The Watchful Waiting Strategy in Standard-Essential Patents: The Case of 5G Technology

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***Abstract*—In recent years, the relevance of communication technology has steadily been increasing. This technology is represented by technical standards as a means for faster technology diffusion and regulation. In turn, they are supported by standard-essential patents (SEPs) that protect inventions related to the standard and can be licensed as a pool. However, there is no standard-essentiality check, which induces patent applicants to declare either too many or too few patents as standard-essential. In this article, we address the latter deficiency and define a new patent strategy, namely the watchful waiting strategy. Here, patent applicants file patents that are very similar to SEPs without subsequently declaring them standard-essential. We use topic modeling and deep learning to assess SEPs and non-SEPs of 5G technology for standard-essentiality. The results provide information on the type of applicants holding watchful waiting patents. This entails several implications for companies, patent attorneys, and researchers, as the process model presented for identifying watchful waiting patents reduces the risk of patent litigation for companies wishing to use the standard. At the same time, rethinking the current process of SEP declaration opens up new avenues for policy makers and standard-setting organizations.**

***Index Terms*—Artificial intelligence, machine learning, patent strategy, real options, standardization.**

I. Introduction

TECHNOLOGY is an important driver for companies to achieve competitive advantages. Based on the definition provided by [1], technology is described as a complex system comprising multiple entities or subsystems, each interconnected with at least one other entity in the system. In the context of technical standards, the relationship is evident through the role that standards play in shaping and governing the entities as well as the interactions within this complex system.

Technical standards serve as a crucial framework, defining common protocols, specifications, and benchmarks that guide the development, compatibility, and interoperability of various technological components. Standards create a structured environment for different technological entities to communicate and interact effectively within the system. They act as the "glue" that ensures seamless connections, cooperation, and coexistence between the diverse elements, which constitute the broader technology landscape. In essence, technical standards are the means by which technology entities establish a common language and understanding, enabling them to function as integral parts of the larger technological system, as per the multimode interaction perspective articulated by Coccia [1]. Technical standards exist for a multitude of technologies and are of crucial importance to the companies involved in their development [2].

The inclusive purpose of technical standards is quite opposite to the intention of patents. By definition, patents are legal rights to exclude others from using, manufacturing, or selling the protected scope of the patented invention [3]. Since both, technical standards and patents, are prevalent instruments in high-tech industries such as telecommunications, standard-essential patents (SEPs) have been established to compensate for the contrasting intentions. SEPs are pooled and licensed to third party organizations under "fair, reasonable, and nondiscriminatory" (FRAND) conditions in order to exclude unequal treatment of third parties and to prevent monopoly pricing by SEP holders [4]. However, there are no strict rules on how the level of FRAND conditions should be calculated. In the event of disagreement between licensor and licensee, a court decides on the level of FRAND conditions [5], [6].

Organizations are encouraged to declare patents standard-essential if they are essential to a particular technical standard. However, the requirements for this are not clearly defined, and no governing body enforces or prohibits the declaration [7].[1] Therefore, it happens that patents are declared standard-essential without really being essential to the technical standard (*false positives*), or vice versa (*false negatives*). These misclassifications are associated with a number of inefficiencies that particularly affect the patent licensing market. For example, falsely positive SEPs reduce the FRAND margins of truly positive SEPs, which entail serious welfare consequences. Falsely negative SEPs may increase the risk for organizations to pay FRAND licenses for a nonexhaustive technical standard that may eventually even infringe technically relevant patents. When companies develop and hold falsely negative SEPs, this is primarily a question of declaration timing. This reveals a fundamental research gap. Although the timing strategy for falsely negative SEPs is of great importance both for companies and for policy makers involved in setting or applying standards, it has not yet been investigated.

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[1] Whether the claims of a patent are standard-essential and the use of the invention protected by the patent is indispensable for the implementation of the technical standard is not examined by standard setting organizations.

Consequently, our study focuses on the SEP type of false negatives.[2] The litigation between Acer (plaintiff) and Volkswagen AG (defendant) dating from 2021 vividly demonstrates one facet of the inefficiencies that may arise from falsely negative SEPs. In December 2021, Acer filed a lawsuit against Volkswagen for the unauthorized use of SEPs granted to Acer [9]. These patents were declared standard-essential at the European Telecommunications Standards Institute (ETSI) years after they had been filed and years after the related technical standard had been created. Accordingly, these patents may have gone unnoticed by competitors for quite a long time (due to not being declared standard-essential), until they suddenly became relevant, especially with regard to complex products involving a variety of technical standards.

We refer to patents that have not (yet) been declared standard-essential but are potentially relevant for the technical standard as *watchful waiting patents*. In analogy to the watchful waiter strategy originally introduced by Buchholz [10]—who suggested not being the first-to-market but take an approach of *waiting watchfully* instead—the *watchful waiting strategy for SEPs* is to delay the declaration for as long as possible in order to eventually take competitors by surprise. However, as standard-setting organizations neither examine whether a declared patent is suitable nor whether a patent may be a watchful waiting patent, there is as yet no method for the identification of watchful waiting patents. Consequently, the first research question that arises is:

RQ1*: How can watchful waiting patents be identified?*

For this purpose, our study relies on the combination of two state-of-the-art machine learning techniques. By means of unsupervised topic modeling, patent texts are transformed into a numerical patent vector space. Then, supervised deep neural networks are trained to distinguish patents that have already been declared standard-essential from patents that have not (yet) been declared as such, given the information of each patent topic vector. This method does not only serve to identify potential watchful waiting patent candidates but also contributes to the current debate on identifying standard-essentiality, for which both conventional text mining algorithms and expert assessments provide lower accuracy [8], [11].

Second, this study aims to explore the characteristics of patent applicants as well as patents that fall into the scope of the watchful waiting definition. As this strategy postulates highly competitive behavior and knowledge, we expect to find distinct characteristics, e.g., patenting experience or regions of origin, to be more decisive for the watchful waiting practitioner than for other strategy types in relation to SEPs (e.g., [12]). Furthermore, we draw upon the signaling strategy [13], expecting that patents which fall into the scope of the watchful waiting definition maximize search costs for competitors in order to remain undetected. Consequently, the second research question that arises is:

RQ2*: What unique characteristics can be identified in organizations that appear to apply the watchful waiting strategy, and what characteristics do their patents have?*

The rest of this article is organized as follows. Section II comprises background information on technical standards as well as SEPs. Section III outlines the watchful waiting strategy and related propositions. Section IV contains the methodology for identifying watchful waiting patents and for testing the propositions. Section V provides a concise presentation of the findings, including company-relevant insights into the strategy by means of a case example. Finally, conclusions are given in Section VI.

II. Background of Technical Standards and SEPs

Technical standards and SEPs have become more prominent in recent scientific discussions. Nonetheless, this section aims to provide some background information for readers who are not familiar with these concepts. It first addresses technical standards as a means for technology diffusion and regulation. Second, it provides information about SEPs, which are the foundation of a technical standard and thus determine its content.

Technical standards comprise rules that enable the interconnection of devices from different suppliers within a specific technology. This connectivity primarily occurs in the information and communications technology (ICT) industry, and every technology in this sector involves several technical standard documents. The benefits of technical standards are available to a wide range of stakeholders. While economic and social wealth is positively stimulated by technical standards [14], [15], [16], end users also benefit from them, as complementary products expand markets, thus leading to increased market sizes [17]. Furthermore, organizations usually apply one of two basic strategies in terms of technical standards: standard driving or standard accepting. Standard driving organizations are involved in the initial (and further) development of technical standards. They send experts to meetings of the standard setting organization and often belong to industries in which technical standards play a central role. In contrast, standard accepting organizations do not actively participate in the standard setting process. Nevertheless, they may be observing the development of standards very carefully, analyzing how these might influence their business. Standard accepting organizations often belong to industries that can be regarded as users rather than developers of standardized technologies.

