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Analyzing Content of Tasks in Business Process Management. Blending Task Execution and Organization Perspectives

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Abstract

An efficient organization, management, and execution of tasks are central for the successful functioning of any organization. This topic was on the research agenda already in the early 1950s and keeps attracting the scientific community's attention today. Continuous advances and penetration of technologies in organizations are expected to increase task variety and complexity. This creates a constant demand for new methods to analyze, measure, manage, and execute tasks. In this study, we extract relevant task content aspects from textual task descriptions and build a task content model as a basis for the development of various decision-support solutions for process workers and managers. Using the Theory of Situation Awareness, we specify a method for analyzing and measuring the content of tasks and illustrate it by an industry example of ITIL IT ticket processing. We refer to the Strategic Alignment Model while discussing the implications for task management and execution research and practice.

1. Introduction

Task analysis has a long history in organizational, educational, and psychological literature [1,2]. Tasks can be characterized as activities that individuals need to perform in their work and life. They are the most critical elements in the investigation of human performance and behavior. Task characteristics are believed to have a significant impact on individual and group behavior [3,4]. Human performance directly depends on the interplay of (i) task characteristics, such as *structure* [5–7], *cognition* [8], *importance* [9], and *typology* [10], (ii) task performer characteristics, such as professional training and *skills*, and (iii) environmental characteristics, such as physical work conditions.

Tasks are designed to implement a sequence of steps that represent processes. Business processes (BPs) define and connect tasks, jobs, and responsibilities and, by this, shape the work of every employee and machine in the organization [11]. Business Process Management (BPM) is fairly considered an established practice to manage the processes in this context. BPM addresses the management of processes on the level of operational execution and organization of tasks. One of the essential conditions that guarantee an efficient BPM is to ensure that BP participants are aware of the current state of tasks at hand, possible ways of their execution, and the consequences of the decisions. BP participants are often challenged by the need to take important decisions in a limited time and at a high frequency. In cognitive psychology, the concept of Situation Awareness (SA) [12] has been developed as a rational basis for understanding the actions of human subjects and decision-making under complex and dynamic conditions. SA provides decision-makers the ability to make informed decisions enhancing the efficiency of BPs. Hence, we aim to create awareness for task performers based on the Theory of Situation Awareness and Situation

Awareness Model [12] in this study. We use it as a starting point to design the task analysis approach.

Another necessary condition to ensure the flexibility and adaptability of the integrated BPM is establishing instruments to align strategies of the organizational elements, namely BPs, business strategy, IT strategy, IT infrastructure and processes. The Strategic Alignment Model (SAM) is a well-known tool to leverage the impact of IT on today's organizations and achieve a synergetic balance between the mentioned organizational elements. In this study, we use SAM to provide the possibility of flexible strategic alignment of diverse organizational elements such as tasks, their performers, and IT technology.

Moreover, analysts estimate that upward of 80% of enterprise data today is unstructured texts [13,14]. As a rule, tasks also reach their addressees in an unstructured textual form, e.g., via emails, instant messages, specific files with instructions, or they can be directly typed by the addressee within a meeting. Unstructured textual data format, especially coming in large volumes, high frequency, and speed, represents a difficulty for human subjects to analyze and make decisions.

In the BPM context, unstructured textual data is analyzed to solve a wide range of challenges, prevailingly in relation to BP models [15,16] and descriptions [17]. However, the analysis of textual task descriptions for decision support, which is the focus of this research, is not explored. As fairly noted by [18], one major challenge for Natural Language Processing (NLP) researchers in the application to BPM is analyzing and defining tasks based on semantic information, such as the detection of exclusivity, concurrency, decision points, or iteration of tasks described in the text. Furthermore, the same authors highlight other relevant research directions, such as generally enhancing the text analytics methods in the sense of semantics and developing domain or even organization-specific adaptations of common NLP and text analytics approaches.

To sum up, our research focuses on analyzing the content of tasks in the form of textual descriptions to develop various decision-support solutions for BP workers and managers. In particular, we set a goal to define a model and method to extract, analyze, and measure those task content aspects influencing task execution and organization activities. The following highlights make our approach noteworthy:

(i) retrieval of a set of semantic task characteristics with the help of practical context-aware domain-specific text analytics instruments, such as taxonomies and sentiment;
(ii) combination of two management levels, i.e., task execution and task organization, through the lens of BPM;
(iii) ensuring the awareness of a task performer using solid theoretical foundations, such as the Theory of Situation Awareness, and providing possibilities for flexible alignment of strategies based on SAM.

The remainder of the paper is structured as follows. Section 2 gives a brief overview of the related research work, namely, task definitions and classifications, task analysis approaches, and unsolved issues. Section 3 provides a theoretical background on situation awareness and strategic alignment. Section 4 offers a motivating industrial example of ITIL IT ticket processing used in the study. Section 5 presents a task content model and method for measuring task content from execution and organization perspectives and supports the presentation with an industrial example introduced in Section 4. Finally, implications for task organization and execution research and practice are discussed in Section 6. We conclude with threats to validity in Section 7 and a summary in Section 8.

2. Related Work

This section reviews existing task definitions, classifications, and task analysis approaches and highlights the unsolved issues.

2.1. Task Definitions and Classifications

The discussions about task organization extend back to the 1950s [1,2] and are coming up today with a new rigor in the context of industrial progress, digitization, and automation [19–22] as well as sensitive tasks, for example, in the military domain, where slight errors can cause catastrophic consequences [23].

It is noteworthy that the most prominent task definitions and classifications are related to task complexity studies. For a comprehensive review of task complexity definitions, we refer to [24]. Accordingly, Liu and Li [24] differentiate between three approaches. The first approach considers a task from its *structure*, for example, a number of components, goals, solutions, and execution alternatives. The second approach defines tasks based on necessary *resources*, for example, cognitive, physical demands, or knowledge. In the third *interaction* approach, the task is viewed as a product of human-task interaction, such as task difficulty perceived by a task performer or familiarity of the task performer with the task. In Table 1, we list some prominent informative studies on task definitions.

Table 1. Task definitions overview

Approach	Definition	Source
Structure	number of elements and relations	[4,25–27]
Resources	resource requirements, such as cognitive or physical demands	[28–31]
Interaction	result from the interaction between task and task performer characteristics, such as experience and familiarity with the task	[32–34]

In the literature, numerous approaches to task *classification* have been elaborated. Most work is related to the effect of technological change on labor demand [35]. In this context, one prominent classification [36] is based on the question *"how computerization affects skill demands"* and differentiates between routine (manual, cognitive) and non-routine (manual, analytic, interactive) tasks. This classification has been further adjusted to routine, abstract, and manual [37,38] or service tasks [39]. With the growing importance of automation, relevant task classifications have appeared. For example, Frey & Osborne [40] specify the hard-to-automate tasks with the following classification: perception and manipulation tasks, creative intelligence tasks, social intelligence tasks. Koorn, Leopold & Reijers [41] develop a new comprehensive classification. Another perspective worth mentioning is the internationalization and offshoring task classifications, whereby the tasks can be considered easy or hard to offshore. Table 2 provides a summary of the discussed approaches.

Table 2. Task classifications overview

Approach	Classification	Source
Effect of technological change	routine (manual, cognitive), non-routine (manual, analytic, interactive)	[36,42,43]
	routine, abstract, manual	[37,38]
	routine, abstract, service	[39]
Automation potential	easy to automate, hard to automate (perception and manipulation tasks, creative intelligence tasks, social intelligence tasks)	[40]
	creative, adaptive, interactive (routine), analytical (evaluation, standardization), system supervision, routine cognitive, information processing, information exchange (data stream)	[41]
Internationalization and offshoring	easy to offshore (codifiable, described in deductive rules, do not require personal interaction), hard to offshore (based on tacit knowledge, require personal interaction)	[44,45]

Furthermore, we could also consider that tasks are commonly taken into account in the context of HR and skills [46–48], for example, while discussing the competencies [46] or effect of technological change, namely Artificial Intelligence [48] and Virtual Reality [47]. However, while providing some deep dives into the mentioned topics, the research works do not address the HR or skills-based task classification. Alternatively, one can find solid classifications based on organization structure [49], business functional areas [50], and skills classifications based on well-established Occupational Information Network (O*NET) [51].

2.2. Task Analysis Approaches and Unsolved Issues

As our study addresses the method for analyzing tasks, we review the related work and summarize the research gaps regarding existing task analysis approaches. We guide our review along the following questions: (i) which methods and theoretical foundations are used for the task analysis? and (ii) for what purpose is the task analysis performed?

The work on task analysis takes its origin from "The Principles of Scientific Management" by Taylor [52] and focuses on the analysis of physical work for cost-effective design of workplaces [53]. With the technological progress and penetration of computers into workplaces, the focus shifts to information processing and the human operator role in complex systems [54]. As tasks become more complicated and demanding of special skills and knowledge, the research efforts on task analysis move towards training requirements and the development of training instructions [53]. In this context, the Hierarchical Task Analysis (HTA) can be reasonably considered the most popular method. According to the HTA, tasks are decomposed into subtasks. Each subtask is characterized by a goal, input conditions, actions, and feedback regarding the goal achievement [55]. The HTA is widely used in various contexts, such as interface design, training and instructions development, error analysis, and in different domains [55], especially in the high-risk and high-consequence domains, e.g., airspace, maritime, medicine, manufacturing, for the situation awareness creation [56,57].

Based on the ideas of the HTA, further approaches have been introduced. For a comprehensive overview, we refer to [58]. Hereby, the authors use theoretical foundations ranging from ergonomics to cognitive psychology, software engineering, and system design to extend and fine-tune the HTA.

New technologies made accessible vast amounts of digital text, recording an ever-expanding human communication and interaction [59]. While running their daily business, organizations make use of textual data to support decision-making in various settings. Thus, texts from social media, news, and reviews are used to predict asset price developments, analyze customer behavior or political campaigns' effects. In the present work, we suggest studying the textual descriptions of tasks captured in the organizational processes. In this context of BPM, existing work is focused on the analysis of the process-related textual documents with the goal to (i) extract process models from textual process descriptions [16], (ii) compare textual descriptions with process models [60] (iii) identify task automation candidates [61]. Other relevant research directions are (i) the task analysis and classification in crowdsourcing (e.g., on the Amazon Mechanical Turk platform [62,63]), mainly to develop fair remuneration mechanisms, and (ii) analysis of the effects of technological progress and automation on the skills, jobs, and related tasks using text analytics techniques [64].

Outlining the unsolved issues, Annett and Stanton [53] fairly highlight the following:

(i) methodological and practical problem how to collect the necessary data, i.e., what data is needed, and what practical instruments and measurements are required;
(ii) methodological and practical problem how to apply the findings of task analysis and draw conclusions, i.e., establishing methods and methodologies for solving practical problems;
(iii) issues regarding the theoretical orientation and underlying assumptions of the methods and concepts used, i.e., using solid theories to develop and justify methods, methodologies, and tools for task analysis.

Additionally, summarizing the above mentioned, we could observe that most task analysis application areas are concerned with training, system design, collaborative working, error prediction, developing fair pricing models, and studying the effects of technological progress and automation. In the context of BPM, we could identify the lack of research on analyzing unstructured textual task descriptions for decision support and other benefits regarding process understanding and improvement at different levels, which is also confirmed by [18]. Hence, in our research, we address the challenges outlined by both task analysis researchers [53] and BPM researchers in the context of discovering NLP benefits for BPM [18].

In the section below, we review the fundamental theoretical concepts leading to the task analysis methodological framework of this study.

3. Theoretical Background

This section provides an overview of the fundamental theoretical concepts used in this study, i.e., the Theory of Situation Awareness and the Strategic Alignment Model.

3.1. Situation Awareness

In high-risk and high-consequence environments with the critical cost of failures, it is essential to provide adequate training and predict errors with comprehensive task analysis techniques. Hence, the enhancement of the situation awareness of the task performer gains in importance. While many task analysis approaches similar to HTA have been suggested, a lack of theoretical foundations and their justifications is reported [53].

At the same time, in the context of textual data, situation models evolved as a significant theoretical development also in language comprehension research of the 1970s, 1980s, and 1990s. The core idea is that comprehension of the content includes constructing a mental representation of the state of situations denoted by the text rather than only a mental representation of the text itself [65]. Several models in the literature were proposed, like construction-integration, spatial situation models [66], event-indexing models [67]. These developments are motivated by the fact that psychologists studying speech processing need a far better representation of meaning than is provided by words and sentences in the speech itself, i.e., a representation reflecting those semantic relations essential for how people understand, remember, and think [66].

In this regard, to structure and justify our task analysis approach based on the textual descriptions of tasks, we propose using the Theory of Situation Awareness (TSA) and Situation Awareness (SA) Model (see Figure 1). The term *situation awareness* was coined by Endsley at the end of the 80th – beginning of the 90th in a row of studies [12,68,69]. Originating from aircraft and air traffic control, SA has become an important objective for operator interface designs, automation concepts, and training programs in different areas, such as power plants and manufacturing systems [70]. At present, SA is actively researched and applied in maritime [71], disaster and emergency management [72–74], surgery [75], and cyber threat [76]. Hence, the need for SA is relevant in a large variety of settings. In an enterprise context, SA enables managers to make informed operational decisions [77].

Endsley defines two groups of factors influencing SA and three SA levels in the SA model [69]. These factors are (1) task and system (IT technology) factors, such as system characteristics, task complexity, stress, and workload, and (2) individual factors, like training and experience of the task performer. And the three SA levels are (1) perception of the elements in the environment, (2) comprehension of the current situation, (3) projection of future status.

