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Assessing Business Process Complexity Based on Textual Data: Evidence from ITIL IT Ticket Processing

Abstract
Purpose
This study aims to draw the attention of business process management (BPM) research and practice to the textual data generated in the processes and the potential of meaningful insights extraction. We apply standard Natural Language Processing (NLP) approaches to gain valuable knowledge in the form of business process (BP) complexity concept suggested in the study. It is built on the *objective, subjective,* and *meta-knowledge* extracted from the BP textual data and encompassing semantics, syntax, and stylistics. As a result, we aim to create awareness about cognitive, attention, and reading efforts forming the textual data-based BP complexity. Our concept serves as a basis for the development of various decision-support solutions for BP workers.
Design/methodology/approach
The starting point is an investigation of the complexity concept in the BPM literature to develop an understanding of the related complexity research and to put the textual data-based BP complexity in its context. Afterward, utilizing the linguistic foundations and the Theory of Situation Awareness, the concept is empirically developed and evaluated in a real-world application case using qualitative interview-based and quantitative data-based methods.
Findings
In the practical, real-world application, we confirmed that BP textual data could be used to predict BP complexity from the semantic, syntactic, and stylistic viewpoints. We were able to prove the value of this knowledge about the BP complexity formed based on the (i) professional contextual experience of the BP worker enriched by the awareness of cognitive efforts required for BP execution (*objective* knowledge), (ii) business emotions enriched by attention efforts (*subjective* knowledge), and (iii) quality of the text, i.e., professionalism, expertise, and stress level of the text author, enriched by reading efforts (*meta-knowledge*).
In particular, the BP complexity concept has been applied to an industrial example of ITIL Change Management IT ticket processing. We used IT ticket texts from two samples of 28,157 and 4,625 tickets as the basis for our analysis. We evaluated the concept with the help of manually labeled tickets and a rule-based approach using historical ticket execution data. Having a recommendation character, the results showed to be useful in creating awareness regarding *cognitive, attention*, and *reading efforts* for ITIL Change Management BP workers coordinating the IT ticket processing.
Originality
While aiming to draw attention to those valuable insights inherent in BP textual data, we propose an unconventional approach to BP complexity definition through the lens of textual data. Hereby, we address the challenges specified by BPM researchers, i.e., focus on semantics in developing vocabularies and organization- and sector-specific adaptation of common NLP techniques.

Keywords: Business Process Management, Business Process Complexity, Natural Language Processing, Situation Awareness, Decision Support, ITIL IT tickets.

1. Introduction

The significance of natural language in human work and private life cannot be overestimated. It is a means of sharing thoughts and feelings and storing knowledge. Over the last decade, the maturity of Natural Language Processing (NLP) techniques, along with the proliferation of big data, has shifted the focus to new opportunities in a range of applications. In these applications, documents and textual data are extensively used to manage customer service, legal issues, logistics, or accounting (van der Aa, Carmona, *et al.*, 2018). Unstructured text is commonly believed to account for more than 80% of data in companies (Kobayashi *et al.*, 2018). Yet, as also stated by (Kobayashi *et al.*, 2018), few researchers have applied NLP to tackle organizational challenges despite this abundance of textual data. In Business Process Management (BPM), recent research demonstrates the capabilities of NLP-based analysis techniques to support various tasks in a scalable manner (Mendling *et al.*, 2017). However, there are still many challenges of NLP-supported BPM, especially related to its enhancement in the sense of semantics and developing domain or even organization-specific adaptations (van der Aa, Carmona, *et al.*, 2018).

At the same time, due to the fast development and penetration of digital technologies into BPM, the overworked term of process complexity and solutions addressing this complexity gain new attention. In this respect, the mainstream BPM research has been inspired by the software complexity metrics and is directed towards estimating the complexity of technical artifacts (Cardoso *et al.,* 2006). Hence, it does not consider the textual data. This observation explains that while being a popular subject area in business (Müller *et al.*, 2016), Text Analytics and NLP have not been used to study the BP complexity so far.

The demand for complexity research is especially evident in the most impacted IT and IT Service Management (ITSM) domain (Lei *et al.*, 2021). Practitioners state a dramatic increase in software errors and a lack of experts to deal with them. Software maintenance and its costs constituting up to 90% of total software development (Goyal and Sardana, 2021) remain in the research and practice focus (Jang and Kim, 2021; Peimbert-García *et al.*, 2021). This complexity and the dynamic nature of processes make the problem of providing process workers with structured knowledge to enable informed decision-making especially significant (Lee *et al.*, 2020).

Based on the above motivation, we aim to create a textual data-based instrument for increasing the awareness of the BP workers regarding the process complexity. Accordingly, we set to develop a BP complexity concept as a basis for various decision-support solutions for BP workers. The concept development involves solving some important issues, which make up the *specific objectives* of this study:

(i) Extending an understanding and conceptualizing the BP complexity based on the textual data generated in BPs using a theoretical background.
(ii) Developing a set of BP complexity measures based on the textual data using a linguistic justification.
(iii) Exploring, adapting, and illustrating the benefits of the BP complexity concept application using an industrial example.

To achieve these objectives and ensure the comprehensiveness of the examined phenomena, we employ a *triangulation* approach based on the following five steps. *First*, we analyze the related work to develop and extend an understanding of BP complexity and closely associated research in Section 2. *Second*, expert knowledge is used to build the theoretical background for the concept model development and adapt the NLP and linguistic considerations to the BPM context, forming a solid foundation for designing BP complexity measures based on the textual data in Section 3. *Third,* a real-world application case is used to develop a set of BP complexity measures while adapting standard NLP techniques to the BPM context and BP complexity resulting in the BP complexity concept in Section 4. *Fourth*, the BP complexity concept is applied to a real-world scenario to demonstrate its practical value and relevance in Section 5. *Fifth*, expert knowledge collected in onsite workshops, interviews, remote feedback (qualitative evaluation), and statistical methods (quantitative evaluation) is iteratively used to evaluate the results in Section 6.

Hence, the BP complexity concept has been developed in relation to a specific BP from the ITSM domain, which is ITIL Change Management (CHM) IT ticket processing of an international telecommunication provider. The concept aims to create awareness about certain efforts needed to process a ticket[1]: (i) awareness of *cognitive efforts* obtained with the help of domain-specific taxonomy and necessary for the process/task execution, i.e., a comprehensive understanding of the current situation, including the professional contextual experience of the BP worker, (ii) awareness of *attention efforts* to be paid to individual process elements or the entire process, i.e., business emotions contained in the BP text, extracted with the help of domain-specific business sentiment lexicon, and (iii) awareness of *reading efforts* obtained with the help of stylistic features contextually related to the text quality, i.e., indicating professionalism, expertise, and stress level of the text author. Such awareness can serve as prioritization support, necessary expert identification, selection of process automation candidates, and aggregated analyses of BP textual data over specific periods.

[1] By ticket processing, we understand opening a ticket in an IT ticketing system, filling in necessary fields, identifying and performing preparatory and follow-up work required for successful ticket resolution

Thus, our work contributes to BPM by proposing a BP complexity concept based on the three knowledge types, addressing semantics, syntax, and stylistics, and creating awareness about certain efforts necessary for BP execution. To the best of our knowledge, this is the first time in the literature that the BP textual data is analyzed from these three perspectives to predict the BP complexity. Using qualitative and quantitative research methods, we illustratively apply and evaluate our concept based on the ITIL CHM IT ticket processing. Hence, we adapt common NLP techniques to the domain specificity of ITIL CHM to increase their performance on the semantic level.

2. Related Work

According to the research artifact, our study naturally lies at the intersection of (i) BPM, (ii) BP complexity, and (iii) NLP techniques for extracting the knowledge about the latter. This section provides an understanding of BP complexity and complexity-related research and gives an overview of the NLP application in BPM while outlining the research gaps. Thus, Section 2.1. reviews the BP complexity approaches in BPM. Section 2.2. presents the research closely related to but not directly addressing BP complexity. Finally, Section 2.3. introduces the status quo of the NLP research in BPM.

2.1. Business Process Complexity

As organizations develop and expand their businesses, interdependencies between their processes and information systems increase rapidly. To address this problem, organizations modify the technology supporting their businesses. As a result of such developments, organizations face substantial problems. One of the first and most significant problems is complexity, which impedes decision-making and leads to excessively high and often hidden costs. There has been much interest in complexity research from both academia and industry. The term complexity has received much attention in different fields. For example, Organizational Sciences adapt concepts from Complexity Theory and define an organization as a complex dynamic system consisting of elements interacting with each other and their environment (Grobman, 2005). In Computer Sciences, as a rule, the term complexity determines the complexity of an algorithm, i.e., the number of resources required to execute the algorithm (Arora and Barak, 2009).

In this study, we limit our scope to the BPM discipline. BPs are sequences of well-defined actions that must be modeled and redesigned as needed (van der Aalst, 2013). Hence, BPM focuses on modeling whereby processes are recorded, evaluated, planned, and redesigned. This is also a dominant research direction in BPM (Leno *et al.*, 2020), demonstrating its closeness to Computer Sciences. Fundamental concepts and approaches of complexity measures applied to BPs have attracted researchers' attention since the 1970s. The necessity to measure complexity became apparent in software development projects with the purpose of management and control. One of the first essential measures, graph theory-based McCabe complexity (McCabe, 1976), or cyclomatic complexity, was designed to identify software modules that are difficult to test or maintain. Later on, it was applied to different subject areas, including BPs, whereby it is known as control-flow complexity (Cardoso *et al.*, 2006). Another popular measurement applied to BPs is Halstead software complexity (Halstead, 1977), calculated based on program operands (variables and constants) and operators (arithmetic operators and keywords influencing the program control-flow) (Cardoso *et al.*, 2006). Accordingly, various software complexity approaches have been adapted to BPs. The cited (Cardoso *et al.*, 2006) can be reasonably considered one of the pioneers of software complexity adaption in BPM. Other adaptions such as (Henry and Kafura, 1981; Jingqiu Shao and Yingxu Wang, 2003; Jukka Paakki *et al.*, 2000; Woodward *et al.*, 1979) and (Conte *et al.*, 1986; Troy and Zweben, 1981) were studied in detail by (Laue and Gruhn, 2006) and (Vanderfeesten, Reijers and van der Aalst, 2008; Vanderfeesten *et al.*, 2007).