The content of technical standards is based on SEPs. Patents are important instruments for securing the scope of protection for corporate inventions, especially in highly competitive fields of technology [18], [19]. The exclusive rights granted by patents are exactly the opposite of what is intended by technical standards. Licensing is the only way to make areas of technology protected by patents accessible to the public. However, to whom a company grants licenses remains a strategic management decision and is not subject to regulation. Consequently, it is obvious that competitors in particular grant only few licenses to one another, and if they do, then in the context of cross licensing, in which

[2]We refer to the recent study by Bekkers et al. [8] concerning falsely positive SEPs.

TABLE I
DECLARATION TIMING VERSUS RELEVANCE OF PATENTS RELATED TO STANDARDS

		Standard-essentiality	
		Substantial standard essentiality	*Negligible standard essentiality*
Declaration timing	*Early SEP declaration*	*Well-intentioned SEPs*	*Over-declared patents*
	Late or no SEP declaration	*Watchful waiting patents (Under-declared patents)*	*Well-intentioned non-SEPs*

Source: Authors

both or several companies gain access to a pool of patents [19], [20], [21], [22]. This pooling enables organizations to license all patents at once under FRAND payment conditions.

In addition to royalties, SEPs contribute to the patent owner's well-being in various other ways. The declaration of SEPs is strongly associated with a contribution to and influence on the related technical standard. Pohlmann et al. [14] empirically demonstrated a curvilinear relationship between standardization participation and corporate financial performance. In a more recent study, Deng et al. [23] observed positive effects of participation in the standard setting process on a company's implied cost of equity capital. Moreover, SEPs are more strongly patented on a global scale than similar patents that have not been declared standard-essential [4], [24] and are generally more likely to produce cumulative inventions than other patents [25], [26]. At the macroeconomic level, SEPs are found to affect the trade patterns of countries, particularly increasing exports and decreasing imports in the ICT sector [27]. Consequently, there is a large incentive for companies to declare their patents standard-essential [28].

III. PROPOSITION DEVELOPMENT

The current uncertainties of SEP declaration suggest four different declaration strategies, which are outlined in the following sections. Subsequently, prevailing issues in the SEP licensing market are presented. And finally, a strategy regarding the underdeclaration of SEPs is developed.

A. Typology of Principal Declaration Timing Strategies for SEPs

In addition to [29], who introduces basics strategies for SEPs, we use a specific typology for a better understanding of the standard declaration timing strategies. This typology is based on two dimensions: declaration timing and standard-essentiality. The declaration of SEPs may take place at an early stage, i.e., during or shortly after the development of the technical standard. Furthermore, patents can also be declared standard-essential years later (or not at all) at the standard setting organization. The standard-essentiality of patents, i.e., the extent to which they are relevant for a technical standard, may be either substantial or negligible.

Table I represents a 2-by-2 matrix showing four different SEP types.[3] *Well-intentioned SEPs* are declared during or shortly after creation of the respective technical standard and possess a scope of protection that is relevant for this standard. *Well-intentioned non-SEPs*, on the other hand, are not relevant for the technical standard and may be declared years later or even not reported at all. These patents may cover subcomponents of a technology that are not essential for the establishment of a standard. Both types are expected to mitigate transaction costs in the SEP licensing market due to decreasing information asymmetry while increasing transparency. However, transactions costs are significantly increased by the two remaining types. The overdeclaration of SEPs has been studied extensively in the past. *Over-declared patents* are declared to be standard-essential in a similar way to well-intentioned SEPs but do not protect an inventive scope that is relevant for the technical standard. Finally, *under-declared patents* are only declared as standard-essential after the introduction of the corresponding standard or not at all, even though they are of relevance to the technical standard contentwise.[4]

B. Inefficiencies Induced by Standard-Essential Patents

The patent system is characterized by information asymmetry, transparency deficits, and uncertainty about future events, all of which lead to inefficiencies [30]. This is particularly evident in fields of technology where the legal dimensions and boundaries of patents overlap to a considerable extent and patent thickets arise [31]. These patent thickets increase transactions costs for market participants as the scope of individual patents is uncertain. Moreover, patents are no exclusive rights per se; without clear evidence through judicial assertion, they merely give their owner the right to seek to exclude others [32].

SEPs are intended to mitigate these inefficiencies by, for example, reducing transaction costs for new entrants. However, recent research finds little evidence that the current SEP declaration process supports this intention [8], [33]. A general problem arises from the lack of a regulatory institution: Whether

[3]These strategies are not exclusive for an organization. Organizations may practice one, more than one or even all four strategies at the same or different time and technology fields.

[4]Transaction costs of searching for (hitherto) undeclared SEPs vary from case to case and are difficult to calculate, but are obviously substantial. Otherwise, there would be no cases such as Acer versus Volkswagen, in which the latter company accepted extremely high opportunity costs.

a declared patent is really more essential to the standard than a (hitherto) undeclared one is not determined by any governmental institution, since it does not affect the IPR policy of standard setting organizations [34]. The declaration is solely based on the knowledge and goodwill of the patent holders [11]. For this reason, organizations have the possibility of declaring more of their patents as standard-essential than is actually the case, resulting in a higher contribution to the technical standard and in potentially higher FRAND royalties [35]. Consequently, we suggest describing the licensing market inefficiencies of SEPs by the following function:

$$\begin{aligned} & SEP\ licensing\ market\ inefficiencies \\ & = f\,(Patent\ validity\ uncertainty, \\ & Patent\ scope\ uncertainty, \\ & SEP\ declaration\ uncertainty, \\ & FRAND\ royalty\ ratio\ uncertainty)\,. \end{aligned} \tag{1}$$

The combination of these four uncertainties leads to different strategic behaviors in companies. With particular attention to SEP declaration uncertainty, potentially opportunistic behavior by standard driving organizations has been found to lead to overdeclaration of SEPs [36], [37]. Research on 4G technology indicates that the share of truly SEPs ranges from 16.6% to 47.9% [34]. Furthermore, this strategy of overdeclaration has been found to be practiced even in standardization meetings for the sake of pushing boundaries [12]. This article, however, is aimed at analyzing the phenomenon of underdeclaration.

C. Watchful Waiting Strategy in Declaration Timing

Under-declared patents are not in the focus of recent research, although they contribute substantial transaction costs to the licensing market. We employ the analogy of the watchful waiter strategy as established by Levitt [38] and later improved by Buchholz [10]. This could be described as a business strategy, in which an organization deliberately and carefully adopts the practice of pioneering the development of a new product, but only launching this new product after another company has entered the market and opened it up to customers through advertisement and other means. Thereby, the organization reduces market entry risks and purposefully imitates competitors' products.

By analogy, organizations that practice the *watchful waiting strategy* in the SEP spectrum do not declare patents with a protected scope of relevance for the technical standards as standard-essential when the standard is being created but only years later. Thus, they circumvent the restrictive licensing rules under FRAND conditions and at the same time keep the door open for an SEP declaration until the standard is endorsed. In the meantime, other standard driving organizations, as well as users of the standard, have irrevocably committed resources to the implementation of the standard [11], [39]. As a result, watchful waiting patents can potentially generate similar license revenue as well-intentioned SEPs but with much lower risk for the patent holder and much higher transaction costs for users and competitors.

The strategy is reminiscent of a mousetrap: The standard with only a limited number of patents declared as standard-essential symbolizes the bait, which is as attractive for competitors and users as the bacon is for a mouse; the late-declared patents represent the snap mechanism that pushes competitors and users to higher than expected payments.

Patterns of the watchful waiting strategy are examined on the basis of two propositions: First, research studies show that high-tech organizations in particular are involved in the standard setting process. In addition, the propensity to patent appears to have a positively moderating effect on this relationship [12]. Furthermore, the business model and origin of an organization have been found to be decisive factors in declaring patents as standard-essential [7], [25]. All of this leads to our first proposition P1.