3.1.1. Situation Awareness Factors

To answer what information can help us identify the two groups of factors influencing SA based on task descriptions, we suggest using existing task definitions (Table 1) and classifications (Table 2). To ensure a holistic understanding of tasks, we propose considering broad conceptual (task organization) and practical (task execution) perspectives common for the BPM discipline [78,79]. Hence, considering the textual data format and task execution and task organization perspectives, we form our set of task aspects and corresponding measurements. Hereby, we map two groups of SA factors with the task perspectives.

Thus, in the *task execution perspective*, we consider the basic requirements for the definition and classification of tasks (Table 1 and Table 2) and the specifics of the presentation of the information about a task (textual data). Adapting the task definition approaches in Table 1, we propose the following task aspects as characteristics describing the first group of factors in the SA model extracted from the textual task description received by the task performer:

(i) Approach *structure*. It allows defining the main task elements, such as ***R****esources* (nouns), ***T****echniques* (verbs, verbal nouns), ***C****apacities* (adjectives), and ***C****hoices* (adverbs) (RTCC), extracted based on the keywords in the textual description and categorized by parts of speech.

(ii) Approach *resources*. We propose this approach to identify the specific type of resources determining those cognitive efforts required to perform the task. As a source of knowledge, we use the RTCC structural elements of the task enriched by an expert interpretation of their *cognition* level. As cognition level values, we suggest routine and cognitive concepts (see Table 2) and extend these by the third middle value of semi-cognitive.

(iii) Approach *interaction*. In our study, this approach is proposed to identify (a) the task *type* and (b) the way the task performer interacts with the process of task performing expressed in the importance. As a source of knowledge, it is suggested to use (a) the patterns of contextual keywords and expressions indicating the task *type* and (b) lexicon as a set of words and syntactic symbols enriched with an expert interpretation of their domain-oriented "emotional" level, indicating the degree of *importance* of particular task elements.

In the *task organization perspective*, we propose *HR* and *skills* aspects to derive the knowledge about the second group of factors in the SA model. Well-known approaches such as [49,50] or O*NET can be used to derive classification values. Table 3 summarizes the task aspects and classification values used in this study, which will be explained in detail in Section 5.

Table 3. Task aspects and classification values

Perspective	Aspect	Classification value	Source
Task execution	*structure*	Resources, Techniques, Capacities, Choices	extended based on [4,25–31]
	typology	domain and application case specific	[10]
	importance	standard, elevated, high	[9]

Perspective	Aspect	Classification value	Source
	cognition	routine, semi-cognitive, cognitive	adjusted based on [36,41–43]
Task organization	*HR*	approaches based on organization structure and business functional areas	such as [49,50]
	skills	Occupational Information Network (O*NET)	[51]

3.1.2. Situation Awareness Levels

Having identified those aspects to derive the knowledge about the two groups of SA factors, we map the aspects to the three SA levels. The first level is to perceive the status, attributes, and dynamics of relevant elements in the environment and develop a basic understanding of the situation [69]. Taking into account the task execution perspective, such type of perception could be realized by performers' understanding of the basic structure of the task in the business context, i.e., which ***R****esources* (nouns indicating the specificity of business process task items), ***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*) [80] are inherent in the textual task description.

On the second level, the comprehension of the current situation (nature of a particular task) occurs. Such comprehension could be achieved by synthesizing the basic elements of task structure, determined in Level 1, enabling the task activity *type* identification. Moreover, Level 2 goes beyond being aware of the patterns of the elements (task typology) and includes also understanding their significance, i.e., *importance*, for goal achievement of the particular task. Such understanding could be realized by recognizing specific "markers" in the textual task description (words or special characters) that indicate the level of importance of a particular task element. Thus, based on the knowledge from Level 1 elements, when put together with other elements and markers to form the comprehensive patterns, the task performer develops a coherent view of the environment recognizing the importance of its elements and, afterward, builds the way of his/her interaction with the task execution process.

The third and highest SA level is the ability to project the future status of the current situation. Such ability is achieved based on (i) knowing/understanding the elements (Level 1) and (ii) comprehending the nature of a current task (Level 2) and could be realized by assessing the level of *cognition* efforts that will be required from the performer for current task execution. Such a type of assessment could be achieved by recognizing the patterns of specific words ("markers") that identify the task cognition level in the textual task description.

In Figure 1, we provide the discussed SA model adapted from Endsley [69]. The person's perception of the relevant elements in the environment forms the SA basis and determines further task-related decisions followed by the task performance action. Here, two groups of mentioned factors are known to influence this process. First, SA depends on *Task factors*, i.e., tasks may differ in the completeness of information necessary for the task execution, complexity/ cognition, importance, type. Second, individuals vary in their ability to acquire SA, given the same data input, due to their ability to process information directly influenced by the skills, training, experience (*Individual factors*) [69].

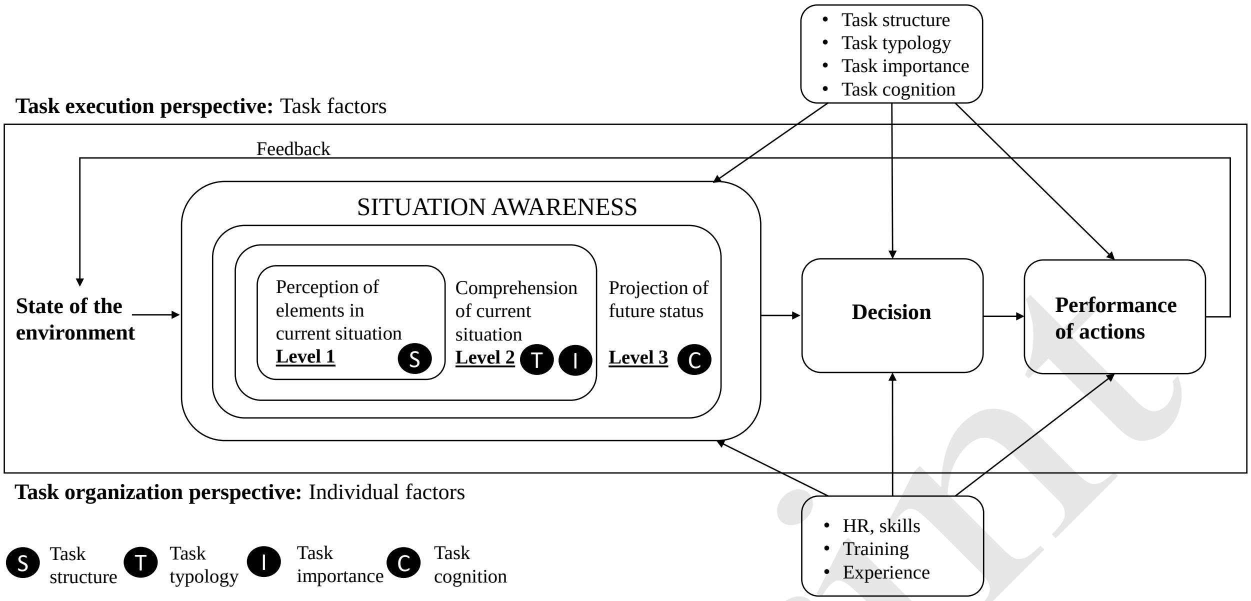

Figure 1. Extended situation awareness model

To sum up, the SA model helps us structure, justify, and understand those essential factors that can be extracted from the textual task description influencing the worker when receiving, reading, and analyzing the task.

3.2. Strategic Alignment Model

Nowadays, one can hardly imagine the isolated existence and functioning of the business and IT in organizations. As a result, the Strategic Alignment Model (SAM) introduced by [81] in 1993 gains considerable attention in the business literature [82–84]. As mentioned in Section 2.2., there is a lack of research on how to present and draw conclusions from the task analysis results. Thus, using SAM, we provide a theoretically guided instrument for presenting the results, drawing conclusions, and making informed strategic decisions.

As a rule, the alignment between the following elements is discussed: (i) four business and IT components (business strategy, IT strategy, business infrastructure and processes) and (ii) IT infrastructure and processes [81]. Accordingly, the alignment of business and IT is defined as "the fit between two or more of these components in terms of addressing the needs, demands, goals, objectives, and/or structures of each component such that management of the business and IT remain in harmony" [85]. The alignment between business and IT strategies reflects strategic planning alignment, whereas the alignment between business and IT infrastructure and processes reflects operational alignment, i.e., the alignment of realized strategy [86]. Along with the defined SAM elements, four types of strategic alignment approaches are highlighted by [81]: (1) *Strategy execution.* A business strategy is the driver of organizational and IT infrastructure design choices; (2) *Technology transformation.* IT infrastructure and processes are the drivers for implementing the chosen business strategy through an appropriate IT strategy; (3) *Competitive potential.* This approach is concerned with exploiting the emerging IT capabilities to gain a competitive advantage; (4) *Service level*. This approach focuses on how to build a world-class IT service organization.

In Figure 2, we summarize the theoretical and methodological background used for task analysis in the study. On the *first* level, our starting point, we consider the task and its core enablers (IT technology and task performer). We observe these core elements in the center of Figure 2. Afterward, on the *second* level, we extract and structure the knowledge from the textual task descriptions using the TSA, its SA model, and BPM *organization* and *execution perspectives*. As there is a lack of practical instruments for business value generation on the *first* and *second* levels, we include SAM on the *third* level, making task analysis an instrument for strategic alignment. As shown in Figure 2, we scope our framework to the two SAM elements (1) business infrastructure and processes and (2) IT infrastructure and processes and the two approaches of strategic alignment (1) *Strategy execution* and (2) *Technology transformation* corresponding to the two SAM elements. Such a scope is justified by the knowledge we can obtain based on the textual task descriptions. The knowledge about *Competitive potential* and *Service level* demands additional sources of information.

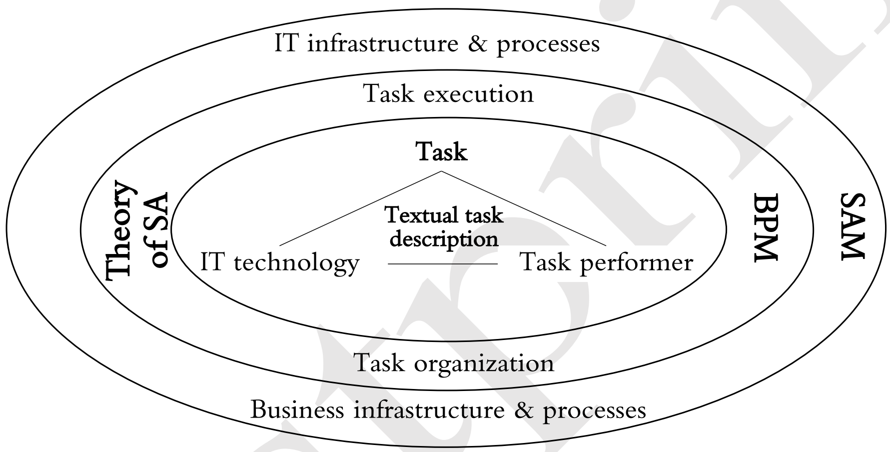

Figure 2. Theoretical and methodological background of task analysis

Hence, in this paper, we aim to address the issues mentioned above and suggest a bottom-up approach considering different organizational levels of tasks. We start our analysis with the smallest and important information granules, original textual task descriptions, i.e., what is needed to be done. Step by step, we apply the established Theory of SA to, first, structure and justify the extracted knowledge, second, arrange it on the two organizational levels of task execution and organization commonly known in BPM, and, third, apply instruments to derive the strategic business value from the extracted knowledge (SAM). To sum up, our approach is remarkable in several points:

(i) We define and extract a set of task characteristics based on unstructured textual task descriptions.

(ii) For this purpose, we propose concrete tools for collecting and analyzing the data and show how we come to results. Additionally, we address the need for context-aware domain-specific text analytics instruments such as taxonomies and sentiment, also declared by [87].

(iii) We consider the tasks from execution and organization perspectives.

(iv) We are guided by sound theoretical foundations of the Theory of SA by developing our approach and by SAM by presenting its strategic business value.

4. Motivating Example

Nowadays, due to the fast-paced technology developments and digitization, any enterprise keeps a wide application portfolio, which is often grown historically. To maintain such a portfolio, companies operate large-scale complex IT service environments [88]. These developments disclose the essential role of IT support systems in the support operations of any organization.

In this context, IT service management (ITSM), focusing on the servitization of IT function, organization and management of IT service provision [89], gains in popularity. To ensure a successful establishment, functioning, and maintenance of IT services in a company, IT practitioners increasingly benefit from using an IT Infrastructure Library (ITIL) framework [90]. Separate sections of ITIL, such as Incident, Problem, and Change Management, deal with a large amount of unstructured text data, i.e., IT tickets issued in relation to the incidents, problems, or changes in the IT infrastructure products and services.

Correct and timely IT ticket processing, prioritization, and assignment are popular topics among practitioners and the scientific community due to the ever-increasing number of tickets, errors, long lead times, and lack of human resources to process them [91–93]. While small companies still perform these steps manually, large organizations dedicate large budgets to various commercial solutions for decision support in IT ticket processing. Usually, these approaches are sophisticated monolithic software focused on accuracy at the cost of explainability and understandability. In the present study, we build on the transparent Text Analytics and Linguistic Analysis techniques to provide decision support on the task execution and organization in the context of IT ticket processing.

The example considered in this study comes from the ITIL Change Management (CHM) department of a big telecommunication provider in Germany with more than 200,000 employees worldwide. This department deals 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 [94]. It is a complex process, including a number of phases, from ticket opening and planning to its implementation and closure. A typical IT ticket processing scenario is the following: (i) a customer request for a change in IT infrastructure products or services is sent per email; (ii) a CHM process worker enters the request into the ticketing software system, creates a ticket, and fills in necessary fields, often using templates; (iii) the ticket is broken down into the tasks which are assigned to the responsible teams; (iv) based on the documented information, the tasks and the ticket are implemented. These tasks, i.e., their textual descriptions, are used as an illustration in the present study. They are usually entered into the system in a free text form by the CHM department workers, as a rule, coordinators. Thus, the ticket example "*Installation of application on SAP backend*" has the following breakdown into three tasks: "*1. Preparation task for the application team. 2. Stop application and set up maintenance page. 3. Application migration from CMO to FMO. !!! IMPORTANT !!! MON 01.09.2018 Activation of new monitoring FMO*".