At the same time, some research work breaks away from the software complexity adaption and explores other subject fields. (Vanderfeesten, Reijers, Mendling, *et al.*, 2008) draw inspiration from Cognitive Sciences. (Kluza *et al.*, 2014; Sánchez-González *et al.*, 2010) link their research to mathematics. Other researchers experiment with visual cognition of BP models (Petrusel *et al.*, 2017) in a broader context of Decision Sciences and test various perspectives to BP model complexity, such as errors and rules (Kluza, 2015; Mendling and Neumann, 2007). A number of studies on BP complexity use the widely deployed BPMN (OMG, 2013) modeling framework (Pozzi *et al.*, 2011; Rolón *et al.*, 2009). With the BPMN counterparts' adoption in the BPM field, i.e., CMMN for the case and DMN for decision modeling, the corresponding work on their complexity has started to appear. The complexity approaches are similar to the BP model complexity (Hasić and Vanthienen, 2019; Marin *et al.*, 2015). It is important to note that whereas complexity considerations for BPMN and DMN are comparable, the complexity in CMMN can get incomparably high. Two other fields worth mentioning are expert systems (Chen and Suen, 1994; Kaisler, 1986; Suen *et al.*, 1990) and IT architectures (Kinnunen, 2006; Solic *et al.*, 2011; Wehling *et al.*, 2016, 2017). To sum up, BPs consist of many different elements (splits, joins, resources, diverse data types, activities, etc.). Therefore, there can be no universal measure of process complexity addressing all BP elements.

As we can conclude from the summary in Table I, most of the existing BP complexity approaches come from the software subject area and consider a BP from the angle of programming language, i.e., as a technical artifact.

Similar to the software complexity, in the sense of the practical contributions, BP complexity research mainly aims to achieve more transparency, understandability, reducing errors, defects, and exceptions of BPs. The observation also proves the intense focus on technical artifacts dominant in the BPM community.

Table I. Related work review of BP complexity

Complexity	Studies	Approach	Pursued goals / practical contributions
Software	(McCabe, 1976)	graph-theoretic complexity measures	management and control of software program complexity
	(Halstead, 1977)	program operands and operators-based measures	
	(Gao and Li, 2009)	complex network theory-based measures	
	(Henry and Kafura, 1981)	information-flow based measures (fan-in and fan-out)	evaluating the structure of large-scale systems
	(Woodward *et al.*, 1979)	knots as a measure of control-flow complexity in program texts	structuring programs
	(Jingqiu Shao and Yingxu Wang, 2003)	a measure of the cognitive and psychological complexity of software as a human intelligence artifact	analysis and prediction of software complexity
	(Jukka Paakki *et al.*, 2000)	discovery of architectural and design patterns	analysis of the quality of architecture
	(Conte *et al.*, 1986; Troy and Zweben, 1981)	five design quality measures - coupling, cohesion, complexity, modularity, size	evaluation of software designs
	(Banker *et al.*, 1989, 1993; Basili and Hutchens, 1983; Gibson and Senn, 1989)	the average size of module's procedures, application's modules, the density of goto statements	understanding and managing computer software complexity in terms of the maintenance costs
BP model	(Cardoso *et al.*, 2006)	number of activities, control-flows, joins and splits in general and unique (not repeating), interface complexity, graph theory-oriented metrics measuring the complexity of a graphic	understandability, fewer errors, defects, and exceptions, more robust processes requiring less time to be developed, tested, and maintained
	(Laue and Gruhn, 2006)	cognitive weights for BP models, information flow, max/ mean nesting depth, number of handles, (anti) patterns	
	(Vanderfeesten, Reijers and van der Aalst, 2008; Vanderfeesten, Reijers, Mendling, *et al.*, 2008; Vanderfeesten *et al.*, 2007)	adapted cohesion and coupling metrics, cross-connectivity (strength of the links between BP model elements)	
	(Mendling and Neumann, 2007)	graph theory-based metrics incl. size, separability, sequentially, structuredness, cyclicity, parallelism	
	(Sánchez-González *et al.*, 2010)	structural metrics incl. diameter, nodes, density, gateway degrees and mismatch, the coefficient of connectivity	
	(Kluza, 2015)	BP model metrics integrated with rules	
	(Petrusel *et al.*, 2017)	visual comprehension of a BP model with an eye-tracking experiment	
	(Kluza *et al.*, 2014)	Durfee and Perfect square	
Work- and control-flow	(Cardoso, 2006, 2008; Lassen and Aalst, 2009)	compound control-flow complexity of all split constructs	
Event log	(Cardoso, 2007)	number of process logs that are generated when workflows are executed	
	(Benner-Wickner *et al.*, 2014)	average trace length, size, event density, trace diversity	metrics which can measure the degree of event log quality that is needed so that discovery algorithms can be applied
DMN	(Hasić and Vanthienen, 2019)	number of decisions, elements, information requirements, density, data objects, Durfee and Perfect square metric, sequentially, diameter, longest path, vertex degree, knot count, network complexity, decision nesting depth, cyclomatic complexity, interface complexity	complexity metrics for DMN models
CMMN	(Marin *et al.*, 2015)	size, length, complexity	complexity metrics for CMMN models
Expert systems and rule bases	(Chen and Suen, 1994; Kaisler, 1986; Suen *et al.*, 1990)	number of rules, decision components, breadth of the search path, depth of search space, number of antecedents and consequents of a rule, content, connectivity and size complexity, entropy-based rule base complexity	systematic and reliable techniques for evaluating expert systems
Enterprise IT architectures	(Wehling *et al.*, 2016, 2017)	variability mining	decision support to determine and remove redundant architectural artifacts

	(Kinnunen, 2006)	interface complexity multiplier	complexity measures for object-process models, compensating the hidden information at interfaces
	(Solic *et al.*, 2011)	Roger Sessions' methodology	reduce complexity to enhance security, increase functionality and reduce costs of maintenance of the IT system

Source: own elaboration

2.2. Research Closely Related to Business Process Complexity

As can be observed in Section 2.1., software complexity originated in the 1970s has paved the way to the major complexity approaches in BPM, i.e., complexities of process models, event logs, work- and control flows. However, along with this mainstream, we could identify other standalone BPM research directions closely related to BP complexity and most relevant for our research. These are (i) task complexity and cognition and (ii) process knowledge intensiveness, approaches that we also partially use, extend, and adapt in our BP complexity concept development.

In fact, BPs represent a sequence of steps in the form of activities or tasks. Although not well recognized in the BPM community, task complexity should be reviewed as closely related to the BP complexity. Along with the software complexity, task complexity research going back to the 1980s (Campbell, 1988; Wood, 1986) can be reasonably considered one of the oldest and most extensively studied in the organizational context (Efatmaneshnik and Handley, 2018). In the literature, task complexity is often used in respect to the discussion on task routineness vs. cognition caused by the effect of technological change on labor demand (Fernández-Macías and Bisello, 2016). Thus, (Autor *et al.*, 2003) pose the question *"how computerization affects skill demands"* and differentiate between routine (manual, cognitive) and non-routine (manual, analytic, interactive) tasks. With the growing importance of automation, the attention of the BPM community also shifts towards new extended perspectives on task classifications. For example, (Koorn *et al.*, 2018) suggest differentiating between such task dimensions as creative, adaptive, interactive (routine), analytical (evaluation, standardization), system supervision, routine cognitive, information processing, information exchange (data stream). Further, in the light of the automation trend and gaining popularity Robotic Process Automation (RPA), (Leopold *et al.*, 2018) propose analyzing textual BP descriptions to derive tasks best fitting the RPA application.

In their very essence, BPs are closely intertwined with knowledge. Variations or deviations from a standard BP, insufficient or unrealistic process rules, or the absence of a well-structured process model may only be overcome by the employee's knowledge to keep the process flowing (Gronau and Weber, 2004). To address this challenge, so-called knowledge-intensive processes (KIPs) have been introduced in BPM. KIPs are concerned with the dynamic knowledge conversion among the individuals engaged in the BP execution and often include tacit and continuously changing pieces of knowledge (França *et al.*, 2012). As fairly stated by (Van Leijen and Baets, 2003), almost every process needs some level of knowledge-intensiveness to recover from errors, handle unusual cases, and improve or adapt the process itself. As a rule, knowledge intensiveness is considered as one of the process complexity characteristics. (Eppler *et al.*, 2008) define knowledge intensiveness by the following: highly dependent outcomes, reliance on random events, many options, creativity in problem-solving, performance dependency on the skills, and extended learning time. To deal with this complexity, recommendations and requirements to KM tools (Eppler *et al.*, 2008), design of specific KM systems for KIPs (Sarnikar and Deokar, 2010), knowledge modeler languages (Gronau and Weber, 2004), frameworks (Van Leijen and Baets, 2003), and lately data mining (Khanbabaei *et al.*, 2019) are suggested.

Considering this work, we also observe the dominant technical perspective in BPM and BP complexity. Although the discussed approaches do not address textual data generated by BP workers in the BP execution, we base our concept on the notion of knowledge intensiveness of the processes and its characteristics. Focusing on the most typical data type in organizations, we aim to deal with the knowledge-intensive processes characterized by large decision scope, long learning time, demand for much contextual knowledge, skills, and complex problem-solving. Thus, knowledge intensity is typically considered in tandem with BP complexity. As also follows from above, another notion closely related to BP complexity is cognition which gained the attention of BPM research in the context of BP automation potential assessment. Accordingly, we consider BP cognition one of the BP complexity determinants when developing the taxonomy-based approach to assess cognitive efforts.

So far, we have reviewed BPM approaches mainly concerned with technical artifacts. Hereby, the question regarding the role of textual data and NLP in BPM remains discarded. Hence, in Section 2.3., we revise those aspects in which BPM research considers textual data and applies NLP.