P1: *The watchful waiting strategy is practiced by organizations with experience in technology and patenting.*

Second, citing signaling theory [13], researchers argue that patents emit signals that may be utilized for a number of purposes. In general, signals can be characterized as "things one does that are visible and that are in part designed to communicate" [40, p. 434]. Consequently, patents produce signals in various forms. For instance, the application for a high-quality patent may attract venture capital funding [41], [42]. Moreover, signals concerning the number of patents per technology field and competitor may stimulate investment in research and development [43].

While these signals reduce information asymmetry, we expect watchful waiting patents to have the opposite effect: They increase information asymmetry. The intention behind watchful waiting patents is to avoid the attention of competitors or third parties. Hence, the holders seek to emit minimal signals by these patents while increasing the cost of searching for them. This leads to our second proposition P2.

P2: *Watchful waiting patents send out fewer signals to other parties in terms of readability and therefore incur higher search costs.*

IV. Research Method

Our research method is based on a sample from the 5G technology, which is also an important driver for other technologies. Variables are defined, particularly for the identification of the watchful waiting strategy. We combine unsupervised and supervised learning in a model to identify potential SEPs. Combining the variables in regression models allows insights into those companies that apply the watchful waiting strategy and into its characteristics in terms of readability.

A. Sample and Data

First, 5G technology is selected for a case study, and a list of granted SEPs and granted quasi-technology non-SEPs is created. 5G technology enables mobile communication by radio transmission for smartphones and other devices, based on cellular networks with high bandwidth that ensure fast data transmission with low latency [44]. It covers a wide range of application areas, such as the networking of cars [45], [46] or smart maritime logistics [47], which could not function autonomously without 5G technology. These application areas can be regarded as drivers of the technology [48].

5G technology is the successor to 4G technology, which had been the fastest telecommunication technology for almost ten years [49]. The development of telecommunication technology is driven by certain events, in this particular case Radio Access Network meetings held by the key players in the field, which lead to new releases. By regularly increasing the transmission volume and shortening the transmission time, there is no technological leap at a particular point in time but rather steady progress. This characterizes a sequential, incremental innovation progress that results in a radical new innovation, as explained in the theory of [50], [51].

5G technology is based on technical standards which, for instance, describe different protocols for communication. Technical standards are not only of great relevance for the telecommunications technology, they can also be found, for example, in data carriers, printers [52], video coding [53], and nonfungible tokens [54]. In contrast to these, the technical standards for 5G technology are supplemented by a large number of publicly available SEPs, which prompted us to select this particular technology for our case example.

The corresponding SEPs are retrieved by means of a keyword search in the ETSI "Intellectual Property Rights"' (IPR) database.[5] By setting the "keywords" filter to "5G – Cellular technology beyond LTE, IMT-2020 conformant," the "patent office filter" to "U.S.—United States,, the "essentiality state as declared by declarer' filter to "Essential," and by preprocessing in which, after the first patent, all patents of the same patent family are excluded, *1849 granted SEPs* relevant to 5G technology are identified.[6]

To identify quasi-technology non-SEPs, we use the patent classification scheme. Patents are categorized by patent examiners into patent classes to facilitate finding patents that cover similar technologies [55], [56]. The distribution of the SEPs' Cooperative Patent Classification (CPC) subclasses is concentrated in the subclasses H04B (18%), H04L (56%), and H04W (83%).[7,8] Accordingly, these subclasses are referred to in combination with the filing and issuance periods of the SEPs to search for a comparable set of patents in the United States Patent and Trademark Office Patent Full-Text and Image Database (USPTO PatFT).[9] A preprocessing is carried out in which, after the first patent, all patents of the same patent family and all patents declared as standard-essential at ETSI in any technology, e.g., 3G, 4G, or 5G, are removed. This produces 421 695 granted non-SEPs and 423 544 granted patents in total.

B. Measures of Variables

In order to model watchful waiting patents, we operationalize the previously proposed typology. While information on declaration timing is publicly available, the quantification of the extent to which a patent is standard-essential remains an open issue in research. Prior research relies on expert assessment [8], [36], quantitative assessment based on citation data [57], or pairwise similarity coefficients between patent and standard documents [11]. However, expert assessment is found to be unsuitable for large patent volumes, and recently proposed that computation-based methods do not accurately capture standard-essentiality.

Therefore, a method based on unsupervised and supervised machine learning is proposed in the following section to distinguish between declared and undeclared patents as well as the extent of their respective standard-essentiality. In particular, we operationalize watchful waiting patents as patents that have not (yet) been declared as standard-essential, although they cover fairly similar technological features as declared SEPs.

We then extract further variables and construct regression models. These additional variables include applicant characteristics and patent readability as well as disruptive factors that may affect the regression models. The descriptive statistics of all variables (except control variables) are shown in Appendix D.

Our main source of applicant characteristics is the "Disclosed Standard Essential Patents" (dSEP) database [25].[10] The dSEP database contains harmonized data regarding more than 40 000 patent disclosures as well as details on the origins and business models of the respective applicants. In total, the database lists 333 different applicants that have declared at least one patent to be standard-essential. Therefore, it can be assumed that each of these applicants is familiar with the standard setting process.

Matching patent applicants from different databases certainly is no easy task. This "name game" is a well-known challenge in working with patents. We rely on two different sources to standardize applicant names. First, we extract disambiguated applicant names from PatentsView.org [58]. According to PatentsView.org, their disambiguation methodology achieves 100% precision and 98% recall. To increase the recall rate, further applicant information is retrieved from the public dataset used by [59]. Specifically, we manually scan the list of 333 applicants for truncations and spelling errors, match misspelled applicants with unique disambiguated identifiers, and finally determine that 238 distinct applicants from the dSEP database can be isolated through the disambiguation process.[11] This disambiguation process reduces the initial patent sample

[5]https://ipr.etsi.org/DynamicReporting.aspx, last accessed July 28, 2022.

[6]We choose patents from the USPTO because the market for the technology at hand is highly relevant it the US and the legal system enables an effective enforcement of patents. Both requirements help ensure that nearly all relevant SEPs are part of the US patent system.

[7]Definitions of the CPC subclasses can be found on the official CPC website: https://www.cooperativepatentclassification.org/cpcSchemeAndDefinitions/table, last accessed July 28, 2022.

[8]The subclasses overlap but also complement each other. In total, 1831 SEPs (99%) are classified in at least one of the three subclasses.

[9]Search query: CPC/(H04B∗ OR H04L∗ OR H04W∗) AND APD/01/02/1997->12/31/2019 AND ISD/01/02/1997->01/12/2021

[10]We used the latest version 1.3 (February 16, 2016).

[11]To validate this process, we drew a random sample of 665 patents from the final sample to assess the precision, and another random sample of 665 patents from the full sample to assess the recall of the disambiguation process. The size of these samples is adequate to capture the actual value of precision and recall within ±5% of the measured value with a confidence level of 99% [60]. Both manual inspections yielded 0 false positives and 0 false negatives, resulting in an estimated precision and recall of 1 with ±5% within the 99% confidence interval.

to 226 845 patents, of which 44 309 are classified as watchful waiting patents.[12]

The matched applicant names are used to determine the extent to which applicants have already filed patents, i.e., whether they have *patenting experience*. Using data from PatentsView.org, the cumulative number of patents per applicant is calculated for each filing year up to the focal calendar year [61].

Furthermore, dummy variables are generated that indicate the origins of the patent applicants, in particular where their organizations' headquarters are located. We create origin variables for *China*, *Europe*, *Japan*, *South Korea,* and the *U.S*. The remaining regions are summarized under the variable *Others regions* as they are clearly underrepresented individually. This applies to Canada, Israel, and parts of Asia other than China, Japan, and South Korea.

The dSEP database also determines by which business model the applicant's organization is best characterized. Bekkers et al. [25] distinguish nine different business models, such as "pure upstream knowledge developer" or "components." We follow the lead of Kang and Bekkers [12] by reducing these nine categories to a single dummy variable indicating organizations that have an *upstream business model* (type 1–4) and those that do not (type 5–9).

