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Research Article

Analysis of Business Method Patents in Türkiye: Trends and Inter-Relationships with Technology Fields

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ABSTRACT

Business Method Patents (BMPs) have been a considerable option for companies to get a competitive advantage in the market. This paper focuses on the BMP applications filed to the Turkish Patent Office within a certain time frame in order to reveal the recent trends and potential inter-relationships with technology fields by topic modeling with Latent Dirichlet Allocation (LDA) and International Patent Classification (IPC) network analysis approaches. For topic modeling operation, the abstracts of the BMPs are used while attributed IPCs for those BMPs are the main anchors for the IPC network configuration. The findings on the final dataset containing 897 BMP applications show that active applicants persistently include technical characteristics of their industrial domain in their BMPs. That behavior consequently causes the BMP trends to shift into the main fields of those proprietors.

Keywords: Latent Dirichlet Allocation, Business Method Patent, Topic Modeling, IPC Network.

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INTRODUCTION

Business methods have remained a controversial topic from the patent perspective.[1] Once it is clear that they are patentable should they fulfill the requirements of technical character and inventive step,[2] they provided an alternative and efficient way for inventors to protect their inventions. Patent data can be useful for especially companies if they want to monitor their competitive position in their field of operation which also allows the firms to manage their strategy.[3]

The usage of patent data to convey hot topics in a certain market has been studied to reveal the trends in the industry of interest.[4] When it comes to BMPs, using patent data for similar purposes is not an exception. Whether having a BMP would pose a competitive advantage in the market against a rival was also put forward.[5]

Data analytics performed on computing platforms were shown to be useful to examine patent data. For instance, Jain *et al.*,[6] used the open-source programming language R to exploit an advanced clustering technique and to understand the technological scope of the patent documents. Our study deals with the BMP applications in Türkiye to introduce the more recent trends along with the relationship between BMPs and other technology fields. In this paper, we use a systematic approach to analyze the patent data with R to answer the following questions:

What are the recent trends for national BMP applications?

How are BMPs affected by the business segments of the applicants?

Are BMPs accompanied by other technology fields?

LITERATURE

A literature review was conducted to understand the researchers' efforts in the field of business methods.

Jiang *et al.*,[7] used patent citations to determine knowledge flows from the software-based BMPs. In the paper, the authors utilized the BMP applications filed to USPTO . To come up with the software-based BMPs, they made use of certain keywords to narrow down the set of applications associated with Class 705 dedicated to business methods. A patent social network analysis was performed to locate the firms in terms of the number of citations they received. Therefore, the efforts of the authors were directed to a citation-based network scheme leveraging relative centrality measure to put forward the most prevailing actors in the knowledge flow based on the number of citations.

Moehrle *et al.*,[8] conducted a keyword search in the USPTO database to obtain the patents related to Radio Frequency Identification Device (RFID) technology. Among the records, they put aside the Class 705 BMPs to make a comparative analysis

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with technological patents and to find out whether technological innovations of the firms are accompanied by business methods using the semantic and informetric approach. In particular, they attempted to list persistent patent assignees in terms of the number of patent applications filed in order to figure out whether there is a link between corresponding business methods and RFID technologies.

No *et al.*,[9] also tackled the topic of knowledge flows from business methods. Having obtained the data from USPTO Class 705, they performed patent citation analysis and text mining to identify the knowledge flow patterns within the business methods.

Lee & Sohn[10] aimed to reveal the trends in financial BMPs. They opted for LDA to be used in patent abstracts as the choice of topic modeling technique. The topics were classified as "hot" or "cold" to differentiate between the trend themes and unpopular ones for a particular year. To categorize the topics, they used the probability threshold approach. Dataset used in the paper was retrieved using certain subclasses of USPTO Class 705 and G06Q/40 IPC group.

Chang *et al.*,[11] attempted to figure out the technology diffusion and classification of BMPs. After retrieving USPTO Class 705 patents, the authors built a patent citation network to demonstrate the linkage and performed a hierarchical cluster analysis to classify the basic patents.

Although there are studies that utilized topic modeling techniques and social networks, in the previous studies, to our best knowledge, there has not been any research to present the recent trends in BMPs by using a topic modeling technique as well as a file-based IPC network scheme. In more detail, previous studies either rely on social networks, exemplarily based on the number of patent citations, or topic modeling to present various aspects regarding BMPs and technology fields. As discussed in the upcoming sections, our study combines both approaches to answer the questions addressed in the introduction. In that sense, it creates a road map for Intellectual Property Rights (IPR) specialists, which is to be used for BMP strategy planning for a variety of technology fields based not only on topic modeling but also on the file-based IPC network. Therefore, the structure used in our study constitutes a double-check mechanism for a set of BMPs regarding corresponding inferences that may emerge from the results presented by both approaches.