2.3. Business Process Management and Natural Language Processing

Thanks to publicly available frameworks and maturity, NLP has become popular in many application areas. As approximately 80% of enterprise data is textual (Kobayashi *et al.*, 2018; Rizkallah, 2017), the business applications based on textual data are rather broad. They range from accounting, production, and logistics to legal office, marketing, and customer service and support such tasks as sentiment analysis, automatic text classification, summarization, and extraction of topics from a large document corpus (Pröllochs and Feuerriegel, 2020; Zamuda and Lloret, 2020). The complete list of analyzed sources is part of the supplementary material[2].

In the context of BPM, NLP research is streamlined along with the three commonly differentiated layers: Multi Process Management (identifying the organization's major processes and their prioritization), Process Model Management (managing a single process in a traditional BPM lifecycle), and Process Instance Management (single enactments of a process, i.e., planning, executing, and monitoring of a process,) (van der Aa, Carmona, *et al.*, 2018; Mendling *et al.*, 2017). Accordingly, there is solid prior research in respect to Multi Process Management dealing with large process model repositories, such as identifying the similarity (Dijkman *et al.*, 2011), matching (Klinkmüller and Weber, 2021; Weidlich *et al.*, 2010) and merging of process models (La Rosa *et al.*, 2013), textual-based (Leopold, van der Aa, Pittke, *et al.*, 2019) and semantic (Thomas and Fellmann, 2011) search, resolution of lexical ambiguity (Pittke *et al.*, 2015), automatic service derivation (Leopold *et al.*, 2015), and refactoring of large process model repositories (Weber *et al.*, 2011). Next, Process Model Management reveals a significant number of research primarily aimed at BP modeling support, for example, the transformation of textual descriptions into process models (Friedrich *et al.*, 2011) and vice versa (Leopold *et al.*, 2014), text annotations (Stenetorp *et al.*, 2012), multiple languages, semantic quality check (Leopold *et al.*, 2013), checking compliance (van der Aa *et al.*, 2017), correctness, and consistency of BP models (Leopold, van der Aa, Offenberg, *et al.*, 2019), BP model discovery (Han *et al.*, 2020), comparing process descriptions with BP models (van der Aa, Leopold, *et al.*, 2018), process description autocompletion (Hornung *et al.*, 2007). Finally, Process Instance Management, a primary objective of BPM at the bottom operational level, reveals rather scarce NLP-related research. Whereas there has been a large amount of study on conversational systems, i.e., chatbots, in recent years, such solutions guiding BP workers through possible options and providing BP execution support are at their early stage (Alman *et al.*, 2020; Han, 2019).

A relatively new research direction is integrating Process Mining with NLP (Fan and Ilk, 2020; Gupta *et al.*, 2020). These approaches aim to include both event logs and textual data into the process analysis. However, such works making BPM discipline more "humanistic" are at their early stage. Moreover, as noted by (van der Aa, Carmona, *et al.*, 2018), NLP research has a great potential in the application to BPM to solve several challenges, for example, (i) improvement of the performance, especially at the semantic level, and (ii) developing domain- and organization-specific adaptations of common NLP techniques.

To sum up, in the BPM-related work, we have seen a strong focus on the technical artifacts, i.e., BP models. The actual support of BP workers in the BP execution (Process Instance Management) remains underresearched. Hence, in the present work, by predicting BP complexity based on the textual data, we address the demand for direct BP execution support while considering the mentioned challenges. In particular, to develop our BP complexity concept, we use three linguistic levels of text understanding realized through semantics, syntax, and stylistics, semantics being in focus. The importance of semantics in NLP is a recognized and attractive research field (Mitra and Jenamani, 2021). However, it remains one of the significant challenges impeding the full exploitation of the NLP benefits in BPM (van der Aa, Carmona, *et al.*, 2018). Further, motivated by the declared need for domain-specific adaptations, we adapt common NLP techniques to the ITSM subject area.

3. Theoretical and Practical Background

From the perspective of the theoretical and practical research background, in this section, we briefly present the three levels of the Theory of Situation Awareness to rationalize the knowledge extraction and situation awareness creation as a basis for the BP complexity concept development. Afterward, we introduce the motivating example to underpin the conceptual model development.

3.1. Conceptual Model Development Based on the Theory of Situation Awareness

In BPM, the term situation awareness (SA) is not new. In this context, major research activities have been devoted to studying how to integrate SA into BP models and facilitate the SA of BPs. Similar to complexity and NLP research in BPM, the goal of these research projects has been directed towards BP modeling. In this study, we use the Theory of Situation Awareness (Endsley, 1995) to theoretically justify the proposed extraction of the three knowledge types and illustrate the value of our approach in awareness creation. Hereby, we consider both social and technical aspects enabling the process workers' decision-making. In any decision-making process, it is important to be able to identify the elements in the environment, understand their relevance for the goal achievement, draw various scenarios of the actions, and make informed decisions. These conditions are realized by the Theory of Situation Awareness (SA), which serves as the basis for developing our conceptual model. Our study adapts the SA model suggested by (Endsley, 1995) to the BPM domain, textual data context in general, and IT ticket processing as a particular example.

Considering our example, IT tickets are issued following the requests for changes in the IT infrastructure of a big telecommunication company. Implementing these changes means interfering with the organizational

[2] See the overview and references of Text Analytics applications in business on our Github project page

environment and its functions, which are often grown historically. The BP worker needs to carefully extract all important information from the textual request he/ she receives, put it together, and enter into the IT ticket processing system. Hereby, a lot of (often critical) information needs to be filled in, such as a ticket description, its feasible impact, affected systems/ items, need for approval by the advisory board, possible service outages, to name only a few. It becomes evident that wrongly entered information can lead to ticket implementation errors with severe service outages. Thus, the domain specificity of our example, including a significant number of BPM cases, can be reasonably considered a high-consequence one, i.e., somewhat similar to those domains common for SA application (Endsley, 1995). However, textual data context needs to be elaborated in detail. According to (Daelemans, 2013), it is commonly distinguished between three levels of text understanding, i.e., types of knowledge that can be extracted from text: (i) *objective* knowledge (answering the who, what, where, when, etc. questions), (ii) *subjective* knowledge (sentiment text component) and (iii) *meta-knowledge* (further information which can be derived from the text apart from its contents).

Following the SA model (Endsley, 1995), on SA Level 1, one perceives the status, attributes, and dynamics of relevant elements in the environment and develops an initial understanding of the situation (Endsley, 1995), i.e., *objectively* assesses the situation. In the BPM context, the primary goal of this level is the *perception of basic professional knowledge* about the process/ task, namely (i) a deep understanding of its structure enhanced by (ii) awareness of the *cognitive efforts* necessary for the process/task execution, which directly follow from the professional context. The first element of such perception is realized by the understanding of the basic elements of the BP text, i.e., ***R****esources* (nouns indicating the specificity of BP elements), ***T****echniques* (verbs of knowledge and information transformation activity affecting ***R****esources*), ***C****apacities* (adjectives describing situation specificity of ***T****echniques*), and ***C****hoices* (adverbs determining the selection of the required set of ***T****echniques*), elements of RTCC framework developed in our previous research (Rizun *et al.*, 2019a). The second perception element, i.e., cognitive efforts awareness, is determined by the expected type of activities: (i) simple routine activities happening every day, (ii) activities including some non-routine BP elements, or (iii) complex activities demanding much cognitive effort. This awareness enables subject matter experts (BP workers) to identify meaningful RTCC elements in the textual descriptions and classify them into the corresponding cognition level.

On SA Level 2, the comprehension of *basic elements* in a current situation occurs. It is facilitated by awareness of (i) *attention efforts* needed to be paid to individual BP elements and entire BP and (ii) *readability efforts* contextually related to the text quality. This awareness is supported by two other types of knowledge indicated by (Daelemans, 2013), i.e., *subjective* and *meta*-knowledge. One common approach to extracting subjective knowledge in the BPM context is BPM-specific sentiment analysis. Hereby, emotionally loaded keywords, capitalizations, and special characters indicate the *attention efforts* needed to address particular BP elements. Additionally, while reading the text, BP workers comprehend meta-knowledge, i.e., the text quality, which (i) directly relates to the text author's professionalism, expertise, level of stress, and some other important psychological and sociological properties (Daelemans, 2013), (ii) influences the understanding of the text and awareness of necessary readability efforts, and (iii) forms the trust (or doubt) to the written content, i.e., if additional refinements, adjustments, and enrichments are needed.

The highest SA Level 3 is defined by the ability to project the future status of the current situation. The main goal is *to select a mental model* directing the decision strategy necessary for the BP execution. Such ability is enabled by the BP worker's awareness of the *BP complexity*.

Fig. 1 provides the extended SA model adapted from (Endsley, 1995). The person's perception and comprehension of the relevant elements in the environment set the foundation for the SA and determine further BP decisions and actions. Hence, the SA is formed based on a comprehensive understanding of the current situation, i.e., the professional contextual experience of the BP worker (SA Level 1), business emotions, and quality of the written text, i.e., professionalism, expertise, and stress level of the text author (SA Level 2). Further, it allows predicting the required BP worker's efforts (cognitive, attention, and reading comprehension) while preparing to execute the process/ task at hand and contributes to the BP complexity identification on the SA Level 3.