To determine the extent of knowledge about the standardization process, a dummy variable is constructed that indicates whether or not the applicant holds an *ETSI* membership. As the dSEP is our main data source for applicant information, all applicants in our sample happen to have experience with the standardization process. However, only a subsample holds an ETSI membership that suggests a higher level of knowledge about the standardization process in general and at ETSI in particular. To construct the related variable, we retrieve a list of ETSI members, containing 897 organizations located around the world that are entitled to participate in standard meetings and thus contribute to the creation of technical standards.[13]

We include two control variables which allow us to adjust for other factors that affect the regression results. Annual particularities are controlled by computing dummy variables for the *filing year* [62]. In addition, we control for technology subclasses by computing dummy variables for each of the *WIPO-35 technology classes* [63].

Patents emit various signals that can be used to promote strategic business decisions. Amplification of these signals may be intended by patent holders for the sake of drawing attention to the patent or the organization. However, it may also be the case that organizations try to emit as few signals as possible to increase search costs and attract less attention. Specifically, these signaling effects are modeled by means of patent readability.

The factor of readability indicates how easily understandable a patent text is formulated. A patent text that is more difficult to understand is associated with higher search costs, which means that the patent's content is not immediately apparent. A patent's abstract is not submitted to a particularly strict review by the examiners since they mainly focus on the claims [64]. Consequently, the applicant can make a strategic decision regarding the complexity level of the abstract. Although readability variables are primarily used for scientific texts, they are increasingly being adapted in current patent literature (e.g., [63], [65]). As there are hundreds of different readability measures, we calculate *abstract readability* based on the five most widely used, tested, and reliable variables, according to [66]: the Flesch Reading Ease (FRES), the Flesch–Kincaid Grade Level, the Gunning Fog, the Simple Measure of Gobbledygook, and the Dall-Chall metric. For details on definition and calculation, we refer to [66]. In addition, we apply some transformations to the variables. Since readability is directly related to the FRES metric but inversely related to the other metrics, the other metrics are multiplied by -1 so that a higher score always means better readability. In addition, each metric is scaled with a min–max scale and multiplied by 100 so that 0 always indicates minimum readability, while 100 indicates maximum readability.

C. Model for the Assessment of Standard-Essentiality

Fig. 1 depicts the four-step process model for finding watchful waiting patents. We operationalize them as (yet) undeclared but similar to already declared SEPs.

In the first step, data are extracted as described above.

In the second step, unsupervised topic modeling is employed to capture the thematic distribution of each SEP and non-SEP [67]. This method is widely used in recent literature (e.g., [68], [69], [70], [71], [72]) and relies on the cooccurrence of observed words in different patents to derive two probability distributions: the distribution of topics per patent and the distribution of words across topics [73]. The distribution of topics per patent is exploited in this study, as it allows the transformation of each patent into a T-dimensional numerical vector.

All patent claims and description texts are retrieved, concatenated, converted to lower case, and preprocessed according to the steps commonly found in the literature (e.g., see [62]). First, components that consist of numbers or single letters only are removed. Second, stop words of low information value are eliminated. These are identified by means of four different sources: the Natural Language Toolkit (NLTK), the Fox [74] "Stop List for General Text," and the Arts et al. [75] stop word list, as well as a list of patent-related stop words by the USPTO. The result is a composite list of 32 965 unique stop words.[14] Third, all words that only appear in a single patent are removed as these are probably spelling errors. Fourth, stemming is applied

[12] A contingency analysis was carried out, cross-tabulating the patents of both datasets with being classified as watchful waiting patents. It shows that only 13 600 of 196 874 patents are classified as watchful waiting in the remaining patents of the full dataset. The chi-squared test is statistically significant, indicating that watchful waiting patents are more likely to belong to the 238 applicants who are familiar with the standard-setting process than the others.

[13] https://www.etsi.org/membership, last accessed May 15, 2022

[14] https://patft.uspto.gov/netahtml/PTO/help/stopword.htm, last accessed July 28, 2022

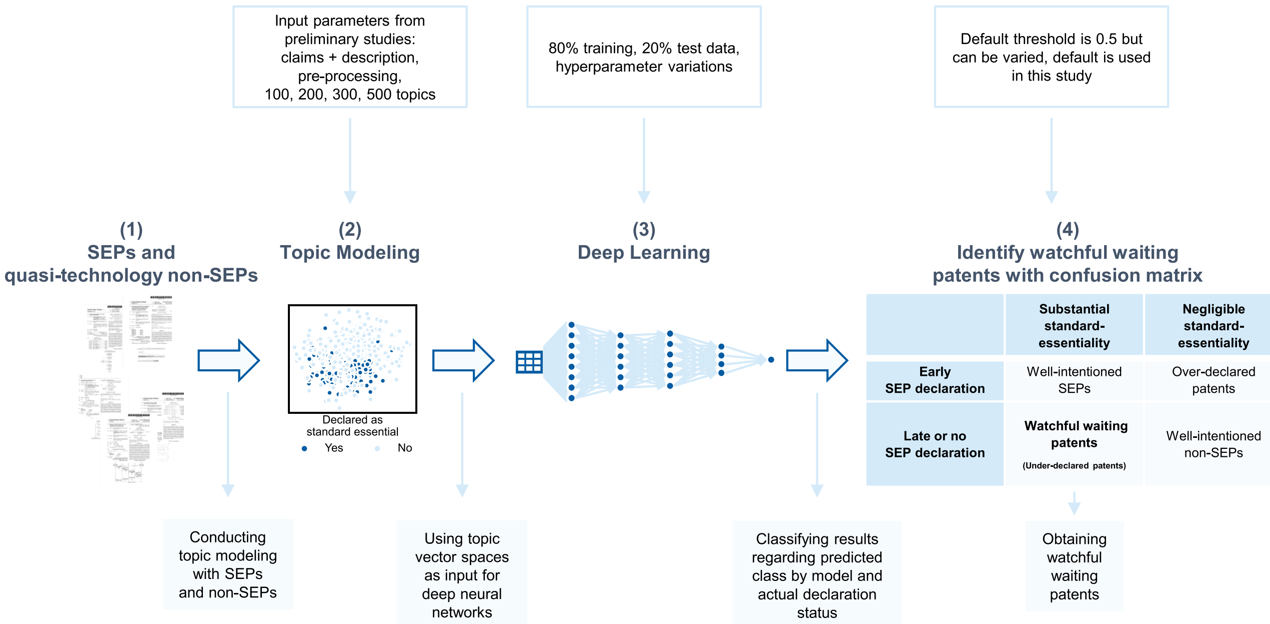

Fig. 1. Machine learning process for the identification of watchful waiting patents. Source: authors.

to each remaining word by means of the PorterStemmer [76] implemented in the NLTK library. At the end of the preprocessing procedure, each patent is represented by a sequence of word stems. These word stems are then used to conduct various topic modeling experiments, varying in the number of topics T. Conclusively, a 200-dimensional topic model is selected, which allows displaying all patents in a tabular data format.[15] Further information on this is to be found in Table VI in Appendix A.

In the third step, deep learning (DL) algorithms are employed to capture latent differences within the topic distribution of SEPs and non-SEPs. Specifically, this step aims to solve a classification problem formulated as follows: To what extent can an algorithm distinguish between an SEP and a non-SEP based solely on the topic distribution of the individual patents? Supervised machine learning algorithms are suitable for solving this problem as well as many others, such as identifying relationships in data [78], [79], [80]. However, there are some major differences between the algorithms. In particular, it is generally acknowledged that there is an inherent conflict between performance and explicability: the most intuitive algorithms, such as logistic regressions or decision trees, often perform worse than more sophisticated but less intuitive algorithms such as neural networks [81], [82].

Because of the complex classification problem, we accept the deficiency in interpretability and make use of complex neural networks.[16] More specifically, we use the so-called deep feed-forward neural networks (henceforth deep neural networks), which represent the most common architecture in DL and are particularly useful for tabular data [83]. DL algorithms are usually developed in three phases, namely the data preparation phase, the learning phase, and the evaluation phase [84].