5. Task Content Model and Method for Measuring Content of Tasks

In the BPM ambiance, tasks can reach us in different forms and ways, or they just exist as common routines. In the present work, we focus on tasks that we receive or that are documented in a textual form. We aim to develop a task content model based on the theoretical and methodological background summarized in Figure 2 (first and second levels). Below, we describe the basis of the task content model, i.e., task execution and task organization aspects.

The task content model and method for measuring the task content are developed based on a triangulation of the results from (1) our own already conducted and ongoing research, (2) literature review, and (3) real-world illustrative example. The work with the materials and subject matter experts (SME) from the ITIL CHM example includes (i) manual compilation of vocabularies (in case of task *cognition* and *importance* aspects) and (ii) manual labeling (task *typology* aspect). Under manual compilation of vocabularies, we understand an iterative process of vocabulary creation for specific goals using (i) computational analysis (in our case, Latent Dirichlet Allocation (LDA) topic modeling [95]) and (ii) involving experts to validate the vocabularies. In the process of manual labeling, we (i) independently label the topics obtained using LDA and then (ii) discuss, refine, and consolidate the topics into final labels. The manual labeling is supported by a computational validation on the task descriptions.

5.1. Task Content Model

5.1.1. Task Execution Aspects

In the task execution aspects, we analyze task *structure*, *typology*, *importance*, and *cognition*. As already mentioned, in the current study, tasks are presented in the form of textual descriptions.

We extract task *structure* and *typology*, aiming to answer the who, what, how questions. Hereby, we make use of such linguistic instruments as semantic loaded parts of speech recognition and taxonomies. Under the *structure* of a task, we understand task elements expressed by certain parts of speech inherent in textual task descriptions and characterizing the task execution. We consider and interpret the following parts of speech as diverse semantic concepts of organizational context: nouns as ***R****esources* indicating the specificity of task items; verbs and verbal nouns as ***T****echniques* of knowledge and information transformation activities affecting existing ***R****esources*; adjectives as ***C****apacities* describing situation specificity of ***T****echniques*; adverbs as ***C****hoices* determining the selection of the required set of ***T****echniques* – elements of the RTCC framework [80].

Under *typology* of tasks, we understand an actual task meaning, i.e., what is needed to be done, – "install the update" (task type "*install*"), "configure the database" (task type "*configure*"). Although similar work areas will have similar task *typology*, it is strongly dependent on the application area. It is suggested to extract the knowledge about task *typology* (i) with LDA and, afterward, (ii) adjust the results manually, involving SME. In the end, tasks are to be organized into a hierarchical taxonomy of types and subtypes, also with SME involvement.

Next, we extract the task *importance* aspect with the help of sentiment analysis. This aspect reflects the level of attention that should be paid to certain task elements. We differentiate between the following levels of attention: *standard* (meaning common daily work), *elevated* (task performer should be cautious with certain task elements), and *high* (the process worker should be especially cautious with certain task elements). For extraction purpose, we propose a specific approach of Business Sentiment (BS) [96]. BS represents an emotional component of a task and its contextual importance perceived by a task performer. This latent information is extracted from task textual description with a BS lexicon and formalized using the mentioned qualitative scale of *standard*, *elevated*, and *high*. For example, an *elevated* level of attention is expressed by a negatively loaded keyword contained in the BS lexicon, such as "blocked", "rejected", "critical", "outage", "emergency", "incident", possibly intensified with intensifiers (importance markers), such as exclamation marks, capitalizations, and special characters.

Under the task *cognition* aspect, we understand categorizing tasks into routine, semi-cognitive, and cognitive based on task clarity (clear rules) and automation potential. The *cognition* aspect is closely related to the *structure* aspect, as we organize the identified parts of speech (the *structure* aspect) – ***R****esources*, ***T****echniques*, ***C****apacities*, ***C****hoices* (RTCC) – into the three levels of Decision-Making Logic (DML) with the help of the taxonomy vocabulary [80]. Hereby, we distinguished the following three DML levels: (i) *routine* DML level tasks are those expressible in rules [97]; (ii) *semi-cognitive* DML level tasks are those where no exact ruleset exists, and there is a clear need for information acquisition and evaluation [21]; (iii) *cognitive* DML level tasks are the most complex ones where not only information acquisition and evaluation is required but also complex problem-solving.

5.1.2. Task Organization Aspects

In the task organization aspects, we consider two most important issues every manager is confronted with: (1) how to timely organize and efficiently plan human resources (HR) (HR planning aspect) and (2) which skills are important for particular tasks and therefore should be developed and trained (skills planning aspect).

Currently, there are more than 12,000 occupations and careers worldwide[1]. For this reason, in the HR planning aspect, we suggest considering the areas typical for any business. In large organizations, employees with the same type of tasks and jobs usually work in functional areas. These areas are dedicated to the main functions that need to be carried out in any company, such as Business Administration (wide area with a variety of business management tasks), HR (tasks concerned with employees working in the organization), Finance (all tasks related to financial activities), Marketing and Sales (task activities related to selling and advertising products or services, increasing sales), Customer Service (any kind of tasks related to assistance regarding products or services provided to customers by an organization), Production (in its broadest sense of making products or providing services) [50].

In the skills planning aspect, we build on the six main categories outlined in the Occupational Information Network (O*NET) database, widely used in research [35]. These are (1) basic skills, such as reading, writing, languages; (2) complex problem-solving skills, i.e., developed capacities used to solve novel, ill-defined problems in complex, real-world settings; (3) resource management skills, like time or financial resources; (4) technical skills, such as programming, technology design, maintenance, installation; (5) system skills, i.e., developed capacities used to understand, monitor, and improve socio-technical systems, such as system analysis, system evaluation; (6) social skills, for example, coordination, instructing, service orientation.

In a nutshell, the task content model in Figure 3 outlines the aspects (i) that are structured and justified based on the Theory of SA and (ii) that we aim to extract along with the two BPM perspectives of task execution and task organization.

[1] https://www.careerplanner.com/ListOfCareers.cfm

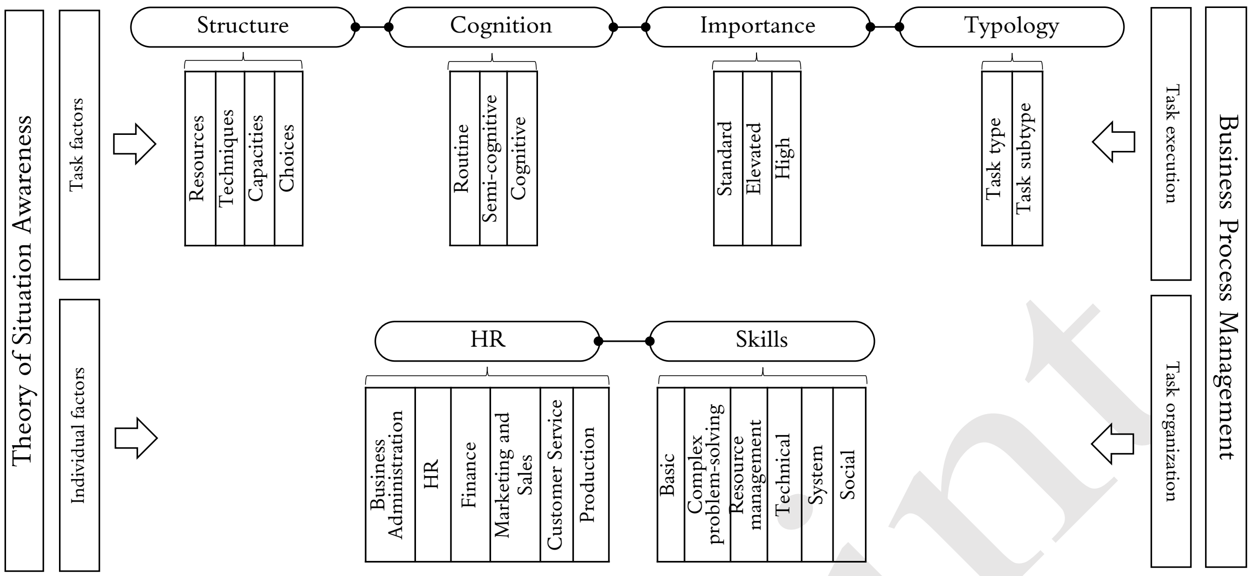

Figure 3. Task content model

5.2. Method for Measuring Content of Tasks

This subsection presents the method for the task content model application, i.e., measuring the content of tasks. We illustrate the presentation by the ITIL CHM dataset and the motivating example introduced in Section 4: ticket "*Installation of application on SAP backend*" and its three tasks "*1. Preparation task for the application team. 2. Stop application and set up maintenance page. 3. Application migration from CMO to FMO. !!! IMPORTANT !!! MON 01.09.2018 Activation of new monitoring FMO*".

We propose a five-step method for measuring the content of tasks, summarized in Table 7.

Step 1. Data Collection and Preprocessing

An important step is collecting textual task descriptions and converting them into the program format in which the computational analysis will be performed. For the purpose of our study, we obtained a dataset containing ticket IDs, textual ticket descriptions, task IDs, and textual task descriptions in the period of January-May 2019 from the ITIL CHM department. The dataset was received in a CSV file format and included English, German, and English-German texts. After removing duplicates and selecting prevailingly English texts (texts with more than 80% of English words), the final dataset comprised 48,563 entries. Preprocessing and extraction of the aspects were conducted using Python 3.6. and NLTK libraries.

The dataset needs to be preprocessed in two different ways to address the requirements of the aspects extraction. For *structure*, *typology,* and *cognition* aspects, classical preprocessing (removal of numbers, special symbols, punctuation, converting to lowercase, stemming) is required. In terms of the motivating example, the output is "*prepar task applic team*", "*stop applic set mainten page*", "*applic migrat cmo fmo import mon activ new monitor fmo*" for the three tasks correspondingly.

The *importance* aspect is related to the extraction of BS relevant information. This information is expressed by the BS lexicon and specific *importance markers* (syntactic intensifiers). For the correct extraction of mentioned *importance* markers, this step requires special preprocessing, i.e., retaining capitalizations, exclamation and question marks, specific symbols such as stars, dashes, equal signs, hash signs, dates. In our motivating example, the output is "*Prepar task applic team*", "*Stop applic set mainten page*", "*Applic migrat CMO FMO !!! IMPORT !!! MON 01.09.2018 Activ new monitor FMO*" for the three tasks correspondingly.

As the textual task descriptions make up the research focus, the final CSV files (according to the two types of processing) comprised two columns: task IDs and textual task descriptions. Further, collecting other process-related information such as manuals, handbooks, process descriptions, and identification of necessary experts must be performed at this step. Hence, we collected such important information as the customized manual of the HP Service Manager (IT ticketing system), existing process descriptions, and official ITIL handbooks and identified relevant experts. All the data, except for the ITIL handbooks, is confidential.

TASK EXECUTION ASPECTS

Step 2. Structure and Cognition Aspect Extraction

In the second step, we propose using the DML taxonomy to extract the structure and cognition aspect [2] [80]. With such a DML taxonomy, it is aimed to understand task elements (***R****esources,* ***T****echniques,* ***C****apacities,* ***C****hoices*) and discover the decision-making nature of task-related activities, i.e., their DML level of *routine, semi-cognitive,* and *cognitive*. First, to get the *structure* aspect, it is suggested to perform a part-of-speech tagging and assign nouns, verbal nouns, verbs, adjectives, and adverbs to the elements (keywords) of the RTCC framework per each task description. Second, to get a task *cognition* aspect, using SME feedback, we identified the most important keywords from the RTCC framework and categorized each keyword into the DML level. For example, the keywords "*start*", "*stop*", "*reboot*" are associated with *routine* decision-making activities; whereas "*freeze*", "*reject*", "*approve*" belong to *cognitive*. Depending on the availability of the experts, this process can take two-three months. Third, when the DML taxonomy is developed, we calculated the relative distribution of *routine*, *semi-cognitive*, and *cognitive* keywords, i.e., RTCC parts of speech, extracted for each task. Fourth, for the identification of DML levels, threshold rules are formed based on (i) the experimental data and (ii) expert evaluation [99]. The threshold is used to define the ranges of *routine*, *semi-cognitive*, and *cognitive* DML keywords, based on which the task cognition of the corresponding level is assigned. Fifth, using calculated relative distribution and defined threshold rules, each task was assigned to one of the three DML levels.

In our motivating example, in task 1 "*1. Preparation task for the application team*", there are three DML keywords: two *routine* ***R****esources* "task" and "application" (2/3 or 67%) and one *semi-cognitive* ***R****esource* "team" (1/3 or 33%). The clearly prevailing category is *routine*. See Appendix I for (i) the DML taxonomy keywords used for illustration in this study, (ii) threshold rules of DML level, and (iii) anonymized task examples.