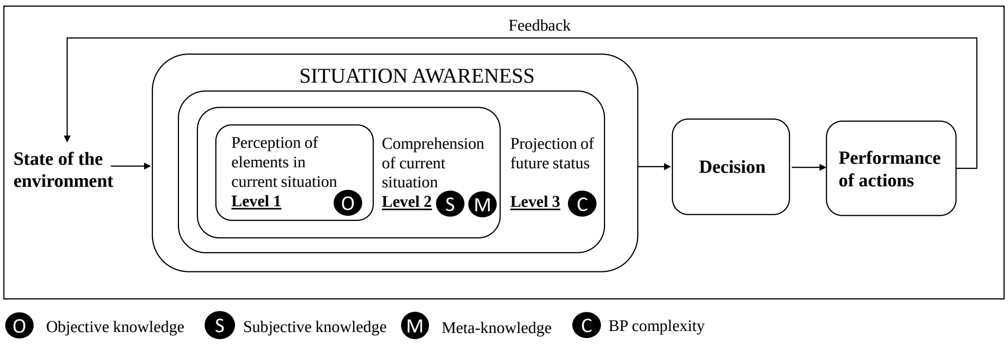

Fig. 1. Extended situation awareness model of BP complexity. Source: own elaboration based on (Endsley, 1995)

3.2. ITIL Change Management IT Ticket Processing Motivating Example

As an illustrative application, a typical BP scenario of IT ticket processing is used. Processing IT tickets is common for most businesses today. It has a clear start, steps, and end. In this process, customer requests, problems, and complaints are recorded in the form of IT tickets. Afterward, further steps are taken to process the ticket. As a rule, such a process is carried out by IT service desks. It starts when a customer submits a request and ends with the resolution of that request. It seems to be straightforward with many existing software solutions. However, the recent literature evidences various challenges in Service Management automation in general and unsolved problems in reporting and processing customer requests in particular (Keller, 2017).

Our study uses ITIL Change Management IT ticket texts from a large telecommunication provider, i.e., customer requests to change, improve, or resolve a problem regarding IT products and services. Change Management (CHM) is a part of ITIL Service Transition dealing with the processing of so-called Requests for Change, IT tickets issued to add, modify or remove anything in the IT infrastructure that could affect IT services (Axelios, 2011). This dataset was chosen due to the following reasons: (i) as a rule, such requests are written in a free manner, i.e., not following a pre-defined pattern, (ii) in theory, it should contain a clear description of the situation, i.e., the information necessary to process the request, implying the tasks or activities required for an IT ticket resolution, (iii) ITIL represents a specific but still rather widely used framework (Global Knowledge, 2020). Furthermore, the employees of the application case department have declared the lack of context and related difficulty in processing customer requests during an onsite workshop. Hence, we envision a BP complexity concept-based decision support to assist the ITIL CHM workers creating an awareness of cognitive, attention, and reading efforts necessary for understanding and processing the IT ticket. As a motivating example, we use the following anonymized IT ticket received by the ITIL CHM worker per email: *"Dear colleagues, please apply SAP R3 PSU patches on server XXX.YYY.ZZZ for database AAA.BBB.CCC. Attachments - READ RunBook !!! ***************Minimum lead time - 10hrs 45mins*************** !!! Otherwise the ticket will be rejected. Disaster recovery tests are prepared by XYZ"*. The motivating example will be used in Section 5. Illustrative application.

The following section describes the knowledge extraction and NLP techniques used on SA Levels 1 and 2 and the resulting textual data-based complexity on SA Level 3, providing decision support to the worker processing the IT ticket.

4. Concept of Business Process Complexity

The previous section introduced an adapted situation awareness model based on the BP complexity, which allows estimating cognitive, attention, and reading efforts necessary for BP execution. This section formalizes the BP complexity concept and its components: objective, subjective, and meta-knowledge.

Definition 1 ***Objective knowledge.*** Core NLP research addresses the extraction of objective knowledge from text, i.e., which concepts, attributes, and relations between concepts can be extracted from the text (Daelemans, 2013). Among diverse approaches, taxonomies and ontologies are widely used, also in business, as a necessary resource for many applications (Khadir *et al.*, 2021). Hence, to realize the concept of *SA Level 1* introduced in Section 3.1., which is the perception of basic professional knowledge and *cognitive efforts*, we suggest a specific approach of objective knowledge extraction. It is based on the RTCC framework and Decision-Making Logic (DML) taxonomy (Rizun *et al.*, 2019a). In this approach, the RTCC framework implements the first part – extracting basic professional knowledge and enabling a deep understanding of the BP textual semantic-syntactic structure considering basic BP elements. These are ***R****esources*, ***T****echniques*, ***C****apacities*, and ***C****hoices* (RTCC). DML taxonomy realizes the possibility of the *cognitive efforts* awareness necessary for the process/ task execution.

To discover the DML, <u>first</u>, we develop an understanding of the three DML levels (Rizun *et al.*, 2019a). Using the systematic literature analysis enhanced with the observation of recent research and market developments, we distinguish three levels, which determine the expected type of activities – *routine*, *semi-cognitive*, and *cognitive* (Rizun *et al.*, 2019a, 2021). The proposed definitions are the following: (i) *routine* activities are those expressible in rules so that they are easily programmable and can be performed by computers at economically feasible costs (Levy *et al.*, 1996); (ii) *semi-cognitive* activities are those where no exact ruleset exists, and there is a clear need of information acquisition and evaluation (Koorn *et al.*, 2018). Here, computer technology cannot substitute but increases employees' productivity (Spitz-Oener, 2006) by partial task processing; (iii) *cognitive* activities are the most complex ones where not only information acquisition and evaluation are required but also complex problem-solving. Computers can offer only minimal support.

<u>Second</u>, using part-of-speech tagging related to the RTCC elements and a Latent Dirichlet Allocation Algorithm (LDA) (Blei, 2012), we identify the most significant keywords in BP texts, in our case, IT tickets. Each of the keywords is associated with an introduced DML level. Performing a systematic literature analysis, we drafted a set of indicators, or contextual variables (Rizun and Taranenko, 2014), based on which subject matter experts (BP workers) categorize words into one of the four RTCC elements and one of the three DML levels. For example, the keywords *interface, tool, client, file* are associated with the IT tickets related to the daily work. In the text, they have an exact, straightforward meaning like *please use file X in the attachment* or *configure interface Y*

for user Z in the application W. Hence, these keywords usually denote *routine **R**esources*. The keyword *CAB (Change Advisory Board)* belongs to *cognitive **R**esources*. The approval of CAB is usually needed when IT tickets are complicated and critical. The process of DML taxonomy development and evaluation is described in (Rizun *et al.*, 2019a).

Third, with the help of the developed domain-specific DML taxonomy, we apply a taxonomy keyword-based pattern matching algorithm to determine the DML level of each ticket. For this, we calculate (i) the total number of routine, semi-cognitive, and cognitive keywords extracted from the tickets and (ii) the relative occurrence of each category's words in the ticket text, and then (iii) derive the DML level based on the context-specific threshold rules defined by the subject matter experts.

To sum up, in this study, *objective knowledge* is defined as the one (i) determining the perception of basic professional knowledge about the process/ task, namely a deep understanding of its structure enhanced by awareness of the cognitive efforts necessary for its execution, and (ii) realized with the BP elements of ***R**esources*, ***T**echniques*, ***C**apacities*, and ***C**hoices* organized into one of the three DML levels of routine, semi-cognitive, and cognitive. The process of objective knowledge extraction and identification of the DML level is summarized in Fig. 2.

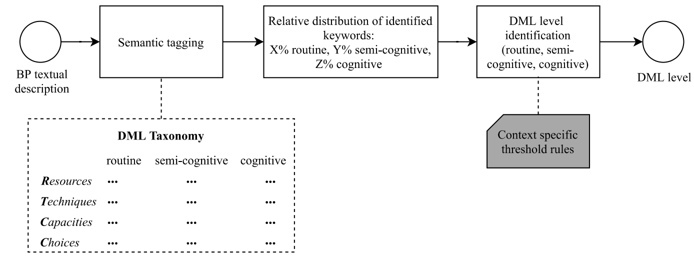

Fig. 2. Objective knowledge extraction and DML level identification. Source: own elaboration

Definition 2 *Subjective knowledge.* To realize the concept of SA Level 2 introduced in Section 3.1., consisting in the comprehension of the elements in a current situation, connected with awareness of the *attention efforts* needed to be paid to individual BP elements, we suggest a specific approach of subjective knowledge extraction (SA Level 2.1.). Subjective knowledge is closely related to sentiment or opinion (Liu, 2012). Hence, we suggest the Business Sentiment (BS) for subjective knowledge extraction in the BPM context. We consider BS as an instrument for measuring awareness of those *attention efforts* needed to be paid to individual BP elements and the entire BP (Rizun and Revina, 2019). We propose extracting this latent information regarding *attention efforts* with the help of a lexicon-based context-specific BS. Hence, in our IT ticket case, we first develop the domain-specific BS lexicon identifying the emotionally loaded keywords and expressions based on two sources: (i) corpus, i.e., IT ticket texts, and (ii) CHM descriptions from the ITIL handbook.

Second, based on the subject matter experts' opinion, we (i) refine the developed BS lexicon and (ii) assign valence scores to the BS lexicon keywords. Each of the BS lexicon words is associated with positive, negative, or neutral business sentiment. Words with valence scores greater than 0 are considered positive, whereas those with less than 0 are considered negative. All other words are considered to have a neutral sentiment. For example, in contrast to such expressions as *no risk*, *no outage* associated with the positive sentiment, the words *offline*, *downtime* have a negative sentiment. They indicate the need to pay specific attention to the process/ task, which will require shutting down the servers or application disconnection. Such activities need to be carefully coordinated with all (possibly) affected parties so that one does not experience any unexpected service outage or other inconvenience.

Third, when the BS lexicon is developed, we apply a lexicon keyword-based pattern matching algorithm to determine the attention efforts in each IT ticket text. For this, (i) we calculate the normalized total score of words with negative, neutral, and positive sentiment with the pre-assigned valence and specific importance markers (syntactic and semantic intensifiers); (ii) a set of threshold rules are defined and fine-tuned by subject matter experts and adjusted to the current setting; (iii) using context-specific threshold rules and normalized score, BS is formalized on the ordinal scale of "low", "medium", or "high".

To sum up, *subjective knowledge* is outlined as the one (i) determining the attention efforts to be paid to the BP in general and BP elements in particular, (ii) reflecting the emotional component of the BP text, and (iii) extracted with the help of a domain-specific BS. For an overview of subjective knowledge extraction and BS identification, we refer to Fig. 3.