In the data preparation phase, stratified random sampling is used to create a holdout dataset containing 20% and a training dataset containing 80% of the patents. Stratified random sampling ensures a similar distribution of SEPs and non-SEPs among both datasets [60]. Next, z-score standardization is applied to the training dataset and adapted to the test dataset in order to reduce computational resources and enable the deep neural network models to converge more quickly [62], [85]. In the learning phase, deep neural networks are trained on the basis of the 80% training dataset. A comprehensive set of individual hyperparameters, e.g., the number of layers or units within each layer, is constructed [86].[17] Hyperparameter tuning, i.e., finding the optimal hyperparameter composition according to an evaluation

[15] A preliminary study was conducted to identify key factors that affect the performance of downstream classification models. In this study, the 1849 SEPs were matched to 1849 non-SEPs similar in content according to the similarity measure proposed by [77]. The study establishes the combination of patent claim and patent description to be the most effective for enhancing the performance of classification algorithms. In addition, different quantities of topics are used as a basis, e.g., 10, 50, 75, 100, 200, 500, and 1000. A total of 200 topics appear to be the most effective with regard to the performance of the classification algorithms. Lastly, pre-processing does not affect the performance in any positive or negative way. However, since the study shows that preprocessing reduces topic modeling processing time by a factor of three, we use preprocessing to accelerate the computing process.

[16] We actually tested less complex machine learning techniques, i.e., decision trees, random forests, support vector machines, or shallow neural networks (one hidden layer). However, these techniques were not able to capture those patterns concealed in the topics that may indicate whether or not a patent has been declared standard-essential.

[17] Despite the findings of the preliminary study with regard to optimal topic modeling settings, we also tested the number of topics for the deep neural networks for 100, 200, 300 and 500 topics. Pearson and Spearman correlation tests are significant to the 0.01 level for all topics; still, the best performance is achieved with 200 topics.

TABLE II
CONFUSION MATRIX OF BEST PERFORMING DEEP NEURAL NETWORK

		Predicted condition	
		SEP	**Non-SEP**
Actual condition	**SEP**	1696 *Well-intentioned SEPs*	153 *Over declared patents*
	Non-SEP	57 909 *Watchful waiting patents*	363 961 *Well-intentioned non-SEPs*

Source: Authors

metric, is conducted by means of a random search with fivefold stratified cross validation [87], [88]. The performance of each trained model is assessed by means of the receiver operating characteristic area under the curve (ROC AUC) score, which is suitable for imbalanced datasets [89]. In the evaluation phase, the generalization abilities of the deep neural network models are assessed. This is particularly important for determining whether or not a model appears to be either ovefitting or underfitting the data [90], [91]. We then test the trained neural network models on the holdout dataset. The deep neural network with the best performance reaches a 0.89 ROC AUC score on the training dataset and a 0.88 ROC AUC score on the holdout dataset. Hence, the model's performance is rated as close to *excellent* or *outstanding* [92], [93]. A detailed supervised machine learning report card, which contains all relevant information on the DL process, is presented in Table VII in AppendixB.

In the fourth step, each patent is classified according to the best performing model, and a confusion matrix is created. The two-by-two confusion matrix in Table II shows that the model predicts 153 falsely positive and 57 909 falsely negative patents. Falsely negative patents fulfil our definition of watchful waiting patents. They have not (yet) been declared as standard-essential, but cover similar topics as the SEPs to such extent that state-of-the-art deep neural networks are unable to distinguish between watchful waiting patents and SEPs. Consequently, the dummy variable *watchful waiting* is created, being 1 if the patent belongs to the identified watchful waiting patents and 0, if it does not.

D. Data Analysis Procedure

The derived propositions are tested by means of different multivariate regression analyses.[18] To test proposition P1, logistic regressions are employed, using the *watchful waiting* variable as a dependent variable. Accordingly, the basic model is assessed to identify the determinants for explaining the likelihood of watchful waiting

$$P\left(\text{watchful waiting}\right) = \frac{1}{1+e^{-z}} \tag{2}$$

$$\begin{aligned} Z = {} & \beta_0 + \beta_1 \times \text{patenting experience} + \beta_2 \times \text{detailed origin} \\ & + \beta_3 \times \text{business model} + \beta_4 \times \text{ETSI membership} \\ & + \theta_1 + \theta_2 + \ \varepsilon \end{aligned} \tag{3}$$

[18]For information on the development of statistical formulas, see [94].

where β_0 denotes the constant term, β_1 denotes the coefficient of the *patenting experience*, β_2 denotes the vector of the coefficients of the individual *detailed origins*, β_3 denotes the *upstream business model* coefficient, β_4 denotes the *ETSI membership* coefficient, θ_1 denotes the *filing year fixed effects* coefficient vector, θ_2 denotes the *WIPO-35 technology classes fixed effects* coefficient vector, and ε denotes the error term.

To test proposition P2, OLS linear regression is employed, using the *readability* variable as a dependent variable

$$\mu\left(\text{readability}_i\right) = \beta_0 + \beta_1 \times \text{watchful waiting} + \theta_1 + \theta_2 + \varepsilon \tag{4}$$

where $\mu(\text{readability}_i)$ denotes any readability metric i mentioned in Section IV-B2), β_0 denotes the constant term, β_1 denotes the coefficient of the *watchful waiting* variable, θ_1 denotes the *filing year fixed effects* coefficient vector, θ_2 denotes the *WIPO-35 technology classes fixed effects* coefficient vector, and ε denotes the error term.

V. FINDINGS

The following sections contain the results of the regression analysis. We first present insights into applicant characteristics, followed by signaling characteristics of watchful waiting patents. To illustrate the practical relevance of our watchful waiting strategy, we present a case example of a company that applies this strategy.

A. Findings Regarding Applicant Characteristics

Table III lists the regression results of the unique applicant characteristics that are decisive for the watchful waiting strategy. We find that all constructed applicant characteristics variables are relevant for distinguishing patents subject to the watchful waiting strategy. The overall fit of the model that contains all variables, measured by the McFadden´s pseudo R-squared, amounts to 0.1965, which is close to very good [95]. First, *patenting experience* appears to affect likelihood in an inverted U-shaped relationship. Second, organizations from outside the U.S. are more likely to practice the strategy, with the coefficients being most pronounced for *South Korea*, *Europe,* and *Japan*.

TABLE III
LOGISTIC REGRESSION RESULTS OF APPLICANT CHARACTERISTICS, ESTIMATING THE LIKELIHOOD OF WATCHFUL WAITING STRATEGY APPLICATION

Variables	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***	***(7)***	***(8)***
Patenting experience								
Lg2 (patenting experience +1)	0.0166*** (0.003)	0.6208*** (0.031)		0.7084*** (0.035)		0.7230*** (0.035)		0.6531*** (0.034)
Lg2 (patenting experience +1) squared		-0.0248*** (0.001)		-0.0303*** (0.001)		-0.0308*** (0.001)		-0.0297*** (0.001)
Applicant region								
China			1.0506*** (0.023)	0.9162*** (0.025)		1.0195*** (0.025)		0.8877*** (0.026)
Europe			1.1821*** (0.016)	1.1128*** (0.017)		1.1991*** (0.018)		1.2100*** (0.018)
Japan			0.8286*** (0.018)	0.9224*** (0.018)		1.0241*** (0.020)		1.0792*** (0.020)
South Korea			1.5325*** (0.018)	1.6573*** (0.019)		1.7365*** (0.020)		1.6953*** (0.020)
Other regions			0.8953*** (0.032)	0.8312*** (0.034)		0.9036*** (0.034)		0.9841*** (0.035)
Business model								
Upstream business model					-0.5555*** (0.013)	0.1827*** (0.017)		0.1647*** (0.017)
Experience with technical standards								
ETSI membership							0.6575*** (0.018)	0.6555*** (0.019)
Filing year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
WIPO-35 technology classes fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
McFadden's pseudo R-squared	0.1400	0.1439	0.1857	0.1907	0.1479	0.1912	0.1464	0.1965
N	226 845	226 845	226 845	226 845	226 845	226 845	226 845	226 845

Source: Authors
Note: We use logistic regression with the watchful waiting variable as a dependent variable. Standard errors are robust and given in parentheses. *** p<0.001. Robustness checks which neglect the filing year fixed effects, the WIPO-35 technology classes fixed effects, or both and use a Probit regression model instead of the Logistic regression model as shown here, remain largely robust. Furthermore, one company (we call it company X) holds around one third of the patents, which are declared as SEPs. In order to check if our results remain stable, we did the regression analyses for the applicant characteristics again without the patents of company X. The results show only a small effect and stay robust for all variables. Information regarding patenting experience is taken from PatentsView.org. The applicant regions are extracted and grouped based on the dSEP database by [25], and US is set as baseline variable. Information on the business model is also extracted from the dSEP database. Information on experience with technical standards is taken from etsi.org.