METHODOLOGY

The established methodology is composed of three subsections; data retrieval and degradation, topic modeling, and the IPC network scheme. The flowchart of the procedure is given in Figure 1. The procedure can be traced widely in the next subsections.

Data Retrieval and Degradation

We first start with retrieving BMP applications from the Turkish Patent Office database. The main method is listing the files with at least one G06Q IPC class, and then extracting the abstracts and IPCs assigned to those files. The BMPs need to satisfy the following criteria for us to present the more recent trends:

The BMP application is to be filed after 2017.

The Search Report of the BMP application is to be published before 2022.

Criterion (ii) is purposefully included for the data degradation because BMPs, and Computer-Implemented Inventions (CII) in general, are susceptible to suffering from the first of the "two hurdles".[12] which means that the invention associated with a business method does not possess a technical character and, for that reason, is not patentable. Criterion (i), on the other hand, is used to select the BMPs with effective filing dates going back as early as to beginning of 2017 as it denotes the date of entry into force of the new code of industrial property (i.e. Code 6769) in Türkiye. This criterion provides a procedural unity for the BMP applications retrieved for the study in which all the files are pertinent to the same industrial property code in terms of prosecution phases and communications dictated by the national office. Furthermore, criterion (ii) provides a more strict IPC check since the examiners may alter the initial IPC codes during the preparation process of the search report. That is, an initial IPC assigned by a formalities officer for a particular application may be subject to a change after an extended analysis of that application by an examiner. In this regard, our approach is expected to improve the reliability of the data since the alteration of the IPC codes is not likely to be different from the ones apparent in the search report for the remaining phases of the patent prosecution process. The year 2022 is set to indicate the starting point of this study as well as to limit the time frame. However, mechanisms of the study are not dependent to a specific checkpoint of time. A practitioner may implement the techniques used herein to update the results with more extended or more restrained datasets by tuning the time frame without departing from the scope of this study. However, the practitioner may be forced to track the changes within the IPC system in order not to suffer from the complexity of the classification of the BMPs. For example, if the practitioner sets a beginning date in which the current IPC scheme is not in effect, then it may be difficult for the practitioner to determine the IPC codes associated with the BMPs.

As denoted, in order to obtain BMP applications, we consider the files having at least one IPC with G06Q subclass.[13] This preference is not a considerable bias. Nevertheless, it may have a slight impact on the results due to the potential existence of BMP applications that are not associated with G06Q IPC subclass. Another effect of this assumption may arise from the core of the invention forming a patent application such that an examiner may opt-in to assign one or more different IPC codes for the application despite the invention having notions of a business method.

Topic Modeling

It has been explained multiple times that topic modeling, specifically LDA is useful for patent data, although having certain drawbacks common in most machine learning algorithms.[14] Patent abstracts are good candidates to infer the topics hidden in them. Therefore, we implement LDA[15] operating on patent abstracts. Figure 2 depicts plate notation of LDA.

A shaded box annotated with "w" is the only observed variable in the notation while others stand for the hyperparameters and latent variables. LDA is a preferable tool for extracting latent topics from patent abstracts which results in dimensionality reduction and it also has the generalization ability that the other contenders such as Latent Semantic Analysis (LSA) and probabilistic Latent Semantic Analysis (*p*LSA) lack.[16] LDA is to assign a probabilistic mixture of generated topics into the patent abstracts known as the LDA's mixture modeling capability. That is, the method assigns multiple topics to each document with a probability score and models the document collection.

Despite its wide use-fields including patent data, LDA, as a topic modeling technique, may be considered a notorious tool from some aspects. To begin with, LDA is an unsupervised machine learning technique, which makes it, in turn, a tool difficult to evaluate in an automated manner. Therefore, a practitioner may turn to consult domain expertise rather than only quantitative methods to generate and interpret the topics including an evaluation of the validity/plausibility of the topics. Where applicable, our study attempts to combine both quantitative and qualitative methods in order to come up with arguably more plausible results, rather than relying on one of these modalities.