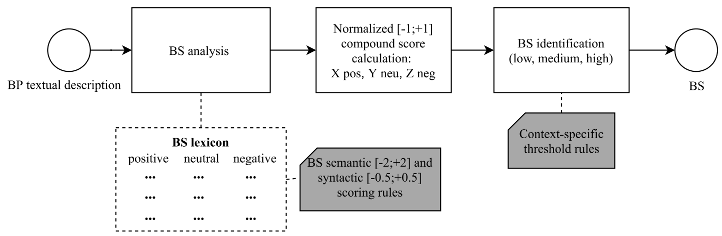

Fig. 3. Subjective knowledge extraction and BS identification. Source: own elaboration

Definition 3 ***Meta-knowledge.*** The complete realization of SA Level 2 introduced in Section 3.1. also implies the presence of such type of BP worker comprehension as (i) clear understanding of the BP text and (ii) his/her awareness of necessary *reading efforts* (SA Level 2.2.). To provide this type of comprehension, we suggest a specific approach of meta-knowledge extraction. In general, meta-knowledge is a conceptually different type of knowledge. As can be seen from the definitions above, objective and subjective knowledge aims to make explicit and structure the knowledge present in the text. Meta-knowledge determines the awareness of the *reading efforts* related to the text quality, i.e., knowledge about the text author or content outside of the text (Daelemans, 2013). Here, as already mentioned, the text quality will likely depend on such factors as the author's professionalism, expertise, and stress level. Undoubtedly, a well-written textual description of BPs facilitates successful and fast execution. Vice versa, a poorly written text complicates the work. In our approach, the Readability concept is used to extract the meta-knowledge, i.e., measure the text quality (Rizun *et al.*, 2019b). In the BPM context, we suggest the following set of Readability measures: (i) *text length*, (ii) *parts of speech (PoS)* and *unique PoS distribution*, (iii) *wording style*, allowing to formalize the text patterns in terms of a combination of BP text size, its linguistic structure, and specificity of BP text presentation correspondingly. To discover the Readability, first, we introduce the Readability measures definitions:

(i) *Text length* is based on the principle of least effort by Zipf (Zipf, 1950), i.e., the tendency to communicate efficiently with the least effort and measures the BP text in the number of words (without stopwords).

(ii) *PoS and unique PoS distribution* reflect the same logic from the perspective of the linguistic text structure. The authors tend to use a concise writing style in case of simple processes or tasks. By this, we understand the high usage of unique BP ***R****esources* (nouns) and ***T****echniques* (verbs and verbal nouns) to accurately describe the essence of the problem/process/task.

(iii) The *wording style* in our study is based on Zipf's word frequency law (Zipf, 1932) and indicates the information presentation flow as condensed versus disperse. We propose to use the approximation in the equation of Zipf's laws y=a+b/x based on the ordinary least squares method. To describe the wording style concept, we interpret the basic coefficients of Zipf's law as an average frequency of identified keywords (coefficient *a*) and approximated values of the average speed of appearance of new words in the text (the slope of the hyperbolic function, coefficient *b*) (Scorobey, 2017). Using these two coefficients, we build the text presentation pattern influencing the specifics of perception and understanding of the text by the BP worker. For example, a *high speed* of new words' appearance can be interpreted as a wording style with a condensed and concrete information presentation pattern. Such a style could testify to transparent and comprehensive Readability and required *low reading efforts*. If the *speed* of new words' appearance *slows down*, the wording style becomes more verbose, the same words (RTCC elements) are used more often. The rest of the words is used randomly, depending on the BP text context. The information presentation flow becomes more dispersed and redundant, decreasing Readability and increasing required *reading efforts*.

Second, a set of threshold rules is defined and fine-tuned by subject matter experts and adjusted to the current setting. Third, using the obtained measures and threshold rules, Readability is identified and formalized on the ordinal scale of "*effortless*", "*involving effort*", and "*telegraphic*". For example, the "telegraphic" Readability is assigned if unique BP ***R****esources*, particularly technical specifications, prevail. Thus, in the ticket *"update XXX.XXX.XXX, YYY.YYY.YYY, install ZZZ.ZZZ.ZZZ, upgrade AAA.BBB.CCC"*, the technical names of specific configuration items are in a clear majority. In this case, the BP worker either already knows what needs to be done (for example, these updates, installation, and upgrading are requested every two months), or the (possible) complexity can be captured via objective or subjective knowledge extraction. In this telegraphic example, the BP ***T****echniques update, install* and *upgrade* belong to *routine* DML. Hence, on SA Level 3, the worker will get the decision support based on objective knowledge.

Thus, *meta-knowledge* can be defined as the one (i) containing the information about the text quality, (ii) directly influencing the comprehension of the text by its readers and necessary reading efforts, (iii) expressed by Readability extracted based on text length, PoS and unique PoS distribution, and wording style. For an overview of the meta-knowledge extraction and Readability identification, we refer to Fig. 4.

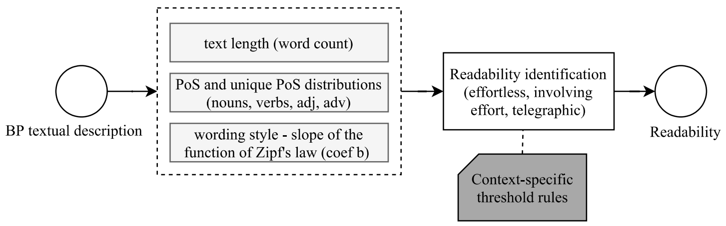

Fig. 4. Meta-knowledge extraction and Readability identification. Source: own elaboration

Definition 4 ***Business Process complexity.*** To realize the SA Level 3 introduced in Section 3.1., consisting of the BP worker's ability to project the future status of the current situation, we propose a concept of *BP complexity*. It aims to create awareness of BP workers regarding the future BP status, i.e., its execution. The knowledge about BP complexity is formed based on the (i) professional contextual experience of the BP worker enriched by the awareness of cognitive efforts required for BP execution (objective knowledge), (ii) business emotions enriched by attention efforts (subjective knowledge), and (iii) quality of the text, i.e., professionalism, expertise, and stress level of the text author, enriched by reading efforts (meta-knowledge).

Using the expert rule-based approach, the output values of DML level (objective knowledge), BS (subjective knowledge), and Readability (meta-knowledge) are aggregated to "low", "medium", or "high" BP complexity. Such a process classification is envisioned to support the BP workers in selecting a mental model directing the strategy necessary for the BP execution. Further, regarding the decision support itself, we refer to the SA enhanced process design in the context of automation and interpret "low", "medium", and "high" BP complexity as follows: (i) BPs with *low* complexity are those which can be easily automated based on clear rules; (ii) BPs of *medium* complexity do not follow exact ruleset and can be only partially automated; (iii) in case of highly challenging BPs (*high* complexity), there is no automation expected but minimal assistance in the form of the history of similar BPs. In Fig. 5, we formalize the BP complexity concept definition and envisioned decision support.

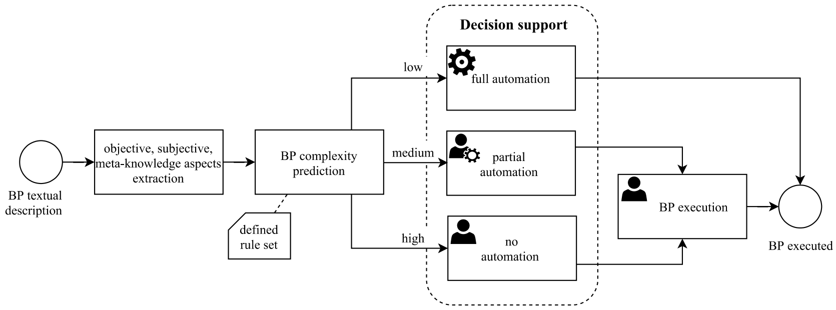

Fig. 5. BP complexity for decision support. Source: own elaboration

To sum up, the concept of *BP complexity* is the one (i) estimated using the objective, subjective, and meta-knowledge extracted from the BP textual description with the help of NLP techniques, (ii) formed based on a comprehensive understanding of the current situation, and (iii) promoting knowledge creation, transfer, and application. Below, we describe the illustrative application of the BP complexity concept based on the ITIL CHM dataset of the motivating example.

5. Illustrative Application

This section presents the BP complexity concept application on the ITIL CHM dataset. We propose five steps, out of which steps 2-4 can be performed in parallel.

Step 1. Data Collection and Preprocessing

An important preparation step is collecting BP textual descriptions and converting them into the format required by the program in which the computational analysis will be performed. In our study, two datasets were obtained from the ITIL CHM department according to their availability. After removing duplicates and empty entries, the final datasets comprised 28,157 and 4,625 entries correspondingly. To extract objective and meta-knowledge, classical preprocessing (removal of numbers, special symbols, punctuation, converting to lowercase, stemming) is required. The subjective knowledge is related to the sentiment-relevant information. This information is expressed by the BS lexicon and specific intensifiers (such as capitalizations, exclamation and question marks, specific symbols). The correct extraction of mentioned intensifiers requires special preprocessing, i.e., only removing numbers and stemming. Preprocessing and extraction of the knowledge types were conducted using Python 3.4. The development of handcrafted threshold rules and quantitative evaluation were implemented iteratively using Microsoft Office Excel 2016. Further, collecting other process-related information such as manuals, handbooks, process descriptions, and identification of necessary experts were performed in this step.