Third, organizations with a focus on *upstream business models*, e.g., software or software-based services, additionally increase the likelihood of the strategy being practiced. Finally, expert knowledge of the standardization process expressed through *ETSI membership* further contributes to the explicability of strategy likelihood.

B. *Findings Regarding Signaling Characteristics*

The results in Table IV refer to readability and show that watchful waiting patents represent a more complex reading. Each readability metric has a negative coefficient, which means that the reader must possess a high level of education to understand the text. To put it differently, the structure of watchful waiting patents comprises more words in fewer sentences and is therefore more intricate and complex.[19] The rather low McFadden´s pseudo R-squared compared to the analysis of applicant characteristics can be explained primarily by the structure of the patents. These exhibit a high degree of standardization in terms of wording. Nevertheless, they show an influence of

[19]As robustness check, we did the analyses for information on more simple metrics, such as number of words, number of sentences, and number of long words. Results show the same effect and are significant to the 0.001 level.

TABLE IV
REGRESSION RESULTS OF READABILITY

Variables	***Flesch Reading Ease (13)***	***Flesch-Kincaid Grade Level (14)***	***Gunning Fog (15)***	***Simple Measure of Gobbledygook (16)***	***Dale-Chall (17)***
Watchful waiting	-0.0029 (0.033)	-0.2492*** (0.032)	-0.3998*** (0.032)	-0.9157*** (0.056)	-0.4562*** (0.037)
Filing year fixed effects	Yes	Yes	Yes	Yes	Yes
WIPO-35 technology classes fixed effects	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.023	0.025	0.027	0.031	0.026
N	226 845	226 845	226 845	226 845	226 845

Source: Authors
Note: We use linear OLS regression to estimate readability. Standard errors are robust and given in parentheses. *** $p < 0.001$.

the independent variable on the dependent variable, which is statistically significant.

C. Case Example

While the regression analyses describe the influence of variables on the watchful waiting strategy in general, we would like to use a specific company from our dataset to validate the results and present a case example. Company X in question is a multinational electronics corporation headquartered in Asia. Its business model is reflected in "Equipment suppliers, product vendors, system integrators." It has an ETSI membership and is highly experienced in patenting. This company underpins the general findings of our regression analysis as it displays most of the characteristics of a watchful waiting applicant. It is also one of the applicants that contribute a particularly high quantity of patents to our dataset, holding the largest number of SEPs with a share of 33.21% (614 of 1849). Furthermore, this company is also ranked in the Top 5 of our watchful waiting patents dataset with a share of 8.58% (3803 of 44 309).

Two points in time are crucial for the analysis of the watchful waiting strategy: the date of the patent grant and the date of the declaration as standard-essential. While the former is known for all patents, the latter is only known for those patents that have already been declared standard-essential. Another relevant factor is the time that elapses before the technical standard is created. The requirements for the 5G standard are regulated in IMT-2020; the proposal period for the standard extends from October 3 to 11, 2017 and from July 9 to 17, 2019. Based on this, we define three time periods: "Pre IMT-2020" for the time before, "Proposals for IMT-2020" for the time during, and "Revision of IMT-2020" for the time after the creation of the technical standard, i.e., when it has been implemented. Fig. 2 depicts the lapse of time between the dates of granting and declaration in the case of the aforementioned company X. To examine its watchful waiting strategy, we compare watchful waiting patents with the SEPs in our dataset and, more importantly, with the company's SEPs.

In terms of the granting and declaration dates, there are five categories that may be applicable. First, the company receives the patent grant before the proposals and issues the declaration during proposals. Second, the company receives the grant during the proposals and also issues the declaration during proposals. Third, the company receives the grant before the proposals and issues the declaration after the completion of IMT-2020. Fourth, the company receives the grant during the proposals and issues the declaration after the completion of IMT-2020. Fifth, the company receives the grant after completion of IMT-2020 and also declares the patent standard-essential after that. Companies pursuing the watchful waiting strategy own patents that were granted before, during, or after the completion of IMT-2020 but refrain from declaring them standard-essential (at least up to the analysis).

Most SEPs (1358 of 1849) are granted before the proposals, whereas 590 are declared during the proposals and 768 after the completion of IMT-2020. Looking at company X, two points stand out.

First, company X is obviously a standard-driving organization. The majority of patents with grant dates before the proposals and declaration after the completion of IMT-2020 are attributable to this company (416 of 768). Furthermore, it only holds four of the 590 patents granted before the proposals and declared during the proposals. For company X, the time lapse between the grant and the declaration as standard-essential is generally around 4.5 years. Company X has a habit of waiting for the technical standard to be established before it declares its SEPs. Thus, the time lapse between the granting date and the

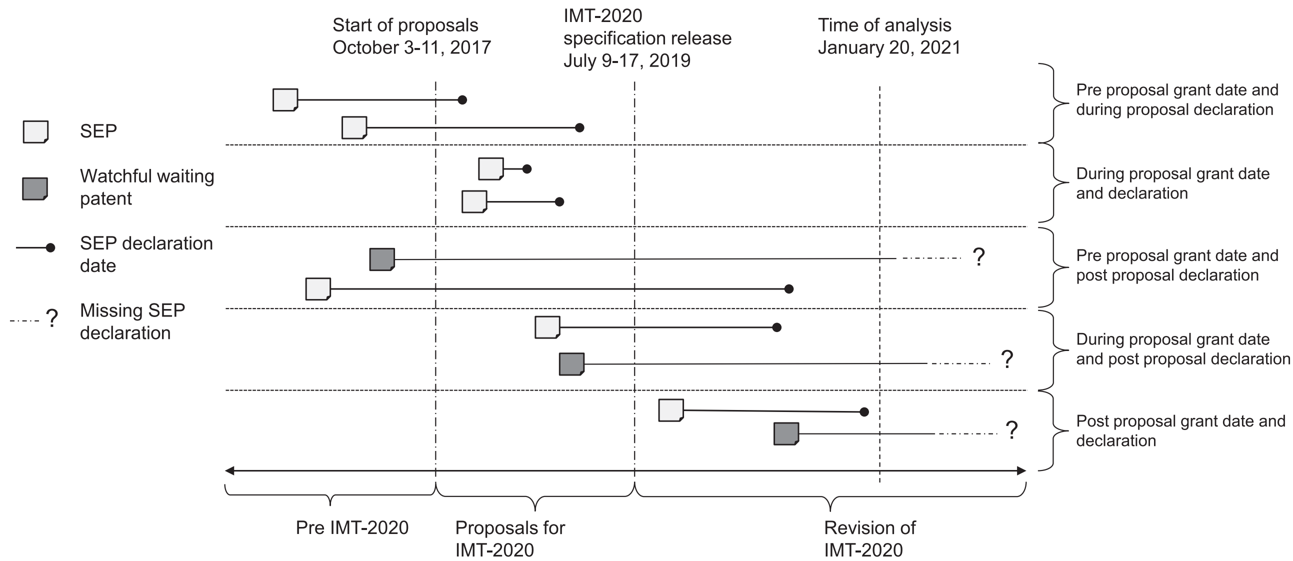

Fig. 2. Relation between declaration date and grant date for company X. Source: authors.