Step 3. Importance Aspect Extraction

In the third step, the BS lexicon is developed following the process described in [96] to identify the *importance* of the task. BS is a specific business sentiment approach we introduced to measure an IT ticket "emotional" component. As a rule, standard lexicons do not work well in domain-specific applications, such as our IT ticket context. This motivated us to develop a domain-specific BS lexicon using the state-of-the-art VADER [99] and LDA[3]. First, we developed the BS lexicon

[2] The developed DML taxonomy and source files, including a detailed README, Python code, and Excel *.csv, are available on our Github project page https://github.com/IT-Tickets-Text-Analytics/Tasks-Structure-Cognition
[3] The developed BS lexicon and source files, including a detailed README, Python code, and Excel *.csv, are available on our Github project page https://github.com/IT-Tickets-Text-Analytics/Tasks-Importance

identifying the emotionally loaded keywords and expressions from two sources: (i) corpus, i.e., contextual task texts, and (ii) CHM descriptions from the ITIL handbook. Second, based on SME feedback, we (i) refined the developed BS lexicon and (ii) assigned valence scores to the BS lexicon keywords. We assume that each keyword is associated with positive, negative, or neutral sentiment. Keywords with valence scores greater than 0 are considered positive, whereas words with a valence score less than 0 are considered negative. Other keywords are considered to have a neutral sentiment. As the DML taxonomy and the BS lexicon compilation are similar in terms of the SME work, these steps can be performed simultaneously to speed up the process. Third, when the BS lexicon is developed, for each task text, we calculate the normalized total score of BS keywords with the pre-assigned valence and specific importance markers (syntactic and semantic intensifiers) [96]. Fourth, a set of threshold rules are defined and fine-tuned with SME [96] and then adjusted to the current setting. Fifth, based on the normalized score and the set of threshold rules, the *importance* on the qualitative scale of *standard*, *elevated*, and *high* is assigned to each task.

As the IT ticketing system of the CHM department HP Service Manager did not allow for highlighting the text, the workers frequently used such intensifiers as capitalizations, special punctuation (a lot of exclamation or question marks), special symbols (stars, dashes, equal signs, hash signs) for drawing attention to certain parts of the text. Thus, in task 3 of motivating example "3*. Application migration from CMO to FMO. !!! IMPORTANT !!! MON 01.09.2018 Activation of new monitoring FMO*", there are one BS lexicon keyword "*important*" with (i) the valence -0.5; (ii) capitalizations, and (iii) exclamation marks, which add to the score -0.5 and -0.5 correspondingly; (iv) and date "*MON 01.09.2018*" adding another -0.5. First, following the VADER score calculation rules, we calculate the total score for positive and negative keywords and the total number of neutral keywords. In the task at hand, there are no positive and neutral BS keywords. The total score for negative keywords is equal to (-2). Based on the number of identified BS lexicon keywords (2) and total scores (-2), the normalized total score is calculated. In our case, -2/2= -1. According to the threshold rules identified in our previous research [96], the assigned *importance* is *high*. See Appendix II for (i) the detailed description, scoring, semantic, and syntactic rules, (ii) the BS lexicon keywords used for illustration in this study, and (iii) anonymized task examples.

Step 4. Typology Aspect Extraction

In the fourth step, the exact meaning of the task, i.e., its *typology*, is extracted. For this purpose, to facilitate the process of manual creation of task typology, a computational analysis of textual task descriptions based on LDA topic modeling is suggested as an initial step. Subsequently, obtained topics are labeled, discussed, refined, and consolidated into final labels by the experts.

In our example, we refer to an IT ticketing system manual where three types of tasks were distinguished: (1) projected service outage (PSO), meaning scheduled downtime start and scheduled downtime end, (2) implementation of the ticket itself, and (3) quality assurance (QA). The PSO task type is related to those tickets and tasks whereby the service disconnection is necessary for performing requested changes. Hence, in the PSO task, the downtime is planned, including exact start and end, coordinated, executed, and checked that the customer is not affected (ensuring a backup service or planning the PSO for out-of-service hours). The implementation task type refers directly to the requested activity, such as installation, update, migration, or preparatory work for the mentioned activities. Finally, QA is necessary for ensuring the agreed service level quality after performing the requested activities. This can be realized by performing the four-eyes principle, i.e., approving or checking by two individuals, monitoring activities, or testing.

To extract the *typology* aspect, first, we created a set of contextual descriptive keywords (CDK) and expressions characterizing each *task type* using (i) LDA algorithm and (ii) SME adjusting. For example, the *PSO task type* included the following set of CDK: "*PSO*", "*downtime*", "*shutdown*", "*offline*", "*outage*", "*stop*", etc. *Implementation task type* included such CDK denoting the technical content of the task as "*implement*", "*update*", "*upgrade*", "*install*", "*recover*", "*add*" ", etc. *QA task type* was described by "*QA*", "*QS*", "*test*", etc.[4] Second, when the first level of task types taxonomy (the set of task types with their contextual descriptive keywords) is developed, we calculated the relative distribution of tasks CDK, extracted for each task text. Third, we classified the whole tasks corpus into three types – PSO, Implementation, and QA – based on the principle of the maximum relative distribution of the specific task type CDK in the task description. Fourth, using (i) the LDA algorithm and (ii) SME feedback, we identified the topics characterizing each task type. As a criterion for choosing the optimal number of topics, the coherence and exclusivity indicators were used. Fifth, we created CDK lists describing task *subtypes* and summarized them in the form of a two-level hierarchical taxonomy. Sixth, for each task type group, we calculated the relative distribution of correspondent subtasks CDK, extracted for each task text. Seventh, based on the principle of the maximum relative distribution, each task was assigned to one of the identified subtasks.

In the typology aspect extraction step, task typology taxonomy compilation is the most time-consuming activity (two-three months). However, as already mentioned, it can be performed simultaneously to step 2 and 3. Table 4 presents the example of extracted task types and subtypes. See Appendix III for (i) the detailed task typology taxonomy and (ii) anonymized task examples.

Table 4. ITIL CHM task typology

Task types	**Task subtypes**
PSO	planning, execution, check
Implementation	preparation, configuration, installation, update, upgrade, capacity, integration, incident/problem, release, service delivery, support, migration, decommission
QA	4 eyes principle (4EP), backup & health check, software monitoring, update test

In our motivating example, task 2 "*Stop application and set up maintenance page*" is defined as (i) type "*PSO*" based on the two detected CDK "*application*" and "*stop*"; and as (ii) subtype "*execution*" as the detected CDK "*set up*" and "*maintenance*" describe the activities behind the PSO execution, i.e., what needs to be done.

Table 5 summarizes the anonymized IT ticket example with the three tasks and extracted task execution aspects.

Table 5. Task execution aspects extraction on the anonymized IT ticket example with three tasks

TICKET: "INSTALLATION OF APPLICATION ON SAP BACKEND"				
Aspect	**All identified aspect values**	**Corresponding words**	**Occurrence of words[5]**	**Final aspect value**
Task 1: "Preparation task for the application team"				
Structure and Cognition	*Routine (2 **R**esources)*	"task", "application"	67% (2/3)	**routine**
	*Semi-cognitive (1 **R**esource)*	"team"	33% (1/3)	
Importance	No BS keywords and intensifiers	-		**standard**
Typology	Type	"application", "team"	n.a.	**implementation**
	Subtype	"preparation"		**preparation**

[4] The developed task typology taxonomy and source files, including a detailed README, Python code, and Excel *.csv, are available on our Github project page https://github.com/IT-Tickets-Text-Analytics/Tasks-Typology
[5] Occurrence of words in relation to all identified words in the task textual description

Task 2: "Stop application and set up maintenance page"				
Structure and Cognition	*Routine (1 **R**esource, 2 **T**echniques)*	"application", "stop", "set up"	100%	**routine**
Importance	No BS keywords and intensifiers	-	-	**standard**
Typology	Type	"stop"	n.a.	**PSO**
	Subtype	"set up", "maintenance"		**execution**
Task 3: "Application migration from CMO to FMO[6]. !!!IMPORTANT!!! MON 01.09.2018 Activation of new monitoring FMO"				
Structure and Cognition	*Routine* (1 ***R**esource*, 2 ***T**echniques*, 1 ***C**apacity*)	"application", "activation", "monitoring", "new"	67% (4/6)	**routine**
	Semi-cognitive (1 ***T**echnique*, 1 ***C**apacity*)	"migration", "important"	33% (2/6)	
Importance	BS keywords	"important" valence -0.5		**high**
	Importance markers	capitalization and exclamation marks of "important" (additional -0.5 and -0.5), date ("MON 01.09.2018") valence -0.5		
Typology	Type	"application"	n.a.	**implementation**
	Subtype	"migration"		**migration**

TASK ORGANIZATION ASPECTS

Step 5. Identification and Mapping of HR and Skills to Tasks

This step is concerned with the specification of *HR* and *skills* required to perform the tasks. This information can be obtained in the process documentation, manuals, handbooks, and interviews with SME. Afterward, *HR* and *skills* are mapped to the task types based on the *typology* aspect. Our motivating example comes from a particular area of IT ticket processing. The CHM department serves as an internal IT Customer Service. Thus, CHM workers are specialists in IT infrastructure and services, ITIL, and CHM. Ticket tasks are closely related to the technical implementation and not to planning or coordination. Therefore, such typical roles of CHM as *manager*, *coordinator*, *approver* remain out of scope. An implementor role is usually performed by a worker responsible for the respective configuration item in the ticket focus. For example, in the case of an Oracle database update, an implementor is a database administrator. However, the set of skills necessary for the CHM IT ticket processing remains broad. We defined this set based on the O*NET database and manuals of our industrial example. We determined that implementors should possess the following set of skills: *organizational skills (coordination, prioritization), analytical skills, complex problem solving, social skills (communication, negotiation, detail orientation), technical skills (basic – technology understanding; general – computer systems, IT administration, operation and control, operation monitoring, equipment maintenance, repairing, programming, databases, installation, quality control analysis, troubleshooting, technology design; specific – SQL, Windows, Linux).*

In Table 6, the listed skills are mapped to the task types. The mapping is performed based on the expert knowledge, existing documentation, and content of the tasks. Furthermore, on a more granular level, a refined skillset can be mapped to the task subtypes.

Table 6. Task types and HR and skills mapping

Task types	**Skills**
PSO	organizational skills (coordination, prioritization), social skills (communication, negotiation), technical skills (basic – technology understanding)
Implementation	analytical skills, complex problem solving, technical skills (general – computer systems, IT administration, repairing, programming, databases, installation, troubleshooting; specific – SQL, Windows, Linux)
QA	analytical skills, social skills (communication, detail orientation), technical skills (basic – technology understanding; general – quality control analysis, operation and control, operation monitoring, equipment maintenance, technology design)

[6] CMO – current mode of operation, FMO – future mode of operation

In our motivating example, we observe two tasks of *implementation* type with *preparation* and *migration* subtypes correspondingly. As a rule, the migration *preparation* activities include planning the size and scope, backing up all the data, and assessing necessary staff and migration tool. Such activities would require primarily *analytical* and *complex problem-solving* skills. Hereby, the *migration* itself would demand specific *technical skills* of *IT administration*. As already mentioned, the service outage needs to be coordinated, scheduled, and executed in the PSO task. This usually requires much communication and synchronization of the work of several individuals or teams. Hence, the PSO *execution* task would demand not only basic *technology understanding* but also *coordination* and *social* skills to this or that extent.

The effort needed to perform this step is directly dependent on the existing documentation and the number of task types and subtypes. Our example is an IT ticket processing operationalized in a large corporation based on the official framework. Hence, the necessary skills and task types are recorded in ITIL and internal process documentation in one form or another. Moreover, our ITIL CHM ticket processing evidences an observable number of task types (three) and subtypes (in total, twenty). Therefore, in this setting, the manual mapping process takes up to one week, including the SME feedback. As a result of the method application, we get an "x-ray" content model of the task considering its *structure*, *cognition*, *importance*, *typology*, and required *HR* and *skills*. This information can be aggregated to reflect the work content and resources needed to perform this work.

Table 7 summarizes the five-step method, including required inputs and outputs and highlighting the necessary manual preparatory work and computational analysis work. Depending on the available resources, steps 2-4 can be performed in parallel. We illustrate the outputs by specifying the CSV file columns (attributes) and corresponding values of the motivating example. Thus, in the first step, which includes standard and special preprocessing, we provide two preprocessed texts of the motivating example as an output.

5.3. Results

In Table 8, we present our experimental results, i.e., the information about the most frequent DML keywords in the *structure* and *cognition* aspects and distribution of the *importance* and *typology* aspects in our dataset. In ***R**esources*, the most frequent *routine* keywords are "application" and "server", *semi-cognitive* – "team" and "PSO", and *cognitive* – "infrastructure", "management", "switch". In ***T**echniques*, the most frequent *routine* keyword is "install", *semi-cognitive* – "check", and *cognitive* – "approve". In ***C**apacities*, the most frequent *routine* keyword is "new", *semi-cognitive* – "affected", and *cognitive* – "expected". In ***C**hoices*, the most frequent *routine* keyword is "automatically" and *semi-cognitive* – "successfully". In the *importance* aspect, the most frequent value is *elevated*. The most frequent task type is *implementation*. We also illustratively present a qualitative deep dive into the *cognition* aspect and analyze the *importance* and *typology* distributions. Thus, the most frequent *routine* tasks are of *standard* and *elevated* importance and *implementation* and *QA* type. The most frequent *semi-cognitive* tasks are of *high* importance and *PSO* type. As *cognitive* tasks are very low (0.28%) in the dataset, the *importance* and *typology* distributions are also low. Hence, *cognitive* tasks show only *implementation* tasks of *elevated* importance.