Step 2. Objective Knowledge Extraction

In the second step (SA Level 1), to extract objective knowledge, we follow Definition 1 in Section 4. Hence, we perform a part-of-speech tagging and assign nouns, verbal nouns, verbs, adjectives, and adverbs to the BP elements of the RTCC framework per each IT ticket text. Using the DML taxonomy developed to determine the *cognitive efforts* necessary to process the IT ticket, we identify routine, semi-cognitive, and cognitive RTCC BP elements in each IT ticket text. Then, the IT tickets are assigned to one of the three DML levels using the taxonomy keyword-based pattern matching algorithm. Accordingly, based on the total number of detected keywords, we calculate the relative occurrence of the keywords of each category. Using the context-specific threshold rules, we identify the DML level. In our motivating example, all the keywords detected based on the DML taxonomy, i.e., five *routine* ***R****esources* (*PSU, patch, database, server*, *attachment*) and two *routine* ***T****echniques* (*apply*, *reject*), belong to the *routine* DML level. Thus, following the threshold rules in Table II, this IT ticket is associated with the expected 100% routine activity type. On SA Level 3, the CHM worker can expect fast processing of this ticket and plan the time for other effort-intensive or creative tasks in accordance with the expected *cognitive efforts*. Additional information is provided in the repositories[3] and Section 6 describing our iterative evaluation and threshold rule establishment.

Table II. Threshold rules of objective knowledge extraction (DML)

#	*Decision-Making Logic Taxonomy* *routine (rout), semi-cognitive (semi-cog), cognitive (cog)*			*DML* *(cognitive efforts)*
1	rout=0	semi-cog=0	cog=1	*cog*
2	0≤rout<0.3	0≤semi-cog<0.5	cog≥0.3	*cog*
3	(rout=1) & (rout=0)	semi-cog=0	cog=0	*rout*
4	rout≥0.5	(semi-cog+cog) ≤0.3		*rout*
5	rout=0	semi-cog=1	cog=0	*semi-cog*
6	rout=0	semi-cog=0	cog≥0.3	*semi-cog*

Source: (Revina and Rizun, 2019)

Step 3. Subjective Knowledge Extraction

In the third step (SA Level 2.1), to extract subjective knowledge, we follow Definition 2 in Section 4. We use the BS lexicon developed based on the process described in (Rizun and Revina, 2019). BS has been introduced as an instrument for measuring the "emotional" component of an IT ticket to determine the *attention efforts* needed to be paid to certain BP elements of the ticket and ticket as a whole. This latent information is extracted from the IT ticket text based on the domain-specific BS lexicon and the lexicon keyword-based pattern matching algorithm. We determine the proportion of words with *negative*, *neutral*, and *positive* valence and the intensifiers (specific punctuation, characters, capitalizations) for each IT ticket text. These values are used to determine the normalized compound score. Finally, the BS is formalized on the ordinal scale of "low", "medium", "high" based on a set of threshold rules. See Section 6 for a detailed description of our iterative evaluation and threshold rule establishment. In our motivating example, the three BS lexicon keywords (*dear*, *please*, *minimum*), one expression (*disaster recovery*) with 0 valence, one keyword (*rejected*) with -2 valence, and time information (*10hrs 45mins*) with -0.5 valence have been identified. Furthermore, extensive intensifier usage, i.e., six exclamation marks, 30 stars (total valence is -0.36), and one capitalized word (valence is -0.1). The author of this text used these signs to draw special attention to the time to be planned for this ticket. On SA Level 3, the CHM worker will be aware of and consider the necessary time window more carefully while planning and allocating the ticket-related tasks. Hence, according to the threshold rules in Table III, the processing of such an IT ticket requires much *attention efforts*, making the BS *high*. A detailed description of the lexicon, its scoring semantic and syntactic rules can be found in (Rizun and Revina, 2019) and the repositories[4].

Table III. Threshold rules of subjective knowledge extraction (BS)

#	*Compound Valence* *positive (pos), neutral (neut), negative (neg)*			*BS (attention efforts)*
1	pos>0.2	neut>2*abs(neg)	0<abs(neg)<0.1	*low*
2	pos≥0	neut=0	neg=0	*low*
3	pos>2*neut	neut>0	neg=0	*low*
4	unrecognized			*low*
5	pos=0	neut=1, neut=0	neg=0	*medium*
6	pos>0	neut>0	neg=0	*medium*
7	pos≥0	neut≥0	0<abs(neg)<0.1	*medium*
else				
8	-			*high*

Source: (Revina and Rizun, 2019)

Step 4. Meta-Knowledge Extraction

In the fourth step (SA Level 2.2.), to extract meta-knowledge, we follow Definition 3 in Section 4. Accordingly, we measure the text quality and the required *reading efforts* based on the relative number of PoS calculated as related to the whole *ticket length*, i.e., 21 in our motivating example. Afterward, the relative number of *unique PoS* is determined in relation to the *PoS number* in the ticket text. In our example, all PoS are unique (no repetitions) with a substantial prevalence of unique nouns. Next, coefficient b (*wording style*) characterizing the speed of new

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[3] See our Github project page repository Decision-Making-Logic-Taxonomy with the DML taxonomy vocabulary, python file for extracting DML keywords (as an input for python files serve ticket textual descriptions and DML taxonomy), excel file with the calculation of DML based on the motivating example, threshold rules (as an input for excel file serve threshold rules)

[4] See our Github project page repository Business-Sentiment with the BS Lexicon, python file for extracting BS (as an input for python file serve ticket textual descriptions and BS Lexicon), excel file with the BS calculation based on the motivating example, threshold rules, and scoring, semantic, and syntactic rules (as an input for excel file serve threshold rules)

words' appearance and allowing to identify the pattern of information presentation is computed. In our case, coefficient *b* has the value 0. This indicates a clearly written text with *effortless* Readability. The latter is assigned using the expert-defined threshold rules (see Table IV and Section 6 for iterative evaluation and threshold rule establishment). Hence, on SA Level 3, the CHM worker will be aware of the high-quality text and low *reading efforts*, which facilitates ticket processing. A comprehensive description of the mentioned Readability measures can be found in (Rizun *et al.*, 2019b) and as a part of supplementary material[5].

Table IV. Threshold rules of meta-knowledge extraction (Readability)

<table>
<tr><th>#</th><th>Text length (L)</th><th>PoS and unique PoS
$\sigma\ (n, v, adj, adv)$</th><th>Wording style
(Zipf's coefficient b)</th><th>Readability
(reading efforts)</th></tr>
<tr><td>1</td><td>L<25 words</td><td>$\sigma\ (n)$>0 and $\sigma\ (v, adj, adv)$=0</td><td>b=0</td><td>telegraphic</td></tr>
<tr><td>2</td><td>-</td><td>$\sigma\ (n, v)$>0 and $\sigma\ (n)$>$\sigma\ (v, adj, adv)$ and $\sigma(n) \geq \sigma\ (\exists!\, n)$</td><td>b<3</td><td>effortless</td></tr>
<tr><td colspan="5">else</td></tr>
<tr><td>3</td><td colspan="3">-</td><td>involving effort</td></tr>
</table>

Source: (Revina and Rizun, 2019)

Step 5. BP Complexity Identification

At the end (SA Level 3), the IT ticket complexity is identified using the expert-defined decision rules in Table V and obtained DML, BS, and Readability values in steps 2-4. The BP worker receives a comprehensive understanding of the situation based on the awareness of the *cognitive, attention*, and *reading* efforts needed to process the IT ticket. At this step, the BP worker can also trace back and analyze which BP ***R**esources*, ***T**echniques*, ***C**apabilities*, and ***C**hoices*, specific sentiment-loaded keywords, punctuation, linguistic text structure, and wording style have led to the suggested complexity level. Such an ability is essential for developing trust in the recommendation and creation and transfer of knowledge regarding the process complexity and those factors contributing to this complexity. Hence, after providing the SA, the decision support itself takes place in the form of a recommendation. In our motivating example, the BP complexity is estimated as *medium* based on the identified *routine* DML, *high* BS, and *effortless* Readability and using the expert-defined decision rules in Table IV. The decision support should be realized as a recommendation to use a pre-filled form from the database and adjust necessary fields. See Table VI for a summary.

Table V. Expert-defined decision rules for BP complexity identification

#	*DML*	*BS*	*Readability*	*BP complexity*
1	routine	low, medium	effortless, involving effort	low
2	semi-cognitive	low	effortless	low
3	routine	-	telegraphic	low
4	routine	high	effortless, involving effort	medium
5	cognitive	low	effortless	medium
6	semi-cognitive, cognitive	low	involving effort	medium
7	semi-cognitive, cognitive	medium, high	effortless	medium
8	semi-cognitive	-	telegraphic	medium
9	semi-cognitive, cognitive	medium, high	involving effort	high
10	cognitive	-	telegraphic	high

Source: (Revina and Rizun, 2019)

Table VI. BP complexity concept application on the motivating example

<table>
<tr><td colspan="4">“Dear colleagues, please apply SAP R3 PSU patches on server XXX.YYY.ZZZ for database AAA.BBB.CCC. Attachments - READ RunBook !!! ***************Minimum lead time - 10hrs 45mins*************** !!! Otherwise the ticket will be rejected. Disaster recovery tests are prepared by XYZ”</td><td>Output</td></tr>
<tr><td colspan="5">Objective knowledge (DML)</td></tr>
<tr><td>routine</td><td>semi-cognitive</td><td colspan="2">cognitive</td><td rowspan="3">DML / cognitive efforts: "routine"</td></tr>
<tr><td>1 (7/7)</td><td>0</td><td colspan="2">0</td></tr>
<tr><td>psu, patch, database, server, attachment, apply, reject</td><td>-</td><td colspan="2">-</td></tr>
<tr><td colspan="5">Subjective knowledge (BS)</td></tr>
<tr><td>positive</td><td>neutral</td><td>negative</td><td>intensifiers</td><td rowspan="3">BS / attention efforts: "high"</td></tr>
<tr><td>0</td><td>0.86 (6/7)</td><td>0.14 (1/7)</td><td>39</td></tr>
<tr><td>-</td><td>read, dear, please, minimum, disaster recovery</td><td>rejected</td><td>capitalization, time, *, !</td></tr>
<tr><td colspan="5">Meta-knowledge (Readability)</td></tr>
<tr><td>relative # of nouns</td><td>relative # of verbs</td><td>relative # of adjectives and adverbs</td><td>wording style (b)</td><td>Readability / reading</td></tr>
</table>

[5] See our Github project page repository Stylistic-Patterns-and-Readability with python file for extracting readability measures (as an input for python files serve ticket textual descriptions), excel file with the calculation of readability based on the motivating example and threshold rules (as an input for excel file serve threshold rules), illustrative application of Zipf's Law on tickets (wording style)

0.52 (11/21)	0.19 (4/21)	0.05 (1/21)	0	efforts: "effortless"
colleague, patch, server, database, attachment, lead, time, ticket, disaster, recovery, test	please, apply, reject, prepare	dear	-	
Estimated complexity level = "medium"				
Decision support recommendation: use a pre-filled form as a basis and adjust necessary fields				

Source: own elaboration

Table VII summarizes the five-step application scenario described above and specifies required input, processing, and necessary outputs for each step, highlighting manual and computer-aided tasks.