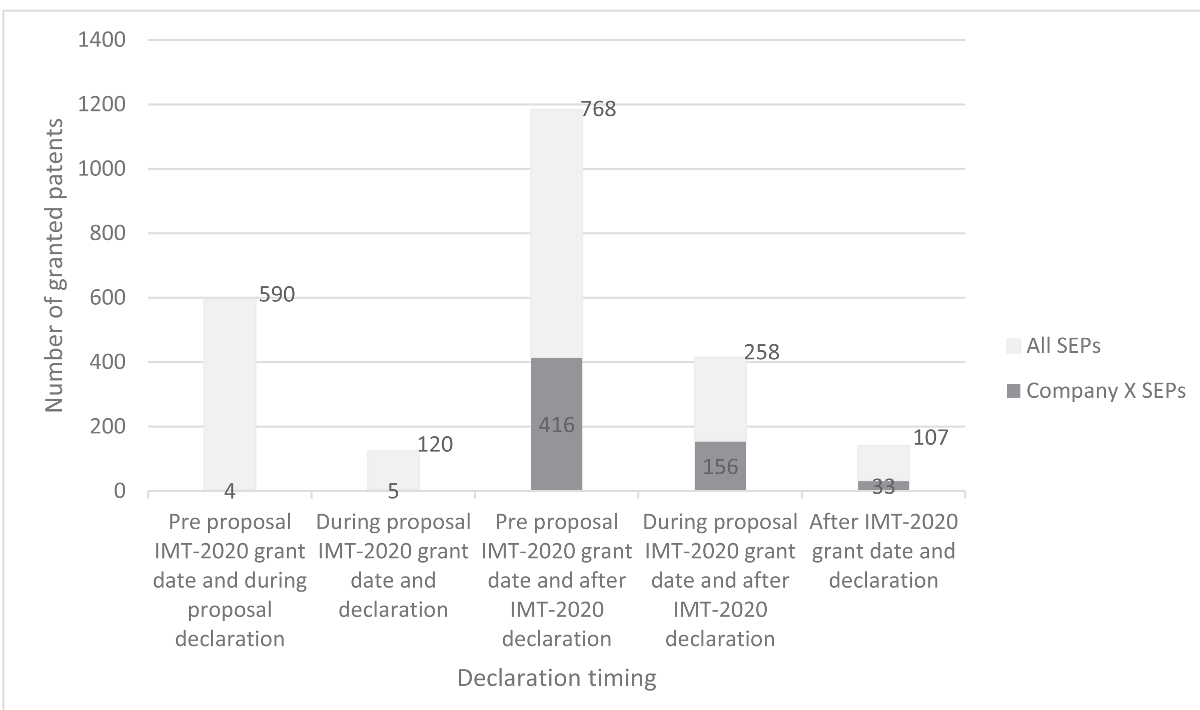

Fig. 3. Comparison of grant date and declaration timing of SEPs between all companies and company X. Source: authors.

declaration date supports the proposition of the watchful waiting strategy; company X does not follow a “just-in-time” patenting strategy as introduced by Kang and Bekkers [12]. The distribution of all identified SEPs and company X´s SEPs is presented in Fig. 3.

Second, however, company X also pursues the watchful waiting strategy. It does not declare all its patents as standard-essential; in fact, the majority remains undeclared. Within our dataset, the company holds 12 930 patents that have not been declared as standard-essential. Among these patents, our process model manages to identify 3803 watchful waiting patents that are more similar to SEPs on the textual level than to non-SEPs. Here, more than half (2196 of 3803) of the watchful waiting patents were granted before the proposals. Consequently, these watchful waiting patents, in particular those connected to a time lapse of approximately 4.5 years between granting and declaration, provide an incentive for further investigation.

VI. Conclusion

The main findings of this study are summarized in Table V. We contribute to theory and method application as well as to practical approaches.

From a theoretical point of view, we define a new patenting strategy for SEPs, the watchful waiting strategy, in which patents related to SEPs are not (yet) declared standard-essential. This opens up a new perspective, as other authors such as in [8] and [96] focus on the assessment of declared SEPs (and not on undeclared ones). This is of theoretical importance, as changes in a technology are often based on changes in the relationships between the technology´s entities [51], and these relationships are often specified in a technical standard. Risks in the building blocks of a standard, namely the SEPs, lead to risks in the standard, which in turn leads to risks in the change in technology. In addition, we provide a timing framework to improve the understanding of SEP strategies. Based on this, scholars could explore further causal links between watchful waiting or interaction effects and other patenting strategies, e.g., by examining whether the strategies go hand in hand with "just-in-time" patenting [12]. Furthermore, the patent strategy of watchful waiting can be regarded as a real options strategy [97], [98]. Watchful waiting practitioners have the option to declare their patent as standard-essential, if this is necessary or useful. The underlying asset of this option is the value of the royalty that could be obtained for an SEP in this technology under FRAND conditions, which may vary in the course of time according to the diffusion of the standardized technology. The price for the option is the value that the watchful waiting company only receives at the time of declaration. Consequently, in practicing watchful waiting, an organization may choose to make use of the patent as such (without declaring it standard-essential) or carefully observe the development of the standardized technology and decide to act at the appropriate moment (see also the analysis of timing in disclosing standard related patents by means of an evolutionary game model [99]).

From a methodical perspective, we extend previous research as described by Bekkers et al. [8] with an automated approach and develop a new method for detecting SEPs and non-SEPs. This method combines topic modeling with DL and considers the similarities between already declared SEPs and potential SEPs.

Our contribution to management and policy is fourfold. First, our basic contribution consists in the concept of watchful waiting patenting. This helps managers understand the behavior of companies that engage in standardization with a specific strategy. Managers in companies owning patents that are potentially standard-essential can apply the watchful waiting strategy in a deliberate way, thus increasing their companies' competitive advantage. Second, we provide a model for identifying potential watchful waiting patents. By using our model, patents can be automatically evaluated and examined for potential standard-essentiality. It is possible to shift the threshold that determines whether a patent is classified as standard-essential. This allows addressing the detectable false positives and false negatives step-by-step, starting with a high threshold and gradually moving to lower thresholds. This is particularly interesting for users of a standard, as they are given the possibility of assessing how many potentially SEPs may be under the radar and which organization owns them. Third, the related knowledge supports the risk management of standards users, enabling them to secure their competitive advantage by estimating license fees that may be demanded later [96]. Furthermore, knowledge of SEP characteristics helps to avoid potential patent disputes by introducing watchful waiting patents at an early stage of the licensing process [100], [101]. Fourth, policy makers, especially those responsible in standard setting organizations, could be encouraged to reconsider the current SEP declaration process and adapt the examination standards of the established patent offices, which, although certainly not flawless, can serve as the initial framework for an appropriate examination procedure of a standard setting organization. A regulated declaration could have a positive effect on nations' or a regions' competitive advantage and innovation output, similar to environmental regulations [102].

At this point, we would like to address some limitations of our study that are primarily related to the data. First, a sufficiently large dataset of SEPs and non-SEPs must be available for the implementation of our method. Second, as the 5G technology in question is still relatively new, not all patents that are part of a technical standard have yet been declared standard-essential. Consequently, SEPs are declared with a time delay, which means that not the entire normative part of all technical standards is represented by SEPs. Third, when creating of the database, we carried out a keyword search for 5G technology. However, the 5G standard comprises approximately 500 technical specifications—for which reason not all SEPs of this technology were considered in our study. Fourth, patents declared at ETSI are considered to be truly standard-essential, although they may actually include non-SEPs as there are cases of overdeclaration [37]. Fifth, despite manual revision, data for the regression analyses are not available for all patents. Sixth, although it is possible to adapt our process model to other technologies, this entails the necessity to renew the topic modeling and retrain the neural network. In addition, a different type of patent search must be carried out in connection with technological characteristics such as greater interdisciplinarity [103].