Table 7. Method for Measuring Content of Tasks. Overview of Steps[7]

Input	Processing	Output
		Motivating example: "*1. Preparation task for the application team. 2. Stop application and set up maintenance page. 3. Application migration from CMO to FMO. !!! IMPORTANT !!! MON 01.09.2018 Activation of new monitoring FMO*".
1. Data Collection and Preprocessing		
1. Textual task descriptions Tools: standard NLP processing software, e.g., Python and NLTK library[8]	1.1. Standard preprocessing: – removal of numbers; – special symbols; – punctuation; – converting to lowercase; – stemming	CSV file 1 (columns): "*Task ID*" and "*Task description*" (preprocessed)
		Motivating example (values): "*ID19384922*", "*applic migrat cmo fmo import mon active new monitor fmo*"
	1.2. Special preprocessing: – retaining capitalization; – exclamation and question marks; – specific symbols	CSV file 2 (columns): "*Task ID*" and "*Task description*" (preprocessed)
		Motivating example (values): "*ID19384922*", "*Applic migrat CMO FMO !!! IMPORT !!! MON 01.09.2018 Activ new monitor FMO*"
2. Structure and Cognition Aspect Extraction		
1. CSV file 1 with preprocessed task texts from step 1.1. 2. DML taxonomy[9] 3. Threshold rules for DML levels defining Tools: Python, NLTK, MS Excel	2.1. Structure Aspect Extraction. Computational analysis: parts-of-speech tagging	Extracted Structure Aspects: *RTCC elements assigned to the parts of speech for each task text*
		CSV file 1 (columns): "*Task ID*", "*Task description*", "*Resources*", "*Techniques*", "*Capacities*", "*Choices*"
		Motivating example (values): "*ID19384922*", "*applic migrat cmo fmo import mon active new monitor fmo*", "*applic*", "*migrat, active, monitor*", "*new, important*", "-"
	2.2. Cognition Aspect Extraction. Computational analysis: – identification of DML keywords; – calculation of the relative occurrence of the keywords of each category; – DML Level identification	Extracted Cognition Aspects: *(i) DML keywords; (ii) Number of DML keywords; (iii) Total relative distributions; (iv) Assigned DML for each task text*
		CSV file 1 (columns): "*Task ID*", "*Task description*"; <u>DML keywords and their number:</u> "*Routine Resources*", "*Number* ", "*Routine Techniques*", "*Number*", "*Routine Capacities*", "*Number*", "*Routine Choices*", "*Number*", "*Semi-cognitive Resources*", "*Number*", "*Semi-cognitive Techniques*", "*Number*", "*Semi-cognitive Capacities*", "*Number*", "*Semi-cognitive Choices*", "*Number*", "*Cognitive Resources*", "*Number*", "*Cognitive Techniques*", "*Number*", "*Cognitive Capacities*", "*Number*", "*Cognitive Choices*", "*Number*", "*Sum*", "*Total Routine*", "*Total Semi-cognitive*", "*Total Cognitive*"; <u>Total relative distributions:</u> "*Total Relative Routine*", "*Total Relative Semi-cognitive*", "*Total Relative Cognitive*"; <u>Assigned DML:</u> "*DML Level*"
		Motivating example (values): "*ID19384922*", "*applic migrat cmo fmo import mon activ new monitor fmo*"; <u>DML keywords and their number:</u> "*applic*", "1", "*activ, monitor*", "2", "*new*","1", "-", "0", "-", "0", "*migrat*", "1", "*important*", "1", "-", "0", "-","0", "-", "0", "-", "0", "-", "0", "6", "4", "2", "0"; <u>Total relative distributions:</u> "0.6666", "0.3333", "0"; <u>Assigned DML:</u> "*routine*"

[7] Check our Github project page Analyzing Content of Tasks in Business Process Management and the three repositories (Tasks-Structure-Cognition, Tasks-Importance, Tasks-Typology) with the developed vocabularies and source files, including a detailed README, Python code, and Excel *.csv

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

[9] should be developed in advance with SME semi-manually, using computational analysis with LDA as described in [80]. For illustrative example, see Appendix I.

3. Importance Aspect Extraction		
1. CSV file 2 with preprocessed task texts from step 1.2. 2. BS lexicon[10] 3. Threshold rules for DML levels defining Tools: Python, NLTK, MS Excel	Computational analysis: – identification of BS keywords and their valence, intensifiers; – calculation of the normalized total score; – Importance Level identification	Extracted Importance Aspects: *(i) BS keywords Score; (ii) BS keywords number; (iii) Total Scores; (iv) Normalized total Scores; (v) assigned Importance Level for each task text* CSV file 2 (columns): *"Task ID", "Task description";* BS keywords Score and Number: *"Task Positive Score", "Task Positive Number", "Task Neutral Score", "Task Neutral Number", "Task Negative Words", "Task Negative Score", "Task Negative Number", "ITIL Positive Score", "ITIL Positive Number", "ITIL Neutral Score", "ITIL Neutral Number", "ITIL Negative Words", "ITIL Negative Score", "ITIL Negative Number", "Expressions Positive Score", "Expressions Positive Number", "Expressions Neutral Score", "Expressions Neutral Number", "Expressions Negative Score", "Expressions Negative Number";* Total Scores*: "Total Positive", "Total Neutral", "Total Negative";* Normalized total Scores*: "Normalized Total Positive", "Normalized Total Neutral", "Normalized Total Negative";* Assigned Importance Level: *"Importance Level"* Motivating example (values): "*ID19384922*", "*Applic migrat CMO FMO !!! IMPORT !!! MON 01.09.2018 Activ new monitor FMO*"; BS keywords Score and number: "0", "0", "0", "0", "*MON 01.09.2018*", "-0.5", "1", "0", "0", "0", "0", "*import*", "-1.5", "1", "0", "0", "0","0", "0", "0"; Total Scores*:*""0", "0", "-2"; Normalized total Scores*:* "0", "0", "-1"; Importance Level: "*high*"
4. Typology Aspect Extraction		
1.CSV file 1 with preprocessed task texts from step 1.1. 2.Task typology taxonomy[11] 3.Principle of the maximum relative distribution Tools: Python, NLTK	Computational analysis: identification of Task Types and Subtypes	Extracted Typology Aspects*: (i) Task type keywords/expressions and their number; (ii) assigned Task Type for each task text*; *(iii) Subask type keywords/expressions and their number;* (*iii) assigned SubTask Type for each task text* CSV file 1 (columns): "*Task ID*", "*Task description*", Task Typology keywords and number: "*PSO Task Keywords*", "*PSO Task Keywords Number*", " *Implementation Task Keywords*", "*Implementation Task Keywords Number*", "*QA Task Keywords*", "*QA Task Keywords Number*", Assigned Task Type for each task text : "*Task Type*"; Subtask Typology keywords and Number: "*SubTask_N Keywords*", " *SubTask_N Keywords Number*",…; Assigned Subtask Type for each task text : "*Subtask Type"* Motivating example (values): "*ID19384922*", "*applic migrat cmo fmo import mon activ new monitor fmo*", Task Typology keywords and Number: "*applic* ", "1", "-", "0", "-", "0", Assigned Task Type for each task text : "*Implementation*"; Subtask Typology keywords and Number: "*migration, monitor*", "2", "-", "0",….., ", "-", "0"; Assigned Subtask Type for each task text: "*Migration*"
5. Identification and Mapping of HR and Skills to Tasks		
1. Process documentation, manuals, handbooks, interviews with SME 2. Task typology taxonomy	– Manual identification of HR and skills using available documents – Manual mapping of HR and skills to task types	Extracted knowledge: *(i) Task types mapped with HR and skills; (ii) skills for each task text* CSV file 1 (columns): "*Task ID*", "*Task description*", "*Task type*", "*Task subtype*", "*Skills*" Motivating example (values): "*ID19384922*", "*applic migrat cmo fmo import mon activ new monitor fmo*", "*implementation*", "*migration*", Skills*:* "*IT administration*"

[10] should be developed in advance with SME semi-manually, using computational analysis with LDA as described in [96]. For illustrative example, see Appendix II.
[11] should be developed in advance with SME semi-manually, using computational analysis with LDA to extract the most frequent task types (topics with descriptive keywords and expressions) followed by manual labeling and refinement of topics with SME. For illustrative example, see Appendix III.

Table 8. Distribution of task execution aspects

Aspect value	Distribution		
Structure and cognition (most frequent values)			
***R**esources (R)*			
Routine	*application 10%, server 9%, system 6%*		
Semi-cognitive	*team 30%, pso 26%, service 7%*		
Cognitive	*infrastructure 10%, management 9%, switch 9%*		
***T**echniques (T)*			
Routine	*install 31%, start 13%, stop 12%*		
Semi-cognitive	*check 36%, implement 13%, update 12%*		
Cognitive	*approve 54%, delegate 2%, freeze 1%*		
***C**apacities (C)*			
Routine	*new 30%, attached 11%, active 13%*		
Semi-cognitive	*affected 34%, main 11%, successful 10%*		
Cognitive	*expected 20%, relative 15%, possible 19%*		
***C**hoices (C)*			
Routine	*automatically 33%, accordingly 14%, correctly 9%*		
Semi-cognitive	*successfully 61%, urgently 2%, previously 26%*		
Cognitive	-		
Importance			
Standard	0.31%		
Elevated	99.07%		
High	0.62%		
Typology			
PSO	13%		
Implementation	51%		
QA	36%		
Cognition			
Routine	63.25%		
Semi-Cognitive	36.47%		
Cognitive	0.28%		
Cognition by Importance			
	Standard	Elevated	High
Routine	63.16%	63.48%	26.33%
Semi-Cognitive	36.84%	36.24%	73.67%
Cognitive	0.00%	0.28%	0.00%
Cognition by Typology			
	Implementation	PSO	QA
Routine	83.05%	31.27%	61.03%
Semi-Cognitive	16.11%	68.73%	38.97%
Cognitive	0.84%	0.00%	0.00%

Table 9 provides the obtained values of accuracy, precision, and recall calculated for every task execution aspect. The evaluation process consisted of three steps. First, we randomly selected 500 textual task descriptions from our dataset with the corresponding task execution aspects obtained using the method described above. Second, two experts independently labeled the selected tasks, i.e., assigned the aspect values to each task text. Afterward, the labels were compared, the cases of discrepancies discussed, and a joint decision taken. Third, using these expert labels, we calculated accuracy, precision, and recall for the task execution aspect values obtained based on our method. As the evaluation shows, the performance of our method to extract the task execution aspects is acceptable. We observe relatively low accuracy, precision, and recall in the *standard* and *high importance* aspect values and *PSO* task type, which can be explained by the dataset imbalance.

Table 9. Accuracy, precision, and recall of the task execution aspects

Aspect value	Accuracy	Precision	Recall
Structure and cognition			
Routine	0.755	0.556	0.689
Semi-cognitive	0.645	0.482	0.653
Cognitive	0.775	0.552	0.563
Averages	**0.725**	**0.530**	**0.635**
Importance			
Standard	0.422	0.365	0.400
Elevated	0.883	0.528	0.659
High	0.493	0.369	0.478
Averages	**0.599**	**0.421**	**0.512**
Typology			
PSO	0.711	0.222	0.349

Aspect value	Accuracy	Precision	Recall
Implementation	0.743	0.632	0.567
QA	0.777	0.599	0.519
Averages	**0.744**	**0.484**	**0.478**

In this perspective, we would like to emphasize that our prediction is based only on the textual data and is advisory. Moreover, with our approach, we aim to build transparent recommendations, meaning that the BP worker gets not only the recommendation, i.e., task *structure*, *cognition*, *importance*, and *typology* aspects, but also the information (those keywords) that led to the recommendation. Based on this, the BP worker is still able to make the right decision. Additionally, sophisticated ML classification pipelines report accuracy in a rather broad range from 30% to over 90% [100,101].

Nonetheless, in regards to further developing the method, exploring its potential, and discovering the lessons learned, it is necessary to conduct a more in-depth analysis of those factors influencing the misclassifications, finding the reasons, and developing ideas and rules on how to improve our approach.

Looking into the misclassifications of the *importance* aspect, we could identify that the most frequent misclassifications are related to (i) false *standard* value with true value *elevated* and (ii) false value *high* with true value *elevated*. We would like to highlight that, in both cases, these are "low weight" errors. In contrast, "high weight" errors would be false *standard* value with true value *high* and vice versa false *high* value with true value *standard*. Whereas in the *cognition* aspect, one main factor influences the prediction, i.e., threshold rules, in the *importance* aspect, there are (i) syntactic and semantic intensifiers (importance markers), (ii) corresponding scoring rules, and (iii) threshold rules. The number of factors increases the probability of wrong predictions, which we also could observe in our experiments. Let us consider the first factor – syntactic and semantic intensifiers. In the case of faulty *standard* values, we could note the necessity of a new semantic rule "Dates". In the tasks' texts, CHM process workers emphasize the deadlines and dates, which make an essential part of the ticket processing in general and task execution in particular. Hence, such a task as "grant admin rights to XXX implementer group on server farm YYY, please before Tue, 23:00/07/05/2019" is wrongly classified as of *standard* importance. With the new rule, "Dates" adding the -0.5 valence to the task text, this misclassification could be addressed. Next, according to another scoring rule regarding capitalizations, we added +/-0.5 to the capitalized keywords from the BS lexicon (depending on their positive or negative valence). To all other capitalized words, the valence -0.5 was added per default. However, very often, the names of the implementer groups, internal customers, or configuration items were capitalized for convenience. In general, in many cases, we could observe the misuse of capitalization due to the mentioned fact that the HP Service Manager did not provide typical text highlighting functions like bold, cursive, underline. Hence, such a task as "QA, check CUSTOMER_X on SERVER_Y access rights if granted" is wrongly classified as of *high* importance. In some cases, the CHM workers do capitalize the names to bring out their importance for the task implementers. Thus, we define a slight -0.1 valence for capitalized neutral BS keywords or words outside the BS lexicon in a new scoring ruleset. One more factor which influences the prediction quality is threshold rules. In Appendix II.3., we show the threshold rules used in the experiments to identify the *importance* aspect. As one can conclude, the ruleset of *high* importance is defined in a rather generic way, i.e., covering all the remaining cases not addressed in rules 1-7 of *low* and *elevated* importance. Experimenting with specifying the ruleset of *high* importance can potentially improve the classification results.