IPC Network Scheme

The final dataset of BMPs comprises 897 patent applications based on the criteria given in Section 3.1. It is common for patent applications to have multiple IPC codes assigned by examiners. In our dataset, we categorize the IPC codes per application as "Business Method" and "Relevant Technology Field" (if exists) according to their assigned IPC codes. We find out that, out of 897 BMPs, 433 distinct applications have links to relevant technology fields with a total of 590 connections, signaling a plurality of relevant technology fields for some BMPs. The IPC dataset is formed by applying the following algorithm given in Figure 3 for each file.

Figure 3 depicts a method to determine a IPC group of a BMP application along with an IPC subclass (i.e. 4 digits) of a relevant technology field, provided that there is an assigned IPC different from G06Q subclass and its diffractions. The left side of Figure 3 shows that BMP IPC codes (i.e. greater than 6 digits) are truncated into IPC groups (i.e. equal to 6 digits). We then check whether the BMP application contains multiple IPC groups. For example, whether a BMP application involves G06Q10 and G06Q40 IPC groups after performing the truncation. In such a case, we determine the IPC code of that application as "G06Q-Mixed", implying that the BMP application involves multiple G06Q IPC groups. In contrast, if we observe a single IPC group (e.g. G06Q10) for the BMP application after truncation, we determine that the IPC code is the observed IPC group (e.g. G06Q10).

Although Figure 3 shows that the IPC code is one of G06Q10, G06Q20, G06Q30, G06Q40 and G06Q50, there are G06Q90 and G06Q99 IPC groups within the IPC scheme. Nevertheless, none of the BMP applications is associated with a single IPC group in our dataset. That is, the applications having such IPC groups are accompanied by another BMP IPC group without an exception, which effectively renders the determined IPC code for those BMPs as G06Q-Mixed.

The right side of Figure 3 reveals a process for determining an IPC code indicative of a relevant technology field. If a technology field IPC code (>4 digits) is observed for a BMP application, we truncate the code into an IPC subclass (=4 digits). In that way, a higher-level observation is made possible for an inquiry aiming to identify the technology fields linked with a respective BMP application. Truncation performed in accordance with the given algorithm also prevents sparsity of the data, thereby preventing an inquiry from suffering from lack of observations.

Analysis

Data analysis is performed in R under the sections of text preprocessing, topic modeling with LDA, and file-based IPC network as discussed in the previous section.

Text Preprocessing

The first step of modeling is to perform conventional text preprocessing steps including lower-case conversion, removal of common stopwords in the Turkish language, and lemmatization. We *normalize unigram* tokens with listed known approaches. Lemmatization, instead of stemmization or no-operation approach, is preferred taking into account the size of our dataset because stemming may result in obscure wording due to its heuristic process and the no-operation approach is likely to diminish the frequency of identical terms due to suffixes. Besides, text preprocessing techniques may have a large impact on a model that attempts to provide accurate text classification.[17] Patent abstracts are an example of unstructured text. Therefore, erroneous separations of prefixes and suffixes of the tokens are consolidated beforehand so that prefixes and suffixes alone cannot represent a token to cause additional noise.

In addition to conventional preprocessing techniques to normalize the tokens, we carefully create an *in-context stop-words* dictionary for patent abstracts, for some non-informative terms in patent abstracts such as "*buluş*" (*invention*) or "*yapılandırılan*" (*configured*) are used quite often in the abstracts of national patent applications. We find it essential to eliminate the corpus-specific stopwords not to suffer from the possible noise in the generated topics.[18] In the next step, we make use of the Turkish constituency parse treebank[19] derived from the English Penn treebank[20] as the lemmatizer and the final stage is to implement the LDA model.

Certain drawbacks can be attributed to lemmatization, such as computational expense compared to stemming. Stemming, on the other hand, faster and time-saving technique in natural language processing. Considering the dataset size and the nature of the language, we assume that using lemmatization is critical due to Turkish being an agglutinating language. This character of the language allows for generating a variety of words from a single stem, each word implies a different meaning, and potentially, a different technical field within the context of patents. Although lemmatization is expected to lead to more sensible outcomes than stemming, the results may still be affected by other characteristics of the language, such as homonymic words. However, we expect such effects to have very limited impact on the findings.

Topic Modeling with LDA

LDA is a powerful and widely used technique to extract topics from a document collection (i.e. corpus). We utilize *quanteda*[21] to quantitively analyze the patent abstracts and *topicmodels*[22] to fit the LDA model. In our study, the hyperparameters defined by the user are K and α where K refers to a positive integer denoting the number of topics and α refers to the Dirichlet hyperparameter.