Table VII. Generalized summary of the five-step application scenario of BP complexity prediction

Input	Processing	Output
Step 1. Data Collection and Preprocessing		
BP textual descriptions Tools: standard NLP processing software, e.g., Python and NLTK library[6]	1. Standard preprocessing: removal of numbers, special symbols, punctuation, converting to lowercase, stemming	Preprocessed BP texts for the extraction of objective and meta-knowledge
	2. Special preprocessing: only removal of numbers and stemming	Preprocessed BP texts for the extraction of subjective knowledge
Step 2. Objective Knowledge Extraction		
*.csv file with preprocessed BP texts from step 1.1. DML taxonomy Threshold rules Tools: Python, NLTK, MS Office Excel	1. Computational analysis: parts-of-speech tagging	Parts of speech assigned to the RTCC elements for each BP text
	2. Computational analysis: identification of DML keywords; calculation of the relative occurrence of the keywords of each DML level Manual implementation of threshold rules to identify DML in MS Excel	DML keywords and assigned DML for each BP text
Step 3. Subjective Knowledge Extraction		
*.csv file with preprocessed BP texts from step 1.2. BS lexicon Threshold rules Tools: Python, NLTK, MS Office Excel	Computational analysis: identification of BS keywords and their valence, intensifiers; calculation of the normalized compound score Manual implementation of threshold rules to identify BS in MS Excel	BS keywords, normalized compound score, and assigned BS for each BP text
Step 4. Meta-Knowledge Extraction		
*.csv file with preprocessed BP texts from step 1.1. Threshold rules Tools: Python, NLTK, MS Office Excel	Computational analysis: calculation of BP text length (word count), PoS and unique PoS identification, calculation of coefficient b Manual implementation of threshold rules to identify Readability in MS Excel	Text length, PoS, and unique PoS distribution, coefficient b, and assigned Readability for each task text
Step 5. BP Complexity Identification		
Excel *.csv file with BP texts and identified DML, BS, and Readability for each BP text Decision rules Tools: MS Office Excel	Manual implementation of decision rules to identify BP complexity	BP complexity for each BP text

Source: own elaboration

6. Evaluation

In the context of the practical implications of the research artifact, special attention was paid to the evaluation. We conducted quantitative computer experiments and qualitative interviews and discussions in the experimental and evaluation phase consisting of six main steps (see Fig. 6).

[6] https://www.nltk.org/

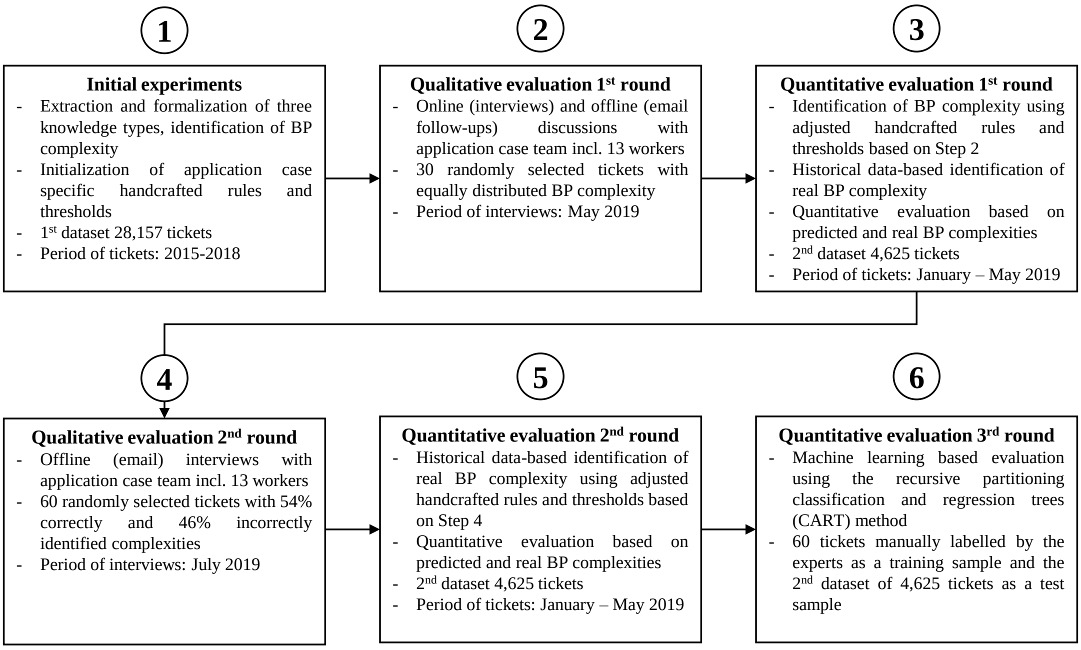

Fig. 6. Evaluation process. Source: own elaboration

In *Step 1*, using the dataset of 28,157 tickets, the initial experiments were carried out. The goal was to extract and formalize the three knowledge types, set up initial application case-specific handcrafted rules and thresholds, and identify BP complexity based on these values. In *Step 2*, to evaluate the obtained values, 30 randomly selected tickets with equally distributed predicted, i.e., textual data-based, *BP complexity* values were presented to the experts, i.e., 13 workers of the application case department. This first qualitative evaluation round, including online discussion (see the evaluation questionnaire as a basis for the interviews[7]) and offline follow-up sessions, was conducted in May 2019. The interview was divided into three parts. First, we introduced the objectives of the interview, research motivations, theoretical and methodological background. Second, the method of knowledge extraction and BP complexity prediction was illustratively presented using the sample of 30 tickets. Afterward, the experts estimated the IT ticket complexity based on the available historical data regarding IT ticket processing.

The discussion of the discrepancies between *predicted BP complexity* and historical data-based complexity, further referred to as *real BP complexity*, was shifted to offline (email). Additional information from the IT ticketing system was needed to estimate *real BP complexity*. In the scope of the research, *real BP complexity* is exclusively used to evaluate the research artifact. Third, a Q&A session was conducted following a so-called funnel model (Runeson and Höst, 2009). We started with open questions and moved towards more specific ones regarding possible practical implications of the complexity prediction. Hereby, providing recommendations in the form of templates or historical ticket data (see illustrative process models[8]), prioritization of an incoming ticket as a dashboard for the correct time and workforce management in the team, and automatic filling in of the ticket complexity field in the IT ticketing system were mentioned as possible use cases of BP complexity concept application. The offline discussion of the BP complexity values yielded the results presented in Table VIII, point 1. The table gives an overview of qualitative and quantitative evaluation results of BP complexity prediction. Overall precision is the relative number of correctly identified *predicted BP complexity* compared to the whole number of identified *real BP complexity*. Recalls are calculated for each of the three possible *predicted BP complexity* values and represent a fraction of relevant values that have been retrieved over the total amount of relevant values.

Table VIII. Evaluation results of IT ticket complexity prediction

	low	medium	high
1. Qualitative evaluation of initial experiment results (28,157 tickets) based on 30 tickets – predicted vs. expert complexity			
Recall	69%	55%	67%
Overall precision	63%		
2. Quantitative historical data-based evaluation of follow-up experiments results (4,625 tickets) – handcrafted rules			
Recall	51.2%	28.4%	9.1%
Overall precision	45%		
3. Qualitative evaluation of experiment results (4,625 tickets) based on 60 tickets – real vs. expert complexity			
Recall	62%	10%	0%
Overall precision	54%		
4. Quantitative historical data-based evaluation of follow-up experiments results (4,625 tickets) – handcrafted rules			

[7] See the evaluation questionnaire used as a preparation for the interviews
[8] See the process models illustrating the recommendations

Recall	73.9%	71.9%	40.7%
Overall precision	61.75%		
5. Quantitative historical data-based evaluation of follow-up experiments results (4,625 tickets) – CART based rules			
Recall	75.6%	61.6%	50.2%
Overall precision	62.27%		

Source: own elaboration

In the discussions, we obtained the following findings for qualitative improvements: (i) enrichment of the DML taxonomy and BS lexicon with the one- and bi-grams indicating simple vs. complex problem solving, (ii) development of the handcrafted threshold rules, and (iii) identification of necessary historical ticket data allowing to calculate the *real BP complexity*. Hence, we amended the mentioned vocabularies with such one- and bigrams as "(no, not) affected", "(no) PSO" (Projected Service Outage), "(no) impact", "(no, short, zero) downtime", "test", "(no, not) production", "(no, not) prod". We also added German equivalents of such adverbs as "no", "not", i.e., "kein(e)", "nicht", for the case of English-German ticket texts. Next, the following handcrafted rules and historical data were selected to identify the *real BP complexity*: (i) the presence of the mentioned one- and bi-grams in the IT ticketing system fields "Impact description" and "Brief description" of the ticket (RegEx (Prasse *et al.*, 2015) based free text search), (ii) number of tasks per ticket (count of tasks, integer data type), (iii) number of configuration items, specifically applications involved in the ticket (count of applications, integer data type), (iv) risk type of ticket (enumeration, ordinal scale of "low", "medium", "high").