As shown in Table 9, the PSO task type of the *typology* aspect demonstrates relatively low prediction quality. In our approach, to identify the type of task (and subtask), we use the principle of the maximum relative distribution of specific task type CDK in the task description. For example, in the task "PSO master task, configuration control and reboot, PSO", the majority of identified keywords ("PSO, control, reboot, PSO") belongs to the PSO task type (80%). However, there is still the keyword "configuration" indicating implementation task type (20%). Hence, our consideration is to provide not only the major contributing task type and corresponding CDK but also all the task types identified in the text and their relative distribution as a prediction (recommendation) for BP workers. Moreover, while analyzing the PSO task type-related misclassifications, we could note that the PSO task is frequently present within the implementation tasks. In this case and in a general case of mixed type tasks, the suggested solution might improve the prediction.

Regarding the *cognition* aspect evaluation results, these show relatively high accuracy values. However, the recall values evidence a need for improvement. Here, we could also work on the fine-tuning of the threshold rules. As presented in Appendix I.2, we currently use six rules that cover all the cases. These rules could be specified in a more detailed way to increase the prediction quality. Alternatively, as decision support, one could demonstrate the relative percentual distributions of all the three possible *cognition* values, *routine*, *semi-cognitive*, and *cognitive*, identified in the task text, without aggregating them to the specific one.

6. Discussion

Following our research focus regarding the task content analysis, we developed the task content model consisting of task execution and task organization aspects and suggested its application method. Below, we discuss the methodological and practical contributions and highlight implications for research and practice.

6.1. Methodological Contributions

First, the major methodological contribution of the work is the *introduction of the method for measuring the content of tasks*. We demonstrated how theoretical foundations of situation awareness and various text analytics instruments could be successfully used to build task content models based on the textual task descriptions. As already noted, the Theory of Situation Awareness is widely researched and used in its original high-risk domains, like aircraft [69] or surgery [75], and also in business [77]. The SA is recently applied for classical task analysis, such as goal-directed task analysis [102]. Regarding textual data analysis for building SA, social media can be considered a well-researched domain [72,103,104]. [103] fairly states that there is difficulty identifying semantically relevant information in the deluge of data in social media and propose an interactive learning model in which the user iteratively corrects the relevance of the tweet. Such an approach works well in the social media contexts where the user is just searching for relevant information. However, it would create an extra workload for the BP workers performing tasks. Additionally, as stated by [18], NLP has matured significantly and, owing to a large number of publicly accessible frameworks, is widely used in many areas. In the context of BPM, NLP research shows unrealized potential and the ability to increase the value of BPM practices at various levels. For example, such challenges as (i) improving the performance of individual text analytics approaches, especially at the sematic level, (ii) domain adaptation methods to tune generic NLP techniques to deal with BP textual data in a particular organization or sector, and (iii) analyzing and defining tasks based on semantic information, such as the detection of exclusivity, concurrency, decision points, or iteration of tasks described in the text can be found in the application to BPM [18]. In our research, we aim to address these challenges at different levels.

Hence, we propose the task content model based on the domain-specific taxonomies and lexicons as pro-active decision support. Hereby, we also address two main unsolved issues in task analysis research indicated by [53]: (i) theoretical orientation, justifications, and underlying assumptions of the methods and concepts used and (ii) methodological and practical problems regarding collecting the necessary data and practical instruments and measurements for its analysis.

Furthermore, we *use a solid theoretical background of SAM to derive and show the strategic business value of the results* and address the third main issue highlighted by [53] how to present and draw conclusions from obtained results. We provide a task content analysis-based method for *aligning tasks, task performer characteristics, and IT technology*. Much research has been done on the strategic alignment of Business and IT [105]. While prevailingly generic strategic methods are discussed, we suggest the first task content-based approach to align *tasks, task performers,* and *IT* (see Figure 4) and specify the necessary data and text analytics instruments for its analysis. Below, we provide details on the suggested SAM application.

In the following, we adopt and modify the core concepts from [105]. Based on [81], we focus on two dominant strategy types: (1) *Strategy execution* – the identified business problem (in our context HR and skills) is solved by an adjustment of business approach through business strategy, e.g., relevant organizational design choices; (2) *Technology transformation* – the identified business problem is solved by an adjustment of business approach through IT technology design choices.

According to [105], the strategic alignment is reached by connecting three domain types: anchor domain (initiator of the change), pivot domain (directly affected by the change), and impacted domain (indirectly impacted by the change). In our case, textual task descriptions represent a source of information based on which the strategy is chosen. The strategic alignment occurs around the three core elements of a task – task itself, task performer, and IT technology necessary for the task execution. Using the extracted aspects, based on their semantic meaning and SA factors (see Figure 1), we propose the following measures of the SAM elements: (i) task and IT assessed based on the knowledge obtained from the *structure*, *cognition*, *importance*, and *typology* aspects, (ii) task performer – based on *HR* and *skills* aspects respectively. In our case, the tasks constitute an anchor domain.

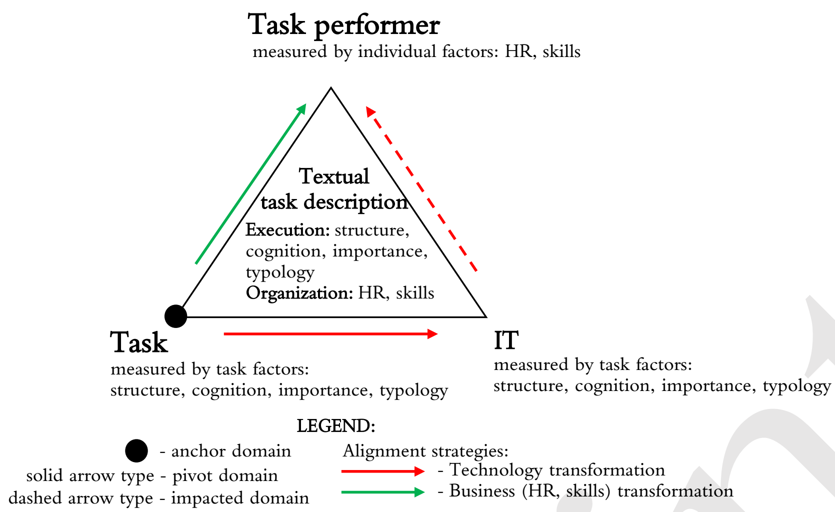

Figure 4. Strategic alignment of business and IT

We illustrate the proposed strategic alignment with an example. As a result of applying the method of measuring the content of tasks, the following problem was identified: an increasing number of migration task types (*typology*) on the ***Resource*** database (*structure*) was identified as a reason for high workload, overtime, and **delays in IT ticket processing**. This problem can be addressed by two types of strategies: (1) *Strategy execution*. One directly adjusts the business approach of IT ticket processing by increasing necessary HR and/ or developing necessary skills (task performers as pivot domain); (2) *Technology transformation*. One indirectly adjusts the business approach of IT ticket processing by changing the database concept in the company, for example, by introducing one holistic database solution to avoid constant data migrations (IT as pivot domain). Hereby, a new solution might need additional HR trainings (task performer as an impacted domain).

6.2. Practical Contributions

Unlike major studies on the Theory of SA and task analysis, we use the SA concepts for introducing the method for task analysis in the BPM context. This way, we address the need for research on analyzing unstructured textual task descriptions in BPM while considering task *execution* and *organization* perspectives.

One possible practical utilization of a task content model we would like to mention is a dashboard supporting the decision-making process and enabling a better understanding of the upcoming tasks' nature in the sense of the task *execution* aspects, i.e., *structure*, *cognition*, *importance*, and *typology*. See Figure 5 for the exemplary dashboard representation of the three tasks relating to the anonymized IT ticket example from Table 6.

In Figure 5, the bars represent separate tasks of the ticket. Y-axis reflects the *importance* aspect of the task as a whole with the indicated values of *standard*, *elevated*, and *high*. Hence, the higher the bar, the more important the task is. In the example, two tasks are of *standard* importance and one of *high*, demanding a higher level of attention. Different colors within the bar reflect the relative distribution of the cognition aspect values in the task. Green color identifies *routine*, yellow and red – *semi-cognitive* and *cognitive* values correspondingly. To ensure transparency and trust in the provided decision support, it is also suggested to include those keywords extracted from the task text leading to the proposed color distribution. For example, one can conclude that the most straightforward and simple task in the ticket is task 2. It contains only green color, i.e., one *routine* ***R****esource* "application" and two *routine* ***T****echniques* "stop" and "set up". On the x-axis, we can see the typology aspect (task type and subtype) assigned to each task (bar). For example, task 2 is of a PSO type and execution subtype. Such a dashboard can provide instant decision support to process workers who analyze, prioritize, and assign tasks.

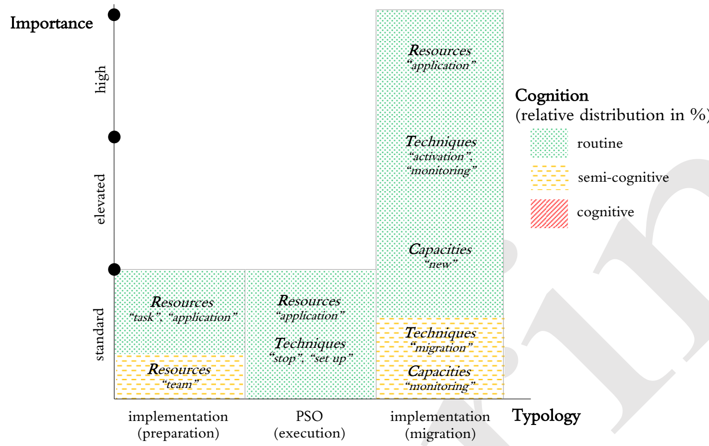

Figure 5. IT ticket tasks content model in the form of a dashboard

Furthermore, in our anonymized example, brief descriptions of tasks were selected. However, in total, the length of tasks could vary from 4 words up to 150. Hence, especially in the case of large volumes of long texts, our task content model in the form of a dashboard can support correct prioritization and execution planning.

Next, our method allows for obtaining aggregated values of the task *organization* and *execution* aspects for defined periods. This information reveals (i) most frequent ***R****esources*, ***T****echniques*, ***C****apacities*, and ***C****hoices* and their *cognition* level; (ii) distribution of the *importance* aspect; (iii) distribution of the *typology* aspect; (iv) qualitative deep dives into different aspects, such as distributions within *cognition* aspect in Table 8.

In our illustrative application on the dataset comprising five-month period January-May 2019 (see Table 8), the most frequently used routine ***R****esource* is "application" and semi-cognitive ***R****esource* – "infrastructure", routine ***T****echnique* – "install" and cognitive ***T****echnique* – "approve". In the *typology* aspect, the most frequent task type is implementation (51%), and the most frequent subtypes are "upgrade", "capacity". Such a high frequency can indicate a high workload of the capacity management team responsible for implementing the capacity upgrades. Very often, a high workload triggers motivation decrease and errors. Hence, using this information, managers can proactively interview the task performers and prove if the workload is adequate and, if it is not the case, search for possible solutions. The distribution values of the *importance* aspect can also indicate specific problems. For example, in our illustrative application, we have identified 99% of the tasks with "elevated" importance. This observation should be proven by the SME to clarify the reason: (i) a real demand on the elevated level of attention while performing those tasks, or (ii) an abusive usage of intensifiers while composing the tasks. The first one can be addressed by putting additional HR. The latter can be solved by establishing the rules of writing the tasks.

In the distribution of the *importance* aspect within the *cognition* aspect, we identified that there are 63.16% *routine* tasks with *standard* importance. This is a relatively high amount of tasks that are simple, repetitive, clearly described, and of low risk. For the department manager seeking to implement process automation, this information indicates potential tasks that can be easily automated.

Furthermore, the information regarding HR and skills mapped to the tasks can help better prepare for task execution and increase the performance (speed of execution). Managers can also use such information cumulatively, for example, to assess the work of a department for a certain period and to make strategic HR decisions, i.e., answer such questions as *"What HR/skills are the most or the least demanded in this quarter?"*, *"Are there any trends over 3-5 years in this context?"*, *"Which skills are mostly demanded?"*, *"Is there a need for HR trainings?"*. In Table 10 below, we summarize the contributions of our research.

Table 10. Summary of research contributions

Type of contribution	Contribution
Methodological and theoretical contributions	• Introducing the method for measuring the content of tasks based on domain-specific text analytics approaches and considering the semantic aspects, we address the challenges described by BPM researchers [18]. • Specifying the method in the sense of necessary data and instruments and measurements for its analysis, we address the methodological challenges mentioned by task analysis researchers [53]. • Building our research on the sound theoretical background of the Theory of Situation Awareness, we address the challenge of insufficient theoretical orientation and justifications of the methods and concepts used in the task analysis [53].
Practical contributions	• Our method enables the creation of the situation awareness for BP workers of such task execution aspects as *structure, cognition, importance,* and *typology* regarding the task at hand. • Based on such awareness, diverse decision support solutions can be designed, for example, the discussed tasks content model in the form of a dashboard (see Figure 5). • Using the values of task execution aspects aggregated for specific periods, managers can proactively assess the workload, stress level of BP workers, and lack of resources in their department. • The aggregated values of task organization aspects, i.e., *HR* and *skills* mapped to task types, enable managers to make better-informed HR planning decisions. • Our method serves as a basis and an instrument for the strategic alignment of business and IT technology decisions.

Finally, it is worth mentioning the overall efforts necessary for the method development and application. As explained in Section 5.2 and summarized in Table 7, we propose the five-step method for measuring the content of tasks. The preparatory work, such as data collection, its preprocessing, collection of relevant documentation like manuals, handbooks, guidelines, identification of experts, is a relatively fast step. The most time-consuming steps 2-4, including the development of various vocabularies with SME in a semi-manual way, can be performed concurrently, which will speed up the method development significantly. In our case, steps 2-4 were performed subsequently, as the method development evolved, and took approximately two months, each of the steps. However, such factors as the availability of experts and their readiness to invest the time, internal motivation, management support can either accelerate or hamper the process considerably. The efforts necessary for the last step 5, which is entirely manual, depend on (i) the documentation of tasks and skills existing in a department or organization and their formalization level, for example, using standard frameworks and (ii) the number of task types and subtypes in the application case department. In our setting, the CHM ticket processing was organized based on the widely used ITIL framework, i.e., we could rely on the existing documents and records containing task classifications and skills. The number of task types and subtypes was also tangible. Hence, in our case, step 5 took nearly one week.