One way to select the number of topics is to look at the perplexity measure. Using perplexity measure for evaluating how well the dataset in the hand is described by the statistical model is a common approach. The lower perplexity score indicates a better distinction among topics.[23] Thematic texts like journalistic texts tend to have lower perplexity when a lower alpha is assigned for the LDA model.[24] That approach may also apply to patent abstracts due to both restrictions on the length of patent abstracts and the patent abstracts also being thematic by their nature. Furthermore, patent abstracts often reflect the core of the corresponding invention by incorporating the features of the subject matter of the first independent claim.

However, it is worth noting that much lower α may damage the model since translating the parameter to the extremes would disturb the LDA's mixed-membership probabilistic model structure by pushing the model to behave as a hard-clustering mechanism. We compute 5-fold Cross-Validation (CV) to display the perplexity score against the number of topics, K. Number of folds can be increased to inject more granularity to the dataset. Nevertheless, a 5-fold CV is expected to reveal only subtle differences compared to a, for example, 10-fold CV in our dataset. 5-fold CV, on the upside, has less computational complexity.

Referring to Figure 4, we observe that assigning a lower α (5/K) than the default value (50/K) decreases the perplexity. Although Figure 4 shows a smooth decrease in the perplexity score for the higher number of topics, picking the highest K value is not recommended due to dimensionality. Instead, if locatable, looking for an *elbow point* would be a better option.[25] Yet, our graph shows no clear sign of such a spot due to smoothers. For our graph, locating a point from which the trajectory of an observable trend begins to decelerate can be a viable option. Nonetheless, it is also controversial to claim an exact point from Figure 4. It may be said that the trajectory of the trend seems to decelerate after K=20, and an arguably optimal K can be found between K=[20-30]. Therefore, we consult human interpretation and domain expertise, as the selection of K based solely on the perplexity score does not guarantee the optimal number of topics since there is no known analytical formula to calculate the best value for K. Furthermore, the perplexity score is known to have an unstable characteristic with varying results for even the same dataset once the selected seed is changed.[26] Human interpretation works differently from the evaluation of machines, because machines may capture nuances to come up with topics that are semantically less meaningful.[27] After careful consideration of face validity, we propose that α=5/K and K=24 give a more distinctive set of topics. Figure 5a and 5b presents the topics and their top terms. To come up with the values, we observe the deceleration trend as discussed and attempt to find a plausible value for K, which gives a set of topics differentiable from each other for a human patent specialist. Our proposal for the value of K includes subjectivity and other candidate values may also be attempted in exchange for increasing the dimensionality of the topic set for arguably better discernibility. However, each value for K inevitably contains a measure of subjectivity due to the absence of certainty within this context.

We determine the corresponding labels for the topics as shown in Table 1. The collection of top terms in a topic might be regarded as semantically ambiguous from the human perspective. Nevertheless, top terms alone do not strictly need to reveal a certain theme, although they are the best candidates for humans to come up with a relevant label. So, when it becomes difficult to generate a descriptive label for a topic by assessing the top terms, we utilize the peripheral terms displayed via LDAvis[28] to assign the label.

File-Based IPC Network

It is factual that individual patent applications may have multiple IPC codes belonging to different IPC classes. Although there have been several studies proposing an automated IPC code assignment for patent files,[29,30] most IP offices, if not all, continue to rely on examiners as patent classifiers. They manually determine the IPC codes of a file after an exhaustive examination of the indispensable components: description, drawings, and claims. Table 2 displays the BMPs grouped by business method

IPC code and the corresponding cumulative sum of connections with relevant technology fields. An instant takeaway from Table 2 would be that, G06Q90 and G06Q99 IPC groups are not preferred by examiners as singular BMP codes.

We consider the G06Q groups (6 digits) as the inventive class nodes (sources) and the non-G06Q IPC subclasses (4 digits) as the related technology field class nodes (targets). A weighted graph approach is adopted to indicate the node strength in the directionless network implied by the node size and edge width in Figure 6. That is, larger nodes with wider edges are considered to be stronger nodes compared to smaller ones with narrower connection widths. As the preferred layout of the social network of IPC codes the Yifan-Hu, a force-directed algorithm, is selected[31] and the node strength measure is used as weights.[32] In addition to creating appealing visualizations of a social network, Yifan-Hu algorithm also attempts to minimize overlapping portions of the nodes on a layout.

For a given network, G=<V, E> where V and E stand for the set of nodes and edges, respectively. Strength measured for node n_j can be simply given by $S_{n=}\kappa(n_j)$ where κ denotes the total number of connections of n_j in a non-directional graph.