In *Step 3*, we obtained the second dataset of 4,625 tickets with the historical data necessary to identify *real BP complexity,* as discussed with the experts in Step 2. The first quantitative evaluation results were not satisfying, revealing the overall precision of approximately 45% with the following recalls of *predicted BP complexity* – low 51.2%, medium 28.4%, and high 9.1% (see Table VIII, point 2). Therefore, in *Step 4*, we conducted the second qualitative evaluation round in the form of an interview in an offline (email) mode in July 2019. For this purpose, 60 randomly selected tickets with *predicted* and *real BP complexity values* were presented to the experts. The sample contained 54% correctly and 46% incorrectly identified complexities with the random structure of low, medium, and high values. The goal was to adjust the rules and thresholds to identify *real BP complexity* based on the historical data. In the offline discussions, the cases of discrepancies between the *real BP complexity* and the one assigned by the experts were reviewed in detail (for the evaluation results, see Table VIII, point 3). Finally, in *Step 5*, we conducted the second quantitative evaluation round. Using adjusted rules regarding the keywords and thresholds for the historical ticket data, such as number of applications and tasks, we achieved an improvement resulting in a better prediction (see Table VIII, point 4).

Additionally, in *Step 6*, to compare the evaluation results, we applied a machine learning (ML) based approach, i.e., the recursive partitioning classification and regression trees (CART) method (Podgorelec *et al.*, 2002) with complexity parameter cp=0.056 and measures of the error in classification xerror=0.39. For this purpose, we used the mentioned set of 60 tickets manually evaluated by the experts as a training sample and a dataset of 4,625 tickets as a test sample. The results can be seen in Table VIII, point 5. Comparing the evaluation results of points 4 and 5 in Table VIII, we observe relatively consistent results and can conclude that the performance of our method is acceptable. Looking into ML-based ticket classification approaches in the literature, sophisticated ML classification pipelines report accuracy in a rather broad range from 30% to 90% (Banerjee *et al.*, 2012; Mandal *et al.*, 2019).

The dataset structure obtained at the end of the experiments and evaluation is presented in Table IX. Considering both datasets, we could identify some clear trends. Hence, in the DML distribution, the predominant values are *routine* and *semi-cognitive*, with only a few *cognitive* values. This trend follows a general understanding and expectation of the distribution of daily tasks. In the BS distribution, there is an evident discrepancy between the two datasets. In the first case, the prevalent BS is *medium* (68.5%). Generally, CHM workers tended to use the BS intensifiers (capitalizations, special characters, punctuation) to highlight certain text parts. The reason was that the IT ticket processing software did not support standard text highlighting functions like bold or cursive letters, underlining, colors. Thus, we observe most tickets of *medium* BS in the first dataset. In the second dataset, the majority of tickets evidence *low* BS (63.2%). Such a discrepancy can be explained by the different sizes of the datasets and their imbalance. The *high* BS is distributed almost equally in both datasets. The distribution values of Readability demonstrate a trend similar to that of DML. The most common values are *effortless* and *involving effort*, with relatively few *telegraphic* values. The most frequent value in the first dataset is *effortless,* and in the second – *involving effort*. The IT ticket complexity values of both datasets reveal comparable distributions, i.e., prevailing *low* complexity tickets followed by *medium* and *high*.

Table IX. Distribution statistics of DML, BS, Readability, and IT ticket complexity

DML (objective knowledge)	BS (subjective knowledge)	Readability (meta-knowledge)	IT ticket complexity
1. Dataset of 28,157 tickets			
routine – 60% semi-cognitive – 39% cognitive – 1%	low – 8.7% medium – 68.5% high – 22.8%	effortless – 53.1% involving effort – 43.6% telegraphic – 3.3%	low – 56.3% medium – 26.8% high – 16.9%
2. Dataset of 4,625 tickets			

routine – 48.6% semi-cognitive – 49.5% cognitive – 1.9%	low – 63.2% medium – 11.3% high – 25.5%	effortless – 35.5% involving effort – 52.8% telegraphic – 11.7%	low – 52.4% medium – 31.7% high – 15.9%

Source: own elaboration

Tables II-IV in Section 5 provided the final values for the case study-specific handcrafted rules and thresholds of the knowledge aspects extraction. These were obtained after the experiments and evaluation rounds described in this section. The final case study-specific rules for the *predicted BP complexity* are illustratively presented in Table V.

7. Discussion, Contribution, and Limitations

This study develops the BP complexity concept using the Theory of SA and targets the awareness of BP workers regarding *cognitive, attention, and reading efforts* needed to perform the BP task or activity. Such awareness is realized with common NLP techniques addressing domain-specific semantics, syntax, and stylistics. Hereby, we rely on the three levels of text understanding well-known in linguistics (Daelemans, 2013), i.e., objective, subjective, and meta-knowledge. Finally, we adapt and illustrate our research findings using a real-world IT ticket processing case.

Hence, the main *theoretical* contributions of our work are:

(i) We propose a novel textual data-based BP complexity based on the three levels of text understanding following the theoretical foundations of computational linguistics by Daelemans (Daelemans, 2013).
(ii) Our BP complexity concept includes three linguistic perspectives: semantics, syntax, and stylistics, the semantics being in the most focus. The latter is a declared challenge impeding the full exploitation of the NLP benefits in BPM (van der Aa, Carmona, et al., 2018).
(iii) Motivated by the recent studies (Karami et al., 2020) and a declared need for domain-specific adaptations (Endsley, 2015), we use the Theory of SA to adapt the well-known linguistic foundations to the BPM context.
(iv) Hereby, the major contribution to the literature is the confirmation that BP textual data can be used to predict BP complexity from the semantic, syntactic, and stylistic viewpoints.

The *methodological* contribution of our research is the combination of common NLP techniques to operationalize the knowledge extraction on the three levels of text understanding differentiated by linguists. In particular, the three levels of text understanding, i.e., objective, subjective, and meta-knowledge, are realized by (i) domain-specific taxonomy, (ii) sentiment lexicon, and (iii) stylistic features such as text length, parts of speech (PoS) and unique PoS distribution, and wording style calculated based on the Zipf's Law. These are widely used NLP techniques, which can be relatively easily implemented. The difficulty consists in the preparatory work of vocabularies' compilation and threshold rule establishment. However, one can think about implementing ML approaches using our linguistic features as text representation.

The mentioned *theoretical* and *methodological* contributions enable the realization of the incremental *practical* research value:

(i) The three levels of text understanding aim to provide awareness regarding the *cognitive, attention, and reading efforts* required to perform the BP task or activity, hence estimating the BP complexity.
(ii) The knowledge about the BP complexity is formed based on the (i) professional contextual experience of the BP worker enriched by the awareness of cognitive efforts required for BP execution (objective knowledge), (ii) business emotions enriched by attention efforts (subjective knowledge), and (iii) quality of the text, i.e., professionalism, expertise, and stress level of the text author, enriched by reading efforts (meta-knowledge).
(iii) This work uses a real-world industrial dataset of IT ticket processing to receive expert feedback regarding the BP, i.e., IT ticket processing, complexity.
(iv) Further, our BP complexity concept allows a granular perspective on the analyzed data. BP workers can trace back the suggested level of complexity. This is especially important in the context of erroneous classifications and the Explainable Artificial Intelligence (XAI) paradigm.

Lastly, we are aware that our contributions have generalization problems and limitations. The concept of BP complexity reveals certain constraints resulting in additional efforts of the different degree and limitations to adjust the approach while applying in different areas, in particular:

(i) The threshold rules should be adjusted with the subject matter experts for each application case.
(ii) The assumptions underlying the meta-knowledge extraction are made based on the mentioned Zipf's Law, the principle of least effort, and observations and interviews with the subject matter experts. There is a need to prove, extend, or refine these assumptions with the corresponding subject matter experts in other cases.
(iii) Current vocabularies of DML taxonomy and BS lexicon are developed for the ITIL CHM ticket processing. The efforts to adjust these vocabularies for ITIL-related ticket processing cases, such as Incident or Problem Management, should be minimal. In other IT ticket processing cases, the efforts are estimated to be moderate, i.e., some parts of the mentioned vocabularies can be reused. It is worth mentioning that ITIL is widely used, having been ranked in the ten top-paying IT Certifications for 2020 based on the survey

conducted in the United States (Global Knowledge, 2020). Moreover, managing IT tickets, in general, remains a crucial concern for the IT service industry (Paramesh and Shreedhara, 2019).

(iv) In entirely different cases, like other Customer Services areas, Marketing, Software Development, or Strategy, all the vocabularies need to be developed from scratch following the processes described in this paper.

(v) If the textual descriptions are written in a language other than English, all the vocabularies also need to be compiled from the beginning.

8. Conclusion and Future Work

This research work aimed to propose a concept of BP complexity and a set of measures based on the unstructured textual data generated in BPs. The BP complexity can be used to prioritize the BP tasks and activities correctly, estimate necessary effort, and provide adequate decision support. The theoretical background of computational linguistics and situation awareness was used to develop, structure, and justify a set of the three knowledge types, i.e., objective, subjective, and meta-knowledge. Diverse common NLP techniques were implemented to extract the knowledge. Afterward, data analysis based on an industrial example from the ITIL CHM department of a telecommunication provider illustrated the concept application.

Our study evidences certain limitations opening the opportunities for future work. For example, manual adjustment of threshold rules is a rather tedious and time-consuming process demanding the constant involvement of subject matter experts. Further, as the goal of our study states, we use textual data to determine the process complexity. Hereby, the event logs known to contain important process insights remain out of scope. Hence, as a part of future work, we plan to further exploit the potential applications of our complexity concept and experiment with (i) ML approaches in combination with the three knowledge types as the text representation to avoid manual adjustments of threshold rules, (ii) Process Mining, i.e., event logs, based complexity prediction, and (iii) combining textual and Process Mining based complexities into one framework. Bringing these two perspectives together represents a promising but understudied research area (Fan and Ilk, 2020). At the same time, as a demonstration of the practical value of the research, the following business cases of the concept can be developed: (i) dashboard for prioritization of an incoming ticket for the correct time and workforce management in the team and (ii) prototype of a recommender system for BP workers (Revina and Rizun, 2019) that automatically extracts the knowledge types of the BP complexity concept from the incoming textual requests and adapts the type and the way of recommendation according to the identified BP complexity.

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