7. Threats to Validity

Validity is an important issue when doing the research. Since this work includes empirical parts, we aim to discuss the several threats to validity and our tactics to address them in the best way. The term *threats to validity* comes from the software engineering domain and is defined as those factors that can limit the ability to interpret and draw conclusions from the study results [106]. Our use of the term *threats to validity* includes the level of rigor behind the approach we introduce and, hence, the suggested decision-making support solutions. Hereby, we refer to the four criteria for validity outlined by [107].

Construct validity reflects the problem of accordance between measured variables and intended meanings of the theoretical terms. To address this *validity*, we use sound definitions of the Theory of SA while developing the task content model and providing the method for measuring tasks' content and the SAM guidelines to present the strategic business value. When a definition could not be found, as in the case of task aspects and the respective suggested classification values, we extended and combined existing definitions and explicitly stated our definitions and explanations, supporting them with illustrative examples.

Internal validity is about the study design, especially if the results do follow from the data. To increase internal validity, we provided a comprehensive description of the data supporting it by anonymized examples. Additionally, we provided thorough information on the analysis of the data. In Section 5.3. Results, we discussed the experimental results and evaluation in detail, paying attention to misclassifications, reasons, and possible ways to address them.

External validity is concerned with the rationale of the results' generalizability. In this respect, our approach has certain constraints resulting in additional efforts of the different degree to adjust the approach while applying in different areas, in particular:

(i) The threshold rules of DML taxonomy and BS lexicon should be adjusted with the SME for each application case. Though we set a particular value on the explainability and transparency, we consider investigating the potential of using Machine Learning algorithms for task aspects' extraction, i.e., task content model building, as a possible alternative to a rule-based approach.

(ii) Current vocabularies of DML taxonomy, BS lexicon, and task typology taxonomy 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 remains widely used, having been ranked in the ten top-paying IT Certifications for 2020 based on the survey conducted in the United States [108]. Moreover, managing IT tickets, in general, remains a crucial concern for the IT service industry [91].

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

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

Reliability means whether the same results can be obtained when other researchers reproduce the approach. To address this criterion, we comprehensively described our method specifying inputs, processing, and outputs illustrated by the examples for each of the steps in Table 7 and extended the description with the references to Github repositories. Further, we consider the opportunity of cooperating with other researchers to apply our method in their (similar) settings, such as ITIL Incident Management of a different organization. Additionally, to draw attention to our method, we will examine the Graphical User Interface design possibilities of a dashboard to provide optimal decision support for process workers presented in Figure 5.

8. Conclusion

In the present paper, we closely studied the content of tasks to propose a task content model and method of its application, i.e., analysis of task content. We focused on both task execution and organization perspectives. We examined the tasks expressed in a textual form.

We introduced a set of task execution aspects, *structure, cognition, importance,* and *typology*, directly extracted from task textual descriptions. Task organization aspects HR and skills are to be mapped to the task execution aspects subsequently. We illustrated our research with an IT ticket processing application case from the ITIL CHM area. The main methodological contributions are the introduction of (i) task content model and method for measuring the content of tasks and (ii) task content-based approach of Business and IT alignment. As main practical contributions, we list the following: (i) instant task content analysis support for task performers and (ii) aggregated values of the task execution and organization aspects for defined periods.

Finally, we discussed the threats to validity of our approach, including theoretical construct validity, the internal validity of the study design, external validity in the context of generalizability, and reliability in respect to reproducibility.

Appendix I. Taxonomy of Decision-Making Logic Levels. Following [80], we consider diverse semantic concepts: ***R****esources*, ***T****echniques*, ***C****apacities*, and ***C****hoices*, elements of the RTCC framework. We designed contextual variables [109], based on which experts categorized words into one of the three DML levels and one of the four semantic concepts.

Appendix I contains **Appendix I.1**. Taxonomy of Decision-Making Logic
Appendix I.2. Threshold rules of the cognition aspect
Appendix I.3. Examples of anonymized tasks related to the cognition aspect and Decision-Making Logic.

Appendix I.1. Taxonomy of Decision-Making Logic

CONTEXTUAL VARIABLES	TASK DECISION-MAKING LOGIC		
	routine	*semi-cognitive*	*cognitive*
	CONCEPTUAL ASPECTS		
	RESOURCES		
Problem Processing Level	user, user request, test, target, release, contact role, interface, tool, client, file system, node, jboss, script, installation, connection, log, admin, point, todo, worker, image, logon, login, tab, console, ip, nonprod	team, leader, project, colleague, property, process, coordinator, segment, duration, procedure, pilot, infrastructure, vlan, wlan, lan, internet, cluster, maintenance	management, CAB, measure, approval, incident, violation
Accuracy	time, application, app, product, configuration, item, configuration item, CI, instance, machine, minute, hour, day, week, detail, description	environment, requirement, validity, reason, solution, method, problem, rule, modification, reorganization, reorganisation	
Situation Awareness	name, password, group, directory, number, email, package, phone, ID, IP, attachment, mode, execution, replacement, backout	request for change, RfC, customer, rollout, quality	server farm, farm
Information	server, file, location, dataset, network, data, patch, port, information, info, type, root, certificate, account, device, cable, parameter, agent, folder, disk, fallback, backup, version, firewall, system, hotfix, supervisor, reference, instruction, format, status	requestor, software, downtime, pso, outage, shutdown, production, prod, power-supply, service, case, database, db	risk, freeze, impact
	TECHNIQUES		
Experience	need, see, document, monitor(ing), use, follow, note, provide, test, contain, accompany, inform, consist, describe, batch, connect, work, control, replace, create, exit, fill, mark	implement(ation), support, require, classify, plan, affect, relink, help	approve, delegate, propose
Action Choice	start, startup, finish, import, export, run, stop, step, end, put, send, switch, install, reject, update, upgrade, include, replace, remove, move, begin, make, get, migrate, open, initialize, revoke	deploy(ment), migrate, process, modify, forget, increase, miss	freeze, block
Effort	cancel, rundown, decommission, restart, delete, set, add, activate, reboot, specify, agree, mount, execute, transfer, write, find	perform, modify, assign, sign, check, need, expect, verify	define
	CAPACITIES		
Specificity	additional, preapproved, initial, attached, internal, external, reachable, regular, active, scheduled, next, whole, formal, virtual, wrong, individual, administrative, local, right	secure, separate, specific, affected, technical, urgent, corrected, minor, normal, international	related, multiple, multi-solution, major, high, small, big
Decisions Formulation	new, old, preinstalled, fixed, ready, following, current, valid, primary, necessary, first, second	available, necessary, important, significant, successful, appropriate, relevant, main, further	possible, many, desired, different, various
Predictability	actual, full, online, standard, responsible, existing, minimum, same, visible	strong, temporary, offline, previous, last, other, more, much, similar, standard	random, strong randomized, encrypted, expected
	CHOICES		
Precision	automatically, instead, manually, there, where, here, separately, additionally, internally	normally, newly, shortly, urgently, temporarily	maybe, randomly, likely
Scale	permanently, currently, still, now, often, never, already, just, always, yet, anymore, firstly, secondly, before, together, daily, meanwhile, really, furthermore, afterwards	again, later, however, usually, previously, recently	soon

Ambiguity	correctly, therefore, accordingly, actually, consequently, completely, simultaneously, anyway, necessarily	well, enough, immediately, easily, simply	approximately, properly

Appendix I.2. Threshold rules of the cognition aspect [99]

#	**Decision-Making Logic Taxonomy routine, semi-cognitive, cognitive**			**cognition**
1	rout=0	semi-cog=0	cog=1	*cognitive*
2	0≤rout<0.34	0≤semi-cog<0.5	cog≥0.34	*cognitive*
3	(rout=1) & (rout=0)	semi-cog=0	cog=0	*routine*
4	rout≥0.5	(semi-cog+cog) ≤0.34		*routine*
5	rout=0	semi-cog=1	cog=0	*semi-cognitive*
6	rout=0	semi-cog=0	cog≥0.34	*semi-cognitive*

Appendix I.3. Examples of anonymized tasks related to the cognition aspect and Decision-Making Logic

routine	***semi-cognitive***	***cognitive***
restart of databases ZZZ	check if requirements are fulfilled: SAP R/3 system is enabled and routing via ZZZ is set. Monitor the system in CMO	IT-Serverfarm DBaaS DX defective hardware repair, logon to AAPSS set file/location/DB start/DB stop
stop task, stop SAP webserver	QA, check functionality together with vendor and customer	build-up MS serverfarm, installation, configuration modification, packages and manuals will be provided either by developers or directly by MS support team
please deliver hostnames to the IP ranges (see attached excel files)	responsible system admin - set EXTRA network routes to the backup environment, i.e. parallel net routes to old AND new environment are necessary for migration - modify hosts according to local prerequisites, further information: managed backup documentation index chapter 8 backup client installation, location matrix	hardening of servers XXX, see external documentation for background information, please agree with the customer X for critical security deviations, change manager has to document the approval/disapproval
start application XXX and block users	change of security certificates of external partners, support for external partners	downtime task, approve downtime for 5 h, with 1 h for backout
install the software packages on the following servers as user "xxx_admin" by using the script "yyy_run": z1, z2, z3, z4	modification of SAP HANA FGNV, modify according to change description	IT-Serverfarm DBaaS DX complete shutdown of location XXX for performing major change
stop monitoring web application XXX	support task for MSS team during rollback	Serverfarm installation expert release XXX, please accompany the change and possibly intervene and block CAB
installation of hotfix ZZZ	offline task - migration of LDOMs FFF566, FFF789 from FFF678 back to original asset FFF874	QS task, shared OS4 production, reorganization of firewall infrastructure
preparation task for installation team YYY	implementation --> modify mountpoints, reconfigure filesystem mountpoints . The following servers are affected: XXX, YYY, ZZZ. Please change the mountpoints as follows: Configuration is also shown in attached file.	standby support in case of system incidents on external servers MS, verify there's no alerts in the monitoring system FFF567 Wednesday 19:00-24:00 xx/xx/xxxx FFF568 Thursday 19:00-24:00 xx/xx/xxxx FFF569 Friday 19:00-24:00 xx/xx/xxxx
create admin accounts in XYZ platform for users xxx1@example.com, xxx2@example.com	IMPLEMENTATION TASK, please implement the Change as described in the description.	reconfiguration and reorganization of servers XXX in serverfarm location YYY
preparation task, preparation task for new service conditions import	update Linux name service, more info in the change, please communicate via telcos	installation serverfarm Z, check no user is connected, set all affected servers in maintenance, possibly reboot datacollector, ensure all personal configurations on all devices, reboot servers, all servers should be likely connected
disabling MS Office agent monitoring on old MS servers before decommission	automatic update of MS Office agent. Pay attention!!! all affected systems have to be marked in tab configuration item in the main change	CAB change after multiple software installations on network-LAN-switches, triggered by compliance-violations, QS
please install the following hotfixes on HHH production environment: 111_222_333, 444_555_666, online installation	migrate data from production database XXX to test environment database YYY. 1. Copy the database schemas SCH_1 and SCH_2 in XXX to SCH_1_test and SCH_2_test,	encryption, QS-Task !!! IMPORTANT !!! check whether connection is enrypted or not

	modify database jobs on the production database XXX	
stop database instances as needed and requested from SAP R/3 team because of test	please plan migration on production servers: XXX, YYY, ZZZ	QS task, shutdown task, shutdown of all physical servers on XXX location and QS
please create following accounts in the database SAP HANA and grant the roles basic_user for: xxx1@example.com, xxx2@example.com, inform users about their password via email message.	switch from XXX, YYY to XXX1, YYY1, start monitoring, destination servers for instances: 111.222.333, 444.555.666, 777.888.999	block multiple LINUX virtual machines, task by responsible OS team. Define the risk of implementation by checking affected VMs, see change description.
start task, start application server YYY	rebalance application processes between XXX and YYY	Extend customer XXX migration maintenance window 23:00-06:30 AM xx/xx/xxxx - xx/xx/xxxx . !!! IMPORTANT !!! Major change, do not approved for change freeze periods

Appendix II. Business Sentiment Lexicon with assigned valences. As the BS Lexicon development data, two sources were used: 1) corpus, i.e., contextual ticket texts, and 2) CHM descriptions from the ITIL handbook. The following five steps were included in the concept development: 1) we performed standard sentiment analysis with VADER [99] on the application case text corpus. VADER approach (lexicon/ thesaurus-based) was selected due to its general-purpose robustness and popularity as a gold standard list of lexical features, along with their associated sentiment intensity (valence); 2) based on the valence distribution for each ticket text entry in the corpus, keywords with semantic load (negative and positive) were identified; 3) in parallel, we extracted main topics with descriptive keywords CHM descriptions from the ITIL handbook while performing unsupervised LDA analysis; 4) using the keywords from step 2) and 3), the final list was created. The process was supported by the method of expert guesses and a web conference interview with the SME; 5) afterward, considering the logic of VADER and business context, the researchers established a set of semantic and syntactic rules for BS analysis.

Appendix II contains **Appendix II.1.** Business Sentiment lexicon with assigned valences
Appendix II.2. Comparative scoring, semantic, and syntactic rules of VADER and Business Sentiment lexicon
Appendix II.3. Threshold rules of the importance aspect
Appendix II.4. Examples of anonymized tasks related to the importance aspect and Business Sentiment.