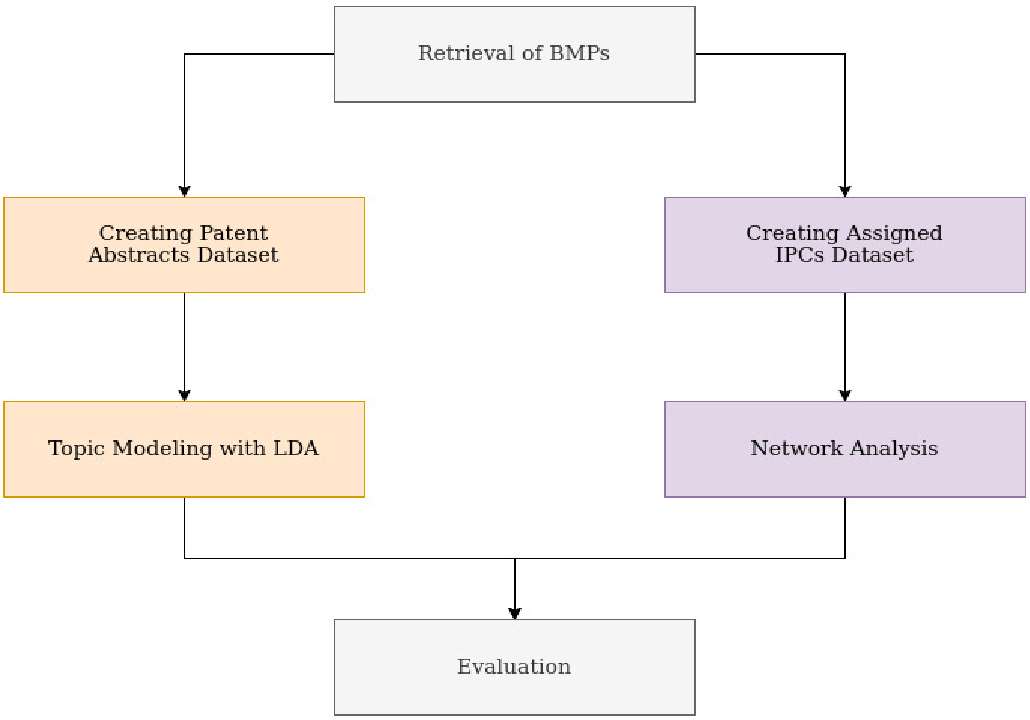

Figure 1: General Flowchart of the Study.

Table 1: Assigned labels for the topics generated by LDA.

Topic No	Label	Topic No	Label
1	E-commerce	13	Education Applications
2	Blockchain Technology	14	Stock Management
3	Artificial Intelligence	15	Market Investigation
4	General Payment Systems	16	Mobile Payment
5	Mobile Advertising	17	Information Presenting
6	Mobile Recommender	18	Risk Calculation
7	Employee Efficacy	19	Healthcare Services
8	Energy Tracking	20	Vehicle Tracking
9	General Data Processing	21	General Transportation
10	Banking Transactions	22	Mobile Applications
11	Customer Oriented Services	23	Virtual Reality
12	Mobile Entertainment	24	Business Administration

Table 2: The number of total connections of BMPs with relevant technology fields categorized by IPC code.

IPC Code	Total Number of Connections
G06Q-Mixed	88
G06Q10	175
G06Q20	70
G06Q30	140
G06Q40	8
G06Q50	109

Table 3: Definitions of the non-G06Q IPC classes having the most connections.

IPC	Definition
G06F	Electric digital data processing
G06K	Graphical data reading
G06N	Computing arrangements based on specific computational models
H04L	Transmission of digital information, e.g. Telegraphic communication
H04M	Telephonic communication
H04W	Wireless communication networks

Table 4: Top three applicants in terms of total applications filed.

Applicant	Total BMP Applications
Turkcell teknoloji araştirma ve geliştirme anonim şirketi	336
Türk telekomünikasyon A. Ş.	34
Vodafone teknoloji hizmetleri A. Ş.	25

Per these findings, we create the file-based IPC network as displayed in Figure 6. Open source application Gephi[33] is used to visualize the network. The IPC network in Figure 6 depicts centralized target nodes denoting relevant technology fields. The reason for those nodes to be placed more centrally compared to other target nodes lies in the fact that bounding of those technology fields to multiple BMP fields (i.e. sources). In that sense, it is observable that the centrally placed technology fields may be relevant to different fields of BMPs, potentially indicating a versatile use case for business method inventions. The target nodes placed in the peripherals, on the other hand, imply that such technology fields are only relevant to certain business methods, potentially indicating a specific use case for business method inventions. As discussed, the size of the nodes represents the frequency of the observations while the edge width represents the number of links observed between any selected node-pair.

