzuki, 2019).
- Some countries, with low filing rates, can establish policies to encourage innovation by increasing the number of invention patents. In Brazil, for example, invention patent filings began to be considered in the evaluations of postgraduate programs from the 2017-2020 quadrennium onwards, causing several programs to substantially increase this indicator. An example of this movement is the increase in deposits within the scope of intellectual property management at the Instituto Militar de Engenharia (IME). According to data obtained from the IME Intranet[16], in the transition between the four-year assessment periods 2013-2016 and 2017-2020, patent filings rose from 2 to 21, representing a 950% increase.

For the use of patents in TRA to be effective, the strength and impact of each patent document must be considered, based on existing fields in the associated databases. A patent is considered strong and impactful when it is negotiated and/or widely cited. Negotiated patents have a high likelihood of being used in products, implying high maturity. Those that are highly

16 https://intraime.ime.eb.br/propriedade-intellectual.html

cited pave de way for technological routes. In this way, we can see that it is not enough to carry out merely quantitative work, as invention patent deposits can indicate both low and high maturity, as well as insignificant technological impacts, even for the ones that establish new technological routes and that can support disruptive innovations. To obtain more assertive results with this data source, it is essential to complement quantitative analyses with qualitative ones.

In summary, there are many open questions regarding the use of patents in TRA. One possible direction, as introduced in the previous paragraph, would be to employ automated tools to explore existing fields in patent databases.

5.3 Advantages and disadvantages of TRA approaches

In addition to the differentiation regarding the use of the TRL scale (section 5.1), some differences can be seen regarding the way in which the technology/product is evaluated within the techniques presented. To summarize all the observations made throughout section 4, Table 2 is presented below, which summarizes the main advantages and disadvantages of each of the TRA approaches.

Table 2 – Advantages and disadvantages of the TRA techniques presented

		Advantages	Disadvantages
- Team of experts		- Deeper analysis - Greater flexibility	- Greater subjectivity - Higher cost - Slower process
Auxiliary tools (more closely related to the *stricto* approach)		- Possibility of inserting an institutional vision in the questions - Greater standardization during analysis	- Need for experts in formulating questions - Need for experts to answer questions
Automation (more closely related to the *lato* approach)	**Quantitative** (bibliometrics)	- Faster, as it does not analyze the content of documents - Lower cos	- Results are still subject to dispute in the literature - Difficulty in formulating a good search string
	Qualitative (text mining)	Lower cost and speed	- Need for documents that portray the real state of technology - Still little studied in the literature - Scarcity of public databases of labeled documents

Source: Prepared by the authors (2023).

It is important to note that the literature review carried out in this work showed that teams of experts and calculators are more commonly used in the context of the classic approach (strict sense). Automated TRA techniques, on the other hand, have been applied in the broad sense, more recent uses, and with a wide range of still-open questions.

6 FINAL CONSIDERATIONS

The TRL scale has become important in a wide range of areas and has been used by different segments—industry, academia, and government—in many countries. It allows for better communication between teams involved in an R&D project, as well as better monitoring of the evolution of a technology's maturity and reliability. In addition to its initial use, it has also been used as a tool in technology prospecting and management, seeking to estimate technological advances.

Given the scarcity of studies on the state of the art of forms of TRA using TRL, this article aims to contribute to filling this gap, analyzing different works on this topic.

In this study, 180 documents were analyzed, a set that was reduced when applying the inclusion criteria. In the end, regarding TRA, three approaches were identified, their positive and negative points.

The first makes use of a team of experts and uses these people's knowledge in relation to technology and the TRL scale in order to classify the level of technological maturity.

The second combines experts with auxiliary tools (calculators). In this way, the technology application expert answers a series of questions regarding the development of the technology. These questions, formulated in advance, can be defined or structured in order to incorporate the institutional vision in the evaluation process.

Finally, the third seeks to automate the process, by extracting information from publications related to a technology of interest. To do so, an artificial intelligence model is trained based on previously labeled examples. Then, new examples are presented to the model, for maturity classification purposes.

In relation to the existing gaps, it was possible to identify in the literature the existence of few works focused on TRA using text mining. This use could be in support of a calculator, as a way of validating the information provided, or even as an independent process. With the exception of Hrica *et al*. (2022), no public datasets were found that have a set of labeled documents, associating the technology present with a TRL level.

Still regarding the gaps identified in the study, we found that there are open questions related to the use of patents in TRA. One suggested direction was the use of automated tools to explore existing fields in patent databases.

Nevertheless, we intend to consider in future work conducting TRA analyses that combine the TRL scale with other scales, such as the Manufacturing Readiness Levels (MRL) (Wu *et al*., 2017) and the Commercial Readiness Level (CRL) (Gerdsri; Manotungvorapun, 2021), extrapolating the list of applications beyond R&D activities, the focus of this text.

Another little explored topic that could give rise to new research is analyzing how Technological Innovation Centers (NIT) are carrying out TRA to support R&D processes, accumulation of technological capacity and prioritization of scientific and technological development of the supported ICT.

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