Finally, our work opens up potential for further research. All the patents we considered, whether SEP or non-SEP, were granted. In this regard, the analysis could include a comparison of patent applications and granted patents to determine whether there are differences in classification, with subsequent analysis of the texts used. Furthermore, the watchful waiting patents we identified can be compared with existing technical standards. In practice, this is done with the aid of claim charts that compare the content of claims with sections of the technical standards [104]. Our analysis takes place at a time when 5G technology is established on the broad market but is still relatively new. Repeating the analysis at a later date could increase the number of SEPs in the dataset, leading to insights into which watchful waiting patents will later be declared SEPs.

TABLE V
SUMMARY OF THEORETICAL, METHODICAL, AND PRACTICAL CONTRIBUTIONS

Type of contribution	**Explanation**
Theoretical contribution	Development of concept of the watchful waiting strategy
	Development of a framework of relationship between declaration timing and standard-essentiality of patents
	Identification of applicant characteristics of users of the watchful waiting strategy
	Identification of patent characteristic of watchful waiting patents
Methodical contribution	Combination of topic modeling and DL for the assessment of standard-essentiality
	Assessment of standard essentiality by means of a patent-to-patent rather than a patent-to-technical standard approach
Practical contribution	Automated assessment of standard essentiality of declared SEPs
	Automated assessment of standard essentiality of potential not (yet) declared SEPs

TABLE VI
PARAMETER SETTING OF PRELIMINARY STUDY

Parameter	**Parameter settings**
Compared patents	$Compared\ patents\ \epsilon\ \{'\boldsymbol{SEPs\ and\ time\ matched\ non-SEPs}', '\boldsymbol{SEPs\ and\ text\ matched\ non-SEPs}'\}$
Number of topics	$T \in \{5, 25, 50, 75, 100, \mathbf{200}, 300, 500, 1000\}$
Preprocessing	$Prep\ \epsilon\ \{'no\ preprocessing', '\boldsymbol{preprocessing}'\}$
Patent part combinations	$Combined\ parts\ \epsilon\ \{'title\ and\ abstract', 'claims', 'description', '\boldsymbol{claims\ and\ description}', 'title\ and\ abstract\ and\ claims', 'title\ and\ abstract\ and\ claims\ and\ description'\}$

Source: Authors.
Note: Bold type refers to the final parameters from the optimization in the preliminary study.

APPENDIX

Appendix A contains information on a preliminary study conducted regarding a small patent dataset to prioritize parameters for classification. Appendix B lists the supervised machine learning card of the best performing algorithm.

A. Preliminary Study Results for Parameter Prioritizing

Results from a preliminary study show that the best parameters for predicting standard-essentiality may be topic modeling with 200 topics, preprocessing, using patent claims and descriptions. This preliminary study was conducted as follows: We selected the same database of SEPs and non-SEPs that was used in the present study. However, we divided the non-SEPs into two smaller groups to obtain a one-to-one match for each SEP. The first group was based on temporal-level-matching, in which each SEP is matched to a non-SEP with the same filing year and grant date, as first proposed by Jaffe et al. [105]. The second group was based on textual-level-matching, in which each SEP is matched to a non-SEP with the same filing year und highest Jaccard similarity, measured according to the title and abstract, as first proposed by Arts et al. [77]. We carried out LDA topic modeling with the parameter settings given in Table VI. The resulting vector representations were evaluated with the classification algorithms Decision Tree, Random Forest, XGBoost, Gaussian Naïve Bayes, k-nearest Neighbors, Ridge, and Shallow Neural Networks (with one hidden layer). While the algorithms performed well on this smaller dataset (ROC AUC up to 0.8513 for training and 0.8432 for test data for time matching, and ROC AUC up to 0.9594 for training and 0.6365 for test data for text matching), they appear to be incapable of capturing the patterns hidden in the data and tend to under- or overfit. By switching to neural networks that contain at least two hidden layers, i.e., the so-called deep neural networks, over- and underfitting effects were mitigated, eventually leading to strong performance results.

B. Supervised Machine Learning Report Card

TABLE VII
SUPERVISED MACHINE LEARNING REPORT CARD OF DL MODEL

<table>
<tr><th colspan="4">Model initiation</th></tr>
<tr><td>Problem statement</td><td colspan="3">Predict whether (1) or not (0) a patent has been declared an SEP in the 5G technology via deep neural networks based on
• declaration status as standard-essential at the ETSI or not and
• topic modeling with 200 topics trained on combined and preprocessed claim and description texts of declared</td></tr>
<tr><td>Data gathering</td><td colspan="3">All variables are computed on the basis of SEPs declared at ETSI and control patents from the USPTO for the target variable with information regarding declaration status gathered from ETSI. Information regarding used patent parts and preprocessing are based on preliminary studies.</td></tr>
<tr><td>Data distribution</td><td colspan="3">1849 SEPs (target = 1) and 421 695 non-SEPs (target = 0). 423 544 patents in total.</td></tr>
<tr><td>Sampling</td><td colspan="3">No sampling</td></tr>
<tr><td>Data quality</td><td colspan="3">No missing values</td></tr>
<tr><td>Data preprocessing methods</td><td colspan="3">Standardization (z-score)</td></tr>
<tr><td>Feature engineering and vectorizing</td><td colspan="3">No additional features</td></tr>
<tr><th colspan="4">Performance estimation</th></tr>
<tr><td rowspan="14">Parameter optimization</td><td colspan="3">Yes</td></tr>
<tr><td rowspan="3">Topic modeling</td><td>Number of topics</td><td>$T \in \{100, \mathbf{200}, 300{,}500\}$</td></tr>
<tr><td>Preprocessing</td><td>$Prep\ \epsilon\ \{'\boldsymbol{preprocessing}'\}$</td></tr>
<tr><td>Patent part combinations</td><td>$Combined\ parts\ \epsilon\ \{'\boldsymbol{claims\ and\ description}'\}$</td></tr>
<tr><td rowspan="8">Search space</td><td>Hidden layer number</td><td>$L \in \{1, \mathbf{2}, 3\}$</td></tr>
<tr><td>Hidden layer unit number</td><td>$U_1 \in \{8, 16, 24, \mathbf{32}, 48, 64\}$
$U_2 \in \{8, 16, \mathbf{24}, 32, 48, 64\}$
$U_3 \in \{8, 16, 24, 32, 48, 64\}$</td></tr>
<tr><td>Unit dropout rates</td><td>$D\ \epsilon\ \{\mathbf{0}, 0.25, 0.5\}$</td></tr>
<tr><td>Activation functions</td><td>$A\ \epsilon\ \{\boldsymbol{`relu'}\}$</td></tr>
<tr><td>L2 regularizer function of activation functions</td><td>$L2_A\ \epsilon\ ]0{,}1[$
$\mathbf{0.001}$</td></tr>
<tr><td>Optimization algorithm</td><td>$O\ \epsilon\ \{\boldsymbol{`Adam'}\}$</td></tr>
<tr><td>Optimizer learning rate</td><td>$L_O\ \epsilon\ ]0{,}1[$
$\mathbf{0.005}$</td></tr>
<tr><td></td><td></td></tr>
<tr><td>Search algorithm</td><td colspan="2">Random search</td></tr>
<tr><td colspan="3"></td></tr>
<tr><td>Data split</td><td colspan="3">Fivefold cross validation</td></tr>
<tr><td>Algorithm</td><td colspan="3">Deep neural network with at least two hidden layers</td></tr>
<tr><td>Sampling</td><td colspan="3">80% training, 20% test</td></tr>
<tr><td>Performance evaluation</td><td colspan="3">ROC AUC score on training data: 0.8900
ROC AUC score on test data: 0.8783</td></tr>
<tr><td colspan="4">Note:
Bold italic writing indicates a problem characteristic or choice from the report card.
Bold writing indicates final parameters from optimization.</td></tr>
</table>

Source: Authors, template taken from [106].

Acknowledgment

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