When it comes to the examiner's perspective, it is possible to observe slightly different IPC preferences for similar applications of the same technical field. Moreover, it was reported that different IP offices attributed different IPC codes to member applications of the same patent family[34] in which each member contains the same or at least very similar content. Therefore, we emphasize that our IPC network depends on the examiners' choices of IPC codes for national BMPs.

RESULTS AND DISCUSSION

We present our findings on the national BMPs obtained during the analysis section. The file-based IPC network demonstrates that the IPC classes for relevant technology fields with the highest number of edges are G06F, H04W, H04L, G06K, G06N, and H04M, respectively. The definitions for those IPC classes according to the IPC system are given in Table 3 in alphabetic

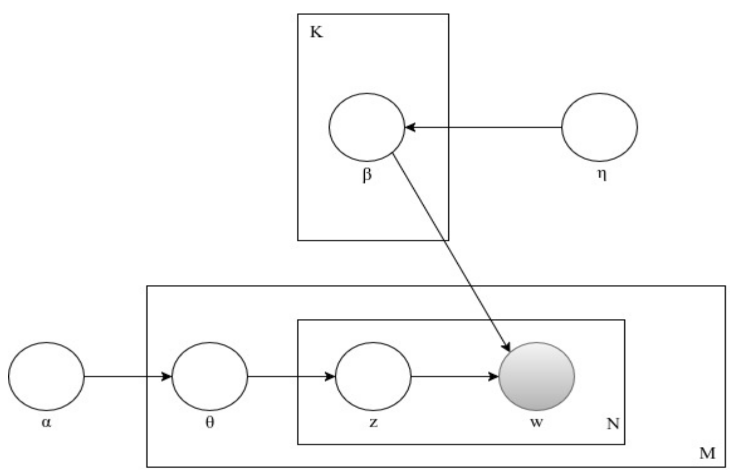

Figure 2: Plate notation of LDA as in the original publication. The symbols refer to as follows: α: Dirichlet hyperparameter; θ: Per document topic proportion; β: Topic; η: Topic hyperparameter; z: Per-word topic assignment, w: Observed word; N, M, K: The number of words per document, documents, and topics, respectively. Plate boxes indicate replicates.