Appendix II.1. Business Sentiment lexicon

Tickets/ Tasks	ITIL	Valence
Expressions		
no risk, no outage		+2
be so kind, would be nice		0.5
disaster recovery, set alarms warnings, poison attack vulnerability, critical security leaks, fan, outstanding windows updates, thank you, kind regards, would like, best regards	request for change, RfC	0
big measure	projected service outage, change advisory board, high impact, major change	-0.5
Single keywords		
kind, success, correct, like, nice	well, successful, happy	0.5
disaster, recovery, affected, stop, disable, dump, alarm, warning, poison, attack, vulnerability, error, prevent, drop, cancel, delete, exclude, problem, problems, faulty, failed, destroy, defective, obsolete, lack, security, leak, crash, please, support, optimize, grant, privilege, create, dear, acceptance, clarity, restore, increase, danger, balance, right, deny, wrong, retire, missing, weak, invalid, see, follow, yes, allow, approve, approval, confirm	problem, failed, information, operational, identify, order, include, adequately, procedure, necessary, assess, criteria, clear, provide, potentially, identification, adequate, initiate, value, KPI, standard, schedule, align, properly, release, accurate, report, organization, continuous, ensure, service, beneficial, stakeholder, requirement, correct, record, essential, clearly, RfC, support, tool, relevant, attempt, subsequently, configuration, different, follow, directly, CI, potential, request, individual, plan, work, evaluate, author, organizational, manage, number, financial, status, low, chronological, recommend, responsible, model, accountable, handle, timescale, business, normal, submit, update, create, manual, consider, backout, accept, item, project, deliver, formal, data, iterative, produce, local, describe, test, improve, result, deployment, deploy, technical, management, repeatable, determine, minimum, develop, appropriate, activate, implement, require, process, evaluation, customer, contractual, authorize, share, acceptable	0
blocked, critical	cost, PSO, CAB, important, unauthorized, major, significant, undesirable, incomplete, delegate, avoid, coordinate, immediately, significantly	-0.5
offline, risk, outage, emergency, downtime	impact, risk, emergency, incident, outage, downtime	-1
rejected	unacceptable, freeze	-2

Appendix II.2. Comparative scoring, semantic, and syntactic rules of VADER and Business Sentiment lexicon

Valence rules	**VADER** [99]	**BS**
Scoring rules	[-4; +4]	[-2; +2]
Semantic rules		
Typical business ethics words (e.g., “please”, “dear”, “thank you”)	strongly positive	decreased to 0
Words denoting complex IT problem solving (e.g., "incident", "emergency", "downtime")	strongly negative	slightly increased to -0.5/-1
Typical daily work of IT ticket domain words (e.g., "problem", "failed", "adequate")	positive/ negative	categorized as neutral with 0 valence as they belong to daily work
Typical positive words (e.g., "well", "successful", "happy")	strongly positive	slightly decreased to +0.5
Syntactic rules (intensifiers)		
Capitalizations in the positive and negative lexicon keywords	additional +0.733/-0.74	additional +/- 0.5
Capitalizations in the neutral lexicon keywords and the words outside the lexicon	-	-0.1
Dates	-	-0.5
"!", "*", "=", "-", "#" in the positive and negative lexicon keywords	-	additional +/- 0.5
"!", "*", "=", "-", "#" in the neutral lexicon	-	-0.1

keywords and the words outside the lexicon		
Negation	regular negation words	"no", "not"

Appendix II.3. Threshold rules of the importance aspect [96]

#	*Compound Valence positive (pos), neutral (neut), negative (neg)*			*importance*
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	*elevated*
6	pos>0	neut>0	neg=0	*elevated*
7	pos≥0	neut≥0	0<abs(neg)<0.1	*elevated*
else				
8	-			*high*

Appendix II.4. Examples of anonymized tasks related to the importance aspect and Business Sentiment

standard	***elevated***	***high***
stop application	implementation task !!! In the event of an incident, LAN cable has to be plugged back !!!	****CRITICAL CUSTOMER INSTALLATION**** Installation SAP R/3 Don't change the shell! Login as user sdfkjs on each server: xxx/yyy/zzz
start application / database	LAN team - implementation task - standby support during migration!!!	HIGH IMPACT CHANGE!!!! Shutdown server farms XXX YYY, coordinate over central office
execution task, implementation of updates by vendor XXX	QA task !!!! quality assurance check !!!! Describe activities that have been performed: - system is running, - accesses are working, - application is OK, - test was successful.......	New data import, follow the db schema XXX YYY ZZZ, unlimited size and quota. NOTE!!! Contact example@example.com for information about RISK and see attachment AAA
add the route entry for the following YYY servers: YYY1, YYY2, YYY3, YYY4, YYY5	execution task, according to change description ************shutdown of the old connection to ZZZ server, startup and, if necessary, configuration of the new connection, adjustment of the routing if necessary ************	IT Serverfarm SAP HANA, importing sensitive bank data. MAX. RISK !!! Will be executed by XXX from SAP and YYY from IBM.
grant access rights to PROD server ZZZ for implementation group CCC	installing latest PSU patch to !!! ALL !!! SAP R/3 databases, stop all SAP R/3 databases, install latest patch SET UPDATE 11.1.1.2.22222, start all SAP R/3 databases	execution task, !!! EMERGENCY !!! change, routing fault, calls hang too long in the queue of a customer service, incorrect display of the waiting time. Control the waiting time, check for errors
QA task – ongoing check after each implementation step on each device, check behavior and connectivity	installation of latest security Windows updates on servers. ==== After installing Microsoft update reboot of servers is NEEDED ====. After reboot healthcheck will be done of servers. -----> Servers names S1, S2, S3, S4	QA monitoring feedback BPM Incidents QA NOT successful: ***** Information to BPM: PAC File corrupted QA NOT successful: ***** Fallback ==> Reuse of old PAC file !!!!
Stap task, stop XXX	4 eyes principle task, MINIMIZE ELIMINATE human error	iOS INCIDENT WITH EXCHANGE SERVERS XXX YYY ZZZ, verify and document the alerts in the monitoring system !!!
QA task, check event log data for error messages after change is implemented	ERP EU team - 4EP extended control task, *** *** ************** ASSIGNMENT *** *** ************** 1) in case of XXX server team1, 2) YYY team2, 3) ZZZ team3**********	Implemetation offline, plan service outage from Saturday tttt/dd/mm/yyyy to Monday tttt/dd/mm/yyyy -----> COORDINATE OUTAGE with YYY team
4EP – SAP R/3 update and windows update	SUPPORT IF PROBLEM DURING UPDATE	For change XYZ NOTE AGREED DOWNTIME Friday tttt/dd/mm/yyyy to Monday tttt/dd/mm/yyyy, communicate to implementation team XXX!!
PSO task for application XXX, reorganization of firewall infrastructure	configuration task: please install the hotfixes on XXX production environment: YYY, ZZZ, HHH, XXX MUST NOT BE RUNNING during the fix installation, expected time up to five hours !!! NOTE pre and post installation tasks	CUSTOMER SERVICE OUTAGE, support task, disconnect faulty server XXX, activate backup server YYY

standard	*elevated*	*high*
QA, quality check: - check whether MS Office upgrades have been successfully installed -check if servers have been successfully restarted -check if the appropriate services are running.	provision new vDisk on MS provisioningserver XXX !!! no PSO as no active user on farm !!! - copy ZZZ file from YYY, - SET and VERIFY parameter for the vDisk, - check replication status for the new vDisk, - set ALL worker server for farm BBB to maintenance, - shutdown all workerserver for BBB	PLEASE REJECT !!! /Install netbackup-client module in SAP HANA
QA, test of the moved components for accessibility	downtime: DOWNTIME TASK, TASK for the planned downtime of a change controlled by coordination colleagues	PLEASE REJECT !!! / Set additional net routes to Backup Oracle environment XXX
4EP,update FUUG_123 deployment schedule	Patch GRID infrastructure and TEST STANDBY databases	!!!!UPDATE RECOVERY POLICY!!!! FREEZE the cluster XXX to prevent from switching between the nodes during the implementation
after successful QA, set application AAA online	please verify that XX tasks have been done in the change !!!BEFORE you start updating the database XXX, YYY. If not, contact the coordinator. Otherwise do not proceed with your Change Task!	approve task, IMPORTANT !!! additional approval needed for CHANGE FREEZE PERIODS for XYZ unit changes
4EP task for planning backout method, change runs fully automatically, the task is used as a backup in case of an error and for any manual actions needed	ERP EU team - restart servers after updates, ** ASSIGNMENT ** 1) in case of XXX server team1, 2) YYY team2, 3) ZZZ team3**********	UNACCEPTABLE SECURITY LEVELS, adjust PROXIES on XXX

Appendix III. Task typology taxonomy.

Appendix III contains **Appendix III.1.** Task typology taxonomy
Appendix III.2. Examples of anonymized tasks related to task types.

Appendix III.1. Task typology taxonomy

Generic keywords of task type Projected Service Outage (PSO)	
offline, index, mode, downtime, page, tool, session, pso, outage, shutdown	
Specific keywords and expressions of task subtypes	
planning	plan, assign, process, projected, coordinator service, time, status, duration, worker, replication, available, provision, needed, virtual, active, whole, affected
execution	pso, add, restricted, enabled, faulty, partial, standby, proxies, parameter, webserver, perform, replacement, restrict, bugfix, enabling, flash, execution, rebuild
check	check, analyze, checkup, review, control, reboot, set, copy, agree
Generic keywords of task type Implementation	
application, team, server, production, environment, user, requirements, service, script, database, delete	
Specific keywords and expressions of task subtypes	
preparation	preparation, prepare, preparatory, ready, organize, arrange, arrangement, orderly, efficient, coordinate, coordination, systematically, systemize
configuration	configuration, configure, deconfiguration, reconfigure, arrange, setup, design, restore, items, backup, deployment, routing, disconfigure, service agents, customer configurator, config file, monthly report, table, cluster
installation	install, installation, reinstall, reinstallation, deinstall, deinstallation, post-installation, deploy, new, latest, instance, version, package, backend, hotfix, given fixes, install script
update	update, existing, field, cumulative, schedule, automatic, host, properties, licenses, sequences
upgrade	upgrade, certificate, OS, java, oracle, android, asset manager, marketplace, firmware, patchset
capacity	capacity, capacity management, load, measure, measurement, filesystem capacity, capacity procedure, separate
integration	integration, server integration services, integration update, integration procedure, data integration, software integration, integration check, integration installation, integrationserver, bus, fixpack
incident/ problem	incident, OS incident support, trouble, incident handling, test incident, OS problem support, performance problems, onsite problems, database problem ticket, memory problems, problem handling
release	release, rollout, notes, software release, OS release, installation release, implementation release, update release, deployment release
service delivery	delivery, request delivery db-instances, easy, installation delivery, delivery production environment, delivery ticket, delivery database objects, delivery name, available, delivery package, provisioning, delivery tables, manual file delivery, new application version delivery
support	support, assist, on duty support, standby support, support team, support web site, offer support, early life support, fulltime support, onsite support task, necessity
migration	migration, transfer, import, monitoring, export, relocate, boxer, CMO, FMO, firewall cluster, migration baremetal, internet firewall migration, public IP addresses, migration back original asset, online vm migration, migration preparation, boxer migration, installation-migration, data migration, customer migration, storage migration, new temporarily storage, database migration
decommission	decommission, disable, disabling, remove, removing, removal, old, software decommission, database decommission
Generic keywords of task type Quality Assurance (QA)	
4 eyes principle, 4EP, four eyes principle, health check, software monitoring, test	
Specific keywords and expressions of task subtypes	
4EP	4EP, 4 eyes principle, four eyes principle
backup & health check	health check, backup
software monitoring	software, monitoring
update test	update test

Appendix III.2. Examples of anonymized tasks related to task types

Task type	***Task example***
PSO	
planning	PSO task, PSO task - Projected Service Outage, please assign to change coordinator group XXX and plan from tttt/dd/mm/yyyy to tttt1/dd1/mm1/yyyy1
execution	PSO: stop applications XXX, YYY, ZZZ
check	PSO: check within console MS_EXCHANGE_Server current security settings/ POP and IMAP
Implementation	
preparation	preparatory work for user XXX, assign the user to server farm Y, block farm Z, and delete user group WWW from farm Y, get ready user account
configuration	undeploy old unused processes, restore previous configuration of central functioning systems XXX
installation	install the correct backuptool client version YYY according to the location matrix on the client ZZZ
update	update Java version to the newest version
upgrade	implementation task, Linux and MS environments upgrade on frontend server
capacity	capacity enhancement database XXX, increase slices from 40 to 200

Task type	*Task example*
integration	iOS client integration, update integration bus to the newer fixpack 111.1 to become compatible to SAP database v.111.2
incident/ problem	adjusting monitoring system, quality assurance task, check alarms in dashboard, check Jira for incidents
release	ONLINE: Google Slovakia Release, 1) Install all packages following the path zzz/zzz/zzz/zzz/zzz/zzz 2) run db-scripts in this order: yyy/yyy/yyy/yyy/yyy/yyy
service delivery	request for delivery of db-instances for SAP R/3 environment
support	support task, please provide assistance backup test on TTT databases
migration	implementation: migration BIB-->FBIB, begin migration mapping
decommission	decommission of old MS instances xxx/xxx/xxx, yyy/yyy/yyy, zzz/zzz/zzz
QA	
4 eyes principle (4EP)	4EP task (QA), it is obligatory to document 4EP by a 4EP control task. Please confirm your status as a 4EP counterpart
health check	iOS health check for VM XXX, YYY, ZZZ in the central functioning unit after reinstallation
software monitoring	special monitoring from production server farm XXX on the first workday after YYY decommission
test	test the routing table after iOS updates, perform ping test for CMO and FMO gateway addresses

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