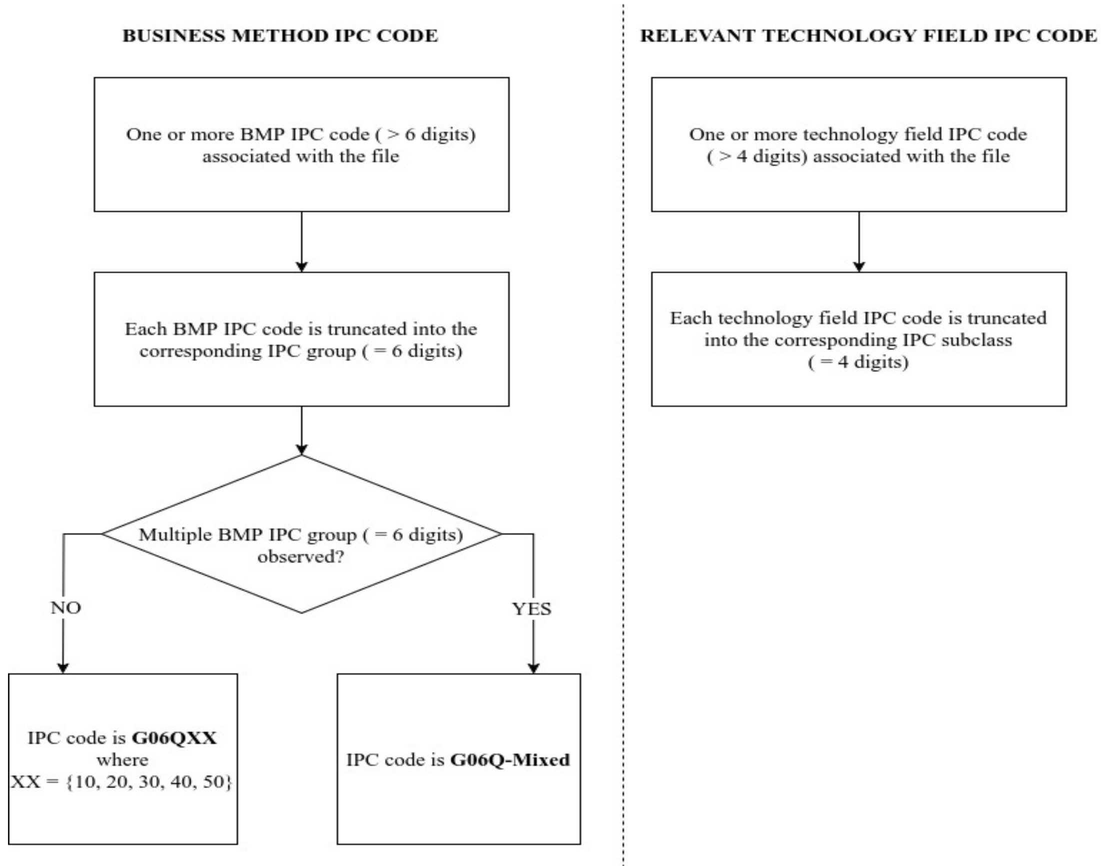

Figure 3: Algorithm of the determination process of the IPC codes of a BMP.

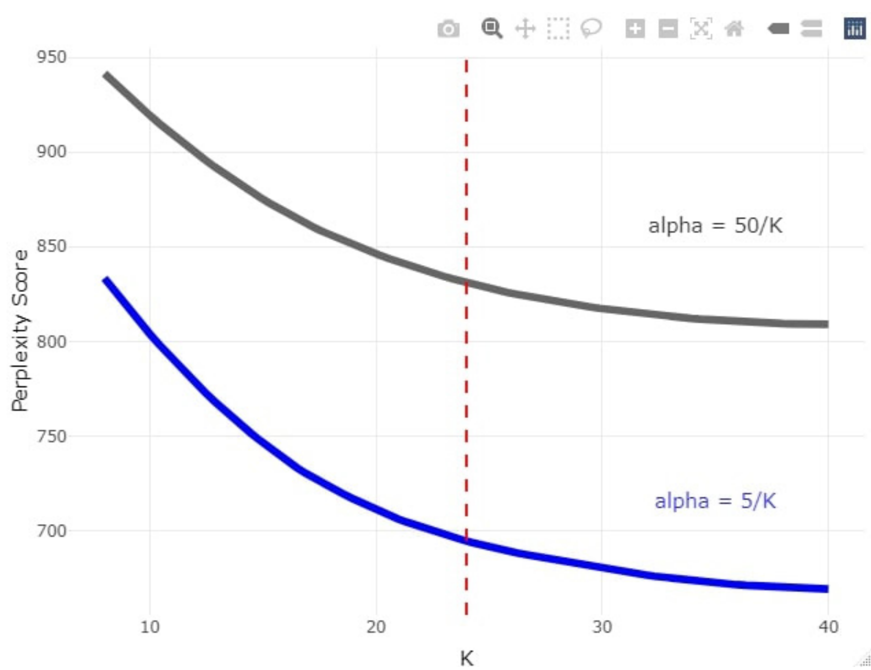

Figure 4: Perplexity score with five-fold cross-validation for α (alpha)=50/K (default) and α (alpha)=5/K (as proposed in Jacobi *et al.*, (24)) where the vertical dotted line denotes K=24.

Figure 5a and 5b: LDA-based generated topics with the most persistent terms and their probability distributions. In-parentheses terms stand for the English counterparts of the equivocal terms in Turkish.

order and in agreement with the WIPO's IPC publication scheme.[35] G06F subclass displayed as the most connected field by business methods is barely unexpected. Actually, business methods were presented as a subsection of the G06F subclass in the previous version of IPC.[36] Accordingly, BMPs exploit the data processing methods and practices introduced within the G06F subclass, maintaining close contact with its former parent subclass. On the other hand, H04 subclasses (i.e. H04L, H04M, H04L) manifesting as three of the most connected technology fields in the IPC network drive us to look for parameters that might have affected the inference. From the topic labels given in Table 1, we ascertain that five of the topics are directly linked to mobile systems.

Table 4 displays the top three applicants in terms of number of BMP applications filed. All three companies listed are globally known telecommunication companies serving as mobile network and internet service providers. The applications filed by the top three constitute approximately 45% of the BMPs in the dataset. In fact, the top applicant has a comfortable margin to end up establishing 37% of the BMPs.

Therefore, we conclude that applicants are more likely to embed technical features of their field of operation into their BMPs. If there are dominating proprietors in terms of the total number of filed BMP applications, then the overall BMP trends are inclined to be more associated with the field of operation of those applicants. Besides, from a low-level perspective, an IPR strategist should keep an eye on whether BMP is accompanied by a technology field and if so, whether this technology field forms a major aspect of the operational field of the patent applicant. An intellectual property policy within the scope of patents may be developed based on such monitoring performed to reveal a link between the BMPs, technology fields, and operation area of the corresponding patent applicants. A competitive advantage may be derived from creating or deriving potential connections among those key anchors, which may lead to a well-structured patent policy for BMP inventions.

We filter the data by a rule-based approach where only BMPs with published search reports are allowed to show up in the dataset. By this means, we mitigate a potential issue of dynamic IPC alteration by the office. That is because an IPC change by an examiner is less likely to be observed after the careful examination of the application to prepare a search report.

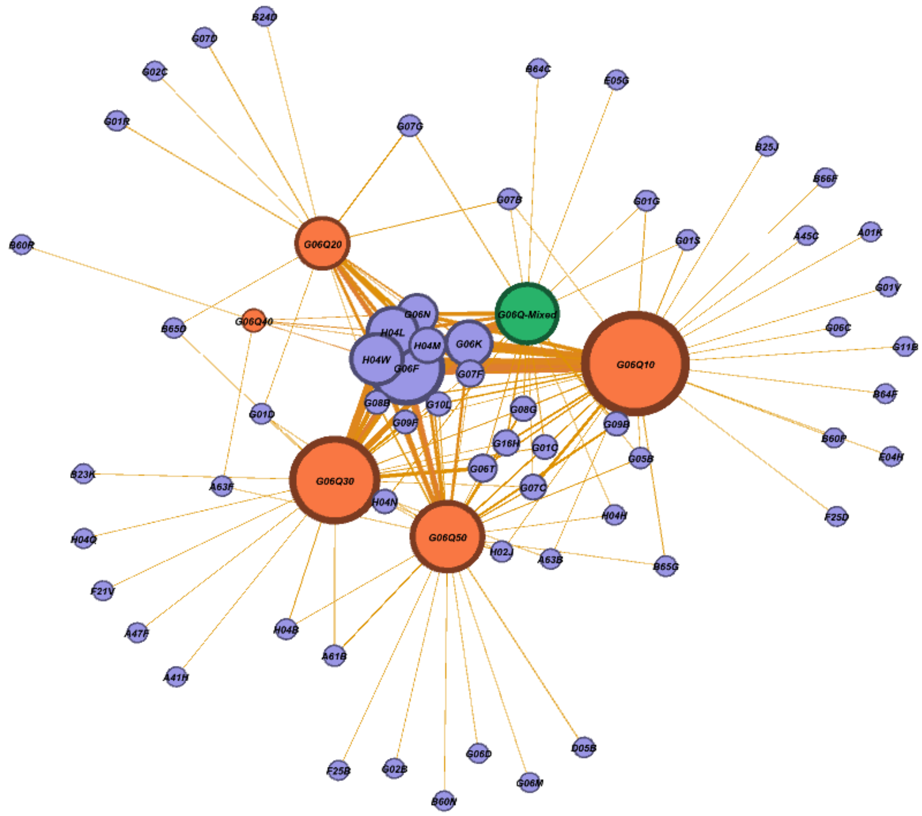

Figure 6: File-based IPC network of BMP applications. Orange nodes denote the business method IPC groups, the green node indicates the BMPs with multiple business method IPC groups, remaining nodes are the target nodes implying the related fields. Node size and edge width stand for the strength of the corresponding node while bigger node size and larger edge width indicate more strength.

CONCLUSION

As discussed, IPC related part of the study strongly depends on the IPCs determined by the classifiers. However, conclusions drawn in this study are not solely based on the IPC network, the topics and the associated terms given by LDA verify and reinforce our inferences regarding business method inventions within the context of patents. Therefore, our study aims to provide insights about the BMP trends and linked technologies by implementing topic modeling in a similar manner to previous studies. However, unlike the previous efforts, our study also leverages a file-based IPC network to reinforce the implications provided by topic models. This mechanism is expected to lead policymakers to construct a more concrete scheme regarding the national BMP application. This study is constrained by BMPs satisfying certain criteria explained in the methodology section. Future works may expand the time window, define additional criteria, or grow the dataset of BMPs provided in this study to inquire about or acknowledge the conclusions reached.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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i Business Method Patent.

ii Latent Dirichlet Allocation.

iii International Patent Classification.

iv United States Patent and Trademark Office.

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